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Operationalizing intersectional vulnerability in climate risk assessments: A mixed methods approach for representing within-country differences

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Abstract

Climate risk is unevenly distributed across society, shaped by intersecting social, economic, and environmental factors. This paper presents a mixed methods approach to analyzing these patterns, recognizing vulnerability as a key element of climate risk. By adopting an intersectional perspective, we acknowledge its emergence from the dynamic interaction of multiple factors, producing differentiated burdens. Applied in the context of heat risk in Austria, we develop qualitative vulnerability profiles based on a literature review, a stakeholder workshop, and semi-structured interviews. These inform quantitative clustering, which integrates socioeconomic indicators (e.g., age, income, employment type) with heatwave exposure on a 1km resolution. By aligning the qualitative profiles with the quantitative clusters, we identify five distinct storylines that illustrate dominant heat risk patterns now and in the future for different combinations of climate and socio-economic change. Examples include blue-collar workers in urban low-income neighborhoods, or elderly individuals whose vulnerability is compounded by low financial coping capacities – both experiencing high relative heat exposure. Projections show that heat risk will increase significantly among all storylines, with annual heatwave days increasing by up to two thirds by 2080, while demographic trends raise exposure and socioeconomic inequality increases vulnerability. The presented methodology enables a nuanced understanding of within-country variation in climate risk, bridging quantitative generalization and context-specific qualitative insight, filling a critical research gap. The resulting storylines can support the development of effective and equitable adaptation strategies.

Keywords

Intersectional vulnerability, heat risk, Austria, mixed methods, climate risk assessment, risk storylines, clustering

Acknowledgements

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1. Introduction

Climate risk is not experienced equally across individuals, but is shaped by a complex interplay of social, economic and environmental factors (Hajat et al., 2010; IPCC, 2022b; Winsemius et al., 2018). Social vulnerability is central to understanding these disparities, as it determines the capacity of individuals and certain groups of society to anticipate, cope with or recover from climate impacts (Füssel, 2012; Otto et al., 2017). As a key component of climate risk (IPCC, 2022), vulnerability is shaped by multiple factors such as age, health or socioeconomic status, which do not act in isolation but often interact in compounding ways (Cutter et al., 2003). Despite broad recognition of this complexity in both scientific and political discourses (e.g. Austria: BMSGPK, 2021), it remains insufficiently integrated into country-level risk assessments. As a result, emergency planning and adaptation policy rely on simplified models that focus on hazard and exposure (e.g., flood and land use1) or on one-dimensional vulnerability indicators (e.g., heat and age2), overlooking how social dynamics shape risk and its justice implications.

Recognizing these gaps, the identification and prioritization of vulnerable groups has become the dominant imperative of justice discourses in climate and disaster risk governance (Breil et al., 2021; Kehler & Birchall, 2021; Swanson, 2021). This spans from the consideration of who is particularly vulnerable (recognitional justice) and who to involve in decision-making processes and how to involve them (procedural justice), to understanding the distributive effects of policies (distributive justice) (Hanger-Kopp et al., 2024; Walker et al., 2024). However, effectively addressing the needs of those most marginalized or least able to cope with climate impacts requires the development of methodologies that capture the complexity and heterogeneity of vulnerability both now (Rufat et al., 2015; Yu et al., 2021) and in the future (Jurgilevich et al., 2017; Prall et al., 2023).

The multidimensional nature of vulnerability to climate change has become a well- studied concept in the social sciences (Thomas et al., 2019), with growing recognition that socioeconomic and demographic aspects intersect to create compounded levels of vulnerability that exceed the mere sum of their parts (Birkmann et al., 2022). Although much of the vulnerability literature has focused on low- to middle-income country contexts (e.g., Donatti et al., 2019; Duvat et al., 2017) or cross-country comparisons (e.g., Chambers, 2020), impacts of the 2003 European heatwave (Robine et al., 2012), or Hurricane Katrina (Elliott & Pais, 2006), underscore that differential vulnerability is also a critical determinant of climate risk in high-income countries.

This paper defines social vulnerability as "the propensity or predisposition to be adversely affected" within groups that share similar characteristics, encompassing the "sensitivity, susceptibility to harm and lack of capacity to cope and adapt" (IPCC, 2022a, p. 2927). Adopting what Kuran et al. (2020, p. 2) describe as an "intersectional perspective" allows us to "uncover qualitative differences in vulnerability", enabling an analysis of how societal structures shape the experience of climate impacts (Kaijser & Kronsell, 2014) and how compounded vulnerability can create additional burdens (Versey, 2021). Originally introduced to describe structural marginalization at the intersection of sexism and racism (Crenshaw, 1989), intersectionality is now increasingly applied in climate risk research, to examine how social dynamics – approximated through social and demographic indicators - shape and compound vulnerability (Amorim-Maia et al., 2022; Vickery, 2018; Walker et al., 2021). This perspective highlights that vulnerability is not an inherent trait of people but rather a consequence of structural conditions and political processes

[1] HORA - Natural Hazard Overview & Risk Assessment Austria, last access: 04.07.2025
[2] HitzeCheck: Gesundheit & Lebensraum, last access: 04.07.2025

(Weatherill, 2025). While intersectional vulnerability has been widely explored in qualitative and conceptual studies, its application in quantitative research remains limited, as complexity is often lost in aggregation processes (Tate et al., 2025).

Storylines offer a structured way to understanding a situation or conditional future (IPCC, 2021), linking physical and human elements (Shepherd et al., 2018). Next to the development of physical climate storylines (van den Hurk et al., 2023), the approach is also useful for analyzing social vulnerability (De Ruiter & Van Loon, 2022). Specifically, for developing heat risk storylines with a particular emphasis on intersectional social vulnerability, we build on the field of archetype analysis, aiming to "achieve a balance between abstract explanations and providing contextually explicit guidance to policymakers" (Eisenack et al., 2019, p.24). As a methodology increasingly used to examine society-environment interactions (Oberlack et al., 2019; Sietz et al., 2019), applications of archetype analysis span diverse contexts (Levers et al., 2018; Riach et al., 2023; Sietz et al., 2017; Thorn et al., 2021), including recent work on differential flood risk across the US (Tate et al., 2025) and variations in vulnerability across farm-household systems (Nazari Nooghabi et al., 2020; Segnon et al., 2021; Vidal Merino et al., 2019).

Shifting the focus from broad regional or household-level vulnerability patterns to individual-level determinants, this study contributes to this growing body of literature and advances a more granular assessment of climate risk. We develop a mixed-methods approach that combines qualitative analysis cluster analysis to explore how demographic, social, economic and environmental factors interact to shape heat risk in Austria. Rather than measuring absolute levels of risk, we focus on unveiling relative differences within the population, allowing for a more nuanced representation of vulnerability that accommodates heterogeneous data sources (Rufat, 2013). Thereby, we operationalize intersectional vulnerability in climate risk assessments, complementing traditional indices and rankings that insufficiently capture compounding interactions that shape differential risk (Cronley, 2022; Rufat et al., 2015; Tate et al., 2025).

This paper makes two key contributions. First, it introduces a novel methodological approach that integrates qualitative and quantitative information on climate risk, offering a transferable framework for identifying vulnerable groups now and in the future through an intersectional perspective across different regional contexts and climate impacts. Second, the results presented in this paper demonstrate the relevance of our approach in providing actionable insights into differentiated risk patterns. This directly supports current needs in Austria, where exacerbating heat stress poses growing threats to health and wellbeing (APCC, 2018), and where the updated national adaptation strategy calls for more granular information on how different groups will be affected by climate change to inform the design of effective and targeted adaptation policies (BMK, 2024a).

2. Methodology

We develop a mixed methods approach, integrating qualitative data from literature, a stakeholder workshop, and semi-structured interviews with a statistical analysis of georeferenced microdata, to characterize heat risk storylines across the Austrian population. Figure 1 summarizes the approach and gives an overview of the structure of the sections of this paper.

Qualitative data (2.2.1) captures lived experiences and complex patterns of social vulnerability to heat stress. Quantitative data (2.1.2) provides a granular view of heat exposure and socioeconomic variables with projections until 2080 available from climate and socioeconomic scenarios (2.1.3). Based on the quantitative data we use a clustering method (2.3) to identify inherent patterns characterizing heat risk across the Austrian population, to quantitatively substantiate the qualitative vulnerability profiles (2.2) and uncover additional patterns shaping vulnerability. Given that the quantitative results from the clustering detect patterns, but do not allow to specify the underlying level of risk, we develop heat risk storylines via a close alignment of vulnerability profiles and quantitative clusters (2.4). In a final step, we project future risk, accounting for climate, demographic and socioeconomic change (2.5).

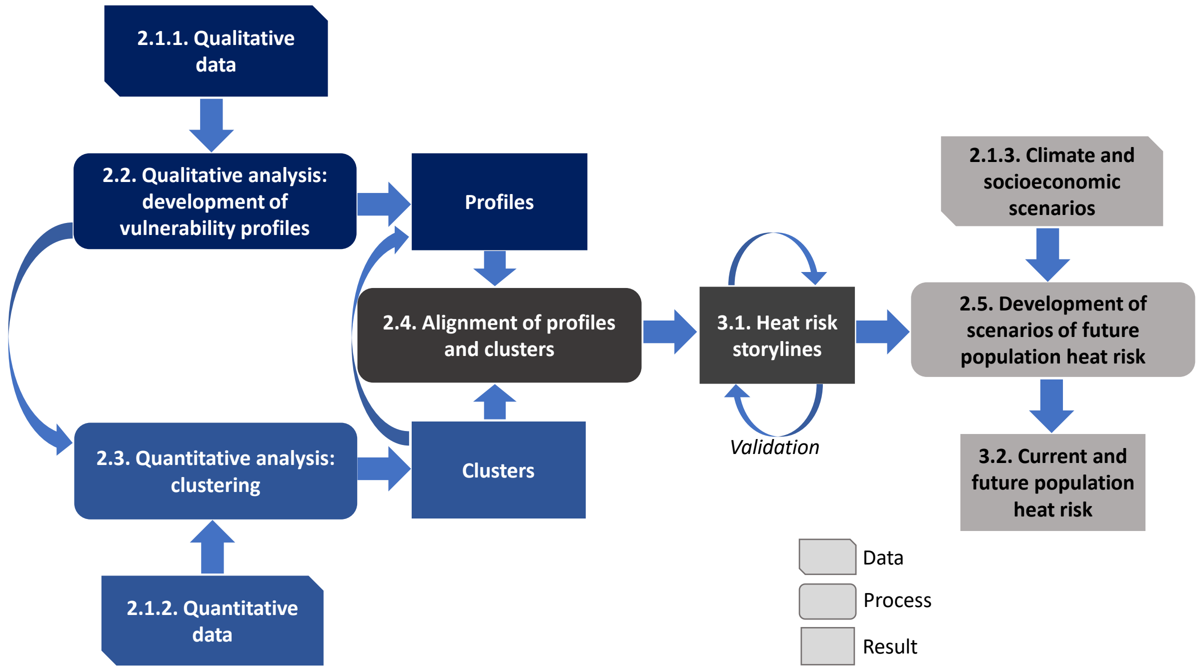


Figure 1: *Overview of the mixed methods approach. Illustration of the sequential and complementary use of qualitative and quantitative data, processes and results. Numbers indicate the sections in the manuscript in which each respective element is discussed in further detail.*

2.1. Data collection

2.1.1. Qualitative data

To establish an overview of previously identified vulnerability factors in Austria, we screened literature identified on Scopus and Google Scholar, complemented by recommendations from experts and stakeholders in Austria. Given the limited availability of studies specifically addressing heat risk in Austria, we analyzed and coded 21 academic and grey literature sources (see the appendix section A2.1.1 for a comprehensive list) that address climate vulnerability and risk more broadly. Using the QDA software NVivo, we identified and extracted references to vulnerability factors, which subsequently informed the coding framework supporting the analysis of the workshop documentation and interviews. Further details on the identified vulnerability factors and the resulting coding framework are provided in appendix Table A2.1.

To collect additional qualitative data on intersectional vulnerability, we conducted a stakeholder workshop and key informant interviews. Stakeholders were selected based on their expertise in climate adaptation and the extent to which their work involves direct engagement with vulnerable groups in Austria. A detailed account of the stakeholder selection process is provided in Lemke et al. (2024). In total, we involved 20 stakeholders in the workshop and conducted 11 interviews with representatives from local to national administrative bodies, policymakers, interest groups, NGOs, research institutes, civil protection, and other relevant actors in the social and climate sectors.

In the interactive workshop, participants validated the vulnerability factors identified in the literature, discussed their relevance in the context of heat stress, and explored how individual and intersecting factors increase vulnerability to heat stress. The discussions were structured around the co-development of two illustrative vulnerability profiles (A2.1.1), each characterized by a combination of intersecting factors. Detailed notes taken during the workshop served as the basis for subsequent qualitative analysis.

The semi-structured expert interviews, each lasting approximately one hour, allowed for deeper exploration of the themes emerging from the workshop. They aimed to generate further insights into intersecting vulnerability factors and prevailing patterns of heat-related risk in the Austrian context. The interview guide (A2.1.1) covered various aspects such as the interviewee's experiences with heat vulnerability, perceived intersections of vulnerability factors, and specific examples drawn from their professional work. Prompting questions based on the literature review and workshop findings helped capture a broad range of intersections between factors. In accordance with data protection standards, we anonymized the interviews and transcribed them with the participants' consent.

2.1.2. *Quantitative data*

The total number of heatwave days in a given year was used as an indicator for heat hazard, following Kysely (2004, p.92), who defined heatwaves as 'consecutive periods of at least 3 days during which the daily maximum temperature is higher than or equal to 30°C'. The average annual number of heatwave days between 2012 and 2022 was used as a reference, derived from the SPARTACUS observation dataset, which provides data at a 1km resolution (GeoSphere Austria, 2020).

Socioeconomic data was available through the annually published integrated wage and income tax statistics provided by the Austrian Federal Statistical Office (Statistics Austria, 2022). At the individual level, the dataset includes total income (defined as the sum of gross labor, capital and transfer income), georeferenced place of residence (at a 1km resolution), and a set of binary variables indicating whether the individual is over 65, a blue-collar worker, or employed in manufacturing, an outdoor sector (agriculture, forestry, construction), or any other sector. The dataset also includes the number of individuals with a main residence in each grid cell, which serves as a proxy for population density. Using the georeferenced data, we calculated average income for each grid cell. The data provides income information in the form of quartiles for groups of individuals within a cell who share the same characteristics (e.g., blue-collar workers in outdoor sectors). To derive individual-level income estimates, we assume a uniform distribution of income within each quartile and group. For data protection reasons, income data for any cell with four or fewer individuals in a given grid cell is not available. In total, the socioeconomic information covers 6 803 247 individuals living across Austria, which corresponds to 76% of Austria's population in 2019 (Statistics Austria, 2020), excluding not only remote places, but also individuals who do not earn any income (e.g. children and individuals living in care institutions).

See Figure A2.1 for illustrations of the regional distribution of heatwave days and population density, and Table A2.2 for descriptive statistics on the socioeconomic data used.

2.1.3. Socioeconomic and climate scenarios

For a quantification of expected future heatwave days, we used data from the Austrian Climate Scenarios - ÖKS15 (Chimani et al., 2016, 2019) based on EURO-CORDEX regional simulations (Jacob et al., 2014) and

CMIP5 global projections (Taylor et al., 2012). We considered RCP4.5 for a medium and RCP8.5 for a high warming scenario for a medium (2050) and far (2080) future.

The underlying demographic and socioeconomic projections are based on the Shared Socioeconomic Pathways (SSPs) (O'Neill et al., 2017), accounting for a socioeconomic development trajectory characterized by sustainable growth in line with SSP1, as well as one defined by increasing inequality in line with SSP4. To capture the socioeconomic dynamics reshaping current conditions through 2050 and 2080, we applied projections for the share of the population aged 65 or older (KC et al. 2024), location-specific population development (Marbler, 2024) and income inequality (GINI) (Rao et al., 2019; available through the SSP Extensions Explorer[3]) to infer socioeconomic dynamics reshaping current socioeconomic conditions through 2050 and 2080.

2.2. Qualitative analysis: development of vulnerability profiles

First, we identified recurring intersections between vulnerability factors. The coding process of the qualitative data combined a deductive and inductive strategy (Bingham, 2023). The predefined set of codes identified in the literature guided the initial analysis of the workshop notes and interview transcripts, ensuring consistency across data sources. As new themes and factors emerged during the analysis, the codebook was expanded and refined. This iterative process captured both widely recognized and context-specific vulnerability factors. In the end, we generated a list of recurring individual vulnerability factors. While coding the individual vulnerability factors, we also documented each perceived intersection between them.

Second, we mapped the intersections and compounding effects of vulnerability factors identifying factors and connections following Hanger-Kopp et al. (2024) in kumu.io. This approach offered a dynamic and systemic analytical approach for the purpose of our study, allowing for the visual representation and analysis of intersections. The resulting map illustrates how vulnerability factors, which are often examined in isolation, interact to create compounded burdens for different societal groups. Each vulnerability factor is represented as an element within the map, while intersections between factors are depicted as connections between elements. This structure enabled the exploration of two-way and multi-way interactions by tracing the connections between elements (see A2.2 and online4). Ultimately, this visualization served as the foundation for the construction of vulnerability profiles.

Third, we identified six profiles by examining patterns within the map and revisiting the two illustrative vulnerability profiles co-developed during the workshop, adding depth, contextual richness and a more nuanced understanding to the patterns detected, with a focus on vulnerability at the individual level. This approach ensured that each profile captures both broader structural patterns and practical insights into lived experiences of vulnerability. We also carried out a validation and refinement of the profiles by comparing them with the characteristics defining each cluster to ensure that the patterns identified qualitatively were also evident in the quantitative findings, and vice versa. The comparison was only possible for vulnerability factors that are reflected in our socioeconomic data.

2.2. Quantitative analysis: clustering

The selection of socioeconomic variables used in the clustering was based on the first set of vulnerability factors identified from the literature and validated during the first stakeholder workshop. To account for

[3] https://ssp-extensions.apps.ece.iiasa.ac.at, last access: 04.07.2025
[4] https://embed.kumu.io/ad0363da850eee149a3e996d96910da6, last access: 04.07.2025

the influence of income and the degree of urbanization on heat risk, we applied a stratified clustering approach. We pre-sorted the data into 12 (4x3) groups, based on: (i) income quartile (4) and (ii) whether individuals live in urban, suburban or rural areas (3) (Statistics Austria, 2021). This reduced the impact of broad disparities across income and urbanization levels, capturing more nuanced intra-group variations. For a full description of stratification criteria see Table A2.3.

Within each of the 12 groups, we applied the k-prototypes clustering algorithm to identify clusters based on the combination of numerical and categorical variables available from the georeferenced microdata (Huang, 1997). The algorithm assigned each individual to a cluster, based on a similarity metric, minimizing Euclidean distance for numerical variables and the simple matching distance for categorical variables. This ensured that the distance between the cluster centroids for numerical data and mode values for categorical data was minimized (Janssen et al., 2012). A cluster is thus a group of individuals who are similar, given their attributes in the underlying data.

Clusters were determined using normalized numerical values, including heatwave days, population density, and mean cell income relative to the Austrian average, as an indicator for neighborhood wealth. Individual income was excluded due to the stratification by income quartiles, as differences in heat coping capacities within each quartile are minor, regardless of their exact position within the quartile. However, population density was included to capture variations. Within urban areas, heat island effects and the access to green or blue spaces vary between more and less densely populated neighborhoods, whereas in rural areas, isolation and community support differ between remote and denser regions. Including population density allowed us to capture these nuances, reflecting stakeholder insights and the diversity within stratified groups.

We determined the number of clusters for further analysis using the elbow method, plotting the within-cluster sum of squares (WCSS) against the number of clusters. This graph typically shows a downward trend. We look for the point where this descent begins to level off – resembling an 'elbow' – which signifies a diminishing return on the improvement of model fit with the addition of more clusters. This inflection point thus indicates the number of clusters that best balance model fit and simplicity. All graphs are included in Figures A2.2-A2.4.

While all individuals contained in the dataset were assigned to a cluster through this process, only a subset of the resulting clusters were subsequently characterized as high-risk clusters. For a list of all clusters see supplementary data (SD) sheet 1. Reference period. To determine which clusters to characterize as such, we developed a risk indicator, grounded in the established notion that risk is a function of hazard (H), exposure (E) and vulnerability (V) (Cardona et al., 2012). In line with Bonadonna et al. (2021), we adopted a multiplicative functional form to combine hazard, exposure and vulnerability, emphasizing the compounding effect of intersecting factors. This approach reflects the understanding that the co-occurrence of multiple vulnerability factors results in a disproportionately higher level of risk than the mere addition of individual factors. In the resulting average cluster risk R_c, hazard corresponds to the average number of heatwave days that each cluster c experiences annually h_c. The number of individuals in each cluster e_c reflects exposure. To compare average individual-level risk across clusters- regardless of size- we divided by e_c, meaning that for average cluster risk, exposure cancels out. So, while exposure matters for overall population risk, it does not affect the expected risk of an individual represented by a specific cluster. A measure for vulnerability was derived based on the intersecting vulnerability factors identified in 2.2.1. While the list of factors identified was manifold, only a limited number are proxied by variables available in the quantitative dataset (x_k). Each factor was first normalized to ensure comparability across dimensions. The vulnerability indicator was constructed to account for compounded effects of intersecting vulnerability factors (e.g., low income and advanced age). Normalized cluster averages were multiplied to quantify the effect of their intersection. This term reflects their joint contribution and ensures that vulnerability is not treated as the sum of its parts but acknowledges the compounding effect that arises when multiple factors co-occur. By summing the products of all individual factors and the identified intersections (i), we derived a cumulative score that reflects expected average cluster vulnerability. For a list of how factors and their intersections were matched with the available data, see Table A2.4. The formula derived for quantifying R_c for a given cluster c is given by:

$$R_c = h_c * \frac{e_c}{e_c} * \sum_{i=1}^{n}(\prod_{k=1}^{n} x_k)_i$$

Clusters with an average risk above the 75th percentile were defined as *high-risk clusters* and selected for further analysis. This threshold was chosen as it allows for a balance between clusters with highest relative risk, while retaining a large enough share of the population for meaningful analysis. We also tested for alternative risk thresholds (65th and 85th percentile). While these change the number of high-risk clusters, they do not qualitatively change the dominance of certain profiles. See Figure A2.4 and the SD for the underlying data.

2.4. Alignment of profiles and clusters

After the identification of high-risk clusters, we aligned them with qualitative profiles developed in 2.2.1. The alignment process is carried out systematically by the authors, who reviewed the features of each high-risk cluster to evaluate their congruence with a corresponding profile. For the majority of high-risk clusters, approximately two thirds, this process revealed distinct patterns that are in clear alignment with the qualitative storylines.

For the remaining clusters, where alignment was ambiguous, we revisited the qualitative data in order to detect subtler themes or patterns within the interview data that have not been prominently highlighted but were still represented within the collected data. Subsequently, we refined and adjusted the profiles to enhance their coherence with quantitative findings where possible, ensuring a more nuanced and consistent alignment.

For instance, while interviewees mentioned differences between urban and rural settings, they did not see an explicit need for separate profiles to reflect affected populations. However, quantitative analysis revealed distinct patterns within these areas, leading us to split the corresponding profile into separate urban and rural specifications to ensure greater homogeneity within assigned clusters (see storylines 1 and 2). Similarly, despite emphasizing the importance of financial coping capacities among elderly individuals, they subsume elderly individuals with high heat exposure under one profile. However, after quantitative analysis and revisiting qualitative findings highlighting the compounding effects of age, limited financial means and social participation, we disentangled this storyline into two (see storylines 4 and 5). This iterative process bridged the gap between quantitative and qualitative findings, adding depth to the identified profiles. Also, three high-risk clusters could be assigned to any of the storylines based on their quantitative features. We did not assign these clusters to any of the profiles. These are later visualized as n/a.

Moreover, one qualitative profile could not be represented by the clusters, as quantitative data did not include the corresponding socioeconomic variables to represent this profile. Despite its absence from the quantitative results, we retained this profile due to its empirical significance within the qualitative dataset. To maintain methodological transparency, a description of this profile is included in A2.2, Figure A2.5.

Overall, this leads to the development five heat risk storylines, combining quantitative and qualitative data to represent the most prominent patterns of heat risk in the Austrian context (see supplementary data sheet 1 for an overview of high-risk clusters and their alignment with a given profile). In a final step, the developed storylines were validated by stakeholders in a workshop setting, ensuring their suitability in representing real-world contexts.

2.5. Projecting future population heat risk

Complementing the analysis of the status quo, or reference period, we develop future heat risk scenarios for 2050 and 2080 by integrating climate projections, demographic and socioeconomic trends.

To quantify future cluster features, we assigned projected heatwave days to the individuals based on their reference period residence, then calculated future cluster averages accordingly. Demographic projections were incorporated by weighting individuals to match future shares of elderly populations and urbanization levels as specified in the SSPs. To reflect changes in income inequality, we redistributed incomes proportionally across the lower- and upper-income quartiles to reflect projected changes in the GINI index. It is important to note that the cluster assignment of individuals remained unchanged during this process.

By adjusting the number of heatwave days each individual is exposed to, given their specific location, cluster averages for hazard changed. Similarly, the distribution of income between higher and lower incomes to reflect changes in income inequality, changed the vulnerability of clusters. By weighting individuals to match the expected share of elderly and urbanization trends as proposed by the SSPs changes the total number of people within a cluster, thus cluster size – indicating a change in exposure.

For the identification of future high-risk clusters, average cluster risk R_c was calculated for each cluster considering cluster characteristics in each scenario. For comparability to current population heat risk, we used the 75th percentile threshold from the reference period to identify future high-risk clusters. Based on the cluster characteristics, high-risk clusters were again aligned with qualitative profiles, as described in the previous section. For a comprehensive list of cluster characteristics, resulting cluster risk and profile alignment for each scenario, see supplementary data.

3. Results: Storylines characterizing heat risk in Austria now and in the future

This section presents the developed heat risk storylines based on quantitative and qualitative insights, characterizing heat risk across Austria's population. Storylines represent the most prominent patterns but do not capture all possible configurations of risk, especially for vulnerability. They represent key trends rather than an exhaustive map of all vulnerability configurations.

3.1. Heat risk storylines

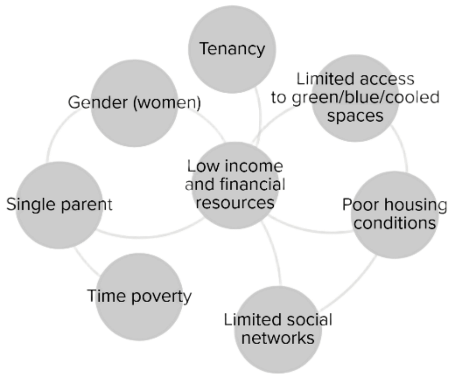
The heat risk storylines highlight recurring patterns of hazard, exposure and vulnerability in Austria. Stakeholder interaction emphasized that vulnerability arises from the compounding effect of multiple factors, rather than from any single dominant driver, a perspective essential for interpreting the profiles presented below.

Each profile is illustrated by a figure with two panels. The left panel visualizes qualitative vulnerability factors as interconnected circles, highlighting their intersections and compounding effects. The right panel presents a radar plot of normalized quantitative variables characterizing the clusters aligned with the profile, where outermost points indicate the most extreme values. The radar plot provides an overview of shared patterns within each profile and differences across profiles, while a more detailed quantitative breakdown of individual clusters can be found in Figures A3.1 – 3.5 and Tables A3.1-A3.5.

Storyline 1: Individuals at-risk-of-poverty in urban heat islands

Representing approximately 7% of the observed population, clusters assigned to this storyline (illustrated in Figure 2) experience an average of 25 heatwave days per year, well above the overall cluster average of 16 days. With an annual average income of EUR 12 600, individuals are challenged by their precarious economic position below the at-risk-of-poverty threshold[5]. Clusters are located in urban areas, two out of four within extremely densely populated areas with per capita incomes lying below national averages.

This storyline represents individuals facing economic hardship in Austria's densely populated urban areas. Interviews highlight **low income and financial resources** as a key factor of vulnerability, exacerbated by **poor housing conditions** (i.e. insufficient thermal insulation of the building stock) and **limited access to green, blue or cooled spaces**. Within this group, an intersecting factor that exacerbates vulnerability of individuals in this profile is **tenancy,** which together with financial constraints, restricts their capacity to modify living spaces for better heat resilience. Interviews particularly emphasized the challenges faced by **single parents** within this profile, especially **women**, as they juggle part-time wage labor and unpaid care work, contributing to **time poverty.** This leaves little capacity for building and maintaining **social networks** that could otherwise provide support during heatwaves.



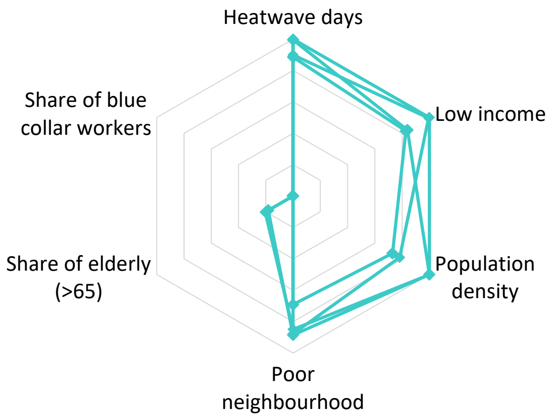


Figure 2**: **Individuals at-risk-of-poverty in urban heat islands (Storyline 1). *The left panel visualizes qualitative vulnerability factors as interconnected circles building the qualitative profile. The right panel presents a radar plot of normalized quantitative variables characterizing the clusters aligned with the storyline, where outermost points indicate the most extreme values.*

[5] In 2019 the at-risk-of-poverty threshold in Austria was EUR 15 437 annual income for a single person household. Eurostat (2024), ILC [Statistics | Eurostat]().

Storyline 2: Individuals at-risk-of-poverty in suburban and rural areas

Similar to storyline 1, storyline 2 (illustrated in Figure 3) is characterized by **low income and financial resources** but is located in suburban and rural areas. The clusters assigned to this storyline cover 4% of the observed population, experiencing on average 21 heatwave days annually. With a mean income of EUR 10 300, individuals again face a precarious economic position below the at-risk-of-poverty threshold. Clusters are dispersed across rural and suburban areas and not concentrated in low-income neighborhoods and thus less spatially clustered than storyline 1.

While in this case, economic hardship is not compounded by urban environmental conditions, interviews highlight the link with **low levels of education** and **poor housing conditions,** often leaving people exposed to heat in their home without financial capacities to adapt with resulting in hesitation to invite people to their home as a result of feeling ashamed. Vulnerability may be further compounded by **energy poverty**, as this interplay leads to year-around vulnerability to temperature extremes, struggling to afford heating in winter and cooling in summer. Financial constraints also intersect with **limited mobility**, making it difficult to own a car or afford public transport, which in turn limits access to cooler spaces such as forests, lakes, or public pools during heatwaves or could lead to isolation (which can be particularly harmful for individuals living on their own). This interplay exacerbates **limited social participation** due to stigmatization.

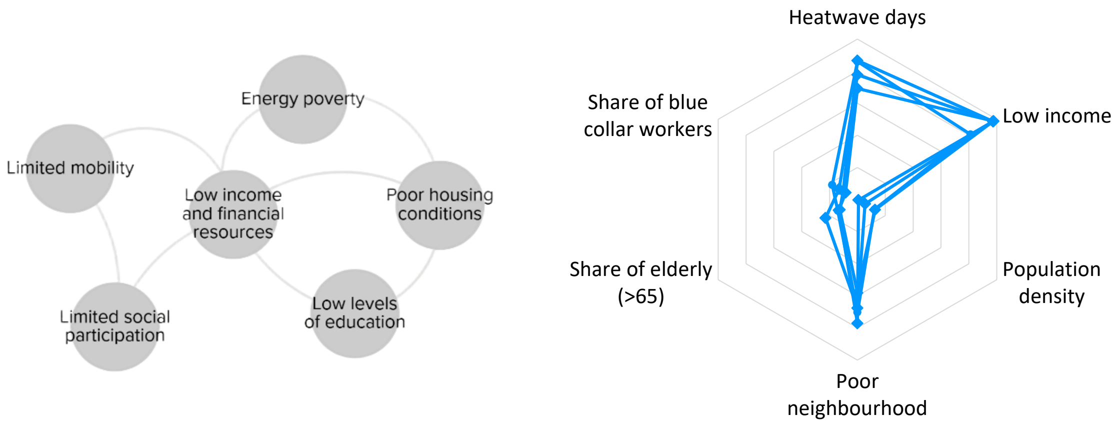


Figure 3: Individuals-at-risk-of-poverty in rural and suburban areas (Storyline 2). *The left panel visualizes qualitative vulnerability factors as interconnected circles building the qualitative profile. The right panel presents a radar plot of normalized quantitative variables characterizing the clusters aligned with the storyline, where outermost points indicate the most extreme values.*

Storyline 3: Blue collar workers with high heat exposure

Individuals represented by this storyline (illustrated in Figure 4) are blue-collar workers, thus typically performing manual labor. Four clusters are assigned to this storyline, comprising 3 % of the observed population. Their employment makes individuals characterized by this storyline vulnerable to suffer from heat stress and increases risk especially for the 10% working in construction or agriculture, where avoiding heat exposure is nearly impossible. Living in relatively low-income urban areas, individuals experience an average of 22 heatwave days per year. Their average income of EUR 12 400 suggests a high prevalence of seasonal workers, reinforcing the link between precarious employment (e.g.in construction and harvesting) and heightened heat risk.

These workers face heat stress from dual exposure not only at work, but also at home, where they suffer urban heat island effects. Due to l**ow income and financial resource**s many live in **poor housing conditions** within low-income urban neighborhoods **with limited access to green, blue or cooled spaces** for recreation. Limited financial resources also restrict mobility, making it difficult to access cooler recreational spaces. **Tenancy** is a further compounding factor, as tenants have little control over housing adaptations that reduce heat exposure (e.g. installing air conditioning or improving insulation). Within this storyline, individuals with a **migration history** may be disproportionally affected as it often intersects with other factors in this profile such as precarious working or living conditions.

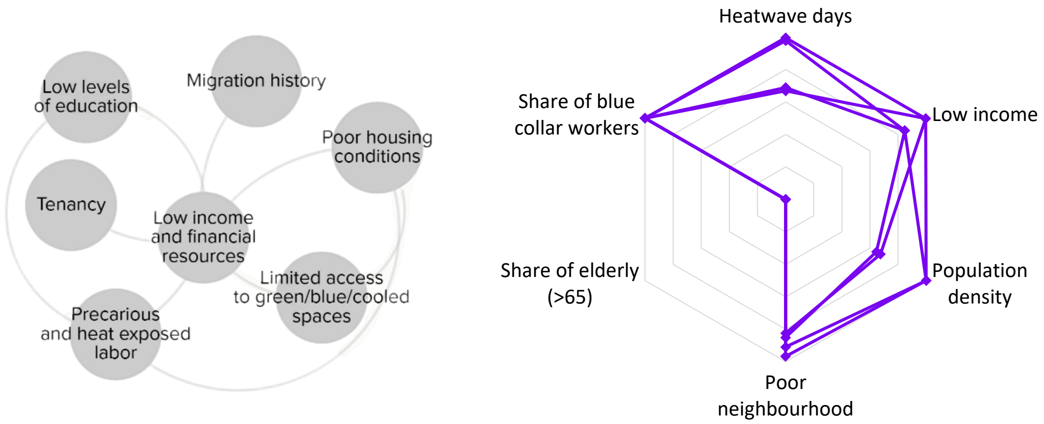


Figure 4: Blue collar workers with high heat exposure (Storyline 3). *The left panel visualizes qualitative vulnerability factors as interconnected circles building the qualitative profile. The right panel presents a radar plot of normalized quantitative variables characterizing the clusters aligned with the storyline, where outermost points indicate the most extreme values.*

Storyline 4: Elderly with limited financial means

The clusters aligned with this storyline (illustrated in Figure 5) comprise individuals above the age of 65 experiencing an average of 18 heatwave days per year and represent 3% of the observed population. The mean annual income is EUR 12 400 – which is well below the poverty threshold. While interviewees primarily associated this profile with urban areas, suitable clusters also appear rural settings

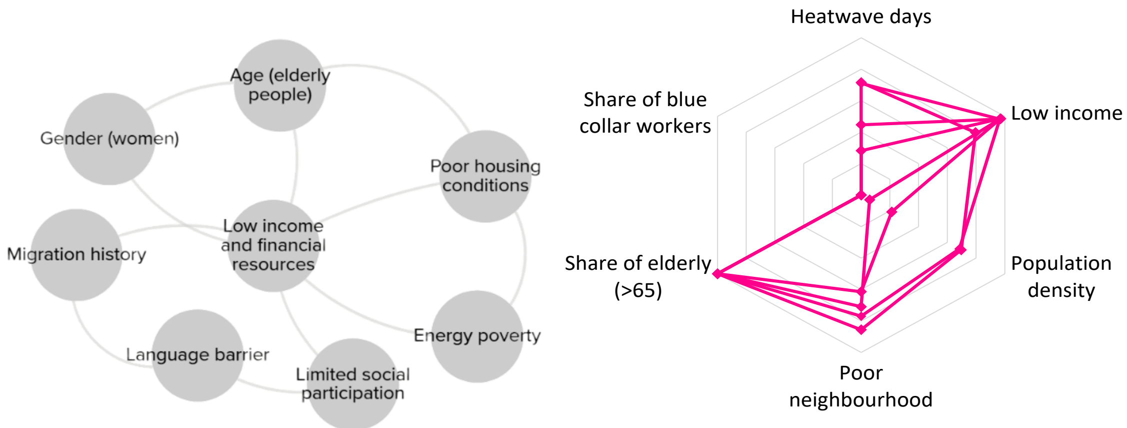


Figure 5: Elderly with limited financial means (Profile 4). *The left panel visualizes qualitative vulnerability factors as interconnected circles building the narrative of this storyline. The right panel presents a radar plot of normalized quantitative variables characterizing the clusters aligned with the storyline, where outermost points indicate the most extreme values.*

This storyline represents **elderly people**, who face heightened vulnerability due to the intersection of advanced age, **low income and financial resources**. While advanced age itself increases susceptibility to heat-related health risks, socioeconomic factors further compound this vulnerability. Within this group of individuals, financial constraints may restrict **social participation** and thereby the ability to seek (temporary) relief from heat. Also, the financial situation may put individuals within this storyline at risk of falling into old-age poverty which makes cooling unaffordable and often confines them to **poor housing conditions** in hotter urban or suburban neighborhoods, prolonging exposure to indoor heat. In addition, **gendered** economic disparities and **energy poverty** create compounding vulnerabilities, especially among **women**, due to lower lifetime earnings as a consequence of unpaid care work during their working age. Vulnerability of this profile is further exacerbated by the intersection with **migration history** or **language barriers**, which are often associated with pre-existing socio-economic inequalities and further restrict access to information on heat stress and adaptation measures.

Storyline 5: Elderly with health impairments and high exposure

This storyline (illustrated in Figure 6) holds 2% of the observed population. With an average of EUR 40 000, individuals represented by this storyline are not characterized by financial constraints. However, their risk results from their old age (>65), paired with an average exposure to 22 annual heatwave days in urban heat islands.

Elderly people characterized by this storyline may be limited in their capacity to reduce their exposure to heat stress, due to **limited social participation** resulting from pre-existing **health impairments** or isolation. While the risk of this profile may seem to be driven primarily by high exposure, contextualization by the interviewees shows that factors frequently intersecting with advanced age, such as **limited mobility**, and **single person household**s create compounded vulnerabilities. Elderly individuals with **health impairments** (e.g. chronic conditions or physical limitations) commonly experience **limited access to green, blue, or cooled indoor spaces** and **limited social participation**. This may reinforce social isolation, as individuals are more likely to spend prolonged times in heat-exposed indoor spaces.

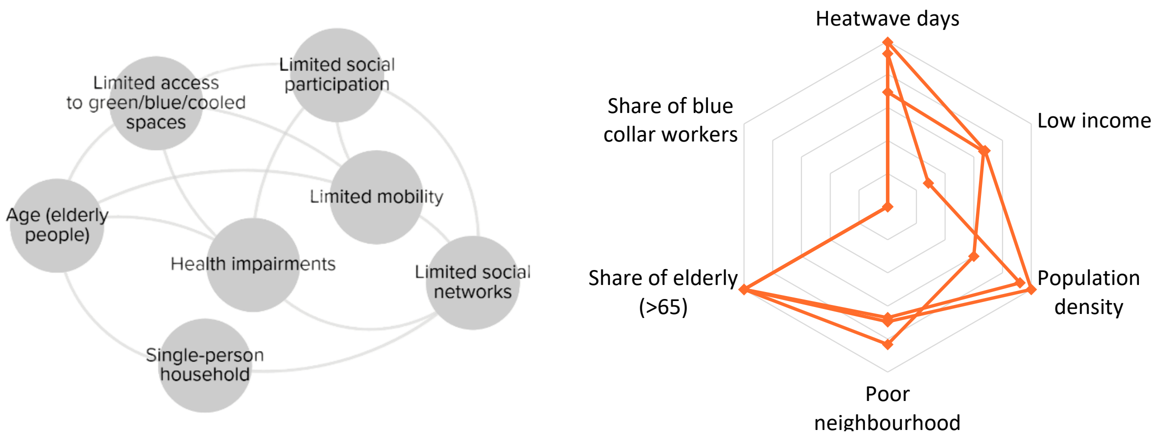


Figure 6: Elderly with high exposure (Profile 5). *The left panel visualizes qualitative vulnerability factors as interconnected circles building the narrative of this storyline. The right panel presents a radar plot of normalized quantitative variables characterizing the clusters aligned with the storyline, where outermost points indicate the most extreme values.*

3.2. Current and future population heat risk

The storylines presented in 3.1 provide a more differentiated understanding of risk across Austria's population. Panel a) in Figure 7 visualizes this, with heatwave days on the vertical axis, population exposure represented by the bubbles, sized according to the number of people it comprises, and the horizontal axis reflecting average cluster vulnerability (as described in section 2.2.2). By construction, high risk clusters are thus located rather in the upper right corner of each plot. High-risk clusters are color-coded by storylines, while unassigned high-risk clusters appear in yellow and those below the 75th percentile – and thus not defined as high-risk clusters – in grey. In the reference period, the largest high-risk group falls under Storyline 1, followed by Storyline 2, its rural counterpart. While Storylines 3 and 5 generally face more heatwave days, clusters assigned to Storyline 4 are characterized by relatively high vulnerability.

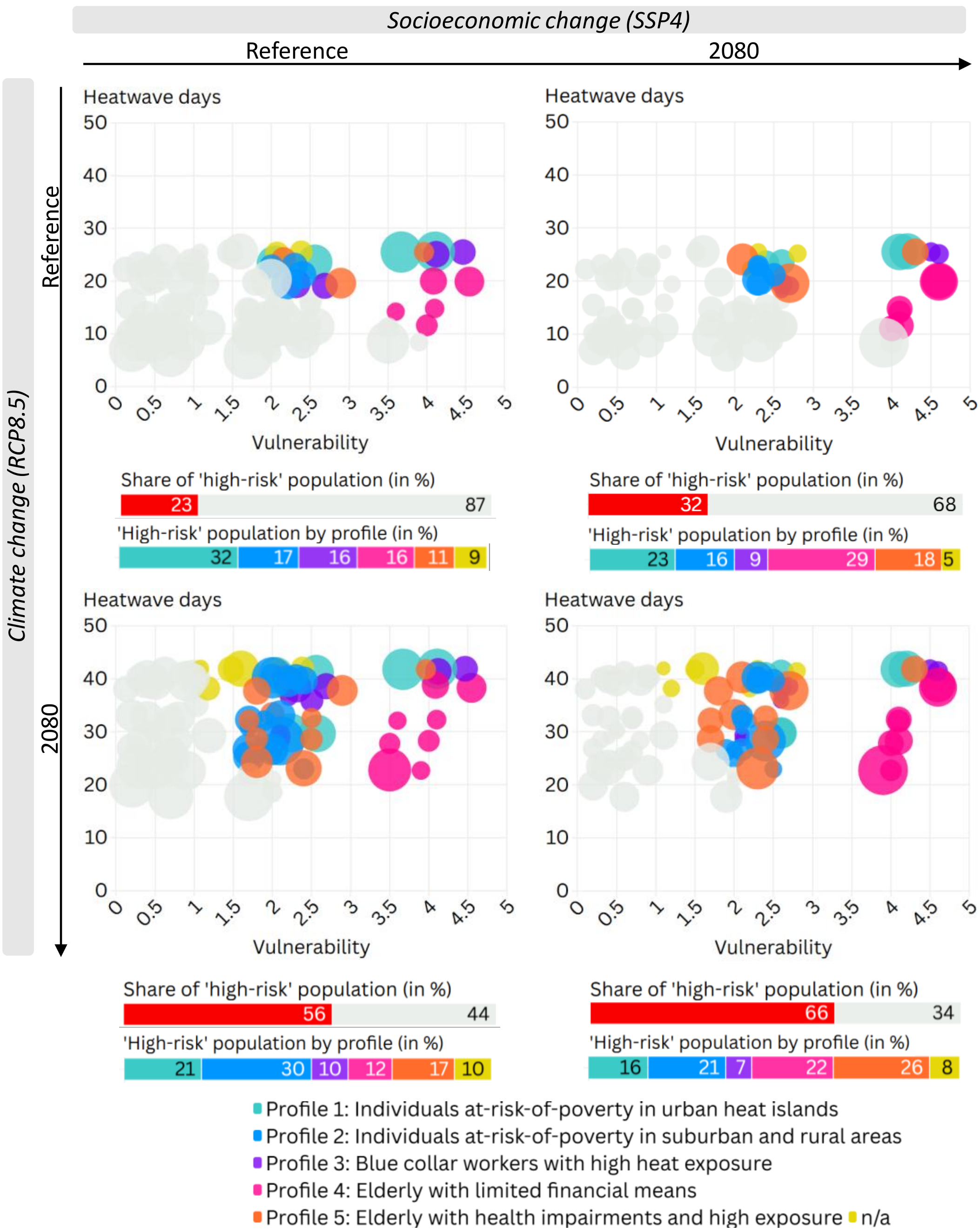


Figure 7: *Cluster-level representation of population heat risk during the a) reference period and for 2080 considering b) and socioeconomic trends characterized by increasing inequality (SSP4), c) climate change under a high-emission scenario (rcp8.5) and d) demographic and socioeconomic trends characterized by increasing inequality (SSP4) and climate change under a high emission scenario (RCP8.5). Colored bubbles highlight clusters considered high-risk, defined by a fixed threshold at the 75th percentile risk level from the reference period, consistent across all scenarios. High risk clusters that cannot be aligned with any of the five risk profiles are denoted n/a. For underlying quantifications see SD sheets 1.-4.*

Towards 2080, hazard changes coincide with demographic and socioeconomic dynamics. Under SSP4 quantifications, Austria's population will see a significant rise in the share of elderly and urbanization rates. These trends are reflected in panel b), where bubbles for Storylines 4 and 5 (elderly populations) grow significantly, while the rural Storyline 2 shrinks. Increasing income inequality shifts low-income clusters rightward, raising their vulnerability. As a result, the share of the population considered 'high-risk' increases from 23% in the reference period to 32% in 2080, using the 75th percentile cluster risk level from the reference period as a threshold.

Panel c) in Figure 7 illustrates heat risk in 2080 under a high warming scenario (RCP8.5) for the reference population. Climate change more than doubles the median number of heatwave days, shifting all clusters upward along the vertical axis while exposure and vulnerability remain constant. The share of the population in high-risk clusters rises from 23% to 56%, with nearly one-third in Storyline 2, signaling increased heat risk in rural areas.

The combination of socioeconomic and climate change is illustrated in panel d) of Figure 7. By 2080, 66% of the population is characterized by high-risk clusters, indicating a very strong increase (nearly a tripling when compared to the reference), which is driven more strongly by climate change than socio-economic change. Additionally, an increasing share of high-risk clusters no longer aligns with existing profiles, suggesting new heat risk patterns may emerge. For results until 2050 and for SSP1- RCP4.5, see Figure A3.6 and A3.7 and SD for underlying quantifications.

4. Discussion

This section discusses the findings of this paper, outlining further research needs that emerged from the development and application of the presented methodology.

4.1. Unveiling Austria's heat risk

The derived storylines underscore that heat risk in Austria's population takes different forms. As a major determinant of risk, vulnerability does not stem from a single factor, but rather arises from the interplay of multiple structural inequalities that reflect broader socio-political and economic conditions. Interviews pointed to how dimensions such as poverty, unpaid care work, discrimination, or precarious working conditions – particularly among individuals with low socioeconomic status and/or migration background – interact to shape differentiated exposure and vulnerability. These insights contribute to a more nuanced understanding of heat risk in Austria, moving beyond one-dimensional categorizations of vulnerable groups, pointing to vulnerability as a process shaped by intersecting and context-specific conditions. With projections suggesting that the share of the population considered at high heat risk may rise from 23% to up to 66% by 2080, climate and socioeconomic trends shift heat risk increasingly into the center of society. The storylines developed in this study offer a way to make these complex dynamics more tangible.

4.2. Methodological strengths & challenges

The mixed methods approach presented in this paper offers a contribution to understanding within-country differences in heat risk by bridging the strengths of both qualitative and quantitative research. It enables the identification of recurring patterns while avoiding the overgeneralization of large-scale quantitative studies, and at the same time allows for abstraction from the context-specificity of qualitative analysis (Eisenack et al., 2019). By integrating lived experiences with more regionally specific socioeconomic microdata, the method fosters a differentiated understanding of the context-specific group-specific vulnerabilities and susceptibility to harm. The resulting storylines should be seen as illustrative rather than exhaustive – qualitative abstractions reflected in quantitative patterns. While not everyone will identify with a given storyline, they offer a structured lens to explore the social complexity of climate risk and make intersectional vulnerability more visible and interpretable.

Some methodological trade-offs were necessary, particularly regarding geographic resolution and data availability. Prioritizing high-resolution microdata allowed for the identification of individual-level patterns that would otherwise be obscured by regional averages. However, this choice came with constraints: certain qualitative dimensions – such as disabilities, gender, homelessness household characteristics, or migration background could not be quantified, leading to blended profiles of quantitative and qualitative data. Future research could expand on this by incorporating alternative data sources alongside official statistics to improve the granularity and inclusivity of quantitative pattern detection. Refining climate risk assessment metrics to accommodate qualitative data provides contextual understanding of people's realities, which, if not integrated in vulnerability assessments, might get lost in quantifications.

4.3. Representation of equity and justice in climate risk assessments

A nuanced consideration of intersectional social vulnerability in climate and disaster risk assessments is essential to inform to current justice discourses in risk governance. While omission of vulnerable groups in current climate risk reduction raises equity and justice concerns (Reckien et al., 2025), the presented approach facilitates their explicit consideration and participation in three ways. First, it enables the recognition of different factors that may intersect to shape social vulnerability (recognitional justice). Second, the identification of multi-dimensional storylines provides a reference for more targeted, but also sensitive engagement with vulnerable groups in the future (procedural justice). Finally, identifying dominant patterns of risk, enables not only the development of more targeted, but also more equitably designed policy instruments, giving sufficient consideration to vulnerable groups (distributive justice).

4.4. Implications for adaptation research

This study focuses on risk, in particular vulnerability, as the system boundary of analysis, and does not extend into the deeper examination of coping or adaptive capacities. While we categorize certain population groups as a priori vulnerable, we recognize that vulnerability and adaptive capacity are closely linked, often shaped by overlapping factors. For example, financial constraints (e.g. due to low income) may limit access to resources needed for adaptation (Azad & Pritchard, 2022). However, as Barnett (2020) emphasizes, being vulnerable does not equate to being powerless. Investigating how the identified groups respond to and manage risk – through everyday strategies or informal support systems, represents an important direction for future research.

Robust adaptation planning requires understanding how climate and societal factors shape future heat risk. While our findings highlight how socioeconomic, demographic or environmental factors intersect and thereby show who is particularly prone to heat risk in Austria, they do not fully shed light on the underlying dynamics or root causes (Teebken, 2024) that lead to some people being more vulnerable than others in the first place. Scholars argue that vulnerability stems from deep-rooted issues like social, economic or power relations, including unequal access to resources and political marginalization (Eriksen et al. 2015; Warner and Kuzdaz 2017; Fedele et al. 2019). These root causes remain to be explored in the context of heat stress vulnerability in Austria.

4.5. Practical applications and policy considerations

The approach presented in this paper goes beyond existing practices by enhancing country-level risk information, which serves as the basis for adaptation decision making. While current assessments and available tools tend to identify potential hotspots, they are unable to cover the multidimensionality of risk and overlook high risk individuals outside geographical hotspots. By presenting heat risk through profiles, we highlight the varying impacts across the Austrian population, based on their patterns of exposure and vulnerability, transcending regional factors. We see that future heat risk will be significantly influenced by climate change, but also demographic and socioeconomic trends, which potentially lead to a sharp rise in high-risk populations and a change in risk patterns. Those are crucial insights to consider in adaptation practice and policymaking, to ensure just and effective adaptation and avoid lock-ins that further harm vulnerable groups.

By providing information that goes beyond the cartographical illustration of where to prioritize adaptation action, but also who to address now and in the future, the proposed methodology enhances social inclusiveness of adaptation options and their feasibility (Singh et al., 2020). While across the EU, adaptation policy leans towards short-term solutions (EEA, 2024), our insights can inform long-term adaptation planning, helping to avoid harmful path dependencies from short-term planning that does not consider the unequal distribution of burdens and benefits. Moreover, this methodology connects to national and European scale adaptation strategies, stressing the need for a more explicit consideration of vulnerable groups (BMK, 2024b) and an equitable share of the benefits of adaptation (EC, 2021).

5. Conclusion

This paper presents a mixed methods approach to capture intersectional vulnerability patterns, offering a more nuanced understanding of heat risk now and in the future. The application of the developed approach revealed five heat risk profiles, comprising qualitative storylines, contextualized with results from the clustering of socioeconomic variables. Two profiles are characterized by populations with incomes below the poverty threshold – one where vulnerability is, among other factors, exacerbated by urban environmental conditions and another in rural areas, where stigmatization and limited social participation further intensify vulnerability. A third profile captures the challenges faced by individuals in physically demanding and often precarious jobs, who experience high heat exposure both at work and at home. Additionally, two profiles focused on people above the age of 65 – one characterized by low financial resources and another where age intersects with urban environmental stressors and health conditions. Climate and socioeconomic dynamics increase heat risk in Austria until 2080, with the share of population considered 'high risk' increasing from 23% to as much as 66%.

The findings underscore the value of integrating qualitative insights with quantitative data, enriching the understanding of vulnerability and enhancing existing risk assessments. We identify a need for tailored adaptation strategies that address the specific vulnerabilities of different population groups. Meeting the needs of highly vulnerable groups is not only a matter of social justice but also essential for the overall effectiveness of adaptation strategies. The projected increase in heat risk emphasizes the urgency for proactive planning, that anticipates changes rather than waiting for impacts to manifest.

The dynamic nature of climate risk requires ongoing research and monitoring. As socioeconomic conditions and climate impacts evolve, continuous assessment of vulnerability and risk patterns will be essential for adapting policies and strategies effectively. While this methodology has been applied in the context of heat stress in Austria, it should be applicable in other regional settings and for different climate impacts. By identifying high-risk individuals beyond geographical hotspots, the approach enables inclusivity and effectiveness in adaptation planning.

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Appendix

A2 Methodological approach

A2.1.1. Qualitative Data

Literature reviewed during the qualitative data collection

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Description of coding framework

Table A2.1: *Coding framework. Each line represents a code, 'files' refers to the number of data files (interview transcripts) coded to that specific code, and 'references' refers to the number of excerpts coded to that specific code.*

Vulnerability factor	Description	Files	References
1. Access to information	Lack of access to information on heat adaptation measures or warnings.	3	3
2. Access to public transport	Closely linked to mobility	3	4
3. Access to recreational activities	Accessibility of green and blue spaces or cooled indoor spaces - including social participation.	4	10
3.1. Accessibility of cooled indoor spaces		3	3
3.2. Accessibility of green and blue spaces		5	8
4. Age	Children and elderly	0	0
4.1. Children		5	16
4.2. Elderly		7	13
5. Agency		4	7

6. Care Dependency	Being dependent on someone else's care work	3	6
7. Caretaking responsibilities	Being responsible for care work among family, friends, elderly, among others	1	1
8. Disability	Including vision impairment, physical disability, mental health conditions, deaf, among others – including social participation.	5	10
9. Energy poverty		1	3
10. Equipment residential surroundings	Equipment of immediate living environment - Lack of nearby infrastructure like parks, café's, cooled indoor rooms, social spaces, open spaces, among others.	3	4
11. Gender	Particularly focused on women	7	11
12. Health	Health impairments such as pre-existing health conditions	9	33
13. Homelessness		2	3
14. Income and Financial Situation	Including social participation	10	48
15. Knowledge about adaptation options		1	1
16. Lack of and barriers in public infrastructure	Lack of and barriers in public infrastructure, including inaccessibility of infrastructure for people with disabilities (e.g. wheelchair users) or inadequate equipment of public infrastructure in the face of heat stress (e.g. no shade).	2	3
17. Language barrier		6	6
18. Level of education		8	14
19. Limited mobility	Due to inaccessible (public) transportation or an individual's health/physical limitations	5	10
20. Migration history		5	11
21. Housing conditions	Physical and social factors leading to poor housing conditions, including inaccessibility (not barrier free),	7	34

	building type, location, absence of air conditioning, persion blinds, balcony, or bathtub, poor insulation, and tight living space (overcrowded housing), among others		
22. Poverty	Including social participation	1	4
23. Precarious and heat-exposed work	May be unsecure job, low wage, lower worker's protection, working outdoors, working in hot indoor rooms, among others	6	15
24. Risk awareness and knowledge		3	4
25. Single parent		6	12
26. Single person household		3	4
27. Social networks	Lack of social networks such as family, friends, neighbours or other communities	7	18
28. Tenancy	People renting their homes	6	9
29. Time poverty	Lack of sufficient time to fulfill responsibilities, engage in social situations, and others.	2	3

Two example households/illustrative vulnerability profiles developed in the first stakeholder workshop

Household 1

In Vienna's 10th district, the Wildczek family lives in a multi-unit residential building that consists mainly of rental apartments and some owner-occupied units. The building was constructed in the 1970s, faces south, and has poor insulation. It has high heating costs in winter, and some apartments have issues with mold. In front of the Wildczeks' apartment is a large parking lot that absorbs heat in the summer. The building lacks external blinds, having only internal blinds. Some residents have installed air conditioning units, which further heat the outside air in front of their windows.

The location of the building is rather unfavorable: there is heavy traffic, and public transport connections are poor. The nearest park is relatively far away.

The Wildczek family lives in a rental apartment on a middle floor with their four children. The father works in precarious employment as a construction worker for a temporary employment agency. In summer, he struggles with the heat during his long commute on non-air-conditioned public transport and his outdoor job. His wife is unemployed and stays at home with the children. She suffers from a chronic heart condition, which worsens in hot weather. Three of their children are under six years old, and one is ten. The ten-year-old attends school (without afternoon care) and suffers from severe pollen allergies and asthma, which are exacerbated by heat. Two of the younger children attend kindergarten part-time, while the youngest child stays at home.

As a result, five family members often spend their afternoons in a small, hot living space due to the limited availability of full-day childcare. The father faces a double burden in the heat: working outdoors and returning to a cramped, overheated home.
When the Wildczeks try to ventilate their apartment in the mornings or evenings, it is often too noisy due to traffic. They must choose between heat and noise. Although Mr. Wildczek is skilled in manual work, he cannot make improvements to the apartment since they are renters. Moving to a better apartment is not an option due to financial constraints—the family is already struggling to make ends meet.

Household 2
In a multi-unit residential building (built in 1965) in central Graz, Mrs. Barisha lives alone in a rented attic apartment. She moved to Austria from Kosovo with her husband in the 1980s. Now widowed, she has a modest pension. Her apartment is on the top floor—the hottest part of the building—with poor insulation. Despite being in the attic, the space remains dark in summer, has low ceilings, and lacks cross-ventilation. Since it is a rental unit, Mrs. Barisha has limited ability to modify her apartment to reduce heat exposure. Rising rent costs and other expenses are becoming increasingly difficult for her to manage financially. Even if she had the money, construction work would be messy, and she wouldn't know exactly what measures to take to reduce the heat.
Mrs. Barisha speaks basic German but prefers watching Kosovar television. She often feels lonely and has few people in her social circle who can assist her when problems arise. Her health is declining—she experiences mild dementia and hearing loss, which lead to misunderstandings. She has become distrustful, feeling that people around her are dishonest, and she believes that newspapers spread lies.
Daily tasks such as dressing and grocery shopping are becoming more difficult for her, especially in hot weather. She has received some general information on heat safety but finds reading in German tiring, and the advice seems too generic.
For example, one common recommendation is to drink plenty of water. However, her doctor has prescribed diuretics, which cause frequent and sudden urges to urinate. This makes her hesitant to leave her home, and when she does go out, she avoids drinking water for several hours to prevent accidents in public—no matter how hot it is.

Interview Guide

The following interview guide has been translated from German.

Explanation + Clarifying Questions
This interview is conducted as part of the ACRP-funded DISCC-AT project.
Climate change will increasingly have negative socio-economic impacts in the future. These impacts vary depending on social groups and types of climate risks. However, aspects of distribution and justice in the context of climate change remain insufficiently researched. In order to develop targeted and fair climate adaptation measures by public authorities in Austria, better data and information are needed.

The interviews conducted as part of the DISCC-AT project aim to address this gap. We seek to understand how current and future risks of flooding and heat affect different parts of the population, particularly vulnerable groups. Specifically, we want to identify the factors (and their intersections) that make households vulnerable and how typical vulnerable households can be characterized (through household archetypes, i.e., clusters of households).

- The interview will last approximately 45 minutes.
- The interview will be recorded and transcribed.
- Before the interview, we sent you a consent form, which you have already signed and returned.
- Do you have any questions about the interview process?

<u>Introduction</u>

- How does your work involve vulnerable groups?
    - Possible prompts:
        - Do you work directly or indirectly with groups/households that are vulnerable to heat? If so, how?
        - Which vulnerable groups do you engage with?
        - In what ways and why are these groups vulnerable?

<u>Discussion on Vulnerability Profiles</u>

Presenting the two example households

- I will now read aloud the two example households vulnerable to heat that were previously developed in a stakeholder workshop. We will then discuss them in detail.

Questions about the example households

- How do you perceive these examples? Do you feel they adequately and comprehensively represent typical cases (in terms of vulnerability factor combinations)?
- What is missing? Based on your experience, what would you add?
- What do you see as the dominant vulnerability factors?
- Can you provide more examples of how different vulnerability factors combine to exacerbate vulnerability?

Questions on additional households/intersectional vulnerability factors (10 minutes)

- Based on your experience, are there other typical vulnerable households? Please describe the characteristics that contribute to their vulnerability.
    - Prompts:
        - From your experience, what are the dominant characteristics that determine vulnerability, and why do they make people particularly vulnerable?
        - Can you provide examples of how different vulnerability factors combine to increase vulnerability?
        - Where do these households live? How are they exposed to heat/flooding?

<u>Consequences of vulnerability</u>

- What are the impacts/consequences of these households' vulnerability?
- What are the knock-on effects of inadequate adaptation to climate risks?

<u>Stakeholder Added Value</u>

- In what format/extent do you prefer to receive research findings?
- Do you have any upcoming events/activities on this topic where our project and findings could contribute?

<u>Conclusion of the Interview</u>

- Thank you very much for your participation. Would you like to add anything or share any final thoughts with us?
- Are you interested in participating in our next stakeholder workshop in the first quarter of 2024?

2.1.2. Quantitative Data

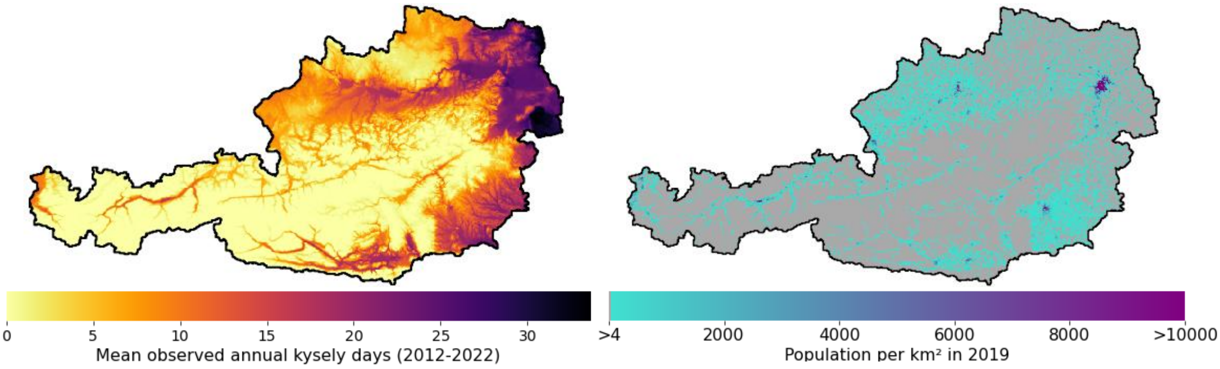

Figure A2.5: *Left panel: mean observed heatwave days ("kysely days"), right panel: population density per km2 in the cells covered in the socioeconomic dataset.*

Table A2.2: *Descriptive statistics of the variables used in the clustering*

Variable		*Type*	*Mean*	*Median*	*Share of total sample*
Income		Continuous	30184	24690	n.a.
Age > 65		Binary	n.a.	n.a.	22%
Blue collar worker		Binary	n.a.	n.a.	20%
Sector of employment	Manufacturing	Binary	n.a.	n.a.	23%
	Outdoor: agriculture, forestry, construction	Binary	n.a.	n.a.	5%
	other		n.a.	n.a.	72%
Population density (inhabitants per grid cell, population weighted)		Continuous	4142	1198	n.a.
Average income of the grid cell relative to average income (population weighted)		Continuous	1.029	0.995	n.a.
Kysely days		Continuous	15	14	n.a.

2.2. Development of heat risk profiles

Kumu Map visualizing heat stress vulnerability in Austria

This figure presents a map illustrating the interconnected nature and complexity of vulnerability factors as identified through the qualitative work, going beyond isolated drivers. By following the connections, distinct storylines of vulnerability emerge (going beyond the profiles presented below), illustrating the ways in which different factors intersect to shape heat-related risk. For a detailed description of each vulnerability factor and its intersections, visit kumu.io here and click on the respective elements and connections. The map is also a visualization of the codebook used in NVivo for analyzing the qualitative data from literature reviews, workshops, and interviews.

Note: During the visualization and mapping process, we realized that 'social participation' was implicitly included in other elements such as income, health impairments, or access to green/blue/cooled spaces. Therefore, we have reassessed this vulnerability factor and added social participation as a distinct element in the map, intersecting with other elements, due to its importance in the interviews.

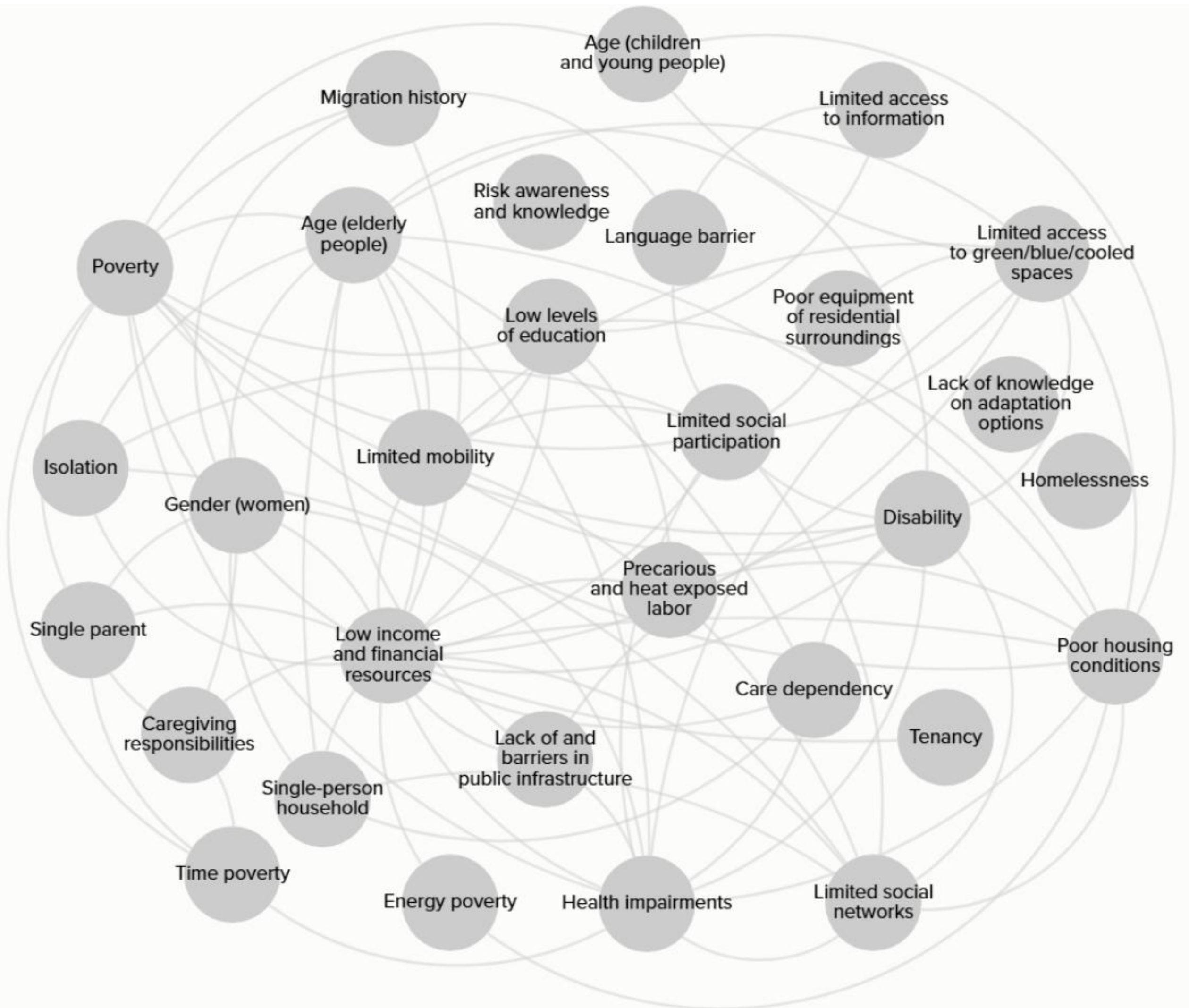

__Figure A2.1:__ Kumu map capturing all mentioned factors and connection. Visit the online version for further description of each factor and an indication of the number of mentions in the interviews.

Table A1.3: *Stratification criteria*

Dimension	***Category***	***Definition***
Income	Q1	Bottom 25% of income distribution
	Q2	25th–50th percentile
	Q3	50th–75th percentile
	Q4	Top 25% of income distribution
Urbanity (based on Statistik Austria, 2021)	Urban	> 2750 inhabitants/km²
	Suburban	1000–2750 inhabitants/km²
	Rural	< 1000 inhabitants/km²

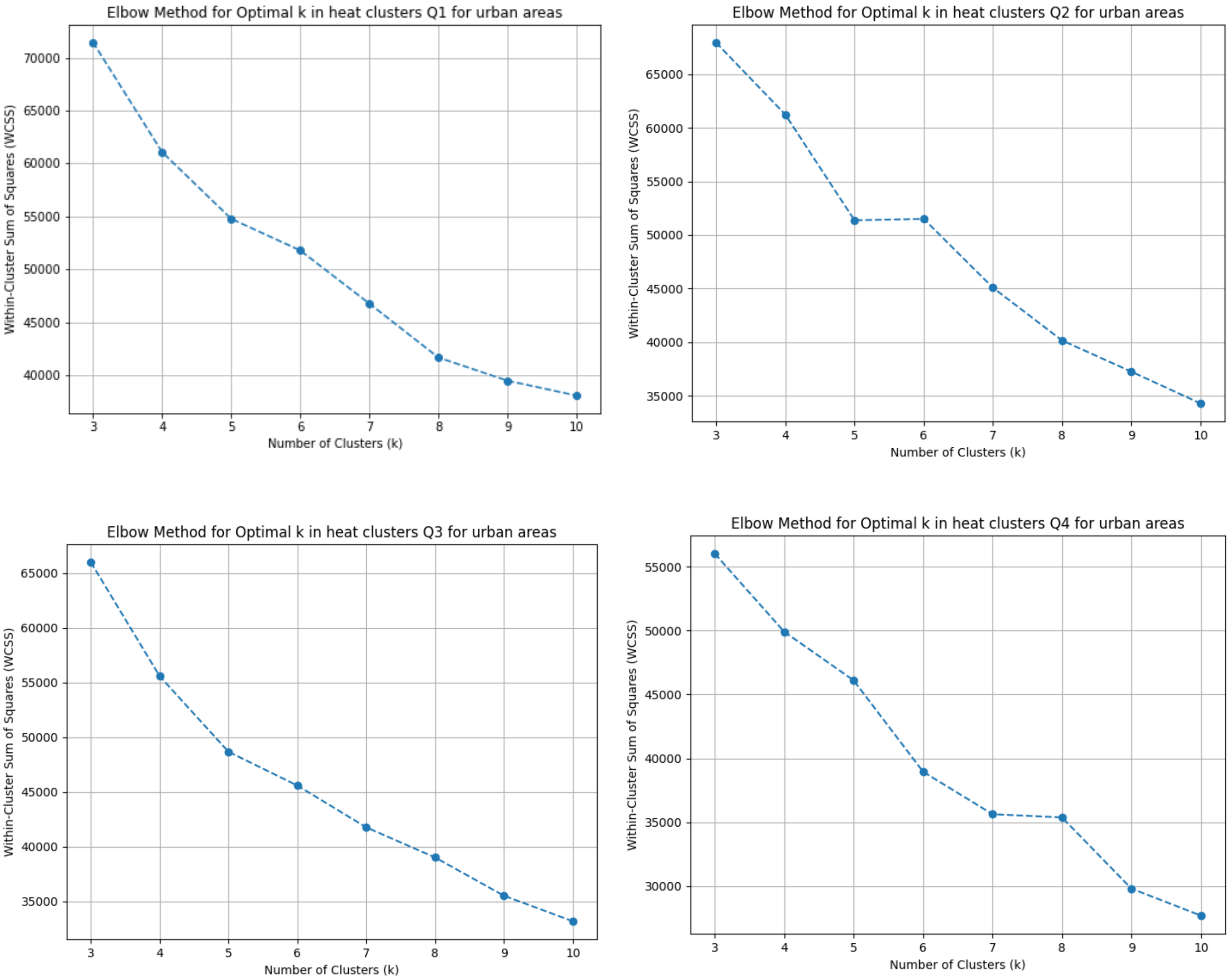

Figure A2.6: *WCCS for clustering of Q1-Q4 in urban areas.*

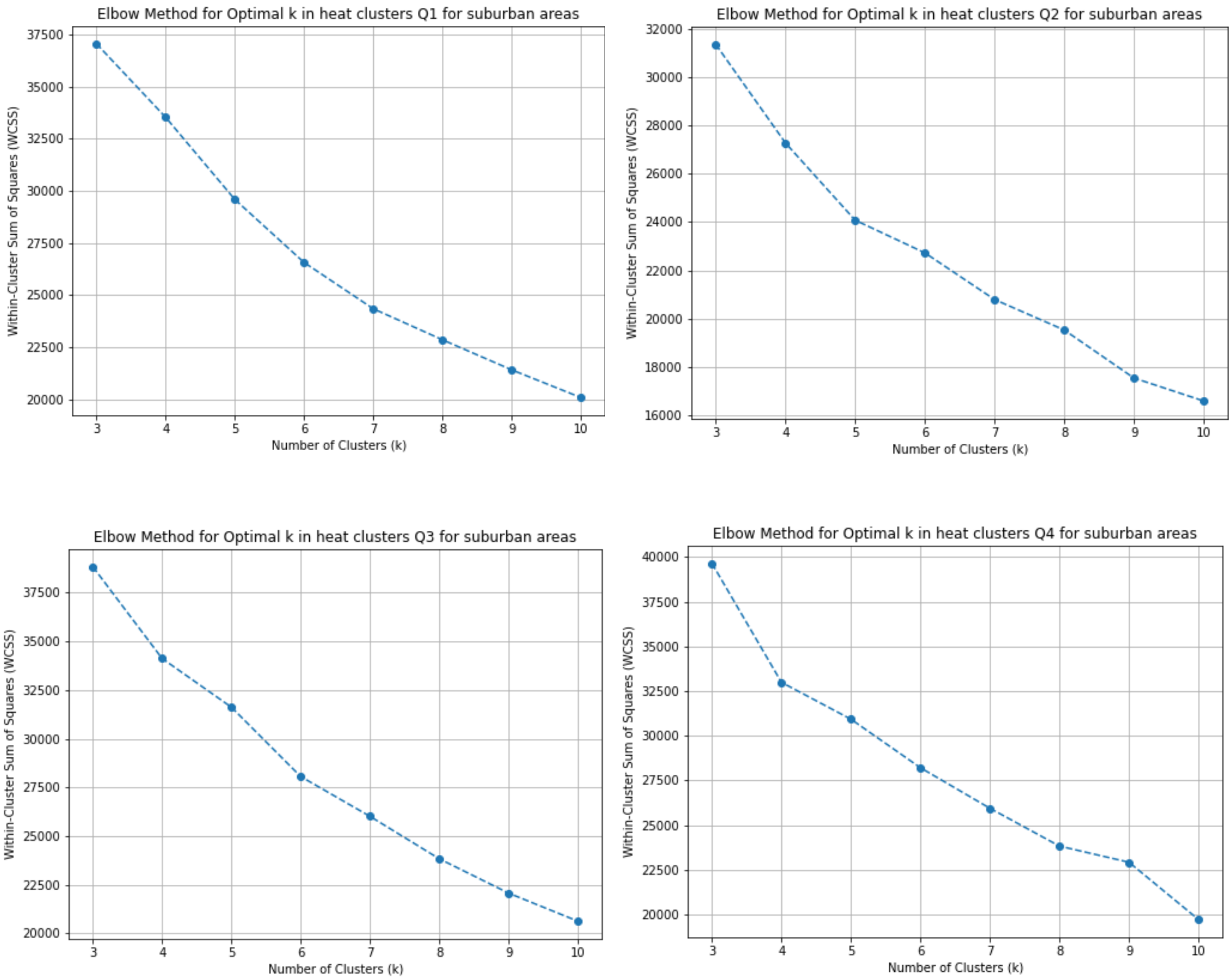

Figure A2.3: *WCCS for clustering of Q1-Q4 in suburban areas.*

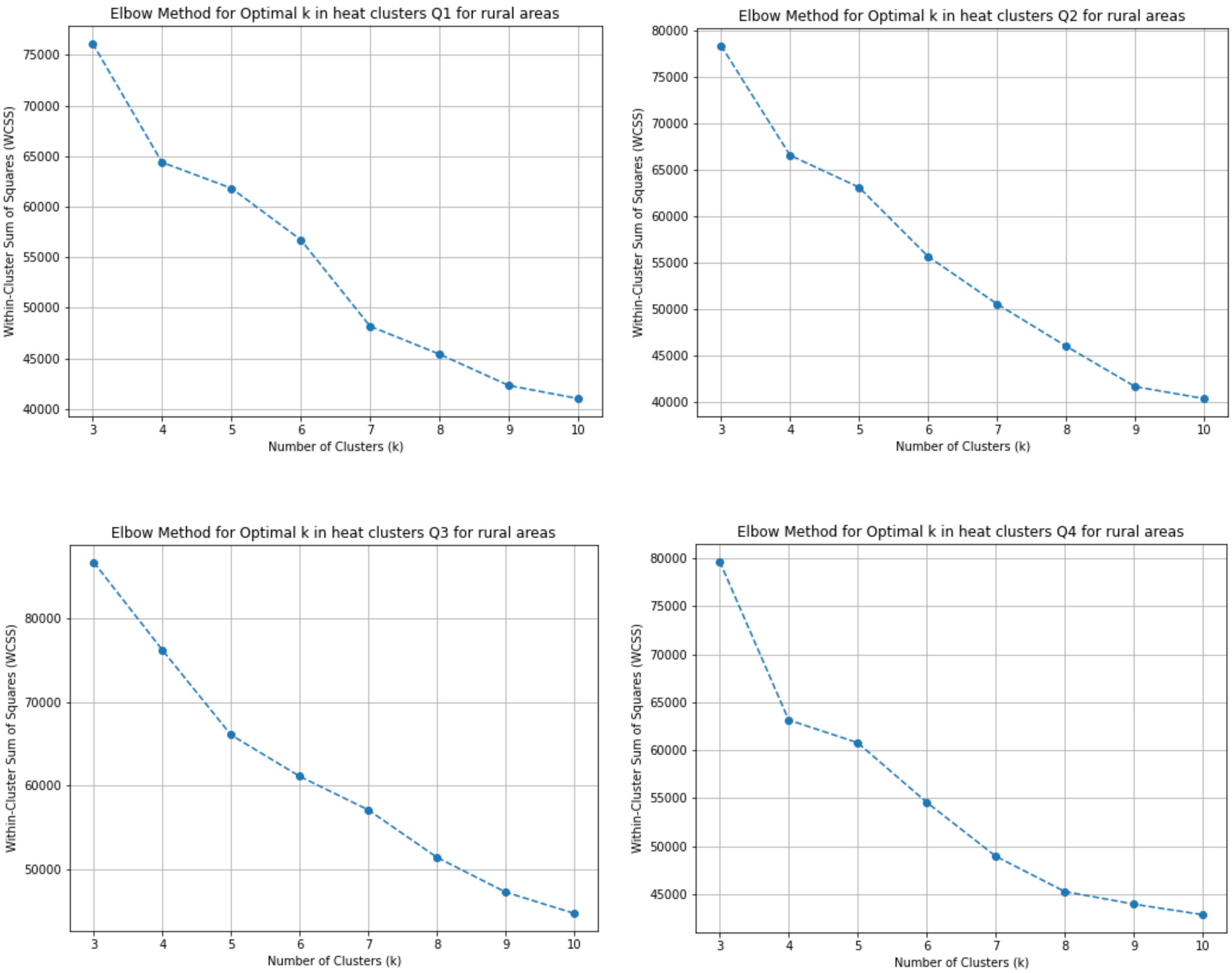

Figure A2.3: *WCCS for clustering of Q1-Q4 in rural areas.*

Table A2.4: *Matching of factors and their intersections based on qualitative results and their proxies in the socioeconomic data.*

	Results from stakeholder mental models	Described interaction with vulnerability	Proxy combination in the clustering dataset
one-dimensional	Income (of the individual)	Income in itself is a vulnerability driver because of affordability of energy demand for cooling, or the ability to adapt when you are a tenant. Income was double counted for Q1 and Q2 clusters, because of the dominant role of low income emphasized during the interviews.	*average cluster individual income*
	Age	Older people are (among kids) more susceptible to suffer from the impacts of heat, especially as older age often correlates with mobility constraints and pre-existing health issues which can leave them isolated	*cluster share of individuals >65*
multi-dimensional	Bad living conditions (distance to parks, insulation of buildings)	Few recreational possibilities to cool down and escape heat in close proximity alongside badly insulated residential buildings	*average cluster population density x average cluster cell income*
	Bad living conditions (distance to parks, insulation of buildings) in combination with low income	If paired with low income, bad living conditions can further exacerbate vulnerability by leaving individuals with low financial capacities to cope with heat exposure.	*average cluster population density x average cluster cell income x average cluster individual income*
	Age in combination with income	Older people (who may suffer from mobility constraints or pre-existing health conidtions) may be more isolated with limited social participation. When this is combined with low income, individuals are often trapped in their home with limited resources to insulate, renovate or install air conditioning.	*cluster share of individuals >65 x average cluster individual income*

Age in combination with income and poor living conditions	Especially elderly women with a low pension may be forced to live in bad circumstances bceause they cannot afford to live in better areas.	*cluster share of individuals >65 x average cluster individual income x average cluster population density x average cluster cell income*
Low socioeconomic status in combination with poor living conditions	Individuals with poor education and low income levels exhibit particularly low adaptive capacities. Additionally, their low socioeconomic status may force them to live in poorly insulated buildings in neighborhoods with no direct access to green or blue areas.	*cluster share of blue collar workers x average cluster individual income x average cluster cell income x average cluster population density*
Physically demanding jobs with high heat exposure	Individuals working in physically demanding jobs are particularly prone to suffer from heat stress with little to no options to reduce exposure	*cluster share of blue collar workers x cluster share of individuals working in manufacturing x cluster share of individuals working in outdoor sectors*
Physically demanding jobs with high heat exposure paired with low income and poor living conditions	Returning to a hot flat by the end of the day that does not allow for recovery or any recreational possibilities from green or blue areas to cool down nearby further further increases the vulnerability of individuals working in physically demanding jobs	*cluster share of blue collar workers x cluster share of individuals working in manufacturing x cluster share of individuals working in outdoor sectors x aver cluster cell income x aerage cluster population density x average cluster individual income*

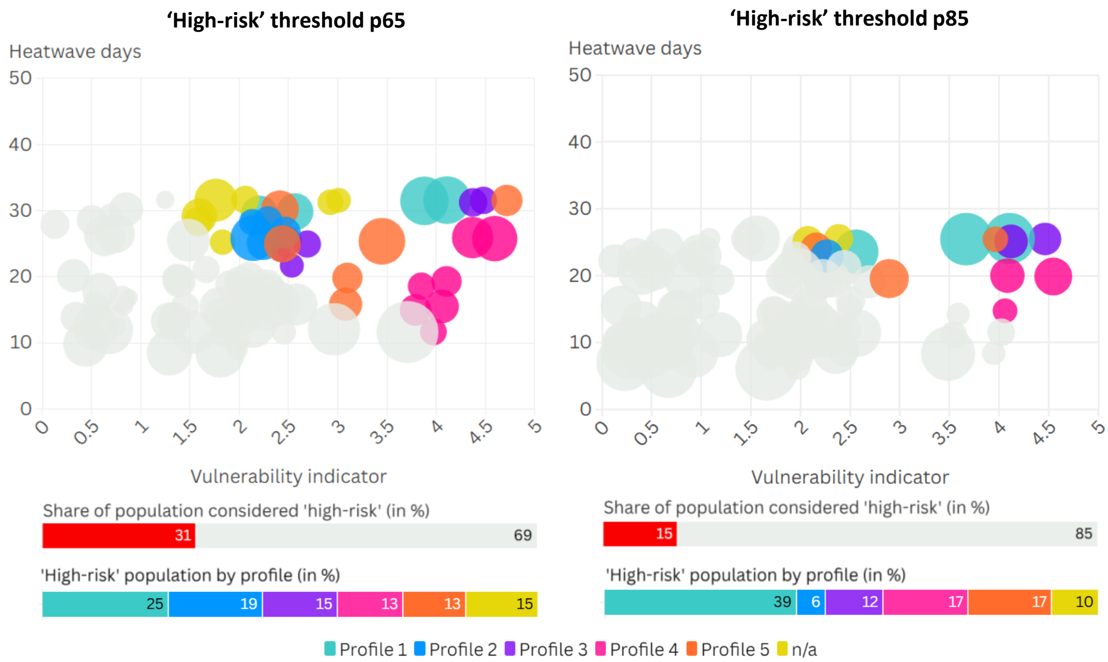

Figure A2.4: *Cluster-level representation of population heat risk during the reference period for risk thresholds at the 65th and 85th percentiles. Colored bubbles highlight clusters considered high-risk, defined by the threshold. High risk clusters that cannot be aligned with any of the five risk profiles are denoted n/a.*

Profile 6: People with disabilities with care dependency in urban heat islands

While this profile could not be directly matched with a quantitative cluster due to the absence of disability-related indicators in the data, it emerged as an important storyline through the qualitative approach. Disability may intersect with multiple factors, shaping people's vulnerability, such as care dependency, poor housing conditions, limited mobility, limited access to infrastructure, and environmental conditions. While financial constraints may also play a role, interviewees emphasized that economic hardship alone does not fully explain or could potentially generalize their heightened vulnerability.

Particularly in urban heat islands, people with disabilities may face compounded risks. Limited access to green and blue spaces or cooling infrastructure (close to the home), barriers in public infrastructure, and mobility restrictions can make it difficult to seek heat relief. Care dependency further exacerbates vulnerability for those who require assistance in their day to day lives, as it can limit their ability to take adaptative measures (or leaving over-heated homes) independently.

This interplay of factors can also contribute to / further intersect with social isolation, as mobility constraints and inaccessible public spaces may reduce opportunities for social participation.

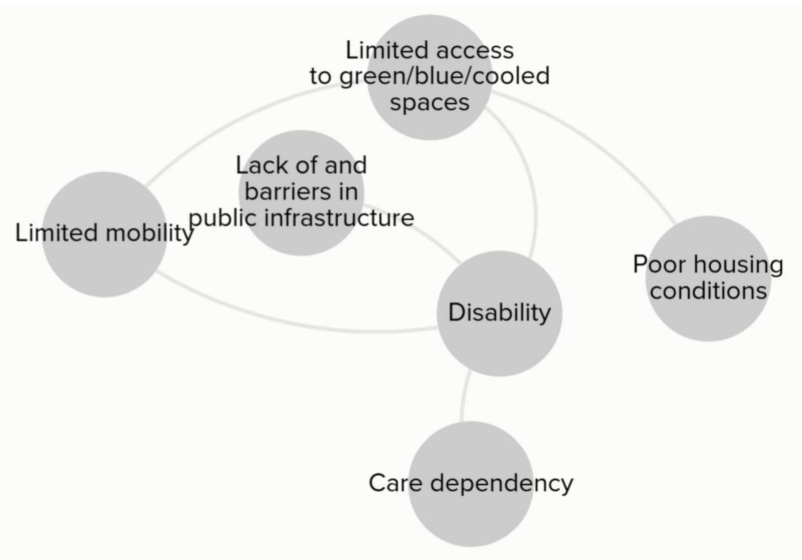

Figure A2.5: *Qualitative vulnerability factors as interconnected circles building profile 6.*

3. Results: Profiles characterizing Austrian heat risk

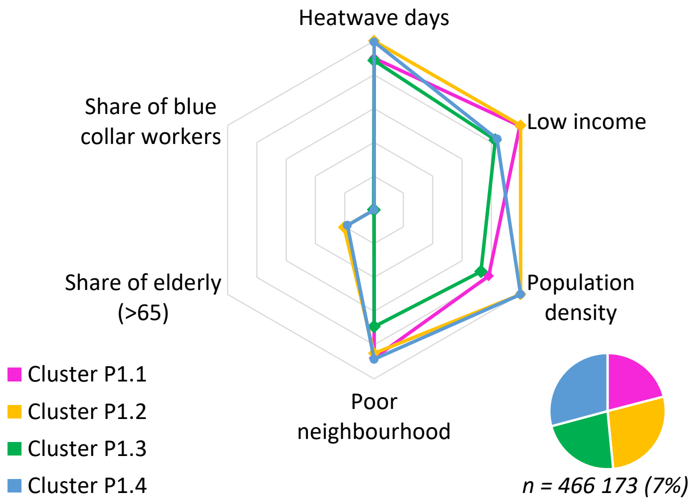

Figure A3.1: *Radar plot of normalized quantitative variables characterizing the four clusters aligned with storyline 1, where outermost points indicate the most extreme values. The pie chart indicates the distribution of individuals assigned to this storyline among clusters, indicating the total and relative number individuals assigned to this storyline as a share of the total observed population.*

Table A3.1: *Quantitative description of each cluster assigned to storyline 1.*

		Cluster average				Cluster share			
Cluster	Cluster size	Kysely days	Income	Population per km2	Cell income relative to average	Individuals > 65	Blue collar workers	Employed in manufacturing	Employed in outdoor sector
Cluster P1.1	97716	24	6514	7855	0.95	0.0	0.0	0.19	0.02
Cluster P1.2	128135	26	6103	21446	0.97	0.21	0.0	0.14	0.01
Cluster P1.3	104257	23	19028	7342	1.07	0.0	0.0	0.0	0.02
Cluster P1.4	136065	25	18133	21911	0.95	0.18	0.0	0.10	0.0
	Weighted averages	*25*	*12591*	*15578*	*0.98*	*0.11*	*0.0*	*0.11*	*0.02*

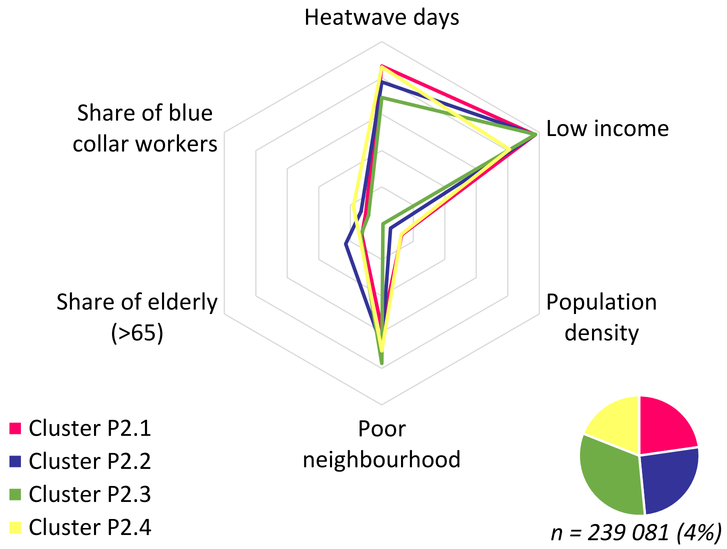

Figure A3.2: *Radar plot of normalized quantitative variables characterizing the four clusters aligned with the storyline 2, where outermost points indicate the most extreme values. The pie chart indicates the distribution of individuals assigned to this storyline among clusters, indicating the total and relative number individuals assigned to this storyline as a share of the total observed population.*

Table A3.2: *Quantitative description of each cluster assigned to storyline 2.*

		Cluster average				Cluster share			
Cluster	Cluster size	Kysely days	Income	Population per km2	Cell income relative to average	Individuals > 65	Blue collar workers	Employed in manufacturing	Employed in outdoor sector
Cluster P2.1	54360	23	8100	1409	1.14	0.1	0.1	0.21	0.04
Cluster P2.2	61502	21	8063.45	707	1.08	0.2	0.1	0.17	0.05
Cluster P2.3	77772	20	7826	234	1.02	0.1	0.1	0.18	0.05
Cluster P2.4	45447	23	20215	1371	1.06	0.1	0.2	0.10	0.05
	Weighted averages	21	10304	839	1.07	0.16	0.12	0.17	0.05

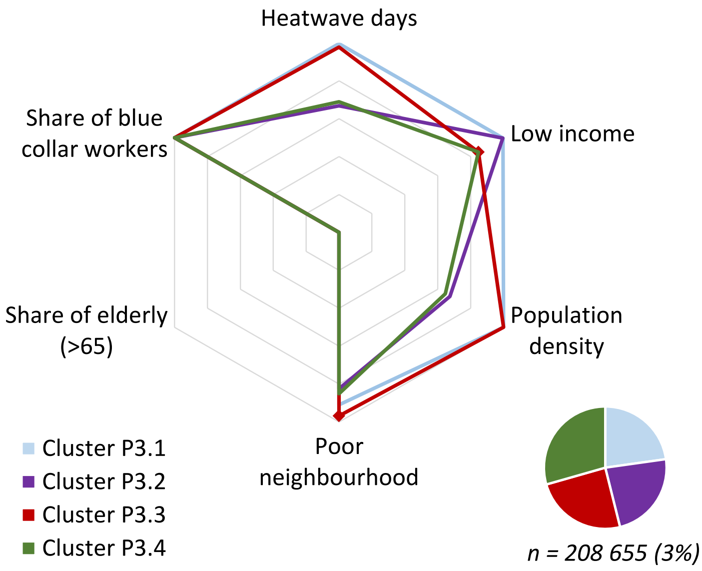

Figure A3.3: *Radar plot of normalized quantitative variables characterizing the four clusters aligned with storyline 3, where outermost points indicate the most extreme values. The pie chart indicates the distribution of individuals assigned to this storyline among clusters, indicating the total and relative number individuals assigned to this storyline as a share of the total observed population.*

Table A3.3: *Quantitative description of each cluster assigned to storyline 3.*

		Cluster average				Cluster share			
Cluster	Cluster size	Kysely days	Income	Population per km2	Cell income relative to average	Individuals > 65	Blue collar workers	Employed in manufacturing	Employed in outdoor sector
Cluster P3.1	52398	25	6380	21152	0.93	0.0	1.0	0.2	0.1
Cluster P3.2	53714	19	6433	6801	0.99	0.0	1.0	0.0	0.1
Cluster P3.3	56295	25	17532	21608	0.89	0.0	1.0	0.2	0.1
Cluster P3.4	67712	19	17521	6519	0.97	0.0	1.0	0.0	0.1
	Weighted averages	22	12399	13608	0.95	0.0	1.0	0.1	0.1

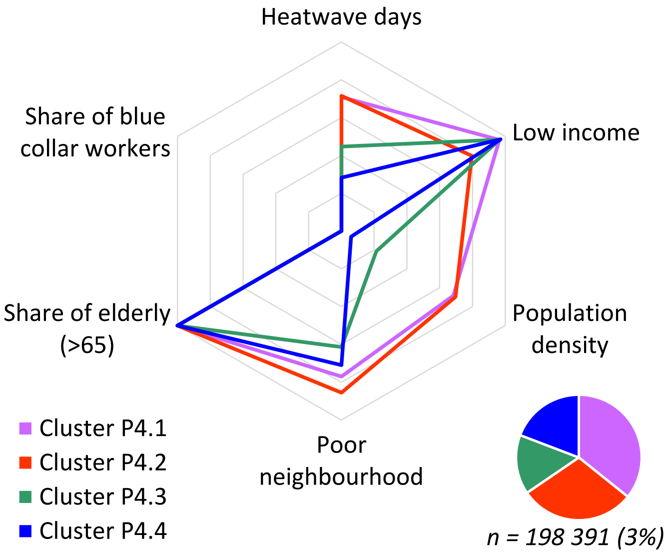

Figure A3.4: *Radar plot of normalized quantitative variables characterizing the four clusters aligned with storyline 4, where outermost points indicate the most extreme values. The pie chart indicates the distribution of individuals assigned to this storyline among clusters, indicating the total and relative number individuals assigned to this storyline as a share of the total observed population.*

Table A3.4: *Quantitative description of each cluster assigned to storyline 4.*

		Cluster average				Cluster share			
Cluster	Cluster size	Kysely days	Income	Population per km2	Cell income relative to average	Individuals > 65	Blue collar workers	Employed in manufacturing	Employed in outdoor sector
Cluster P4.1	70964	20	8749	6886	1.02	1.0	0.0	0.0	0.0
Cluster P4.2	58924	20	21401	7014	0.97	1.0	0.0	0.0	0.0
Cluster P4.3	30410	15	8638	2259	1.12	1.0	0.0	0.0	0.0
Cluster P4.4	38093	12	8245	1372	1.06	1.0	0.0	0.0	0.0
	Weighted averages	18	12393	5156	1.03	1.0	0.0	0.0	0.0

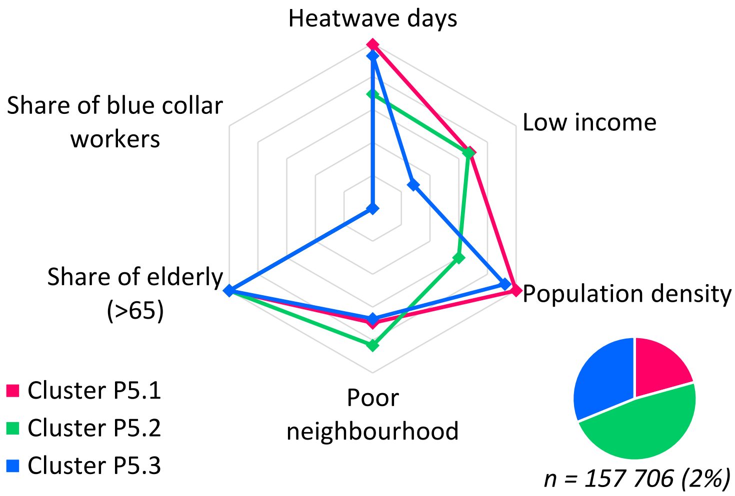

Figure A3.5: *Radar plot of normalized quantitative variables characterizing the four clusters aligned with storyline 5, where outermost points indicate the most extreme values. The pie chart indicates the distribution of individuals assigned to this profile among clusters, indicating the total and relative number individuals assigned to this storyline as a share of the total observed population.*

Table A3.5: *Quantitative description of each cluster assigned to storyline 5.*

		Cluster average				Cluster share			
Cluster	Cluster size	Kysely days	Income	Population per km2	Cell income relative to average	Individuals > 65	Blue collar workers	Employed in manufacturing	Employed in outdoor sector
Cluster P5.1	32632	25	30235	20424	1.07	1.0	0.0	0.0	0.0
Cluster P5.2	75885	20	30982	6064	0.98	1.0	0.0	0.0	0.0
Cluster P5.3	49189	24	59792	9225	1.09	1.0	0.0	0.0	0.0
	Weighted averages	22	39813	10021	1.03	1.0	0.0	0.0	0.0

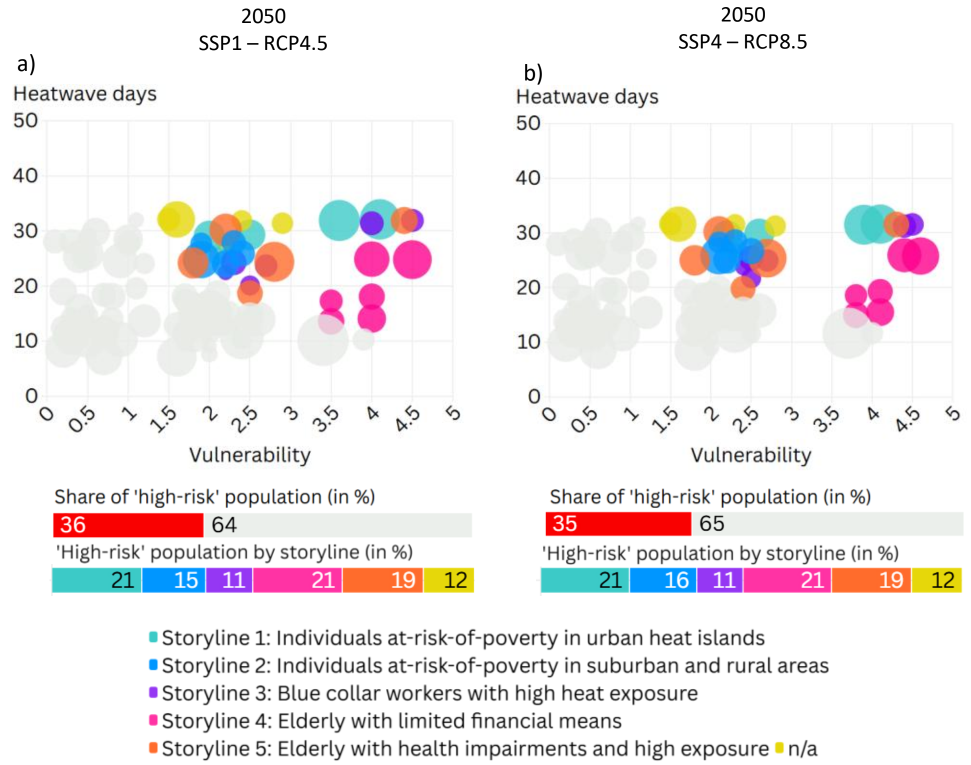

Figure A3.6: *Cluster-level representation of population heat risk in 2050 for scenarios characterized by ssp1-4.5 (panel a)) and ssp4-8.5 (panel b)). Colored bubbles highlight clusters considered high-risk, defined by a fixed threshold at the 75th percentile risk level from the reference period, consistent across all scenarios. High risk clusters that cannot be aligned with any of the five risk profiles are denoted n/a. For underlying data see SD.*

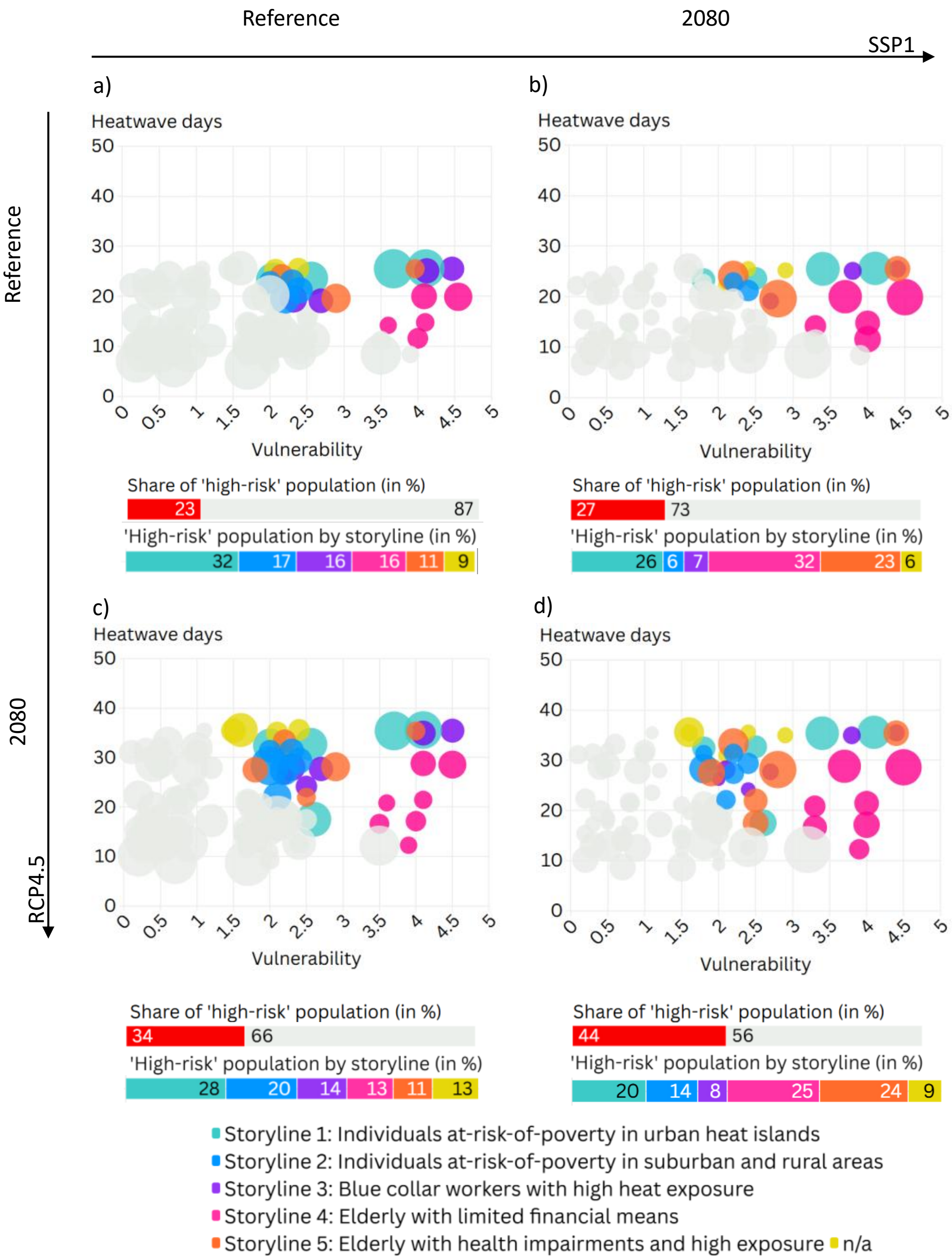

Figure A3.7: *Cluster-level representation of population heat risk during the a) reference period and for 2080 considering b) and socioeconomic trends characterized by decreasing inequality (SSP1), c) climate change under a medium-emission scenario (rcp4.5) and d) demographic and socioeconomic trends characterized by decreasing inequality (SSP1) and climate change under a medium emission scenario (RCP4.5). Colored bubbles highlight clusters considered high-risk, defined by a fixed threshold at the 75th percentile risk level from the reference period, consistent across all scenarios. High risk clusters that cannot be aligned with any of the five risk profiles are denoted n/a. For underlying data see SD.*

Supplementary Data

1. Reference period

Income quartile	Region	Cluster ID	Exposure: Cluster size	Hazard: Average no. of annual heatwave days avg	Hazard: std	Vulnerability: INCOME avg	INCOME std	INCOME norm	POPULATION DENSITY avg	POPULATION DENSITY std	POPULATION DENSITY norm	RELATIVE INCOME OF CELL avg	RELATIVE INCOME OF CELL std	RELATIVE INCOME OF CELL norm	Share of elderly (>65)	Share of blue collar workers	Share working in manufacturing	Share working in outdoor sector	VULNERABILITY INDICATOR (of cluster)	AVERAGE CLUSTER RISK	Risk > Percentile 0.75	Storyline of high-risk clusters	Risk > Percentile 0.65	Storyline of high-risk clusters	Risk > Percentile 0.85	Storyline of high-risk clusters
Q1	urban	Q1urban1	97716	23.6	2.4	6514.1	1573.7	1.0	7855.2	3233.0	0.33	1.0	0.1	0.9	0.0	0.0	0.2	0.0	2.6	60.4	y	1	y	1	y	1
Q1	urban	Q1urban2	41967	16.3	5.0	8347.5	1867.6	1.0	6086.4	2756.6	0.25	1.0	0.2	0.9	0.0	0.7	1.0	0.0	2.5	40.8	y	0	y	3	n	0
Q1	urban	Q1urban3	70964	19.9	4.6	8748.7	973.0	1.0	6885.9	3350.2	0.29	1.0	0.2	0.77	1.0	0.0	0.0	0.0	4.5	90.5	y	4	y	4	y	4
Q1	urban	Q1urban4	52398	25.5	1.5	6379.9	2801.8	1.0	21151.8	4402.8	0.89	0.9	0.2	0.9	0.0	1.0	0.2	0.1	4.5	113.8	n	3	y	3	y	3
Q1	urban	Q1urban5	39351	22.2	3.2	7668.2	1725.6	1.0	5379.9	2479.3	0.22	1.5	0.2	0.1	0.1	0.1	0.2	0.0	2.2	48.1	y	6	y	6	n	0
Q1	urban	Q1urban6	53714	19.1	4.5	6433.3	2857.9	1.0	6800.8	2795.9	0.28	1.0	0.2	0.8	0.0	1.0	0.0	0.1	2.7	51.3	y	3	y	3	n	0
Q1	urban	Q1urban7	111491	11.4	3.5	6825.5	1378.4	1.0	5231.9	2359.9	0.22	1.0	0.2	0.8	0.1	0.1	0.1	0.0	2.6	29.4	n	0	n	0	n	0
Q1	urban	Q1urban8	128135	25.6	1.7	6102.6	1268.9	1.0	21445.8	3897.5	0.91	1.0	0.2	0.8	0.2	0.0	0.1	0.0	4.1	105.0	n	1	y	1	y	1
Q2	urban	Q2urban1	104257	23.3	2.6	19027.7	2964.4	0.8	7341.6	3272.7	0.31	1.1	0.3	0.7	0.0	0.0	0.0	0.0	2.0	47.6	y	1	y	1	n	0
Q2	urban	Q2urban2	25696	18.1	5.9	20555.8	2868.7	0.8	6624.7	3254.3	0.28	1.0	0.2	0.8	0.0	1.0	1.0	0.0	2.2	40.1	y	0	y	3	n	0
Q2	urban	Q2urban3	34067	20.3	4.6	20846.9	2305.9	0.8	7689.2	3595.7	0.32	1.0	0.2	0.9	0.0	0.0	1.0	0.0	2.1	43.0	y	0	y	1	n	0
Q2	urban	Q2urban4	56295	25.1	1.5	17532.1	3472.7	0.8	21608.3	4383.2	0.91	0.9	0.2	1.0	0.0	1.0	0.2	0.1	4.1	103.6	n	3	y	3	y	3
Q2	urban	Q2urban5	58924	20.0	4.7	21401.3	1911.9	0.8	7013.6	3437.1	0.29	1.0	0.1	0.9	1.0	0.0	0.0	0.0	4.1	81.8	y	4	y	4	y	4
Q2	urban	Q2urban6	67712	19.5	4.6	17521.1	3339.5	0.8	6518.6	2789.0	0.27	1.0	0.2	0.9	0.0	1.0	0.0	0.1	2.3	45.2	y	3	y	3	n	0
Q2	urban	Q2urban7	119708	11.5	3.6	18916.1	3084.3	0.8	5384.8	2393.9	0.22	1.0	0.2	0.8	0.1	0.1	0.1	0.0	2.2	25.8	n	0	n	0	n	0
Q2	urban	Q2urban8	136065	25.5	1.7	18132.7	3170.4	0.8	21910.6	3970.3	0.93	0.9	0.2	0.9	0.2	0.0	0.1	0.0	3.7	93.4	y	1	y	1	y	1
Q3	urban	Q3urban1	42595	25.5	0.9	29182.0	2808.5	0.7	23654.5	2666.1	1.00	0.9	0.1	1.0	0.0	0.0	0.2	0.0	2.4	60.9	n	6	y	6	y	6
Q3	urban	Q3urban2	53321	15.9	5.2	30885.5	4180.8	0.7	5927.7	2702.8	0.25	1.1	0.2	0.7	0.0	0.7	1.0	0.0	1.0	16.2	n	0	n	0	n	0
Q3	urban	Q3urban3	32632	25.5	1.6	30234.8	2894.7	0.7	20424.1	4588.1	0.86	1.1	0.1	0.7	1.0	0.0	0.0	0.0	4.0	100.9	y	5	y	5	y	5
Q3	urban	Q3urban4	46673	19.4	4.6	29148.6	2966.7	0.7	6443.1	2730.5	0.27	1.0	0.2	0.8	0.0	1.0	0.0	0.0	1.2	22.8	y	0	n	0	n	0
Q3	urban	Q3urban5	91742	23.0	2.6	32032.0	3999.8	0.7	6440.2	2569.2	0.27	1.0	0.2	0.8	0.0	0.0	0.2	0.0	1.0	22.7	n	0	n	0	n	0
Q3	urban	Q3urban6	46248	25.2	1.5	29595.9	4325.2	0.7	21425.4	4617.7	0.91	1.1	0.2	0.6	0.0	1.0	0.2	0.2	2.1	52.2	n	6	y	6	y	6
Q3	urban	Q3urban7	75885	19.6	4.5	30981.6	3622.0	0.7	6064.2	2581.3	0.25	1.0	0.2	0.8	1.0	0.0	0.0	0.0	2.9	56.6	n	5	y	5	y	5
Q3	urban	Q3urban8	55190	25.5	2.0	32808.3	3481.7	0.6	16758.8	2675.8	0.71	1.1	0.1	0.7	0.0	0.0	0.2	0.0	1.5	37.5	n	0	y	6	n	0
Q3	urban	Q3urban9	99043	11.2	3.4	31434.3	3684.7	0.7	5300.9	2438.4	0.22	1.0	0.1	0.8	0.1	0.1	0.1	0.0	1.2	13.3	y	0	n	0	n	0
Q4	urban	Q4urban1	84337	24.0	2.0	62744.3	11824.7	0.2	8564.3	3664.9	0.36	1.0	0.1	0.9	0.0	0.0	0.0	0.1	0.6	15.0	n	0	n	0	n	0
Q4	urban	Q4urban2	37312	23.2	2.4	63491.7	20839.1	0.2	6196.9	2649.9	0.26	1.1	0.2	0.7	0.0	0.1	1.0	0.0	0.5	11.0	n	0	n	0	n	0
Q4	urban	Q4urban3	49189	24.1	2.4	59791.5	14424.6	0.3	9225.4	4658.3	0.39	1.1	0.2	0.7	1.0	0.0	0.0	0.0	2.2	52.0	n	5	y	5	y	5
Q4	urban	Q4urban4	22940	25.5	1.6	67309.4	17177.2	0.2	20144.5	4489.6	0.85	1.0	0.2	0.9	0.0	0.0	1.0	0.0	1.1	27.6	n	0	n	0	n	0
Q4	urban	Q4urban5	54070	22.2	3.3	81051.7	38582.2	0.0	5521.6	2624.5	0.23	1.5	0.2	0.0	0.1	0.0	0.0	0.0	0.1	2.8	n	0	n	0	n	0
Q4	urban	Q4urban6	47599	13.4	3.7	58334.2	15212.9	0.3	5356.2	2387.2	0.22	1.0	0.2	0.8	1.0	0.0	0.0	0.0	2.0	26.8	n	0	n	0	n	0
Q4	urban	Q4urban7	48131	12.1	3.4	58650.1	17360.7	0.3	4984.4	2257.9	0.21	1.0	0.2	0.8	0.0	0.3	1.0	0.0	0.5	6.5	n	0	n	0	n	0
Q4	urban	Q4urban8	104427	25.6	1.7	64600.6	17607.5	0.2	22064.4	3498.2	0.93	1.0	0.2	0.8	0.2	0.0	0.0	0.0	1.6	39.9	y	0	y	6	n	0
Q4	urban	Q4urban9	91012	13.0	3.5	66393.2	16344.5	0.2	5451.1	2421.5	0.23	1.0	0.2	0.8	0.0	0.0	0.0	0.1	0.4	5.2	n	0	n	0	n	0
Q1	suburban	Q1suburban1	72014	15.3	6.3	7428.7	1703.4	1.0	2346.6	244.0	0.09	1.1	0.2	0.6	0.0	0.1	0.2	0.0	2.1	31.8	y	0	n	0	n	0
Q1	suburban	Q1suburban2	54360	22.9	3.3	8099.8	1763.7	1.0	1408.9	258.4	0.05	1.1	0.2	0.6	0.1	0.1	0.2	0.0	2.3	52.0	n	2	y	2	y	2
Q1	suburban	Q1suburban3	33915	12.1	5.1	9024.1	2079.9	1.0	2025.7	284.1	0.08	1.1	0.2	0.7	0.0	0.7	0.8	0.0	2.1	25.2	n	0	n	0	n	0
Q1	suburban	Q1suburban4	30410	14.8	6.1	8638.5	1233.5	1.0	2259.0	278.0	0.09	1.1	0.2	0.6	1.0	0.0	0.0	0.0	4.1	60.0	y	4	y	4	y	4
Q1	suburban	Q1suburban5	32677	11.6	4.9	7628.8	2919.9	1.0	1338.0	233.7	0.05	1.0	0.2	0.7	0.0	1.0	0.3	0.1	2.1	24.5	y	0	n	0	n	0
Q1	suburban	Q1suburban6	80021	10.1	3.6	7726.9	1469.8	1.0	1378.4	250.7	0.05	1.1	0.2	0.7	0.0	0.0	0.2	0.0	2.0	20.5	n	0	n	0	n	0
Q1	suburban	Q1suburban7	38093	11.6	4.9	8244.5	1140.2	1.0	1372.4	240.2	0.05	1.1	0.2	0.7	1.0	0.0	0.0	0.0	4.0	46.5	n	4	y	4	n	0
Q1	rural	Q1rural1	61502	21.2	4.2	8063.4	1788.2	1.0	706.6	150.6	0.02	1.1	0.2	0.7	0.2	0.1	0.2	0.0	2.4	51.7	n	2	y	2	n	0
Q1	rural	Q1rural2	27317	8.4	5.0	7545.5	1887.5	1.0	201.0	147.1	0.00	0.9	0.2	0.9	1.0	0.0	0.0	0.0	3.9	33.2	n	0	n	0	n	0
Q1	rural	Q1rural3	45447	10.8	5.2	9132.9	2122.7	1.0	486.9	161.9	0.01	1.0	0.2	0.8	0.0	0.7	0.9	0.0	2.0	21.1	y	0	n	0	n	0
Q1	rural	Q1rural4	33935	6.4	3.5	7362.4	2138.9	1.0	172.8	120.0	0.00	1.0	0.2	0.9	0.0	0.0	0.2	0.0	2.0	12.6	n	0	n	0	n	0
Q1	rural	Q1rural5	26347	7.5	4.9	7048.6	3155.2	1.0	191.0	124.1	0.00	0.9	0.2	0.9		1.0	0.3	0.1	2.0	15.1	n	0	n	0	n	0
Q1	rural	Q1rural6	77772	19.5	4.3	7825.5	2031.0	1.0	234.2	122.5	0.00	1.0	0.2	0.8	0.1	0.1	0.2	0.0	2.2	43.5	n	2	y	2	n	0
Q1	rural	Q1rural7	35778	8.5	3.7	7729.3	1697.1	1.0	744.4	145.2	0.02	1.1	0.2	0.7	0.2	0.1	0.2	0.0	2.4	20.6	y	0	n	0	n	0
Q2	suburban	Q2suburban1	61502	14.3	5.9	20416.5	2886.4	0.8	2282.6	270.2	0.09	1.1	0.2	0.7	0.0	0.0	0.2	0.0	1.7	24.8	n	0	n	0	n	0
Q2	suburban	Q2suburban2	27317	13.1	5.0	20387.8	3943.2	0.8	1477.2	250.4	0.06	1.0	0.2	0.8	0.0	0.8	0.8	0.0	1.7	22.8	y	0	n	0	n	0
Q2	suburban	Q2suburban3	45447	22.8	3.6	20214.9	3061.8	0.8	1371.3	247.8	0.05	1.1	0.2	0.7	0.1	0.2	0.1	0.1	2.0	44.6	n	2	y	2	n	0
Q2	suburban	Q2suburban4	33935	14.2	5.7	18251.0	3762.1	0.8	2213.3	315.2	0.09	1.0	0.2	0.7	0.0	1.0	0.2	0.1	1.9	26.5	n	0	n	0	n	0
Q2	suburban	Q2suburban5	26347	14.2	6.1	20908.2	2185.5	0.8	2259.9	280.8	0.09	1.0	0.2	0.7	1.0	0.0	0.0	0.0	3.6	51.1	n	4	y	4	n	0
Q2	suburban	Q2suburban6	77772	9.4	3.5	19605.9	3096.3	0.8	1338.6	229.7	0.05	1.0	0.2	0.8	0.0	0.2	0.1	0.1	1.7	16.1	n	0	n	0	n	0
Q2	suburban	Q2suburban7	35778	11.1	4.8	20303.6	2209.7	0.8	1368.9	237.9	0.05	1.0	0.2	0.8	1.0	0.0	0.0	0.0	3.5	39.5	n	0	y	4	n	0
Q2	rural	Q2rural1	187212	12.2	6.6	19970.3	3035.4	0.8	744.7	139.9	0.02	1.0	0.2	0.7	0.2	0.2	0.2	0.0	2.1	25.6	n	0	n	0	n	0
Q2	rural	Q2rural2	194495	6.0	3.6	18884.7	3317.0	0.8	165.0	119.7	0.00	0.9	0.2	0.9	0.0	0.1	0.1	0.0	1.7	10.0	n	0	n	0	n	0
Q2	rural	Q2rural3	85239	10.4	5.2	18951.5	4048.8	0.8	227.8	150.0	0.00	1.0	0.2	0.9	0.0	0.7	0.9	0.0	1.7	17.4	n	0	n	0	n	0
Q2	rural	Q2rural4	145851	8.4	5.1	18971.8	3301.3	0.8	182.3	141.2	0.00	0.9	0.2	0.9	1.0	0.0	0.0	0.0	3.5	29.2	n	0	n	0	n	0
Q2	rural	Q2rural5	41864	8.1	5.2	17965.8	3827.2	0.8	352.7	162.6	0.01	1.0	0.2	0.9	0.0	0.9	0.0	0.6	1.7	13.8	n	0	n	0	n	0
Q2	rural	Q2rural6	135288	20.3	4.5	19644.3	3231.9	0.8	284.0	154.3	0.01	1.0	0.2	0.8	0.2	0.1	0.1	0.0	2.0	39.9	n	0	y	2	n	0
Q3	suburban	Q3suburban1	81235	14.8	6.2	31561.8	4185.1	0.7	2329.9	253.3	0.09	1.1	0.2	0.7	0.0	0.2	0.3	0.1	0.8	11.5	n	0	n	0	n	0
Q3	suburban	Q3suburban2	60131	11.6	4.8	30629.0	3802.4	0.7	1616.4	326.6	0.06	1.0	0.2	0.8	0.0	0.8	0.8	0.1	0.8	9.5	n	0	n	0	n	0
Q3	suburban	Q3suburban3	32473	15.2	6.3	30463.5	3256.7	0.7	2261.1	278.5	0.09	1.1	0.2	0.6	1.0	0.0	0.0	0.0	2.5	37.9	n	0	y	5	n	0
Q3	suburban	Q3suburban4	77813	10.0	3.7	31612.0	3912.3	0.7	1318.6	228.8	0.05	1.1	0.2	0.7	0.0	0.2	0.2	0.1	0.7	7.2	n	0	n	0	n	0
Q3	suburban	Q3suburban5	39821	11.8	5.0	29699.7	3001.7	0.7	1372.2	241.5	0.05	1.1	0.2	0.7	1.0	0.0	0.0	0.0	2.5	29.1	n	0	n	0	n	0
Q3	suburban	Q3suburban6	54905	22.8	3.3	31245.8	4097.1	0.7	1399.1	257.2	0.05	1.1	0.2	0.6	0.1	0.2	0.2	0.1	1.0	22.1	n	0	n	0	n	0
Q3	rural	Q3rural1	123216	8.5	4.2	31382.1	3815.4	0.7	715.5	152.8	0.02	1.1	0.2	0.7	0.1	0.1	0.2	0.1	0.9	7.8	n	0	n	0	n	0
Q3	rural	Q3rural2	113580	9.6	5.1	31073.9	3946.4	0.7	207.1	126.3	0.00	1.0	0.2	0.9	0.0	0.8	1.0	0.0	0.7	6.5	n	0	n	0	n	0
Q3	rural	Q3rural3	128360	20.1	4.4	31410.6	3976.2	0.7	262.4	138.9	0.00	1.0	0.2	0.7	0.1	0.1	0.2	0.0	0.9	17.4	n	0	n	0	n	0
Q3	rural	Q3rural4	68474	14.9	6.2	30780.7	3918.5	0.7	712.2	153.4	0.02	1.0	0.2	0.7	0.0	0.7	0.8	0.1	0.7	11.1	n	0	n	0	n	0
Q3	rural	Q3rural5	103472	8.7	5.1	30459.6	4048.8	0.7	194.1	136.7	0.00	1.0	0.2	0.8	1.0	0.0	0.0	0.0	2.4	20.6	n	0	n	0	n	0
Q3	rural	Q3rural6	164931	6.1	3.5	31103.4	3885.5	0.7	169.2	116.2	0.00	1.0	0.2	0.9	0.0	0.1	0.2	0.0	0.7	4.0	n	0	n	0	n	0
Q3	rural	Q3rural7	49291	9.2	5.8	31324.5	3739.2	0.7	304.1	163.1	0.01	1.0	0.2	0.9	0.0	0.9	0.0	0.8	0.7	6.2	n	0	n	0	n	0
Q3	rural	Q3rural8	59876	19.8	5.5	30854.6	3860.2	0.7	713.0	155.3	0.02	1.1	0.2	0.6	0.7	0.0	0.0	0.0	1.8	36.2	n	0	y	5	n	0
Q4	suburban	Q4suburban1	82127	15.5	6.4	70799.5	25097.3	0.1	2320.9	246.6	0.09	1.2	0.3	0.5	0.0	0.0	0.2	0.0	0.2	2.9	n	0	n	0	n	0
Q4	suburban	Q4suburban2	69857	10.2	3.6	69342.4	26295.7	0.2	1393.5	260.3	0.05	1.1	0.3	0.6	0.0	0.0	0.0	0.0	0.2	2.0	n	0	n	0	n	0
Q4	suburban	Q4suburban3	55229	11.6	4.7	61926.5	21690.3	0.3	1371.2	254.7	0.05	1.1	0.2	0.7	0.0	0.2	1.0	0.0	0.3	3.6	n	0	n	0	n	0
Q4	suburban	Q4suburban4	40955	11.9	5.1	54263.3	14404.8	0.4	1369.2	238.1	0.05	1.1	0.3	0.6	1.0	0.0	0.0	0.0	1.8	21.4	n	0	n	0	n	0
Q4	suburban	Q4suburban5	7617	12.6	5.5	49961.1	16264.6	0.4	1578.1	325.8	0.06	1.0	0.2	0.8	0.0	0.8	0.0	1.0	0.5	6.2	n	0	n	0	n	0
Q4	suburban	Q4suburban6	58473	23.1	3.3	67984.6	25860.8	0.2	1414.9	259.2	0.05	1.2	0.3	0.5	0.1	0.0	0.2	0.0	0.3	7.8	n	0	n	0	n	0
Q4	suburban	Q4suburban7	34250	14.7	6.0	57829.8	15678.8	0.3	2248.7	277.2	0.09	1.2	0.3	0.5	1.0	0.0	0.0	0.0	1.7	25.5	n	0	n	0	n	0
Q4	suburban	Q4suburban8	25376	11.7	4.9	52631.3	16186.1	0.4	2101.2	285.2	0.08	1.1	0.2	0.7	0.0	0.6	1.0	0.0	0.5	5.6	n	0	n	0	n	0
Q4	rural	Q4rural1	96047	21.0	4.0	62607.3	21633.5	0.2	713.6	146.6	0.02	1.1	0.2	0.6	0.2	0.1	0.3	0.1	0.5	10.8	n	0	n	0	n	0
Q4	rural	Q4rural2	147695	8.7	3.6	63796.5	24607.7	0.2	749.3	139.7	0.02	1.1	0.2	0.6	0.2	0.1	0.3	0.0	0.5	4.0	n	0	n	0	n	0
Q4	rural	Q4rural3	162609	9.0	4.8	60202.1	23930.0	0.3	235.4	150.1	0.00	1.0	0.2	0.8	0.0	0.3	1.0	0.0	0.3	2.5	n	0	n	0	n	0
Q4	rural	Q4rural4	160394	7.0	3.8	64044.6	27338.5	0.2	195.8	126.3	0.00	1.0	0.3	0.7	0.0	0.0	0.0	0.0	0.2	1.6	n	0	n	0	n	0
Q4	rural	Q4rural5	23755	9.1	5.5	51820.6	17168.9	0.4	315.9	163.4	0.01	1.0	0.2	0.9	0.0	0.7	0.0	0.9	0.4	3.6	n	0	n	0	n	0
Q4	rural	Q4rural6	116505	20.8	4.2	62321.5	25249.1	0.2	244.0	126.3	0.00	1.1	0.2	0.7	0.1	0.0	0.2	0.1	0.4	8.3	n	0	n	0	n	0
Q4	rural	Q4rural7	80931	9.4	5.1	51857.8	22287.1	0.4	270.9	159.0	0.00	1.1	0.3	0.7	1.0	0.0	0.0	0.0	1.8	16.7	n	0	n	0	n	0

TOTAL population	6347839	
Population in profile 1	466173	32%
Population in profile 2	239081	17%
Population in profile 3	230119	16%
Population in profile 4	224738	16%
Population in profile 5	157706	11%
Population in profile n/a	128194	9%
Total high-risk population	1446011	
Share of high-risk populatic	23%	

PERCENTILE 0.75	43.4	y... high-risk cluster
PERCENTILE 0.65	35.8	n... cluster is not considered high-risk
PERCENTILE 0.85	51.9	

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Income quartile	Region	Cluster ID	Exposure: Cluster size	Hazard: Average no. of annual heatwave days avg	Vulnerability: INCOME avg	INCOME norm	POPULATION DENSITY avg	POPULATION DENSITY norm	RELATIVE INCOME OF CELL avg	RELATIVE INCOME OF CELL norm	Share of elderly (>65)	Share of blue collar workers	Share working in manufacturing	Share working in outdoor sector	VULNERABILITY INDICATOR (of cluster)	AVERAGE CLUSTER RISK	Risk > Percentile 0.75	Storyline of high-risk clusters
Q1	urban	Q1urban1	97716	41.2	6514.1	1.0	7855.2	*0.33*	1.0	0.9	0.0	0.0	0.2	0.0	2.5619	105.6	y	1
Q1	urban	Q1urban2	41967	35.9	8347.5	1.0	6086.4	*0.25*	1.0	0.9	0.0	0.7	1.0	0.0	2.5	90.0	y	3
Q1	urban	Q1urban3	70964	38.3	8748.7	1.0	6885.9	*0.29*	1.0	0.77	1.0	0.0	0.0	0.0	4.5	174.3	y	4
Q1	urban	Q1urban4	52398	41.9	6379.9	1.0	21151.8	*0.89*	0.9	0.9	0.0	1.0	0.2	0.1	4.5	186.8	y	3
Q1	urban	Q1urban5	39351	38.1	7668.2	1.0	5379.9	*0.22*	1.5	0.1	0.1	0.1	0.2	0.0	2.2	82.7	y	6
Q1	urban	Q1urban6	53714	38.6	6433.3	1.0	6800.8	*0.28*	1.0	0.8	0.0	1.0	0.0	0.1	2.7	103.7	y	3
Q1	urban	Q1urban7	111491	29.7	6825.5	1.0	5231.9	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	2.6	76.5	y	1
Q1	urban	Q1urban8	128135	41.9	6102.6	1.0	21445.8	*0.91*	1.0	0.8	0.2	0.0	0.1	0.0	4.1	172.1	y	1
Q2	urban	Q2urban1	104257	40.7	19027.7	0.8	7341.6	*0.31*	1.1	0.7	0.0	0.0	0.0	0.0	2.0	83.1	y	1
Q2	urban	Q2urban2	25696	36.6	20555.8	0.8	6624.7	*0.28*	1.0	0.8	0.0	1.0	1.0	0.0	2.2	81.0	y	3
Q2	urban	Q2urban3	34067	39.1	20846.9	0.8	7689.2	*0.32*	1.0	0.9	0.0	0.0	1.0	0.0	2.1	82.7	y	1
Q2	urban	Q2urban4	56295	41.4	17532.1	0.8	21608.3	*0.91*	0.9	1.0	0.0	1.0	0.2	0.1	4.1	170.8	y	3
Q2	urban	Q2urban5	58924	38.8	21401.3	0.8	7013.6	*0.29*	1.0	0.9	1.0	0.0	0.0	0.0	4.1	158.6	y	4
Q2	urban	Q2urban6	67712	38.3	17521.1	0.8	6518.6	*0.27*	1.0	0.9	0.0	1.0	0.0	0.1	2.3	88.8	y	3
Q2	urban	Q2urban7	119708	29.8	18916.1	0.8	5384.8	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	2.2	66.5	y	1
Q2	urban	Q2urban8	136065	41.8	18132.7	0.8	21910.6	*0.93*	0.9	0.9	0.2	0.0	0.1	0.0	3.7	153.4	y	1
Q3	urban	Q3urban1	42595	42.0	29182.0	0.7	23654.5	*1.00*	0.9	1.0	0.0	0.0	0.2	0.0	2.4	100.0	y	6
Q3	urban	Q3urban2	53321	35.2	30885.5	0.7	5927.7	*0.25*	1.1	0.7	0.0	0.7	1.0	0.0	1.0	36.0	n	0
Q3	urban	Q3urban3	32632	41.8	30234.8	0.7	20424.1	*0.86*	1.1	0.7	1.0	0.0	0.0	0.0	4.0	165.7	y	5
Q3	urban	Q3urban4	46673	38.2	29148.6	0.7	6443.1	*0.27*	1.0	0.8	0.0	1.0	0.0	0.0	1.2	45.0	y	6
Q3	urban	Q3urban5	91742	40.4	32032.0	0.7	6440.2	*0.27*	1.0	0.8	0.0	0.0	0.2	0.0	1.0	39.9	n	0
Q3	urban	Q3urban6	46248	41.5	29595.9	0.7	21425.4	*0.91*	1.1	0.6	0.0	1.0	0.2	0.2	2.1	86.0	y	6
Q3	urban	Q3urban7	75885	37.8	30981.6	0.7	6064.2	*0.25*	1.0	0.8	1.0	0.0	0.0	0.0	2.9	109.3	y	5
Q3	urban	Q3urban8	55190	41.8	32808.3	0.6	16758.8	*0.71*	1.1	0.7	0.0	0.0	0.2	0.0	1.5	61.4	y	6
Q3	urban	Q3urban9	99043	29.3	31434.3	0.7	5300.9	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	1.2	34.8	n	0
Q4	urban	Q4urban1	84337	41.1	62744.3	0.2	8564.3	*0.36*	1.0	0.9	0.0	0.0	0.0	0.1	0.6	25.7	n	0
Q4	urban	Q4urban2	37312	40.6	63491.7	0.2	6196.9	*0.26*	1.1	0.7	0.0	0.1	1.0	0.0	0.5	19.2	n	0
Q4	urban	Q4urban3	49189	40.3	59791.5	0.3	9225.4	*0.39*	1.1	0.7	1.0	0.0	0.0	0.0	2.2	86.9	y	5
Q4	urban	Q4urban4	22940	42.0	67309.4	0.2	20144.5	*0.85*	1.0	0.9	0.0	0.0	1.0	0.0	1.1	45.4	y	6
Q4	urban	Q4urban5	54070	38.1	81051.7	0.0	5521.6	*0.23*	1.5	0.0	0.1	0.0	0.0	0.0	0.1	4.9	n	0
Q4	urban	Q4urban6	47599	33.3	58334.2	0.3	5356.2	*0.22*	1.0	0.8	1.0	0.0	0.0	0.0	2.0	66.5	y	5
Q4	urban	Q4urban7	48131	30.3	58650.1	0.3	4984.4	*0.21*	1.0	0.8	0.0	0.3	1.0	0.0	0.5	16.1	n	0
Q4	urban	Q4urban8	104427	41.9	64600.6	0.2	22064.4	*0.93*	1.0	0.8	0.2	0.0	0.0	0.0	1.6	65.4	y	6
Q4	urban	Q4urban9	91012	32.6	66393.2	0.2	5451.1	*0.23*	1.0	0.8	0.0	0.0	0.0	0.1	0.4	13.1	n	0
Q1	suburban	Q1suburban1	72014	33.1	7428.7	1.0	2346.6	*0.09*	1.1	0.6	0.0	0.1	0.2	0.0	2.1	69.0	y	2
Q1	suburban	Q1suburban2	54360	40.3	8099.8	1.0	1408.9	*0.05*	1.1	0.6	0.1	0.1	0.2	0.0	2.3	91.4	y	2
Q1	suburban	Q1suburban3	33915	29.4	9024.1	1.0	2025.7	*0.08*	1.1	0.7	0.0	0.7	0.8	0.0	2.1	61.3	y	3
Q1	suburban	Q1suburban4	30410	32.3	8638.5	1.0	2259.0	*0.09*	1.1	0.6	1.0	0.0	0.0	0.0	4.1	131.2	y	4
Q1	suburban	Q1suburban5	32677	28.6	7628.8	1.0	1338.0	*0.05*	1.0	0.7	0.0	1.0	0.3	0.1	2.1	60.3	y	3
Q1	suburban	Q1suburban6	80021	26.7	7726.9	1.0	1378.4	*0.05*	1.1	0.7	0.0	0.0	0.2	0.0	2.0	54.0	y	2
Q1	suburban	Q1suburban7	38093	28.3	8244.5	1.0	1372.4	*0.05*	1.1	0.7	1.0	0.0	0.0	0.0	4.0	114.0	y	4
Q1	rural	Q1rural1	61502	39.7	8063.4	1.0	706.6	*0.02*	1.1	0.7	0.2	0.1	0.2	0.0	2.4	96.7	y	2
Q1	rural	Q1rural2	27317	22.7	7545.5	1.0	201.0	*0.00*	0.9	0.9	1.0	0.0	0.0	0.0	3.9	89.7	y	4
Q1	rural	Q1rural3	45447	26.7	9132.9	1.0	486.9	*0.01*	1.0	0.8	0.0	0.7	0.9	0.0	2.0	52.3	y	2
Q1	rural	Q1rural4	33935	18.6	7362.4	1.0	172.8	*0.00*	1.0	0.9	0.0	0.0	0.2	0.0	2.0	36.6	n	0
Q1	rural	Q1rural5	26347	21.0	7048.6	1.0	191.0	*0.00*	0.9	0.9		1.0	0.3	0.1	2.0	42.2	n	0
Q1	rural	Q1rural6	77772	39.5	7825.5	1.0	234.2	*0.00*	1.0	0.8	0.1	0.1	0.2	0.0	2.2	87.8	y	2
Q1	rural	Q1rural7	35778	23.0	7729.3	1.0	744.4	*0.02*	1.1	0.7	0.2	0.1	0.2	0.0	2.4	55.8	y	2
Q2	suburban	Q2suburban1	61502	32.3	20416.5	0.8	2282.6	*0.09*	1.1	0.7	0.0	0.0	0.2	0.0	1.7	55.9	y	2
Q2	suburban	Q2suburban2	27317	30.8	20387.8	0.8	1477.2	*0.06*	1.0	0.8	0.0	0.8	0.8	0.0	1.7	53.6	y	2
Q2	suburban	Q2suburban3	45447	40.6	20214.9	0.8	1371.3	*0.05*	1.1	0.7	0.1	0.2	0.1	0.1	2.0	79.3	y	2
Q2	suburban	Q2suburban4	33935	32.1	18251.0	0.8	2213.3	*0.09*	1.0	0.7	0.0	1.0	0.2	0.1	1.9	59.8	y	2
Q2	suburban	Q2suburban5	26347	32.1	20908.2	0.8	2259.9	*0.09*	1.0	0.7	1.0	0.0	0.0	0.0	3.6	115.1	y	4
Q2	suburban	Q2suburban6	77772	25.3	19605.9	0.8	1338.6	*0.05*	1.0	0.8	0.0	0.2	0.1	0.1	1.7	43.4	y	2
Q2	suburban	Q2suburban7	35778	27.8	20303.6	0.8	1368.9	*0.05*	1.0	0.8	1.0	0.0	0.0	0.0	3.5	98.6	y	4
Q2	rural	Q2rural1	187212	28.3	19970.3	0.8	744.7	*0.02*	1.0	0.7	0.2	0.2	0.2	0.0	2.1	59.1	y	2
Q2	rural	Q2rural2	194495	17.8	18884.7	0.8	165.0	*0.00*	0.9	0.9	0.0	0.1	0.1	0.0	1.7	29.5	n	0
Q2	rural	Q2rural3	85239	26.6	18951.5	0.8	227.8	*0.00*	1.0	0.9	0.0	0.7	0.9	0.0	1.7	44.2	y	2
Q2	rural	Q2rural4	145851	22.8	18971.8	0.8	182.3	*0.00*	0.9	0.9	1.0	0.0	0.0	0.0	3.5	79.5	y	4
Q2	rural	Q2rural5	41864	22.0	17965.8	0.8	352.7	*0.01*	1.0	0.9	0.0	0.9	0.0	0.6	1.7	37.4	n	0
Q2	rural	Q2rural6	135288	40.2	19644.3	0.8	284.0	*0.01*	1.0	0.8	0.2	0.1	0.1	0.0	2.0	79.2	y	2
Q3	suburban	Q3suburban1	81235	32.7	31561.8	0.7	2329.9	*0.09*	1.1	0.7	0.0	0.2	0.3	0.1	0.8	25.4	n	0
Q3	suburban	Q3suburban2	60131	28.4	30629.0	0.7	1616.4	*0.06*	1.0	0.8	0.0	0.8	0.8	0.1	0.8	23.4	n	0
Q3	suburban	Q3suburban3	32473	32.6	30463.5	0.7	2261.1	0.09	1.1	0.6	1.0	0.0	0.0	0.0	2.5	81.3	y	5
Q3	suburban	Q3suburban4	77813	26.3	31612.0	0.7	1318.6	0.05	1.1	0.7	0.0	0.2	0.2	0.1	0.7	19.1	n	0
Q3	suburban	Q3suburban5	39821	28.6	29699.7	0.7	1372.2	0.05	1.1	0.7	1.0	0.0	0.0	0.0	2.5	70.4	y	5
Q3	suburban	Q3suburban6	54905	40.4	31245.8	0.7	1399.1	0.05	1.1	0.6	0.1	0.2	0.2	0.1	1.0	39.0	n	0
Q3	rural	Q3rural1	123216	22.7	31382.1	0.7	715.5	0.02	1.1	0.7	0.1	0.1	0.2	0.1	0.9	21.0	n	0
Q3	rural	Q3rural2	113580	25.0	31073.9	0.7	207.1	0.00	1.0	0.9	0.0	0.8	1.0	0.0	0.7	16.7	n	0
Q3	rural	Q3rural3	128360	39.6	31410.6	0.7	262.4	0.00	1.0	0.7	0.1	0.1	0.2	0.0	0.9	34.3	n	0
Q3	rural	Q3rural4	68474	32.3	30780.7	0.7	712.2	0.02	1.0	0.7	0.0	0.7	0.8	0.1	0.7	24.0	n	0
Q3	rural	Q3rural5	103472	23.1	30459.6	0.7	194.1	0.00	1.0	0.8	1.0	0.0	0.0	0.0	2.4	54.4	y	5
Q3	rural	Q3rural6	164931	17.8	31103.4	0.7	169.2	0.00	1.0	0.9	0.0	0.1	0.2	0.0	0.7	11.8	n	0
Q3	rural	Q3rural7	49291	24.2	31324.5	0.7	304.1	0.01	1.0	0.9	0.0	0.9	0.0	0.8	0.7	16.3	n	0
Q3	rural	Q3rural8	59876	37.7	30854.6	0.7	713.0	0.02	1.1	0.6	0.7	0.0	0.0	0.0	1.8	68.9	y	5
Q4	suburban	Q4suburban1	82127	33.1	70799.5	0.1	2320.9	0.09	1.2	0.5	0.0	0.0	0.2	0.0	0.2	6.3	n	0
Q4	suburban	Q4suburban2	69857	26.9	69342.4	0.2	1393.5	0.05	1.1	0.6	0.0	0.0	0.0	0.0	0.2	5.2	n	0
Q4	suburban	Q4suburban3	55229	28.6	61926.5	0.3	1371.2	0.05	1.1	0.7	0.0	0.2	1.0	0.0	0.3	8.7	n	0
Q4	suburban	Q4suburban4	40955	28.7	54263.3	0.4	1369.2	0.05	1.1	0.6	1.0	0.0	0.0	0.0	1.8	51.3	y	5
Q4	suburban	Q4suburban5	7617	30.2	49961.1	0.4	1578.1	0.06	1.0	0.8	0.0	0.8	0.0	1.0	0.5	14.9	n	0
Q4	suburban	Q4suburban6	58473	40.2	67984.6	0.2	1414.9	0.05	1.2	0.5	0.1	0.0	0.2	0.0	0.3	13.6	n	0
Q4	suburban	Q4suburban7	34250	32.2	57829.8	0.3	2248.7	0.09	1.2	0.5	1.0	0.0	0.0	0.0	1.7	55.7	y	5
Q4	suburban	Q4suburban8	25376	28.9	52631.3	0.4	2101.2	0.08	1.1	0.7	0.0	0.6	1.0	0.0	0.5	13.8	n	0
Q4	rural	Q4rural1	96047	39.3	62607.3	0.2	713.6	0.02	1.1	0.6	0.2	0.1	0.3	0.1	0.5	20.1	n	0
Q4	rural	Q4rural2	147695	23.4	63796.5	0.2	749.3	0.02	1.1	0.6	0.2	0.1	0.3	0.0	0.5	10.8	n	0
Q4	rural	Q4rural3	162609	23.5	60202.1	0.3	235.4	0.00	1.0	0.8	0.0	0.3	1.0	0.0	0.3	6.6	n	0
Q4	rural	Q4rural4	160394	19.9	64044.6	0.2	195.8	0.00	1.0	0.7	0.0	0.0	0.0	0.0	0.2	4.5	n	0
Q4	rural	Q4rural5	23755	24.3	51820.6	0.4	315.9	0.01	1.0	0.9	0.0	0.7	0.0	0.9	0.4	9.7	n	0
Q4	rural	Q4rural6	116505	39.9	62321.5	0.2	244.0	0.00	1.1	0.7	0.1	0.0	0.2	0.1	0.4	16.0	n	0
Q4	rural	Q4rural7	80931	24.3	51857.8	0.4	270.9	0.00	1.1	0.7	1.0	0.0	0.0	0.0	1.8	43.5	y	5

TOTAL population	6347839	
Population in profile 1	731439	21%
Population in profile 2	1080606	30%
Population in profile 3	364374	10%
Population in profile 4	433684	12%
Population in profile 5	597083	17%
Population in profile n/a	357424	10%
Total high-risk population	3564610	
Share of high-risk population	56%	

PERCENTILE 0.75 in reference period: 43.4

y... high-risk cluster

n... cluster is not considered high-risk

3. 2080 - ssp4-noCC

Income quartile	Region	Cluster ID	Exposure: Cluster size	Hazard: Average no. of annual heatwave days (avg)	Vulnerability: INCOME (std)	INCOME (norm)	POPULATION DENSITY (avg)	POPULATION DENSITY (norm)	RELATIVE INCOME OF CELL (avg)	RELATIVE INCOME OF CELL (norm)	Share of elderly (>65)	Share of blue collar workers	Share working in manufacturing	Share working in outdoor sector	VULNERABILITY INDICATOR (of cluster)	AVERAGE CLUSTER RISK	Risk > Percentile 0.75	Storyline of high-risk clusters
Q1	urban	Q1urban1	67537	23.6	1445.3	1.0	3233.0	*0.33*	0.9	0.9	0.0	0.0	0.2	0.0	2.6	60.8	y	1
Q1	urban	Q1urban2	28299	16.3	1852.1	1.0	2756.6	*0.25*	0.9	0.9	0.0	0.7	1.0	0.0	2.6	41.8	n	0
Q1	urban	Q1urban3	149766	19.9	1941.1	1.0	3350.2	*0.29*	1.0	0.77	1.0	0.0	0.0	0.0	4.6	92.4	y	4
Q1	urban	Q1urban4	38052	25.5	1415.5	1.0	4402.8	*0.89*	0.9	0.9	0.0	1.0	0.2	0.1	4.5	115.4	y	3
Q1	urban	Q1urban5	31215	22.2	1701.4	1.0	2479.3	*0.22*	1.5	0.1	0.1	0.1	0.2	0.0	2.2	49.0	y	6
Q1	urban	Q1urban6	36754	19.1	1427.4	1.0	2795.9	*0.28*	0.9	0.8	0.0	1.0	0.0	0.1	2.7	51.7	y	3
Q1	urban	Q1urban7	95097	11.4	1514.4	1.0	2359.9	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	2.6	29.7	n	0
Q1	urban	Q1urban8	134346	25.6	1354.0	1.0	3897.5	*0.91*	0.9	0.9	0.2	0.0	0.1	0.0	4.2	106.3	y	1
Q2	urban	Q2urban1	71297	23.3	4221.8	1.0	3272.7	*0.31*	1.0	0.7	0.0	0.0	0.0	0.0	2.4	55.2	y	1
Q2	urban	Q2urban2	17610	18.1	4560.8	1.0	3254.3	*0.28*	0.9	0.8	0.0	1.0	1.0	0.0	2.6	47.4	y	3
Q2	urban	Q2urban3	23478	20.3	4625.4	1.0	3595.7	*0.32*	0.9	0.9	0.0	0.0	1.0	0.0	2.5	50.7	y	1
Q2	urban	Q2urban4	41076	25.1	3889.9	1.0	4383.2	*0.91*	0.8	1.0	0.0	1.0	0.2	0.1	4.6	116.7	y	3
Q2	urban	Q2urban5	124928	20.0	4748.4	1.0	3437.1	*0.29*	0.9	0.9	1.0	0.0	0.0	0.0	4.6	92.9	y	4
Q2	urban	Q2urban6	45807	19.5	3887.5	1.0	2789.0	*0.27*	0.9	0.9	0.0	1.0	0.0	0.1	2.6	51.3	y	3
Q2	urban	Q2urban7	102094	11.5	4197.0	1.0	2393.9	*0.22*	0.9	0.8	0.1	0.1	0.1	0.0	2.6	29.6	n	0
Q2	urban	Q2urban8	137868	25.5	4023.2	1.0	3970.3	*0.93*	0.9	0.9	0.2	0.0	0.1	0.0	4.1	105.0	y	1
Q3	urban	Q3urban1	31165	25.5	35645.5	0.6	2666.1	*1.00*	0.8	1.0	0.0	0.0	0.2	0.0	2.3	58.7	y	6
Q3	urban	Q3urban2	35853	15.9	37726.3	0.6	2702.8	*0.25*	0.9	0.9	0.0	0.7	1.0	0.0	1.1	16.9	n	0
Q3	urban	Q3urban3	74007	25.5	36931.5	0.6	4588.1	*0.86*	0.9	0.9	1.0	0.0	0.0	0.0	4.3	109.1	y	5
Q3	urban	Q3urban4	31571	19.4	35604.7	0.6	2730.5	*0.27*	0.9	0.9	0.0	1.0	0.0	0.0	1.2	22.7	n	0
Q3	urban	Q3urban5	62469	23.0	39126.8	0.6	2569.2	*0.27*	1.0	0.7	0.0	0.0	0.2	0.0	0.9	21.4	n	0
Q3	urban	Q3urban6	33575	25.2	36151.0	0.6	4617.7	*0.91*	0.8	1.0	0.0	1.0	0.2	0.2	2.8	69.8	y	6
Q3	urban	Q3urban7	159206	19.6	37843.8	0.6	2581.3	*0.25*	1.1	0.7	1.0	0.0	0.0	0.0	2.7	52.7	y	5
Q3	urban	Q3urban8	39605	25.5	40075.0	0.6	2675.8	*0.71*	1.0	0.8	0.0	0.0	0.2	0.0	1.5	37.9	n	0
Q3	urban	Q3urban9	86858	11.2	38396.6	0.6	2438.4	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	1.1	12.7	n	0
Q4	urban	Q4urban1	58152	24.0	76641.6	0.2	3664.9	*0.36*	0.9	0.9	0.0	0.0	0.0	0.1	0.6	14.6	n	0
Q4	urban	Q4urban2	25912	23.2	77554.5	0.2	2649.9	*0.26*	1.0	0.7	0.0	0.1	1.0	0.0	0.5	10.6	n	0
Q4	urban	Q4urban3	105892	24.1	73034.7	0.3	4658.3	*0.39*	1.1	0.7	1.0	0.0	0.0	0.0	2.1	51.3	y	5
Q4	urban	Q4urban4	17282	25.5	82217.8	0.2	4489.6	*0.85*	0.9	0.9	0.0	0.0	1.0	0.0	1.1	27.6	n	0
Q4	urban	Q4urban5	46366	22.2	99003.8	0.0	2624.5	*0.23*	1.6	0.0	0.1	0.0	0.0	0.0	0.1	2.8	n	0
Q4	urban	Q4urban6	100499	13.4	71254.7	0.3	2387.2	*0.22*	1.0	0.8	1.0	0.0	0.0	0.0	2.0	26.3	n	0
Q4	urban	Q4urban7	32364	12.1	71640.5	0.3	2257.9	*0.21*	1.0	0.8	0.0	0.3	1.0	0.0	0.5	6.2	n	0
Q4	urban	Q4urban8	109518	25.6	78909.0	0.2	3498.2	*0.93*	0.9	0.9	0.2	0.0	0.0	0.0	1.6	40.1	n	0
Q4	urban	Q4urban9	61820	13.0	81098.6	0.2	2421.5	*0.23*	1.0	0.8	0.0	0.0	0.0	0.1	0.4	5.1	n	0
Q1	suburban	Q1suburban1	49209	15.3	1648.2	1.0	244.0	*0.09*	1.1	0.6	0.0	0.1	0.2	0.0	2.1	32.3	n	0
Q1	suburban	Q1suburban2	47298	22.9	1797.1	1.0	258.4	*0.05*	1.1	0.6	0.1	0.1	0.2	0.0	2.3	53.1	y	2
Q1	suburban	Q1suburban3	23135	12.1	2002.2	1.0	284.1	*0.08*	1.0	0.7	0.0	0.7	0.8	0.0	2.1	26.0	n	0
Q1	suburban	Q1suburban4	69405	14.8	1916.7	1.0	278.0	*0.09*	1.1	0.6	1.0	0.0	0.0	0.0	4.1	61.2	y	4
Q1	suburban	Q1suburban5	22149	11.6	1692.6	1.0	233.7	*0.05*	1.0	0.7	0.0	1.0	0.3	0.1	2.1	24.9	n	0
Q1	suburban	Q1suburban6	54134	10.1	1714.4	1.0	250.7	*0.05*	1.1	0.7	0.0	0.0	0.2	0.0	2.1	20.8	n	0
Q1	suburban	Q1suburban7	82219	11.6	1829.3	1.0	240.2	*0.05*	1.0	0.7	1.0	0.0	0.0	0.0	4.1	47.3	y	4
Q1	rural	Q1rural1	55685	21.2	1789.1	1.0	150.6	*0.02*	1.1	0.7	0.2	0.1	0.2	0.0	2.5	52.7	y	2
Q1	rural	Q1rural2	48461	8.4	1674.2	1.0	147.1	*0.00*	0.9	0.9	1.0	0.0	0.0	0.0	4.0	33.6	n	0
Q1	rural	Q1rural3	27576	10.8	2026.4	1.0	161.9	*0.01*	1.0	0.7	0.0	0.7	0.9	0.0	2.0	21.8	n	0
Q1	rural	Q1rural4	19322	6.4	1633.5	1.0	120.0	*0.00*	0.9	0.9	0.0	0.0	0.2	0.0	2.0	12.8	n	0
Q1	rural	Q1rural5	15045	7.5	1563.9	1.0	124.1	*0.00*	0.9	0.9		1.0	0.3	0.1	2.0	15.3	n	0
Q1	rural	Q1rural6	57497	19.5	1736.3	1.0	122.5	*0.00*	1.0	0.8	0.1	0.1	0.2	0.0	2.3	44.3	y	2
Q1	rural	Q1rural7	32867	8.5	1714.9	1.0	145.2	*0.02*	1.1	0.7	0.2	0.1	0.2	0.0	2.5	21.0	n	0
Q2	suburban	Q2suburban1	39211	14.3	4529.9	1.0	270.2	*0.09*	1.0	0.7	0.0	0.0	0.2	0.0	2.1	29.6	n	0
Q2	suburban	Q2suburban2	16865	13.1	4523.5	1.0	250.4	*0.06*	1.0	0.8	0.0	0.8	0.8	0.0	2.1	27.1	n	0
Q2	suburban	Q2suburban3	36551	22.8	4485.2	1.0	247.8	*0.05*	1.0	0.7	0.1	0.2	0.1	0.1	2.3	52.4	y	2
Q2	suburban	Q2suburban4	21501	14.2	4049.4	1.0	315.2	*0.09*	1.0	0.7	0.0	1.0	0.2	0.1	2.2	30.6	n	0
Q2	suburban	Q2suburban5	52152	14.2	4639.0	1.0	280.8	*0.09*	1.0	0.7	1.0	0.0	0.0	0.0	4.1	58.2	y	4
Q2	suburban	Q2suburban6	48530	9.4	4350.1	1.0	229.7	*0.05*	1.0	0.8	0.0	0.2	0.1	0.1	2.0	18.9	n	0
Q2	suburban	Q2suburban7	68797	11.1	4504.9	1.0	237.9	*0.05*	1.0	0.8	1.0	0.0	0.0	0.0	4.0	44.8	y	4
Q2	rural	Q2rural1	172002	12.2	4430.9	1.0	139.9	*0.02*	1.0	0.7	0.2	0.2	0.2	0.0	2.4	29.8	n	0
Q2	rural	Q2rural2	110404	6.0	4190.0	1.0	119.7	*0.00*	0.9	0.9	0.0	0.1	0.1	0.0	1.9	11.7	n	0
Q2	rural	Q2rural3	48324	10.4	4204.9	1.0	150.0	*0.00*	0.9	0.8	0.0	0.7	0.9	0.0	1.9	20.3	n	0
Q2	rural	Q2rural4	255720	8.4	4209.4	1.0	141.2	*0.00*	0.9	0.9	1.0	0.0	0.0	0.0	3.9	32.7	n	0
Q2	rural	Q2rural5	24911	8.1	3986.2	1.0	162.6	*0.01*	0.9	0.8	0.0	0.9	0.0	0.6	2.0	15.9	n	0
Q2	rural	Q2rural6	108069	20.3	4358.6	1.0	154.3	*0.01*	1.0	0.8	0.2	0.1	0.1	0.0	2.3	46.6	y	2
Q3	suburban	Q3suburban1	52170	14.8	38552.4	0.6	253.3	*0.09*	1.1	0.6	0.0	0.2	0.3	0.1	0.7	10.8	n	0
Q3	suburban	Q3suburban2	37246	11.6	37413.0	0.6	326.6	*0.06*	1.0	0.8	0.0	0.8	0.8	0.1	0.8	8.9	n	0
Q3	suburban	Q3suburban3	65223	15.2	37210.9	0.6	278.5	0.09	1.1	0.6	1.0	0.0	0.0	0.0	2.4	36.5	n	0
Q3	suburban	Q3suburban4	48677	10.0	38613.8	0.6	228.8	0.05	1.0	0.7	0.0	0.2	0.2	0.1	0.7	6.8	n	0
Q3	suburban	Q3suburban5	77141	11.8	36277.9	0.6	241.5	0.05	1.1	0.7	1.0	0.0	0.0	0.0	2.4	28.0	n	0
Q3	suburban	Q3suburban6	44760	22.8	38166.4	0.6	257.2	0.05	1.1	0.6	0.1	0.2	0.2	0.1	0.9	20.9	n	0
Q3	rural	Q3rural1	99420	8.5	38333.0	0.6	152.8	0.02	1.1	0.7	0.1	0.1	0.2	0.1	0.9	7.4	n	0
Q3	rural	Q3rural2	64228	9.6	37956.5	0.6	126.3	0.00	0.9	0.8	0.0	0.8	1.0	0.0	0.6	6.1	n	0
Q3	rural	Q3rural3	93714	20.1	38367.8	0.6	138.9	0.00	1.0	0.7	0.1	0.1	0.2	0.0	0.8	16.5	n	0
Q3	rural	Q3rural4	41764	14.9	37598.3	0.6	153.4	0.02	1.0	0.7	0.0	0.7	0.8	0.1	0.7	10.4	n	0
Q3	rural	Q3rural5	184757	8.7	37206.1	0.6	136.7	0.00	1.0	0.8	1.0	0.0	0.0	0.0	2.3	19.8	n	0
Q3	rural	Q3rural6	94288	6.1	37992.5	0.6	116.2	0.00	0.9	0.8	0.0	0.1	0.2	0.0	0.6	3.8	n	0
Q3	rural	Q3rural7	28786	9.2	38262.6	0.6	163.1	0.01	0.9	0.9	0.0	0.9	0.0	0.8	0.6	5.9	n	0
Q3	rural	Q3rural8	88786	19.8	37688.6	0.6	155.3	0.02	1.1	0.6	0.7	0.0	0.0	0.0	1.8	34.8	n	0
Q4	suburban	Q4suburban1	53053	15.5	86480.9	0.1	246.6	0.09	1.2	0.5	0.0	0.0	0.2	0.0	0.2	2.8	n	0
Q4	suburban	Q4suburban2	43643	10.2	84701.1	0.1	260.3	0.05	1.1	0.6	0.0	0.0	0.0	0.0	0.2	1.9	n	0
Q4	suburban	Q4suburban3	34428	11.6	75642.6	0.2	254.7	0.05	1.1	0.7	0.0	0.2	1.0	0.0	0.3	3.3	n	0
Q4	suburban	Q4suburban4	79554	11.9	66282.1	0.3	238.1	0.05	1.1	0.6	1.0	0.0	0.0	0.0	1.7	20.8	n	0
Q4	suburban	Q4suburban5	4710	12.6	61027.0	0.4	325.8	0.06	1.0	0.7	0.0	0.8	0.0	1.0	0.5	5.9	n	0
Q4	suburban	Q4suburban6	46027	23.1	83042.5	0.2	259.2	0.05	1.2	0.5	0.1	0.0	0.2	0.0	0.3	7.5	n	0
Q4	suburban	Q4suburban7	68743	14.7	70638.6	0.3	277.2	0.09	1.2	0.5	1.0	0.0	0.0	0.0	1.7	24.9	n	0
Q4	suburban	Q4suburban8	15946	11.7	64288.6	0.4	285.2	0.08	1.0	0.7	0.0	0.6	1.0	0.0	0.4	5.2	n	0
Q4	rural	Q4rural1	83109	21.0	76474.2	0.2	146.6	0.02	1.1	0.6	0.2	0.1	0.3	0.1	0.5	10.4	n	0
Q4	rural	Q4rural2	125747	8.7	77926.9	0.2	139.7	0.02	1.1	0.6	0.2	0.1	0.3	0.0	0.4	3.9	n	0
Q4	rural	Q4rural3	93468	9.0	73536.2	0.3	150.1	0.00	1.0	0.7	0.0	0.3	1.0	0.0	0.3	2.4	n	0
Q4	rural	Q4rural4	92876	7.0	78229.8	0.2	126.3	0.00	1.0	0.7	0.0	0.0	0.0	0.0	0.2	1.5	n	0
Q4	rural	Q4rural5	13881	9.1	63298.3	0.4	163.4	0.01	0.9	0.8	0.0	0.7	0.0	0.9	0.4	3.4	n	0
Q4	rural	Q4rural6	85669	20.8	76125.1	0.2	126.3	0.00	1.1	0.6	0.1	0.0	0.2	0.1	0.4	7.9	n	0
Q4	rural	Q4rural7	149884	9.4	63343.8	0.4	159.0	0.00	1.0	0.7	1.0	0.0	0.0	0.0	1.7	16.3	n	0

TOTAL population	5876073.613	
Population in profile 1	434524.9164	23%
Population in profile 2	305099.0232	16%
Population in profile 3	179299.5679	9%
Population in profile 4	547267.5676	29%
Population in profile 5	339106.0415	18%
Population in profile n/a	95955.21919	5%
Total high-risk population	1901252.336	
Share of high-risk population	32%	

PERCENTILE 0.75 in reference period	43.4	y...	high-risk cluster
		n...	cluster is not considered high-risk

4. 2080 - ssp4-rcp8p5

Income quartile	Region	Cluster ID	Exposure Cluster size	Hazard Average no. of annual heatwave days avg	Vulnerability INCOME std	INCOME norm	POPULATION DENSITY avg	POPULATION DENSITY norm	RELATIVE INCOME OF CELL avg	RELATIVE INCOME OF CELL norm	Share of elderly (>65)	Share of blue collar workers	Share working in manufacturing	Share working in outdoor sector	VULNERABILITY INDICATOR (of cluster)	AVERAGE CLUSTER RISK	Risk > Percentile 0.75	Storyline of high-risk clusters
Q1	urban	Q1urban1	67537	41.2	1445.3	1.0	3233.0	*0.33*	0.9	0.9	0.0	0.0	0.2	0.0	2.6	106.3	y	1
Q1	urban	Q1urban2	28299	35.9	1852.1	1.0	2756.6	*0.25*	0.9	0.9	0.0	0.7	1.0	0.0	2.6	92.2	y	3
Q1	urban	Q1urban3	149766	38.3	1941.1	1.0	3350.2	*0.29*	1.0	0.77	1.0	0.0	0.0	0.0	4.6	178.0	y	4
Q1	urban	Q1urban4	38052	41.9	1415.5	1.0	4402.8	*0.89*	0.9	0.9	0.0	1.0	0.2	0.1	4.5	189.5	y	3
Q1	urban	Q1urban5	31215	38.1	1701.4	1.0	2479.3	*0.22*	1.5	0.1	0.1	0.1	0.2	0.0	2.2	84.2	y	6
Q1	urban	Q1urban6	36754	38.6	1427.4	1.0	2795.9	*0.28*	0.9	0.8	0.0	1.0	0.0	0.1	2.7	104.3	y	3
Q1	urban	Q1urban7	95097	29.7	1514.4	1.0	2359.9	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	2.6	77.2	y	1
Q1	urban	Q1urban8	134346	41.9	1354.0	1.0	3897.5	*0.91*	0.9	0.9	0.2	0.0	0.1	0.0	4.2	174.2	y	1
Q2	urban	Q2urban1	71297	40.7	4221.8	1.0	3272.7	*0.31*	1.0	0.7	0.0	0.0	0.0	0.0	2.4	96.3	y	1
Q2	urban	Q2urban2	17610	36.6	4560.8	1.0	3254.3	*0.28*	0.9	0.8	0.0	1.0	1.0	0.0	2.6	95.7	y	3
Q2	urban	Q2urban3	23478	39.1	4625.4	1.0	3595.7	*0.32*	0.9	0.9	0.0	0.0	1.0	0.0	2.5	97.5	y	1
Q2	urban	Q2urban4	41076	41.4	3889.9	1.0	4383.2	*0.91*	0.8	1.0	0.0	1.0	0.2	0.1	4.6	192.4	y	3
Q2	urban	Q2urban5	124928	38.8	4748.4	1.0	3437.1	*0.29*	0.9	0.9	1.0	0.0	0.0	0.0	4.6	180.3	y	4
Q2	urban	Q2urban6	45807	38.3	3887.5	1.0	2789.0	*0.27*	0.9	0.9	0.0	1.0	0.0	0.1	2.6	100.9	y	3
Q2	urban	Q2urban7	102094	29.8	4197.0	1.0	2393.9	*0.22*	0.9	0.8	0.1	0.1	0.1	0.0	2.6	76.5	y	1
Q2	urban	Q2urban8	137868	41.8	4023.2	1.0	3970.3	*0.93*	0.9	0.9	0.2	0.0	0.1	0.0	4.1	172.3	y	1
Q3	urban	Q3urban1	31165	42.0	35645.5	0.6	2666.1	*1.00*	0.8	1.0	0.0	0.0	0.2	0.0	2.3	96.4	y	6
Q3	urban	Q3urban2	35853	35.2	37726.3	0.6	2702.8	*0.25*	0.9	0.9	0.0	0.7	1.0	0.0	1.1	37.5	n	0
Q3	urban	Q3urban3	74007	41.8	36931.5	0.6	4588.1	*0.86*	0.9	0.9	1.0	0.0	0.0	0.0	4.3	179.2	y	5
Q3	urban	Q3urban4	31571	38.2	35604.7	0.6	2730.5	*0.27*	0.9	0.9	0.0	1.0	0.0	0.0	1.2	44.7	y	6
Q3	urban	Q3urban5	62469	40.4	39126.8	0.6	2569.2	*0.27*	1.0	0.7	0.0	0.0	0.2	0.0	0.9	37.6	n	0
Q3	urban	Q3urban6	33575	41.5	36151.0	0.6	4617.7	*0.91*	0.8	1.0	0.0	1.0	0.2	0.2	2.8	115.1	y	6
Q3	urban	Q3urban7	159206	37.8	37843.8	0.6	2581.3	*0.25*	1.1	0.7	1.0	0.0	0.0	0.0	2.7	101.6	y	5
Q3	urban	Q3urban8	39605	41.8	40075.0	0.6	2675.8	*0.71*	1.0	0.8	0.0	0.0	0.2	0.0	1.5	62.0	y	6
Q3	urban	Q3urban9	86858	29.3	38396.6	0.6	2438.4	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	1.1	33.3	n	0
Q4	urban	Q4urban1	58152	41.1	76641.6	0.2	3664.9	*0.36*	0.9	0.9	0.0	0.0	0.0	0.1	0.6	25.0	n	0
Q4	urban	Q4urban2	25912	40.6	77554.5	0.2	2649.9	*0.26*	1.0	0.7	0.0	0.1	1.0	0.0	0.5	18.5	n	0
Q4	urban	Q4urban3	105892	40.3	73034.7	0.3	4658.3	*0.39*	1.1	0.7	1.0	0.0	0.0	0.0	2.1	85.7	y	5
Q4	urban	Q4urban4	17282	42.0	82217.8	0.2	4489.6	*0.85*	0.9	0.9	0.0	0.0	1.0	0.0	1.1	45.3	y	6
Q4	urban	Q4urban5	46366	38.1	99003.8	0.0	2624.5	*0.23*	1.6	0.0	0.1	0.0	0.0	0.0	0.1	4.9	n	0
Q4	urban	Q4urban6	100499	33.3	71254.7	0.3	2387.2	*0.22*	1.0	0.8	1.0	0.0	0.0	0.0	2.0	65.2	y	5
Q4	urban	Q4urban7	32364	30.3	71640.5	0.3	2257.9	*0.21*	1.0	0.8	0.0	0.3	1.0	0.0	0.5	15.4	n	0
Q4	urban	Q4urban8	109518	41.9	78909.0	0.2	3498.2	*0.93*	0.9	0.9	0.2	0.0	0.0	0.0	1.6	65.8	y	6
Q4	urban	Q4urban9	61820	32.6	81098.6	0.2	2421.5	*0.23*	1.0	0.8	0.0	0.0	0.0	0.1	0.4	12.8	n	0
Q1	suburban	Q1suburban1	49209	33.1	1648.2	1.0	244.0	*0.09*	1.1	0.6	0.0	0.1	0.2	0.0	2.1	70.0	y	2
Q1	suburban	Q1suburban2	47298	40.3	1797.1	1.0	258.4	*0.05*	1.1	0.6	0.1	0.1	0.2	0.0	2.3	93.2	y	2
Q1	suburban	Q1suburban3	23135	29.4	2002.2	1.0	284.1	*0.08*	1.0	0.7	0.0	0.7	0.8	0.0	2.1	63.2	y	3
Q1	suburban	Q1suburban4	69405	32.3	1916.7	1.0	278.0	*0.09*	1.1	0.6	1.0	0.0	0.0	0.0	4.1	134.0	y	4
Q1	suburban	Q1suburban5	22149	28.6	1692.6	1.0	233.7	*0.05*	1.0	0.7	0.0	1.0	0.3	0.1	2.1	61.2	y	3
Q1	suburban	Q1suburban6	54134	26.7	1714.4	1.0	250.7	*0.05*	1.1	0.7	0.0	0.0	0.2	0.0	2.1	55.0	y	2
Q1	suburban	Q1suburban7	82219	28.3	1829.3	1.0	240.2	*0.05*	1.0	0.7	1.0	0.0	0.0	0.0	4.1	116.0	y	4
Q1	rural	Q1rural1	55685	39.7	1789.1	1.0	150.6	*0.02*	1.1	0.7	0.2	0.1	0.2	0.0	2.5	98.6	y	2
Q1	rural	Q1rural2	48461	22.7	1674.2	1.0	147.1	*0.00*	0.9	0.9	1.0	0.0	0.0	0.0	4.0	90.8	y	4
Q1	rural	Q1rural3	27576	26.7	2026.4	1.0	161.9	*0.01*	1.0	0.7	0.0	0.7	0.9	0.0	2.0	54.0	y	2
Q1	rural	Q1rural4	19322	18.6	1633.5	1.0	120.0	*0.00*	0.9	0.9	0.0	0.0	0.2	0.0	2.0	37.2	n	0
Q1	rural	Q1rural5	15045	21.0	1563.9	1.0	124.1	*0.00*	0.9	0.9		1.0	0.3	0.1	2.0	42.6	n	0
Q1	rural	Q1rural6	57497	39.5	1736.3	1.0	122.5	*0.00*	1.0	0.8	0.1	0.1	0.2	0.0	2.3	89.4	y	2
Q1	rural	Q1rural7	32867	23.0	1714.9	1.0	145.2	*0.02*	1.1	0.7	0.2	0.1	0.2	0.0	2.5	56.7	y	2
Q2	suburban	Q2suburban1	39211	32.3	4529.9	1.0	270.2	*0.09*	1.0	0.7	0.0	0.0	0.2	0.0	2.1	66.6	y	2
Q2	suburban	Q2suburban2	16865	30.8	4523.5	1.0	250.4	*0.06*	1.0	0.8	0.0	0.8	0.8	0.0	2.1	63.8	y	2
Q2	suburban	Q2suburban3	36551	40.6	4485.2	1.0	247.8	*0.05*	1.0	0.7	0.1	0.2	0.1	0.1	2.3	93.2	y	2
Q2	suburban	Q2suburban4	21501	32.1	4049.4	1.0	315.2	*0.09*	1.0	0.7	0.0	1.0	0.2	0.1	2.2	69.0	y	2
Q2	suburban	Q2suburban5	52152	32.1	4639.0	1.0	280.8	*0.09*	1.0	0.7	1.0	0.0	0.0	0.0	4.1	131.3	y	4
Q2	suburban	Q2suburban6	48530	25.3	4350.1	1.0	229.7	*0.05*	1.0	0.8	0.0	0.2	0.1	0.1	2.0	51.1	y	2
Q2	suburban	Q2suburban7	68797	27.8	4504.9	1.0	237.9	*0.05*	1.0	0.8	1.0	0.0	0.0	0.0	4.0	111.9	y	4
Q2	rural	Q2rural1	172002	28.3	4430.9	1.0	139.9	*0.02*	1.0	0.7	0.2	0.2	0.2	0.0	2.4	68.8	y	2
Q2	rural	Q2rural2	110404	17.8	4190.0	1.0	119.7	*0.00*	0.9	0.9	0.0	0.1	0.1	0.0	1.9	34.6	n	0
Q2	rural	Q2rural3	48324	26.6	4204.9	1.0	150.0	*0.00*	0.9	0.8	0.0	0.7	0.9	0.0	1.9	51.8	y	2
Q2	rural	Q2rural4	255720	22.8	4209.4	1.0	141.2	*0.00*	0.9	0.9	1.0	0.0	0.0	0.0	3.9	89.2	y	4
Q2	rural	Q2rural5	24911	22.0	3986.2	1.0	162.6	*0.01*	0.9	0.8	0.0	0.9	0.0	0.6	2.0	43.2	n	0
Q2	rural	Q2rural6	108069	40.2	4358.6	1.0	154.3	*0.01*	1.0	0.8	0.2	0.1	0.1	0.0	2.3	92.3	y	2
Q3	suburban	Q3suburban1	52170	32.7	38552.4	0.6	253.3	*0.09*	1.1	0.6	0.0	0.2	0.3	0.1	0.7	23.9	n	0
Q3	suburban	Q3suburban2	37246	28.4	37413.0	0.6	326.6	*0.06*	1.0	0.8	0.0	0.8	0.8	0.1	0.8	22.0	n	0
Q3	suburban	Q3suburban3	65223	32.6	37210.9	0.6	278.5	0.09	1.1	0.6	1.0	0.0	0.0	0.0	2.4	78.4	y	5
Q3	suburban	Q3suburban4	48677	26.3	38613.8	0.6	228.8	0.05	1.0	0.7	0.0	0.2	0.2	0.1	0.7	17.9	n	0
Q3	suburban	Q3suburban5	77141	28.6	36277.9	0.6	241.5	0.05	1.1	0.7	1.0	0.0	0.0	0.0	2.4	67.9	y	5
Q3	suburban	Q3suburban6	44760	40.4	38166.4	0.6	257.2	0.05	1.1	0.6	0.1	0.2	0.2	0.1	0.9	37.0	n	0
Q3	rural	Q3rural1	99420	22.7	38333.0	0.6	152.8	0.02	1.1	0.7	0.1	0.1	0.2	0.1	0.9	19.9	n	0
Q3	rural	Q3rural2	64228	25.0	37956.5	0.6	126.3	0.00	0.9	0.8	0.0	0.8	1.0	0.0	0.6	15.7	n	0
Q3	rural	Q3rural3	93714	39.6	38367.8	0.6	138.9	0.00	1.0	0.7	0.1	0.1	0.2	0.0	0.8	32.5	n	0
Q3	rural	Q3rural4	41764	32.3	37598.3	0.6	153.4	0.02	1.0	0.7	0.0	0.7	0.8	0.1	0.7	22.5	n	0
Q3	rural	Q3rural5	184757	23.1	37206.1	0.6	136.7	0.00	1.0	0.8	1.0	0.0	0.0	0.0	2.3	52.5	y	5
Q3	rural	Q3rural6	94288	17.8	37992.5	0.6	116.2	0.00	0.9	0.8	0.0	0.1	0.2	0.0	0.6	11.1	n	0
Q3	rural	Q3rural7	28786	24.2	38262.6	0.6	163.1	0.01	0.9	0.9	0.0	0.9	0.0	0.8	0.6	15.3	n	0
Q3	rural	Q3rural8	88786	37.7	37688.6	0.6	155.3	0.02	1.1	0.6	0.7	0.0	0.0	0.0	1.8	66.2	y	5
Q4	suburban	Q4suburban1	53053	33.1	86480.9	0.1	246.6	0.09	1.2	0.5	0.0	0.0	0.2	0.0	0.2	6.0	n	0
Q4	suburban	Q4suburban2	43643	26.9	84701.1	0.1	260.3	0.05	1.1	0.6	0.0	0.0	0.0	0.0	0.2	4.9	n	0
Q4	suburban	Q4suburban3	34428	28.6	75642.6	0.2	254.7	0.05	1.1	0.7	0.0	0.2	1.0	0.0	0.3	8.2	n	0
Q4	suburban	Q4suburban4	79554	28.7	66282.1	0.3	238.1	0.05	1.1	0.6	1.0	0.0	0.0	0.0	1.7	50.0	y	5
Q4	suburban	Q4suburban5	4710	30.2	61027.0	0.4	325.8	0.06	1.0	0.7	0.0	0.8	0.0	1.0	0.5	14.0	n	0
Q4	suburban	Q4suburban6	46027	40.2	83042.5	0.2	259.2	0.05	1.2	0.5	0.1	0.0	0.2	0.0	0.3	13.1	n	0
Q4	suburban	Q4suburban7	68743	32.2	70638.6	0.3	277.2	0.09	1.2	0.5	1.0	0.0	0.0	0.0	1.7	54.4	y	5
Q4	suburban	Q4suburban8	15946	28.9	64288.6	0.4	285.2	0.08	1.0	0.7	0.0	0.6	1.0	0.0	0.4	13.0	n	0
Q4	rural	Q4rural1	83109	39.3	76474.2	0.2	146.6	0.02	1.1	0.6	0.2	0.1	0.3	0.1	0.5	19.4	n	0
Q4	rural	Q4rural2	125747	23.4	77926.9	0.2	139.7	0.02	1.1	0.6	0.2	0.1	0.3	0.0	0.4	10.4	n	0
Q4	rural	Q4rural3	93468	23.5	73536.2	0.3	150.1	0.00	1.0	0.7	0.0	0.3	1.0	0.0	0.3	6.2	n	0
Q4	rural	Q4rural4	92876	19.9	78229.8	0.2	126.3	0.00	1.0	0.7	0.0	0.0	0.0	0.0	0.2	4.2	n	0
Q4	rural	Q4rural5	13881	24.3	63298.3	0.4	163.4	0.01	0.9	0.8	0.0	0.7	0.0	0.9	0.4	9.1	n	0
Q4	rural	Q4rural6	85669	39.9	76125.1	0.2	126.3	0.00	1.1	0.6	0.1	0.0	0.2	0.1	0.4	15.3	n	0
Q4	rural	Q4rural7	149884	24.3	63343.8	0.4	159.0	0.00	1.0	0.7	1.0	0.0	0.0	0.0	1.7	42.3	n	0

TOTAL population	5876073.613	
Population in profile 1	631715.5544	16%
Population in profile 2	815317.68	21%
Population in profile 3	252882.2511	7%
Population in profile 4	851448.8614	22%
Population in profile 5	1003809.081	26%
Population in profile n/a	293931.2244	8%
Total high-risk population	3849104.652	
Share of high-risk populat	66%	

PERCENTILE 0.75 in reference period	43.4	y...	high-risk cluster
		n...	cluster not considered high-risk

5. 2050 - ssp4-rcp8p5

Income quartile	Region	Cluster ID	Exposure: Cluster size	Hazard: Average no. of annual heatwave days (avg)	Vulnerability: INCOME (std)	INCOME (norm)	POPULATION DENSITY (avg)	POPULATION DENSITY (norm)	RELATIVE INCOME OF CELL (avg)	RELATIVE INCOME OF CELL (norm)	Share of elderly (>65)	Share of blue collar workers	Share working in manufacturing	Share working in outdoor sector	VULNERABILITY INDICATOR (of cluster)	AVERAGE CLUSTER RISK	Risk > Percentile 0.75	Storyline of high-risk clusters
Q1	urban	Q1urban1	82465	29.83588793	4217.0	1.0	3233.0	*0.33*	0.9	0.9	0.0	0.0	0.2	0.0	2.6	76.5	y	1
Q1	urban	Q1urban2	35529	21.67600633	5403.8	1.0	2756.6	*0.25*	0.9	0.9	0.0	0.7	1.0	0.0	2.5	54.8	y	3
Q1	urban	Q1urban3	125992	25.76520573	5663.6	1.0	3350.2	*0.29*	1.0	0.76	1.0	0.0	0.0	0.0	4.6	118.3	y	4
Q1	urban	Q1urban4	45929	31.53730084	4130.1	1.0	4402.8	*0.89*	0.9	0.9	0.0	1.0	0.2	0.1	4.5	141.8	y	3
Q1	urban	Q1urban5	35482	27.90450856	4964.1	1.0	2479.3	*0.22*	1.4	0.1	0.1	0.1	0.2	0.0	2.2	61.1	y	6
Q1	urban	Q1urban6	45662	24.93816402	4164.7	1.0	2795.9	*0.28*	0.9	0.8	0.0	1.0	0.0	0.1	2.7	67.1	y	3
Q1	urban	Q1urban7	108133	15.77745639	4418.5	1.0	2359.9	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	2.6	40.7	n	0
Q1	urban	Q1urban8	138850	31.59375314	3950.6	1.0	3897.5	*0.91*	0.9	0.9	0.2	0.0	0.1	0.0	4.1	130.7	y	1
Q2	urban	Q2urban1	87223	29.42714885	12317.8	0.9	3272.7	*0.31*	1.0	0.7	0.0	0.0	0.0	0.0	2.2	64.9	y	1
Q2	urban	Q2urban2	21807	23.65090436	13307.0	0.9	3254.3	*0.28*	0.9	0.8	0.0	1.0	1.0	0.0	2.4	57.1	y	3
Q2	urban	Q2urban3	28916	26.2853674	13495.5	0.9	3595.7	*0.32*	0.9	0.9	0.0	0.0	1.0	0.0	2.3	60.6	y	1
Q2	urban	Q2urban4	49611	31.24966664	11349.6	0.9	4383.2	*0.91*	0.8	1.0	0.0	1.0	0.2	0.1	4.4	136.9	y	3
Q2	urban	Q2urban5	105072	25.91764782	13854.4	0.9	3437.1	*0.29*	0.9	0.9	1.0	0.0	0.0	0.0	4.4	113.2	y	4
Q2	urban	Q2urban6	56945	25.37067185	11342.4	0.9	2789.0	*0.27*	0.9	0.8	0.0	1.0	0.0	0.1	2.5	62.7	y	3
Q2	urban	Q2urban7	116282	15.90337047	12245.5	0.9	2393.9	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	2.4	38.2	n	0
Q2	urban	Q2urban8	144429	31.48245712	11738.4	0.9	3970.3	*0.93*	0.9	0.9	0.2	0.0	0.1	0.0	3.9	122.9	y	1
Q3	urban	Q3urban1	37636	31.55926217	32111.2	0.7	2666.1	*1.00*	0.8	1.0	0.0	0.0	0.2	0.0	2.3	73.8	y	6
Q3	urban	Q3urban2	45022	21.10788148	33985.7	0.6	2702.8	*0.25*	0.9	0.8	0.0	0.7	1.0	0.0	1.1	23.0	n	0
Q3	urban	Q3urban3	60564	31.54232243	33269.7	0.7	4588.1	*0.86*	0.9	0.9	1.0	0.0	0.0	0.0	4.3	136.3	y	5
Q3	urban	Q3urban4	39282	25.23577449	32074.5	0.7	2730.5	*0.27*	0.9	0.8	0.0	1.0	0.0	0.0	1.2	30.1	n	0
Q3	urban	Q3urban5	76685	29.15060173	35247.3	0.6	2569.2	*0.27*	1.0	0.7	0.0	0.0	0.2	0.0	1.0	27.7	n	0
Q3	urban	Q3urban6	40544	31.25918771	32566.6	0.7	4617.7	*0.91*	0.8	1.0	0.0	1.0	0.2	0.2	2.8	87.9	y	6
Q3	urban	Q3urban7	134177	25.36568564	34091.5	0.6	2581.3	*0.25*	1.1	0.7	1.0	0.0	0.0	0.0	2.7	69.2	y	5
Q3	urban	Q3urban8	47793	31.64046563	36101.5	0.6	2675.8	*0.71*	1.0	0.8	0.0	0.0	0.2	0.0	1.5	47.6	y	6
Q3	urban	Q3urban9	97530	15.41151559	34589.6	0.6	2438.4	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	1.2	17.8	n	0
Q4	urban	Q4urban1	70878	30.21014125	69042.5	0.2	3664.9	*0.36*	0.9	0.8	0.0	0.0	0.0	0.1	0.6	18.5	n	0
Q4	urban	Q4urban2	31510	29.33155376	69864.9	0.2	2649.9	*0.26*	1.0	0.7	0.0	0.1	1.0	0.0	0.5	13.5	n	0
Q4	urban	Q4urban3	87367	30.20351651	65793.2	0.3	4658.3	*0.39*	1.0	0.7	1.0	0.0	0.0	0.0	2.1	64.6	y	5
Q4	urban	Q4urban4	20542	31.62883214	74065.8	0.2	4489.6	*0.85*	0.9	0.9	0.0	0.0	1.0	0.0	1.1	34.2	n	0
Q4	urban	Q4urban5	50970	27.90968044	89187.5	0.0	2624.5	*0.23*	1.5	0.0	0.1	0.0	0.0	0.0	0.1	3.6	n	0
Q4	urban	Q4urban6	85827	18.2940209	64189.7	0.3	2387.2	*0.22*	1.0	0.8	1.0	0.0	0.0	0.0	2.0	36.1	n	0
Q4	urban	Q4urban7	40828	16.65738146	64537.2	0.3	2257.9	*0.21*	1.0	0.8	0.0	0.3	1.0	0.0	0.5	8.6	n	0
Q4	urban	Q4urban8	113450	31.58568035	71085.1	0.2	3498.2	*0.93*	0.9	0.8	0.2	0.0	0.0	0.0	1.6	49.6	y	6
Q4	urban	Q4urban9	77916	17.85160393	73057.5	0.2	2421.5	*0.23*	1.0	0.8	0.0	0.0	0.0	0.1	0.4	7.1	n	0
Q1	suburban	Q1suburban1	60223	19.87205673	4809.0	1.0	244.0	*0.09*	1.1	0.6	0.0	0.1	0.2	0.0	2.1	41.7	n	0
Q1	suburban	Q1suburban2	52678	28.42649942	5243.5	1.0	258.4	*0.05*	1.1	0.6	0.1	0.1	0.2	0.0	2.3	65.1	y	2
Q1	suburban	Q1suburban3	28631	16.12451104	5841.8	1.0	284.1	*0.08*	1.0	0.7	0.0	0.7	0.8	0.0	2.1	34.1	n	0
Q1	suburban	Q1suburban4	56814	19.27763876	5592.2	1.0	278.0	*0.09*	1.1	0.6	1.0	0.0	0.0	0.0	4.1	79.1	y	4
Q1	suburban	Q1suburban5	27485	15.64526448	4938.6	1.0	233.7	*0.05*	1.0	0.7	0.0	1.0	0.3	0.1	2.1	33.2	n	0
Q1	suburban	Q1suburban6	67297	13.77994	5002.1	1.0	250.7	*0.05*	1.0	0.7	0.0	0.0	0.2	0.0	2.0	28.2	n	0
Q1	suburban	Q1suburban7	69780	15.49696684	5337.2	1.0	240.2	*0.05*	1.0	0.7	1.0	0.0	0.0	0.0	4.1	62.9	y	4
Q1	rural	Q1rural1	61930	26.67094495	5220.0	1.0	150.6	*0.02*	1.1	0.7	0.2	0.1	0.2	0.0	2.5	65.7	y	2
Q1	rural	Q1rural2	44388	11.66398957	4884.6	1.0	147.1	*0.00*	0.9	0.9	1.0	0.0	0.0	0.0	4.0	46.3	y	0
Q1	rural	Q1rural3	35989	14.55142494	5912.3	1.0	161.9	*0.01*	1.0	0.7	0.0	0.7	0.9	0.0	2.0	29.0	n	0
Q1	rural	Q1rural4	26018	8.992954806	4766.1	1.0	120.0	*0.00*	0.9	0.8	0.0	0.0	0.2	0.0	2.0	17.8	n	0
Q1	rural	Q1rural5	20186	10.49522327	4563.0	1.0	124.1	*0.00*	0.9	0.9		1.0	0.3	0.1	2.0	21.2	n	0
Q1	rural	Q1rural6	69169	25.07362513	5065.9	1.0	122.5	*0.00*	1.0	0.7	0.1	0.1	0.2	0.0	2.2	56.3	y	2
Q1	rural	Q1rural7	35992	11.59403806	5003.6	1.0	145.2	*0.02*	1.1	0.7	0.2	0.1	0.2	0.0	2.5	28.4	n	0
Q2	suburban	Q2suburban1	50497	18.77715425	13216.8	0.9	270.2	*0.09*	1.0	0.7	0.0	0.0	0.2	0.0	1.9	35.7	n	0
Q2	suburban	Q2suburban2	22048	17.47816017	13198.2	0.9	250.4	*0.06*	1.0	0.8	0.0	0.8	0.8	0.0	1.9	33.4	n	0
Q2	suburban	Q2suburban3	42822	28.2525936	13086.3	0.9	247.8	*0.05*	1.0	0.7	0.1	0.2	0.1	0.1	2.1	60.2	y	2
Q2	suburban	Q2suburban4	27749	18.67026042	11815.0	0.9	315.2	*0.09*	1.0	0.7	0.0	1.0	0.2	0.1	2.0	37.6	n	0
Q2	suburban	Q2suburban5	45699	18.57725676	13535.1	0.9	280.8	*0.09*	1.0	0.7	1.0	0.0	0.0	0.0	3.8	71.5	y	4
Q2	suburban	Q2suburban6	62590	12.7575369	12692.1	0.9	229.7	*0.05*	1.0	0.7	0.0	0.2	0.1	0.1	1.9	23.9	n	0
Q2	suburban	Q2suburban7	60787	14.9644352	13143.7	0.9	237.9	*0.05*	1.0	0.8	1.0	0.0	0.0	0.0	3.8	56.7	y	4
Q2	rural	Q2rural1	189010	16.14340574	12928.0	0.9	139.9	*0.02*	1.0	0.7	0.2	0.2	0.2	0.0	2.3	36.6	n	0
Q2	rural	Q2rural2	148746	8.487281842	12225.2	0.9	119.7	*0.00*	0.9	0.9	0.0	0.1	0.1	0.0	1.8	15.3	n	0
Q2	rural	Q2rural3	65314	14.30609283	12268.4	0.9	150.0	*0.00*	0.9	0.8	0.0	0.7	0.9	0.0	1.8	25.9	n	0
Q2	rural	Q2rural4	235827	11.63354889	12281.6	0.9	141.2	*0.00*	0.9	0.9	1.0	0.0	0.0	0.0	3.7	43.1	n	0
Q2	rural	Q2rural5	32631	11.09045564	11630.3	0.9	162.6	*0.01*	0.9	0.8	0.0	0.9	0.0	0.6	1.8	20.4	n	0
Q2	rural	Q2rural6	125915	25.81691808	12716.9	0.9	154.3	*0.01*	1.0	0.8	0.2	0.1	0.1	0.0	2.1	55.2	y	2
Q3	suburban	Q3suburban1	66929	19.36683931	34729.9	0.6	253.3	*0.09*	1.1	0.6	0.0	0.2	0.3	0.1	0.8	14.5	n	0
Q3	suburban	Q3suburban2	48428	15.49506375	33703.4	0.7	326.6	*0.06*	1.0	0.7	0.0	0.8	0.8	0.1	0.8	12.3	n	0
Q3	suburban	Q3suburban3	56707	19.81539729	33521.4	0.7	278.5	0.09	1.1	0.6	1.0	0.0	0.0	0.0	2.4	48.4	y	5
Q3	suburban	Q3suburban4	62851	13.62658372	34785.2	0.6	228.8	0.05	1.0	0.7	0.0	0.2	0.2	0.1	0.7	9.5	n	0
Q3	suburban	Q3suburban5	67973	15.82566654	32680.9	0.7	241.5	0.05	1.1	0.7	1.0	0.0	0.0	0.0	2.4	38.2	n	0
Q3	suburban	Q3suburban6	52056	28.33050369	34382.1	0.6	257.2	0.05	1.1	0.6	0.1	0.2	0.2	0.1	0.9	26.6	n	0
Q3	rural	Q3rural1	114593	11.57392955	34532.2	0.6	152.8	0.02	1.0	0.7	0.1	0.1	0.2	0.1	0.9	10.4	n	0
Q3	rural	Q3rural2	86877	13.26434436	34193.1	0.6	126.3	0.00	0.9	0.8	0.0	0.8	1.0	0.0	0.6	8.6	n	0
Q3	rural	Q3rural3	113146	25.53906405	34563.5	0.6	138.9	0.00	1.0	0.7	0.1	0.1	0.2	0.0	0.8	21.5	n	0
Q3	rural	Q3rural4	54788	19.6404193	33870.4	0.6	153.4	0.02	1.0	0.7	0.0	0.7	0.8	0.1	0.7	14.1	n	0
Q3	rural	Q3rural5	168452	12.0421497	33517.1	0.7	136.7	0.00	1.0	0.8	1.0	0.0	0.0	0.0	2.3	27.8	n	0
Q3	rural	Q3rural6	126494	8.493348076	34225.5	0.6	116.2	0.00	0.9	0.8	0.0	0.1	0.2	0.0	0.6	5.5	n	0
Q3	rural	Q3rural7	38152	12.62230813	34468.8	0.6	163.1	0.01	0.9	0.8	0.0	0.9	0.0	0.8	0.7	8.2	n	0
Q3	rural	Q3rural8	84273	24.97853363	33951.7	0.6	155.3	0.02	1.1	0.6	0.7	0.0	0.0	0.0	1.8	44.7	y	5
Q4	suburban	Q4suburban1	67852	20.14907342	77906.2	0.1	246.6	0.09	1.2	0.5	0.0	0.0	0.2	0.0	0.2	3.7	n	0
Q4	suburban	Q4suburban2	56445	13.88637158	76302.8	0.2	260.3	0.05	1.1	0.6	0.0	0.0	0.0	0.0	0.2	2.6	n	0
Q4	suburban	Q4suburban3	44671	15.60329329	68142.5	0.2	254.7	0.05	1.1	0.7	0.0	0.2	1.0	0.0	0.3	4.6	n	0
Q4	suburban	Q4suburban4	70039	15.94377757	59710.2	0.3	238.1	0.05	1.1	0.6	1.0	0.0	0.0	0.0	1.8	28.1	n	0
Q4	suburban	Q4suburban5	6131	16.78685711	54976.1	0.4	325.8	0.06	1.0	0.7	0.0	0.8	0.0	1.0	0.5	8.0	n	0
Q4	suburban	Q4suburban6	54268	28.57929848	74808.7	0.2	259.2	0.05	1.2	0.5	0.1	0.0	0.2	0.0	0.3	9.5	n	0
Q4	suburban	Q4suburban7	59753	19.25245001	63634.7	0.3	277.2	0.09	1.1	0.5	1.0	0.0	0.0	0.0	1.7	32.9	n	0
Q4	suburban	Q4suburban8	20644	15.57081872	57914.3	0.4	285.2	0.08	1.0	0.7	0.0	0.6	1.0	0.0	0.5	7.2	n	0
Q4	rural	Q4rural1	94006	26.51144618	68891.7	0.2	146.6	0.02	1.1	0.6	0.2	0.1	0.3	0.1	0.5	13.3	n	0
Q4	rural	Q4rural2	142002	11.90659153	70200.3	0.2	139.7	0.02	1.1	0.6	0.2	0.1	0.3	0.0	0.5	5.4	n	0
Q4	rural	Q4rural3	125331	12.36090819	66245.0	0.3	150.1	0.00	1.0	0.7	0.0	0.3	1.0	0.0	0.3	3.4	n	0
Q4	rural	Q4rural4	123817	9.782182277	70473.2	0.2	126.3	0.00	1.0	0.7	0.0	0.0	0.0	0.0	0.2	2.2	n	0
Q4	rural	Q4rural5	18406	12.5051049	57022.2	0.4	163.4	0.01	1.0	0.8	0.0	0.7	0.0	0.9	0.4	4.8	n	0
Q4	rural	Q4rural6	102982	26.19951625	68577.2	0.2	126.3	0.00	1.1	0.6	0.1	0.0	0.2	0.1	0.4	10.2	n	0
Q4	rural	Q4rural7	133818	12.7759782	57063.2	0.4	159.0	0.00	1.0	0.7	1.0	0.0	0.0	0.0	1.8	22.5	n	0

TOTAL population	6414945.332	
Population in profile 1	481882.7459	21.4%
Population in profile 2	352513.8651	15.7%
Population in profile 3	255482.9669	11.3%
Population in profile 4	464143.8886	20.6%
Population in profile 5	423087.9242	18.8%
Population in profile n/a	274905.1127	12.2%
Total high-risk population	2252016.503	
Share of high-risk populat	35%	

PERCENTILE 0.75 in reference period: 43.4

y... high-risk cluster

n... cluster not considered high-risk

6. 2050 - ssp1-rcp4p5

			Exposure	Hazard	Vulnerability													
Income quartile	Region	Cluster ID	Cluster size	Average no. of annual heatwave days avg	INCOME std	INCOME norm	POPULATION DENSITY avg	POPULATION DENSITY norm	RELATIVE INCOME OF CELL avg	RELATIVE INCOME OF CELL norm	Share of elderly (>65)	Share of blue collar workers	Share working in manufacturing	Share working in outdoor sector	VULNERABILITY INDICATOR (of cluster)	AVERAGE CLUSTER RISK	Risk > Percentile 0.75	Storyline of high-risk clusters
Q1	urban	Q1urban1	87946	29.3	6926.0	1.0	3233.0	*0.33*	0.9	0.9	0.0	0.0	0.2	0.0	2.5	74.5	y	1
Q1	urban	Q1urban2	37163	20.1	8875.3	1.0	2756.6	*0.25*	0.9	0.8	0.0	0.7	1.0	0.0	2.5	49.9	y	3
Q1	urban	Q1urban3	139811	24.8	9301.9	1.0	3350.2	*0.29*	1.0	0.75	1.0	0.0	0.0	0.0	4.5	112.2	y	4
Q1	urban	Q1urban4	49091	31.9	6783.3	1.0	4402.8	*0.89*	0.9	0.9	0.0	1.0	0.2	0.1	4.5	142.3	y	3
Q1	urban	Q1urban5	37954	27.9	8153.1	1.0	2479.3	*0.22*	1.4	0.1	0.1	0.1	0.2	0.0	2.2	60.5	y	6
Q1	urban	Q1urban6	47895	23.7	6840.1	1.0	2795.9	*0.28*	1.0	0.8	0.0	1.0	0.0	0.1	2.7	63.4	y	3
Q1	urban	Q1urban7	113202	14.0	7257.1	1.0	2359.9	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	2.6	35.9	n	0
Q1	urban	Q1urban8	151239	32.1	6488.5	1.0	3897.5	*0.91*	0.9	0.9	0.2	0.0	0.1	0.0	4.1	131.8	y	1
Q2	urban	Q2urban1	92972	29.0	20230.9	0.8	3272.7	*0.31*	1.0	0.7	0.0	0.0	0.0	0.0	2.0	58.0	y	1
Q2	urban	Q2urban2	22943	22.5	21855.6	0.8	3254.3	*0.28*	1.0	0.8	0.0	1.0	1.0	0.0	2.2	48.6	y	3
Q2	urban	Q2urban3	30545	25.4	22165.2	0.8	3595.7	*0.32*	0.9	0.8	0.0	0.0	1.0	0.0	2.1	52.3	y	1
Q2	urban	Q2urban4	53022	31.4	18640.7	0.8	4383.2	*0.91*	0.9	1.0	0.0	1.0	0.2	0.1	4.0	127.2	y	3
Q2	urban	Q2urban5	117027	24.9	22754.6	0.8	3437.1	*0.29*	0.9	0.8	1.0	0.0	0.0	0.0	4.0	99.9	y	4
Q2	urban	Q2urban6	60263	24.3	18629.0	0.8	2789.0	*0.27*	0.9	0.8	0.0	1.0	0.0	0.1	2.3	55.0	y	3
Q2	urban	Q2urban7	121606	14.2	20112.3	0.8	2393.9	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	2.2	31.0	n	0
Q2	urban	Q2urban8	157044	31.9	19279.3	0.8	3970.3	*0.93*	0.9	0.9	0.2	0.0	0.1	0.0	3.6	115.4	y	1
Q3	urban	Q3urban1	40114	31.9	28656.7	0.7	2666.1	*1.00*	0.8	1.0	0.0	0.0	0.2	0.0	2.4	76.3	y	6
Q3	urban	Q3urban2	46964	19.6	30329.5	0.7	2702.8	*0.25*	0.9	0.8	0.0	0.7	1.0	0.0	1.1	21.9	n	0
Q3	urban	Q3urban3	68072	31.9	29690.6	0.7	4588.1	*0.86*	0.9	0.9	1.0	0.0	0.0	0.0	4.4	139.2	y	5
Q3	urban	Q3urban4	41486	24.1	28623.9	0.7	2730.5	*0.27*	0.9	0.8	0.0	1.0	0.0	0.0	1.2	29.5	n	0
Q3	urban	Q3urban5	81929	28.5	31455.5	0.7	2569.2	*0.27*	1.0	0.7	0.0	0.0	0.2	0.0	1.0	27.9	n	0
Q3	urban	Q3urban6	43357	31.4	29063.1	0.7	4617.7	*0.91*	0.9	1.0	0.0	1.0	0.2	0.2	2.9	89.9	y	6
Q3	urban	Q3urban7	148804	24.4	30424.0	0.7	2581.3	*0.25*	1.0	0.6	1.0	0.0	0.0	0.0	2.8	67.9	y	5
Q3	urban	Q3urban8	51108	32.1	32217.8	0.6	2675.8	*0.71*	1.0	0.8	0.0	0.0	0.2	0.0	1.5	49.2	y	6
Q3	urban	Q3urban9	102203	13.7	30868.5	0.7	2438.4	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	1.2	16.3	n	0
Q4	urban	Q4urban1	75624	29.8	61615.0	0.2	3664.9	*0.36*	0.9	0.8	0.0	0.0	0.0	0.1	0.6	18.5	n	0
Q4	urban	Q4urban2	33765	28.8	62348.9	0.2	2649.9	*0.26*	1.0	0.7	0.0	0.1	1.0	0.0	0.5	13.5	n	0
Q4	urban	Q4urban3	98144	30.2	58715.3	0.3	4658.3	*0.39*	1.0	0.7	1.0	0.0	0.0	0.0	2.2	65.0	y	5
Q4	urban	Q4urban4	21986	32.0	66097.9	0.2	4489.6	*0.85*	0.9	0.9	0.0	0.0	1.0	0.0	1.1	34.5	n	0
Q4	urban	Q4urban5	54634	28.1	79592.8	0.0	2624.5	*0.23*	1.4	0.0	0.1	0.0	0.0	0.0	0.1	3.6	n	0
Q4	urban	Q4urban6	93462	16.5	57284.3	0.3	2387.2	*0.22*	1.0	0.8	1.0	0.0	0.0	0.0	2.0	33.0	n	0
Q4	urban	Q4urban7	42498	14.7	57594.4	0.3	2257.9	*0.21*	1.0	0.8	0.0	0.3	1.0	0.0	0.5	7.8	n	0
Q4	urban	Q4urban8	123657	32.1	63437.8	0.2	3498.2	*0.93*	0.9	0.8	0.2	0.0	0.0	0.0	1.6	50.3	y	6
Q4	urban	Q4urban9	80628	16.0	65198.1	0.2	2421.5	*0.23*	1.0	0.8	0.0	0.0	0.0	0.1	0.4	6.4	n	0
Q1	suburban	Q1suburban1	64190	18.7	7898.4	1.0	244.0	*0.09*	1.1	0.6	0.0	0.1	0.2	0.0	2.1	38.8	n	0
Q1	suburban	Q1suburban2	56097	27.9	8611.9	1.0	258.4	*0.05*	1.1	0.6	0.1	0.1	0.2	0.0	2.3	63.0	y	2
Q1	suburban	Q1suburban3	30229	14.7	9594.7	1.0	284.1	*0.08*	1.0	0.7	0.0	0.7	0.8	0.0	2.1	30.4	n	0
Q1	suburban	Q1suburban4	63862	18.1	9184.7	1.0	278.0	*0.09*	1.1	0.6	1.0	0.0	0.0	0.0	4.0	73.2	y	4
Q1	suburban	Q1suburban5	29107	14.2	8111.2	1.0	233.7	*0.05*	1.0	0.7	0.0	1.0	0.3	0.1	2.1	29.9	n	0
Q1	suburban	Q1suburban6	71217	12.3	8215.5	1.0	250.7	*0.05*	1.0	0.7	0.0	0.0	0.2	0.0	2.0	24.9	n	0
Q1	suburban	Q1suburban7	75928	14.1	8765.8	1.0	240.2	*0.05*	1.0	0.7	1.0	0.0	0.0	0.0	4.0	56.7	y	4
Q1	rural	Q1rural1	64261	25.9	8573.3	1.0	150.6	*0.02*	1.0	0.6	0.2	0.1	0.2	0.0	2.4	63.0	y	2
Q1	rural	Q1rural2	46647	10.3	8022.6	1.0	147.1	*0.00*	0.9	0.8	1.0	0.0	0.0	0.0	3.9	40.6	n	0
Q1	rural	Q1rural3	36377	13.2	9710.4	1.0	161.9	*0.01*	1.0	0.7	0.0	0.7	0.9	0.0	1.9	25.8	n	0
Q1	rural	Q1rural4	25959	7.7	7827.9	1.0	120.0	*0.00*	0.9	0.8	0.0	0.0	0.2	0.0	2.0	15.1	n	0
Q1	rural	Q1rural5	20166	9.2	7494.3	1.0	124.1	*0.00*	0.9	0.9		1.0	0.3	0.1	2.0	18.4	n	0
Q1	rural	Q1rural6	70307	24.0	8320.4	1.0	122.5	*0.00*	1.0	0.7	0.1	0.1	0.2	0.0	2.2	53.3	y	2
Q1	rural	Q1rural7	37409	10.3	8218.0	1.0	145.2	*0.02*	1.0	0.7	0.2	0.1	0.2	0.0	2.4	25.0	n	0
Q2	suburban	Q2suburban1	52449	17.5	21707.5	0.8	270.2	*0.09*	1.0	0.7	0.0	0.0	0.2	0.0	1.7	29.6	n	0
Q2	suburban	Q2suburban2	22624	16.1	21677.0	0.8	250.4	*0.06*	1.0	0.7	0.0	0.8	0.8	0.0	1.7	27.4	n	0
Q2	suburban	Q2suburban3	44691	27.7	21493.1	0.8	247.8	*0.05*	1.0	0.7	0.1	0.2	0.1	0.1	1.9	53.1	y	2
Q2	suburban	Q2suburban4	28772	17.4	19405.1	0.8	315.2	*0.09*	1.0	0.7	0.0	1.0	0.2	0.1	1.8	31.7	n	0
Q2	suburban	Q2suburban5	49809	17.3	22230.3	0.8	280.8	*0.09*	1.0	0.7	1.0	0.0	0.0	0.0	3.5	60.9	y	4
Q2	suburban	Q2suburban6	63945	11.4	20845.7	0.8	229.7	*0.05*	1.0	0.7	0.0	0.2	0.1	0.1	1.7	19.1	n	0
Q2	suburban	Q2suburban7	65386	13.6	21587.5	0.8	237.9	*0.05*	1.0	0.7	1.0	0.0	0.0	0.0	3.5	47.4	y	4
Q2	rural	Q2rural1	196130	15.0	21233.1	0.8	139.9	*0.02*	1.0	0.7	0.2	0.2	0.2	0.0	2.0	30.6	n	0
Q2	rural	Q2rural2	148227	7.2	20078.8	0.8	119.7	*0.00*	0.9	0.9	0.0	0.1	0.1	0.0	1.6	11.8	n	0
Q2	rural	Q2rural3	65456	12.9	20149.9	0.8	150.0	*0.00*	1.0	0.8	0.0	0.7	0.9	0.0	1.6	21.0	n	0
Q2	rural	Q2rural4	247426	10.2	20171.5	0.8	141.2	*0.00*	0.9	0.9	1.0	0.0	0.0	0.0	3.4	35.2	n	0
Q2	rural	Q2rural5	32853	9.9	19101.8	0.8	162.6	*0.01*	1.0	0.8	0.0	0.9	0.0	0.6	1.7	16.5	n	0
Q2	rural	Q2rural6	128702	24.8	20886.5	0.8	154.3	*0.01*	1.0	0.8	0.2	0.1	0.1	0.0	1.9	48.0	y	2
Q3	suburban	Q3suburban1	69820	18.1	30993.7	0.7	253.3	*0.09*	1.1	0.6	0.0	0.2	0.3	0.1	0.8	14.1	n	0
Q3	suburban	Q3suburban2	49647	14.1	30077.7	0.7	326.6	*0.06*	1.0	0.7	0.0	0.8	0.8	0.1	0.8	11.6	n	0
Q3	suburban	Q3suburban3	62188	18.7	29915.2	0.7	278.5	0.09	1.1	0.6	1.0	0.0	0.0	0.0	2.5	46.6	y	5
Q3	suburban	Q3suburban4	64233	12.2	31043.0	0.7	228.8	0.05	1.0	0.7	0.0	0.2	0.2	0.1	0.7	8.9	n	0
Q3	suburban	Q3suburban5	73124	14.5	29165.1	0.7	241.5	0.05	1.0	0.6	1.0	0.0	0.0	0.0	2.5	35.8	n	0
Q3	suburban	Q3suburban6	54451	27.8	30683.4	0.7	257.2	0.05	1.1	0.6	0.1	0.2	0.2	0.1	1.0	26.9	n	0
Q3	rural	Q3rural1	118247	10.3	30817.3	0.7	152.8	0.02	1.0	0.7	0.1	0.1	0.2	0.1	0.9	9.6	n	0
Q3	rural	Q3rural2	86959	11.8	30514.6	0.7	126.3	0.00	1.0	0.8	0.0	0.8	1.0	0.0	0.7	8.0	n	0
Q3	rural	Q3rural3	114997	24.6	30845.2	0.7	138.9	0.00	1.0	0.7	0.1	0.1	0.2	0.0	0.9	21.4	n	0
Q3	rural	Q3rural4	55642	18.4	30226.7	0.7	153.4	0.02	1.0	0.7	0.0	0.7	0.8	0.1	0.7	13.7	n	0
Q3	rural	Q3rural5	177101	10.7	29911.4	0.7	136.7	0.00	1.0	0.8	1.0	0.0	0.0	0.0	2.4	25.3	n	0
Q3	rural	Q3rural6	126106	7.2	30543.6	0.7	116.2	0.00	1.0	0.8	0.0	0.1	0.2	0.0	0.7	4.9	n	0
Q3	rural	Q3rural7	38283	11.3	30760.7	0.7	163.1	0.01	0.9	0.8	0.0	0.9	0.0	0.8	0.7	7.7	n	0
Q3	rural	Q3rural8	89496	24.2	30299.2	0.7	155.3	0.02	1.1	0.6	0.7	0.0	0.0	0.0	1.8	44.4	y	5
Q4	suburban	Q4suburban1	70959	19.0	69525.2	0.1	246.6	0.09	1.1	0.5	0.0	0.0	0.2	0.0	0.2	3.6	n	0
Q4	suburban	Q4suburban2	57725	12.4	68094.3	0.2	260.3	0.05	1.1	0.6	0.0	0.0	0.0	0.0	0.2	2.4	n	0
Q4	suburban	Q4suburban3	45711	14.1	60811.8	0.3	254.7	0.05	1.0	0.7	0.0	0.2	1.0	0.0	0.3	4.3	n	0
Q4	suburban	Q4suburban4	75388	14.7	53286.6	0.4	238.1	0.05	1.1	0.6	1.0	0.0	0.0	0.0	1.8	26.3	n	0
Q4	suburban	Q4suburban5	6283	15.4	49061.9	0.4	325.8	0.06	1.0	0.7	0.0	0.8	0.0	1.0	0.5	7.6	n	0
Q4	suburban	Q4suburban6	56819	28.1	66760.9	0.2	259.2	0.05	1.2	0.5	0.1	0.0	0.2	0.0	0.3	9.5	n	0
Q4	suburban	Q4suburban7	65443	18.1	56788.9	0.3	277.2	0.09	1.1	0.5	1.0	0.0	0.0	0.0	1.7	31.4	n	0
Q4	suburban	Q4suburban8	21243	14.1	51683.9	0.4	285.2	0.08	1.0	0.7	0.0	0.6	1.0	0.0	0.5	6.7	n	0
Q4	rural	Q4rural1	97334	25.8	61480.4	0.2	146.6	0.02	1.1	0.6	0.2	0.1	0.3	0.1	0.5	13.2	n	0
Q4	rural	Q4rural2	147204	10.6	62648.3	0.2	139.7	0.02	1.1	0.6	0.2	0.1	0.3	0.0	0.5	4.9	n	0
Q4	rural	Q4rural3	125700	10.9	59118.5	0.3	150.1	0.00	1.0	0.7	0.0	0.3	1.0	0.0	0.3	3.1	n	0
Q4	rural	Q4rural4	123874	8.5	62891.8	0.2	126.3	0.00	1.0	0.7	0.0	0.0	0.0	0.0	0.2	2.0	n	0
Q4	rural	Q4rural5	18464	11.2	50887.9	0.4	163.4	0.01	1.0	0.8	0.0	0.7	0.0	0.9	0.4	4.5	n	0
Q4	rural	Q4rural6	104813	25.4	61199.8	0.3	126.3	0.00	1.1	0.6	0.1	0.0	0.2	0.1	0.4	10.2	n	0
Q4	rural	Q4rural7	141351	11.5	50924.4	0.4	159.0	0.00	1.0	0.7	1.0	0.0	0.0	0.0	1.8	20.6	n	0

TOTAL population	6744988.39	
Population in profile 1	519746.0348	21%
Population in profile 2	364058.5223	15%
Population in profile 3	270376.3993	11%
Population in profile 4	511822.3148	21%
Population in profile 5	466703.1627	19%
Population in profile n/a	296191.5333	12%
Total high-risk population	2428897.967	
Share of high-risk populat		36%

PERCENTILE 0.75 in reference period: 43.4

y... high-risk cluster

n... cluster not considered high-risk

7. 2080 - nossp-rcp4p5

			Exposure	Hazard	Vulnerability													
Income quartile	Region	Cluster ID	Cluster size	Average no. of annual heatwave days avg	INCOME avg	INCOME norm	POPULATION DENSITY avg	POPULATION DENSITY norm	RELATIVE INCOME OF CELL avg	RELATIVE INCOME OF CELL norm	Share of elderly (>65)	Share of blue collar workers	Share working in manufacturing	Share working in outdoor sector	VULNERABILITY INDICATOR (of cluster)	AVERAGE CLUSTER RISK	Risk > Percentile 0.75	Storyline of high-risk clusters
Q1	urban	Q1urban1	97716	32.68840056	6514.1	1.0	7855.2	*0.33*	1.0	0.9	0.0	0.0	0.2	0.0	2.5619	83.7	y	1
Q1	urban	Q1urban2	41967	24.14657015	8347.5	1.0	6086.4	*0.25*	1.0	0.9	0.0	0.7	1.0	0.0	2.5	60.5	y	3
Q1	urban	Q1urban3	70964	28.57810555	8748.7	1.0	6885.9	*0.29*	1.0	0.77	1.0	0.0	0.0	0.0	4.5	129.9	y	4
Q1	urban	Q1urban4	52398	35.44212501	6379.9	1.0	21151.8	*0.89*	0.9	0.9	0.0	1.0	0.2	0.1	4.5	158.2	y	3
Q1	urban	Q1urban5	39351	30.98964364	7668.2	1.0	5379.9	*0.22*	1.5	0.1	0.1	0.1	0.2	0.0	2.2	67.2	y	6
Q1	urban	Q1urban6	53714	27.68702432	6433.3	1.0	6800.8	*0.28*	1.0	0.8	0.0	1.0	0.0	0.1	2.7	74.4	y	3
Q1	urban	Q1urban7	111491	17.52073504	6825.5	1.0	5231.9	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	2.6	45.1	y	1
Q1	urban	Q1urban8	128135	35.56365435	6102.6	1.0	21445.8	*0.91*	1.0	0.8	0.2	0.0	0.1	0.0	4.1	146.0	y	1
Q2	urban	Q2urban1	104257	32.40653695	19027.7	0.8	7341.6	*0.31*	1.1	0.7	0.0	0.0	0.0	0.0	2.0	66.2	y	1
Q2	urban	Q2urban2	25696	26.22625035	20555.8	0.8	6624.7	*0.28*	1.0	0.8	0.0	1.0	1.0	0.0	2.2	58.0	y	3
Q2	urban	Q2urban3	34067	29.19451642	20846.9	0.8	7689.2	*0.32*	1.0	0.9	0.0	0.0	1.0	0.0	2.1	61.7	y	1
Q2	urban	Q2urban4	56295	34.95543491	17532.1	0.8	21608.3	*0.91*	0.9	1.0	0.0	1.0	0.2	0.1	4.1	144.1	y	3
Q2	urban	Q2urban5	58924	28.81116244	21401.3	0.8	7013.6	*0.29*	1.0	0.9	1.0	0.0	0.0	0.0	4.1	117.7	y	4
Q2	urban	Q2urban6	67712	28.07887056	17521.1	0.8	6518.6	*0.27*	1.0	0.9	0.0	1.0	0.0	0.1	2.3	65.0	y	3
Q2	urban	Q2urban7	119708	17.66847672	18916.1	0.8	5384.8	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	2.2	39.4	n	0
Q2	urban	Q2urban8	136065	35.38301909	18132.7	0.8	21910.6	*0.93*	0.9	0.9	0.2	0.0	0.1	0.0	3.7	129.9	y	1
Q3	urban	Q3urban1	42595	35.5877001	29182.0	0.7	23654.5	*1.00*	0.9	1.0	0.0	0.0	0.2	0.0	2.4	84.8	y	6
Q3	urban	Q3urban2	53321	23.54391083	30885.5	0.7	5927.7	*0.25*	1.1	0.7	0.0	0.7	1.0	0.0	1.0	24.1	n	0
Q3	urban	Q3urban3	32632	35.37592873	30234.8	0.7	20424.1	*0.86*	1.1	0.7	1.0	0.0	0.0	0.0	4.0	140.2	y	5
Q3	urban	Q3urban4	46673	27.95536201	29148.6	0.7	6443.1	*0.27*	1.0	0.8	0.0	1.0	0.0	0.0	1.2	32.9	n	0
Q3	urban	Q3urban5	91742	31.9141477	32032.0	0.7	6440.2	*0.27*	1.0	0.8	0.0	0.0	0.2	0.0	1.0	31.5	n	0
Q3	urban	Q3urban6	46248	34.97593584	29595.9	0.7	21425.4	*0.91*	1.1	0.6	0.0	1.0	0.2	0.2	2.1	72.5	y	6
Q3	urban	Q3urban7	75885	28.13928986	30981.6	0.7	6064.2	*0.25*	1.0	0.8	1.0	0.0	0.0	0.0	2.9	81.4	y	5
Q3	urban	Q3urban8	55190	35.43861238	32808.3	0.6	16758.8	*0.71*	1.1	0.7	0.0	0.0	0.2	0.0	1.5	52.1	y	6
Q3	urban	Q3urban9	99043	17.21418807	31434.3	0.7	5300.9	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	1.2	20.4	n	0
Q4	urban	Q4urban1	84337	33.16542356	62744.3	0.2	8564.3	*0.36*	1.0	0.9	0.0	0.0	0.0	0.1	0.6	20.8	n	0
Q4	urban	Q4urban2	37312	32.14223113	63491.7	0.2	6196.9	*0.26*	1.1	0.7	0.0	0.1	1.0	0.0	0.5	15.2	n	0
Q4	urban	Q4urban3	49189	33.32192285	59791.5	0.3	9225.4	*0.39*	1.1	0.7	1.0	0.0	0.0	0.0	2.2	71.9	y	5
Q4	urban	Q4urban4	22940	35.4546935	67309.4	0.2	20144.5	*0.85*	1.0	0.9	0.0	0.0	1.0	0.0	1.1	38.4	n	0
Q4	urban	Q4urban5	54070	31.09446766	81051.7	0.0	5521.6	*0.23*	1.5	0.0	0.1	0.0	0.0	0.0	0.1	4.0	n	0
Q4	urban	Q4urban6	47599	20.50756795	58334.2	0.3	5356.2	*0.22*	1.0	0.8	1.0	0.0	0.0	0.0	2.0	41.0	n	0
Q4	urban	Q4urban7	48131	18.25953445	58650.1	0.3	4984.4	*0.21*	1.0	0.8	0.0	0.3	1.0	0.0	0.5	9.7	n	0
Q4	urban	Q4urban8	104427	35.57852896	64600.6	0.2	22064.4	*0.93*	1.0	0.8	0.2	0.0	0.0	0.0	1.6	55.5	y	6
Q4	urban	Q4urban9	91012	19.89064644	66393.2	0.2	5451.1	*0.23*	1.0	0.8	0.0	0.0	0.0	0.1	0.4	8.0	n	0
Q1	suburban	Q1suburban1	72014	22.13880432	7428.7	1.0	2346.6	*0.09*	1.1	0.6	0.0	0.1	0.2	0.0	2.1	46.2	y	2
Q1	suburban	Q1suburban2	54360	31.36781223	8099.8	1.0	1408.9	*0.05*	1.1	0.6	0.1	0.1	0.2	0.0	2.3	71.1	y	2
Q1	suburban	Q1suburban3	33915	18.06719963	9024.1	1.0	2025.7	*0.08*	1.1	0.7	0.0	0.7	0.8	0.0	2.1	37.6	n	0
Q1	suburban	Q1suburban4	30410	21.44520855	8638.5	1.0	2259.0	*0.09*	1.1	0.6	1.0	0.0	0.0	0.0	4.1	87.1	y	4
Q1	suburban	Q1suburban5	32677	17.29480386	7628.8	1.0	1338.0	*0.05*	1.0	0.7	0.0	1.0	0.3	0.1	2.1	36.4	n	0
Q1	suburban	Q1suburban6	80021	15.25764899	7726.9	1.0	1378.4	*0.05*	1.1	0.7	0.0	0.0	0.2	0.0	2.0	30.9	n	0
Q1	suburban	Q1suburban7	38093	17.14190739	8244.5	1.0	1372.4	*0.05*	1.1	0.7	1.0	0.0	0.0	0.0	4.0	69.0	y	4
Q1	rural	Q1rural1	61502	29.36258603	8063.4	1.0	706.6	*0.02*	1.1	0.7	0.2	0.1	0.2	0.0	2.4	71.6	y	2
Q1	rural	Q1rural2	27317	12.27354636	7545.5	1.0	201.0	*0.00*	0.9	0.9	1.0	0.0	0.0	0.0	3.9	48.4	y	4
Q1	rural	Q1rural3	45447	15.77579261	9132.9	1.0	486.9	*0.01*	1.0	0.8	0.0	0.7	0.9	0.0	2.0	30.9	n	0
Q1	rural	Q1rural4	33935	9.280662357	7362.4	1.0	172.8	*0.00*	1.0	0.9	0.0		0.2	0.0	2.0	18.3	n	0
Q1	rural	Q1rural5	26347	11.03193253	7048.6	1.0	191.0	*0.00*	0.9	0.9		1.0	0.3	0.1	2.0	22.1	n	0
Q1	rural	Q1rural6	77772	27.38404614	7825.5	1.0	234.2	*0.00*	1.0	0.8	0.1	0.1	0.2	0.0	2.2	60.9	y	2
Q1	rural	Q1rural7	35778	12.61631906	7729.3	1.0	744.4	*0.02*	1.1	0.7	0.2	0.1	0.2	0.0	2.4	30.7	n	0
Q2	suburban	Q2suburban1	61502	21.10148654	20416.5	0.8	2282.6	*0.09*	1.1	0.7	0.0	0.0	0.2	0.0	1.7	36.5	n	0
Q2	suburban	Q2suburban2	27317	19.34583307	20387.8	0.8	1477.2	*0.06*	1.0	0.8	0.0	0.8	0.8	0.0	1.7	33.7	n	0
Q2	suburban	Q2suburban3	45447	31.31638032	20214.9	0.8	1371.3	*0.05*	1.1	0.7	0.1	0.2	0.1	0.1	2.0	61.2	y	2
Q2	suburban	Q2suburban4	33935	20.86963669	18251.0	0.8	2213.3	*0.09*	1.0	0.7	0.0	1.0	0.2	0.1	1.9	38.9	n	0
Q2	suburban	Q2suburban5	26347	20.83522523	20908.2	0.8	2259.9	*0.09*	1.0	0.7	1.0	0.0	0.0	0.0	3.6	74.8	y	4
Q2	suburban	Q2suburban6	77772	14.2119562	19605.9	0.8	1338.6	*0.05*	1.0	0.8	0.0	0.2	0.1	0.1	1.7	24.4	n	0
Q2	suburban	Q2suburban7	35778	16.61549493	20303.6	0.8	1368.9	*0.05*	1.0	0.8	1.0	0.0	0.0	0.0	3.5	58.9	y	4
Q2	rural	Q2rural1	187212	17.69181728	19970.3	0.8	744.7	*0.02*	1.0	0.7	0.2	0.2	0.2	0.0	2.1	36.9	n	0
Q2	rural	Q2rural2	194495	8.720049567	18884.7	0.8	165.0	*0.00*	0.9	0.9	0.0	0.1	0.1	0.0	1.7	14.5	n	0
Q2	rural	Q2rural3	85239	15.23625785	18951.5	0.8	227.8	*0.00*	1.0	0.9	0.0	0.7	0.9	0.0	1.7	25.3	n	0
Q2	rural	Q2rural4	145851	12.20019714	18971.8	0.8	182.3	*0.00*	0.9	0.9	1.0	0.0	0.0	0.0	3.5	42.5	n	0
Q2	rural	Q2rural5	41864	11.89713396	17965.8	0.8	352.7	*0.01*	1.0	0.9	0.0	0.9	0.0	0.6	1.7	20.2	n	0
Q2	rural	Q2rural6	135288	28.30749602	19644.3	0.8	284.0	*0.01*	1.0	0.8	0.2	0.1	0.1	0.0	2.0	55.7	y	2
Q3	suburban	Q3suburban1	81235	21.61075911	31561.8	0.7	2329.9	*0.09*	1.1	0.7	0.0	0.2	0.3	0.1	0.8	16.8	n	0
Q3	suburban	Q3suburban2	60131	17.2771321	30629.0	0.7	1616.4	*0.06*	1.0	0.8	0.0	0.8	0.8	0.1	0.8	14.2	n	0
Q3	suburban	Q3suburban3	32473	21.96540122	30463.5	0.7	2261.1	0.09	1.1	0.6	1.0	0.0	0.0	0.0	2.5	54.7	y	5
Q3	suburban	Q3suburban4	77813	15.09053823	31612.0	0.7	1318.6	0.05	1.1	0.7	0.0	0.2	0.2	0.1	0.7	10.9	n	0
Q3	suburban	Q3suburban5	39821	17.47423503	29699.7	0.7	1372.2	0.05	1.1	0.7	1.0	0.0	0.0	0.0	2.5	43.0	n	0
Q3	suburban	Q3suburban6	54905	31.25967702	31245.8	0.7	1399.1	0.05	1.1	0.6	0.1	0.2	0.2	0.1	1.0	30.2	n	0
Q3	rural	Q3rural1	123216	12.55519702	31382.1	0.7	715.5	0.02	1.1	0.7	0.1	0.1	0.2	0.1	0.9	11.6	n	0
Q3	rural	Q3rural2	113580	14.04111401	31073.9	0.7	207.1	0.00	1.0	0.9	0.0	0.8	1.0	0.0	0.7	9.4	n	0
Q3	rural	Q3rural3	128360	27.93023051	31410.6	0.7	262.4	0.00	1.0	0.7	0.1	0.1	0.2	0.0	0.9	24.2	n	0
Q3	rural	Q3rural4	68474	21.43138044	30780.7	0.7	712.2	0.02	1.0	0.7	0.0	0.7	0.8	0.1	0.7	15.9	n	0
Q3	rural	Q3rural5	103472	12.71558993	30459.6	0.7	194.1	0.00	1.0	0.8	1.0	0.0	0.0	0.0	2.4	29.9	n	0
Q3	rural	Q3rural6	164931	8.714387653	31103.4	0.7	169.2	0.00	1.0	0.9	0.0	0.1	0.2	0.0	0.7	5.8	n	0
Q3	rural	Q3rural7	49291	13.50839642	31324.5	0.7	304.1	0.01	1.0	0.9	0.0	0.9	0.0	0.8	0.7	9.1	n	0
Q3	rural	Q3rural8	59876	27.53770333	30854.6	0.7	713.0	0.02	1.1	0.6	0.7	0.0	0.0	0.0	1.8	50.3	y	5
Q4	suburban	Q4suburban1	82127	22.3270767	70799.5	0.1	2320.9	0.09	1.2	0.5	0.0	0.0	0.2	0.0	0.2	4.3	n	0
Q4	suburban	Q4suburban2	69857	15.34363058	69342.4	0.2	1393.5	0.05	1.1	0.6	0.0	0.0	0.0	0.0	0.2	3.0	n	0
Q4	suburban	Q4suburban3	55229	17.22802343	61926.5	0.3	1371.2	0.05	1.1	0.7	0.0	0.2	1.0	0.0	0.3	5.3	n	0
Q4	suburban	Q4suburban4	40955	17.61224578	54263.3	0.4	1369.2	0.05	1.1	0.6	1.0	0.0	0.0	0.0	1.8	31.5	n	0
Q4	suburban	Q4suburban5	7617	18.84775349	49961.1	0.4	1578.1	0.06	1.0	0.8	0.0	0.8	0.0	1.0	0.5	9.3	n	0
Q4	suburban	Q4suburban6	58473	31.43838623	67984.6	0.2	1414.9	0.05	1.2	0.5	0.1	0.0	0.2	0.0	0.3	10.7	n	0
Q4	suburban	Q4suburban7	34250	21.37035269	57829.8	0.3	2248.7	0.09	1.2	0.5	1.0	0.0	0.0	0.0	1.7	37.0	n	0
Q4	suburban	Q4suburban8	25376	17.40712637	52631.3	0.4	2101.2	0.08	1.1	0.7	0.0	0.6	1.0	0.0	0.5	8.3	n	0
Q4	rural	Q4rural1	96047	29.12605355	62607.3	0.2	713.6	0.02	1.1	0.6	0.2	0.1	0.3	0.1	0.5	14.9	n	0
Q4	rural	Q4rural2	147695	12.92571107	63796.5	0.2	749.3	0.02	1.1	0.6	0.2	0.1	0.3	0.0	0.5	6.0	n	0
Q4	rural	Q4rural3	162609	13.05942347	60202.1	0.3	235.4	0.00	1.0	0.8	0.0	0.3	1.0	0.0	0.3	3.7	n	0
Q4	rural	Q4rural4	160394	10.20847826	64044.6	0.2	195.8	0.00	1.0	0.7	0.0	0.0	0.0	0.0	0.2	2.3	n	0
Q4	rural	Q4rural5	23755	13.44319263	51820.6	0.4	315.9	0.01	1.0	0.9	0.0	0.7	0.0	0.9	0.4	5.4	n	0
Q4	rural	Q4rural6	116505	28.6665117	62321.5	0.2	244.0	0.00	1.1	0.7	0.1	0.0	0.2	0.1	0.4	11.5	n	0
Q4	rural	Q4rural7	80931	13.67542313	51857.8	0.4	270.9	0.00	1.1	0.7	1.0	0.0	0.0	0.0	1.8	24.4	n	0

TOTAL population	6347839	
Population in profile 1	611731	28%
Population in profile 2	446383	20%
Population in profile 3	297782	14%
Population in profile 4	287833	13%
Population in profile 5	250055	11%
Population in profile n/a	287811	13%
Total high-risk population	2181595	
Share of high-risk population	34%	

PERCENTILE 0.75 in reference period	43.4	y...	high-risk cluster
		n...	cluster is not considered high-risk

8. 2080 - ssp1-noCC

			Exposure	Hazard	Vulnerability													
Income quartile	Region	Cluster ID	Cluster size	Average no. of annual heatwave days	INCOME		POPULATION DENSITY		RELATIVE INCOME OF CELL		Share of elderly (>65)	Share of blue collar workers	Share working in manufacturing	Share working in outdoor sector	VULNERABILITY INDICATOR (of cluster)	AVERAGE CLUSTER RISK	Risk > Percentile 0.75	Storyline of high-risk clusters
				avg	std	norm	avg	norm	avg	norm								
Q1	urban	Q1urban1	72208	23.6	*8474.17*	*0.99*	3233.0	*0.33*	0.9	0.8	0.0	0.0	0.2	0.0	2.5	59.8	y	1
Q1	urban	Q1urban2	29764	16.3	*10859.13*	*0.96*	2756.6	*0.25*	0.9	0.8	0.0	0.7	1.0	0.0	2.4	39.9	n	0
Q1	urban	Q1urban3	181094	19.9	*11381.14*	*0.95*	3350.2	*0.29*	1.0	0.74	1.0	0.0	0.0	0.0	4.5	88.9	y	4
Q1	urban	Q1urban4	40574	25.5	*8299.59*	*0.99*	4402.8	*0.89*	0.9	0.9	0.0	1.0	0.2	0.1	4.4	113.0	y	3
Q1	urban	Q1urban5	33937	22.2	*9975.53*	*0.97*	2479.3	*0.22*	1.3	0.1	0.1	0.1	0.2	0.0	2.1	47.7	y	6
Q1	urban	Q1urban6	38534	19.1	*8369.03*	*0.99*	2795.9	*0.28*	1.0	0.8	0.0	1.0	0.0	0.1	2.7	50.8	y	3
Q1	urban	Q1urban7	102369	11.4	*8879.19*	*0.99*	2359.9	*0.22*	1.0	0.7	0.1	0.1	0.1	0.0	2.6	29.2	n	0
Q1	urban	Q1urban8	152567	25.6	*7938.85*	*1.00*	3897.5	*0.91*	0.9	0.8	0.2	0.0	0.1	0.0	4.1	104.7	y	1
Q2	urban	Q2urban1	76064	23.3	*24752.97*	*0.75*	3272.7	*0.31*	1.0	0.7	0.0	0.0	0.0	0.0	1.8	43.1	y	1
Q2	urban	Q2urban2	18528	18.1	*26740.87*	*0.72*	3254.3	*0.28*	1.0	0.8	0.0	1.0	1.0	0.0	2.0	35.7	n	0
Q2	urban	Q2urban3	24864	20.3	*27119.61*	*0.71*	3595.7	*0.32*	0.9	0.8	0.0	0.0	1.0	0.0	1.9	38.3	n	0
Q2	urban	Q2urban4	43706	25.1	*22807.35*	*0.78*	4383.2	*0.91*	0.9	0.9	0.0	1.0	0.2	0.1	3.8	95.6	y	3
Q2	urban	Q2urban5	152053	20.0	*27840.82*	*0.70*	3437.1	*0.29*	0.9	0.8	1.0	0.0	0.0	0.0	3.7	74.9	y	4
Q2	urban	Q2urban6	48701	19.5	*22793.03*	*0.78*	2789.0	*0.27*	1.0	0.8	0.0	1.0	0.0	0.1	2.1	41.2	n	0
Q2	urban	Q2urban7	109419	11.5	*24607.83*	*0.75*	2393.9	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	2.0	23.4	n	0
Q2	urban	Q2urban8	155717	25.5	*23588.67*	*0.76*	3970.3	*0.93*	0.9	0.9	0.2	0.0	0.1	0.0	3.4	87.0	y	1
Q3	urban	Q3urban1	32971	25.5	*26682.63*	*0.72*	2666.1	*1.00*	0.9	1.0	0.0	0.0	0.2	0.0	2.4	62.1	y	6
Q3	urban	Q3urban2	37591	15.9	*28240.19*	*0.69*	2702.8	*0.25*	0.9	0.8	0.0	0.7	1.0	0.0	1.1	18.1	n	0
Q3	urban	Q3urban3	89989	25.5	*27645.26*	*0.70*	4588.1	*0.86*	0.9	0.9	1.0	0.0	0.0	0.0	4.4	111.9	y	5
Q3	urban	Q3urban4	33512	19.4	*26652.08*	*0.72*	2730.5	*0.27*	1.0	0.8	0.0	1.0	0.0	0.0	1.2	24.1	n	0
Q3	urban	Q3urban5	67158	23.0	*29288.54*	*0.68*	2569.2	*0.27*	1.0	0.7	0.0	0.0	0.2	0.0	1.0	22.9	n	0
Q3	urban	Q3urban6	35751	25.2	*27061.03*	*0.71*	4617.7	*0.91*	0.9	1.0	0.0	1.0	0.2	0.2	2.9	72.8	y	6
Q3	urban	Q3urban7	192353	19.6	*28328.14*	*0.69*	2581.3	*0.25*	1.0	0.6	1.0	0.0	0.0	0.0	2.8	55.1	y	5
Q3	urban	Q3urban8	42205	25.5	*29998.35*	*0.67*	2675.8	*0.71*	1.0	0.8	0.0	0.0	0.2	0.0	1.6	39.5	n	0
Q3	urban	Q3urban9	93593	11.2	*28741.99*	*0.69*	2438.4	*0.22*	1.0	0.7	0.1	0.1	0.1	0.0	1.2	13.5	n	0
Q4	urban	Q4urban1	62136	24.0	*57370.43*	*0.25*	3664.9	*0.36*	0.9	0.8	0.0	0.0	0.0	0.1	0.6	15.0	n	0
Q4	urban	Q4urban2	28110	23.2	*58053.82*	*0.24*	2649.9	*0.26*	1.0	0.7	0.0	0.1	1.0	0.0	0.5	11.0	n	0
Q4	urban	Q4urban3	128874	24.1	*54670.51*	*0.29*	4658.3	*0.39*	1.0	0.7	1.0	0.0	0.0	0.0	2.2	52.2	y	5
Q4	urban	Q4urban4	18537	25.5	*61544.54*	*0.19*	4489.6	*0.85*	0.9	0.8	0.0	0.0	1.0	0.0	1.1	27.6	n	0
Q4	urban	Q4urban5	50815	22.2	*74109.79*	*0.00*	2624.5	*0.23*	1.4	0.0	0.1	0.0	0.0	0.0	0.1	2.8	n	0
Q4	urban	Q4urban6	118895	13.4	*53338.03*	*0.31*	2387.2	*0.22*	1.0	0.7	1.0	0.0	0.0	0.0	2.0	26.9	n	0
Q4	urban	Q4urban7	34080	12.1	*53626.84*	*0.31*	2257.9	*0.21*	1.0	0.8	0.0	0.3	1.0	0.0	0.5	6.5	n	0
Q4	urban	Q4urban8	124627	25.6	*59067.71*	*0.23*	3498.2	*0.93*	0.9	0.8	0.2	0.0	0.0	0.0	1.6	40.1	n	0
Q4	urban	Q4urban9	64035	13.0	*60706.73*	*0.20*	2421.5	*0.23*	1.0	0.7	0.0	0.0	0.0	0.1	0.4	5.3	n	0
Q1	suburban	Q1suburban1	52491	15.3	*9663.91*	*0.97*	244.0	*0.09*	1.1	0.6	0.0	0.1	0.2	0.0	2.1	31.5	n	0
Q1	suburban	Q1suburban2	51972	22.9	*10536.91*	*0.96*	258.4	*0.05*	1.1	0.6	0.1	0.1	0.2	0.0	2.2	51.3	y	2
Q1	suburban	Q1suburban3	24448	12.1	*11739.34*	*0.94*	284.1	*0.08*	1.0	0.7	0.0	0.7	0.8	0.0	2.0	24.7	n	0
Q1	suburban	Q1suburban4	84353	14.8	*11237.72*	*0.95*	278.0	*0.09*	1.1	0.6	1.0	0.0	0.0	0.0	4.0	59.1	y	4
Q1	suburban	Q1suburban5	23601	11.6	*9924.27*	*0.97*	233.7	*0.05*	1.0	0.7	0.0	1.0	0.3	0.1	2.1	24.2	n	0
Q1	suburban	Q1suburban6	57554	10.1	*10051.82*	*0.97*	250.7	*0.05*	1.0	0.7	0.0	0.0	0.2	0.0	2.0	20.2	n	0
Q1	suburban	Q1suburban7	96790	11.6	*10725.20*	*0.96*	240.2	*0.05*	1.0	0.7	1.0	0.0	0.0	0.0	4.0	45.9	y	4
Q1	rural	Q1rural1	62578	21.2	*10489.68*	*0.96*	150.6	*0.02*	1.0	0.6	0.2	0.1	0.2	0.0	2.4	51.1	y	2
Q1	rural	Q1rural2	57616	8.4	*9815.85*	*0.97*	147.1	*0.00*	0.9	0.8	1.0	0.0	0.0	0.0	3.9	33.0	n	0
Q1	rural	Q1rural3	28284	10.8	*11880.91*	*0.94*	161.9	*0.01*	1.0	0.7	0.0	0.7	0.9	0.0	1.9	20.7	n	0
Q1	rural	Q1rural4	20032	6.4	*9577.67*	*0.98*	120.0	*0.00*	0.9	0.8	0.0	0.0	0.2	0.0	2.0	12.5	n	0
Q1	rural	Q1rural5	15547	7.5	*9169.42*	*0.98*	124.1	*0.00*	0.9	0.8		1.0	0.3	0.1	2.0	15.0	n	0
Q1	rural	Q1rural6	62742	19.5	*10180.18*	*0.97*	122.5	*0.00*	1.0	0.7	0.1	0.1	0.2	0.0	2.2	43.0	n	0
Q1	rural	Q1rural7	36032	8.5	*10054.94*	*0.97*	145.2	*0.02*	1.0	0.7	0.2	0.1	0.2	0.0	2.4	20.4	n	0
Q2	suburban	Q2suburban1	42038	14.3	*26559.63*	*0.72*	270.2	*0.09*	1.0	0.7	0.0	0.0	0.2	0.0	1.5	22.1	n	0
Q2	suburban	Q2suburban2	17790	13.1	*26522.29*	*0.72*	250.4	*0.06*	1.0	0.7	0.0	0.8	0.8	0.0	1.6	20.3	n	0
Q2	suburban	Q2suburban3	41196	22.8	*26297.36*	*0.72*	247.8	*0.05*	1.0	0.7	0.1	0.2	0.1	0.1	1.8	40.1	n	0
Q2	suburban	Q2suburban4	22958	14.2	*23742.60*	*0.76*	315.2	*0.09*	1.0	0.7	0.0	1.0	0.2	0.1	1.7	24.1	n	0
Q2	suburban	Q2suburban5	63784	14.2	*27199.32*	*0.71*	280.8	*0.09*	1.0	0.7	1.0	0.0	0.0	0.0	3.3	46.9	y	4
Q2	suburban	Q2suburban6	50007	9.4	*25505.21*	*0.73*	229.7	*0.05*	1.0	0.7	0.0	0.2	0.1	0.1	1.5	14.4	n	0
Q2	suburban	Q2suburban7	81904	11.1	*26412.78*	*0.72*	237.9	*0.05*	1.0	0.7	1.0	0.0	0.0	0.0	3.3	36.4	n	0
Q2	rural	Q2rural1	189958	12.2	*25979.23*	*0.73*	139.9	*0.02*	1.0	0.7	0.2	0.2	0.2	0.0	1.9	23.1	n	0
Q2	rural	Q2rural2	114360	6.0	*24566.91*	*0.75*	119.7	*0.00*	0.9	0.8	0.0	0.1	0.1	0.0	1.5	9.0	n	0
Q2	rural	Q2rural3	50390	10.4	*24653.85*	*0.75*	150.0	*0.00*	1.0	0.8	0.0	0.7	0.9	0.0	1.5	15.7	n	0
Q2	rural	Q2rural4	305075	8.4	*24680.32*	*0.75*	141.2	*0.00*	0.9	0.9	1.0	0.0	0.0	0.0	3.2	27.1	n	0
Q2	rural	Q2rural5	25472	8.1	*23371.55*	*0.77*	162.6	*0.01*	1.0	0.8	0.0	0.9	0.0	0.6	1.5	12.5	n	0
Q2	rural	Q2rural6	119164	20.3	*25555.08*	*0.73*	154.3	*0.01*	1.0	0.7	0.2	0.1	0.1	0.0	1.8	36.1	n	0
Q3	suburban	Q3suburban1	56279	14.8	*28858.58*	*0.68*	253.3	*0.09*	1.0	0.6	0.0	0.2	0.3	0.1	0.8	11.8	n	0
Q3	suburban	Q3suburban2	39093	11.6	*28005.67*	*0.70*	326.6	*0.06*	1.0	0.7	0.0	0.8	0.8	0.1	0.8	9.7	n	0
Q3	suburban	Q3suburban3	80092	15.2	*27854.40*	*0.70*	278.5	0.09	1.1	0.6	1.0	0.0	0.0	0.0	2.5	38.5	n	0
Q3	suburban	Q3suburban4	50415	10.0	*28904.51*	*0.68*	228.8	0.05	1.0	0.7	0.0	0.2	0.2	0.1	0.7	7.5	n	0
Q3	suburban	Q3suburban5	91865	11.8	*27155.99*	*0.71*	241.5	0.05	1.0	0.6	1.0	0.0	0.0	0.0	2.5	29.6	n	0
Q3	suburban	Q3suburban6	50496	22.8	*28569.64*	*0.69*	257.2	0.05	1.1	0.6	0.1	0.2	0.2	0.1	1.0	22.7	n	0
Q3	rural	Q3rural1	106915	8.5	*28694.32*	*0.69*	152.8	0.02	1.0	0.7	0.1	0.1	0.2	0.1	0.9	8.1	n	0
Q3	rural	Q3rural2	66906	9.6	*28412.51*	*0.69*	126.3	0.00	1.0	0.8	0.0	0.8	1.0	0.0	0.7	6.7	n	0
Q3	rural	Q3rural3	101604	20.1	*28720.37*	*0.69*	138.9	0.00	1.0	0.7	0.1	0.1	0.2	0.0	0.9	17.9	n	0
Q3	rural	Q3rural4	43436	14.9	*28144.39*	*0.69*	153.4	0.02	1.0	0.7	0.0	0.7	0.8	0.1	0.8	11.4	n	0
Q3	rural	Q3rural5	218889	8.7	*27850.83*	*0.70*	136.7	0.00	1.0	0.8	1.0	0.0	0.0	0.0	2.4	21.0	n	0
Q3	rural	Q3rural6	97387	6.1	*28439.49*	*0.69*	116.2	0.00	1.0	0.8	0.0	0.1	0.2	0.0	0.7	4.2	n	0
Q3	rural	Q3rural7	29617	9.2	*28641.64*	*0.69*	163.1	0.01	1.0	0.8	0.0	0.9	0.0	0.8	0.7	6.5	n	0
Q3	rural	Q3rural8	104995	19.8	*28211.95*	*0.69*	155.3	0.02	1.1	0.6	0.7	0.0	0.0	0.0	1.9	37.0	n	0
Q4	suburban	Q4suburban1	57397	15.5	*64735.69*	*0.14*	246.6	0.09	1.1	0.5	0.0	0.0	0.2	0.0	0.2	3.0	n	0
Q4	suburban	Q4suburban2	45415	10.2	*63403.38*	*0.16*	260.3	0.05	1.1	0.6	0.0	0.0	0.0	0.0	0.2	2.0	n	0
Q4	suburban	Q4suburban3	36014	11.6	*56622.60*	*0.26*	254.7	0.05	1.0	0.7	0.0	0.2	1.0	0.0	0.3	3.6	n	0
Q4	suburban	Q4suburban4	94684	11.9	*49615.81*	*0.37*	238.1	0.05	1.1	0.6	1.0	0.0	0.0	0.0	1.8	21.7	n	0
Q4	suburban	Q4suburban5	4935	12.6	*45682.09*	*0.43*	325.8	0.06	1.0	0.7	0.0	0.8	0.0	1.0	0.5	6.4	n	0
Q4	suburban	Q4suburban6	51610	23.1	*62161.83*	*0.18*	259.2	0.05	1.1	0.5	0.1	0.0	0.2	0.0	0.3	8.0	n	0
Q4	suburban	Q4suburban7	84127	14.7	*52876.84*	*0.32*	277.2	0.09	1.1	0.5	1.0	0.0	0.0	0.0	1.8	25.8	n	0
Q4	suburban	Q4suburban8	16942	11.7	*48123.51*	*0.39*	285.2	0.08	1.0	0.7	0.0	0.6	1.0	0.0	0.5	5.7	n	0
Q4	rural	Q4rural1	92700	21.0	*57245.12*	*0.25*	146.6	0.02	1.1	0.6	0.2	0.1	0.3	0.1	0.5	11.0	n	0
Q4	rural	Q4rural2	136904	8.7	*58332.52*	*0.24*	139.7	0.02	1.1	0.6	0.2	0.1	0.3	0.0	0.5	4.1	n	0
Q4	rural	Q4rural3	96953	9.0	*55045.90*	*0.29*	150.1	0.00	1.0	0.7	0.0	0.3	1.0	0.0	0.3	2.6	n	0
Q4	rural	Q4rural4	95766	7.0	*58559.29*	*0.24*	126.3	0.00	1.0	0.7	0.0	0.0	0.0	0.0	0.2	1.7	n	0
Q4	rural	Q4rural5	14278	9.1	*47382.27*	*0.40*	163.4	0.01	1.0	0.8	0.0	0.7	0.0	0.9	0.4	3.8	n	0
Q4	rural	Q4rural6	92633	20.8	*56983.80*	*0.26*	126.3	0.00	1.0	0.6	0.1	0.0	0.2	0.1	0.4	8.5	n	0
Q4	rural	Q4rural7	175556	9.4	*47416.31*	*0.40*	159.0	0.00	1.0	0.7	1.0	0.0	0.0	0.0	1.8	17.0	n	0

TOTAL population	6567373.17	
Population in profile 1	456555.8335	26%
Population in profile 2	114549.9393	6%
Population in profile 3	122813.8885	7%
Population in profile 4	578074.0722	32%
Population in profile 5	411216.7031	23%
Population in profile n/a	102659.6374	6%
Total high-risk population	1785870.074	
Share of high-risk population	27%	

PERCENTILE 0.75 in reference period	43.4 y...	high-risk cluster
	n...	cluster not considered high-risk

9. 2080 - ssp1-rcp4p5

			Exposure	Hazard	Vulnerability													
Income quartile	Region	Cluster ID	Cluster size	Average no. of annual heatwave days avg	INCOME std	INCOME norm	POPULATION DENSITY avg	POPULATION DENSITY norm	RELATIVE INCOME OF CELL avg	RELATIVE INCOME OF CELL norm	Share of elderly (>65)	Share of blue collar workers	Share working in manufacturing	Share working in outdoor sector	VULNERABILITY INDICATOR (of cluster)	AVERAGE CLUSTER RISK	Risk > Percentile 0.75	Storyline of high-risk clusters
Q1	urban	Q1urban1	72208	32.68840056	*8474.17*	*0.99*	3233.0	*0.33*	0.9	0.8	0.0	0.0	0.2	0.0	2.5	82.8	y	1
Q1	urban	Q1urban2	29764	24.14657015	*10859.13*	*0.96*	2756.6	*0.25*	0.9	0.8	0.0	0.7	1.0	0.0	2.4	59.1	y	3
Q1	urban	Q1urban3	181094	28.57810555	*11381.14*	*0.95*	3350.2	*0.29*	1.0	0.74	1.0	0.0	0.0	0.0	4.5	127.8	y	4
Q1	urban	Q1urban4	40574	35.44212501	*8299.59*	*0.99*	4402.8	*0.89*	0.9	0.9	0.0	1.0	0.2	0.1	4.4	157.1	y	3
Q1	urban	Q1urban5	33937	30.98964364	*9975.53*	*0.97*	2479.3	*0.22*	1.3	0.1	0.1	0.1	0.2	0.0	2.1	66.5	y	6
Q1	urban	Q1urban6	38534	27.68702432	*8369.03*	*0.99*	2795.9	*0.28*	1.0	0.8	0.0	1.0	0.0	0.1	2.7	73.7	y	3
Q1	urban	Q1urban7	102369	17.52073504	*8879.19*	*0.99*	2359.9	*0.22*	1.0	0.7	0.1	0.1	0.1	0.0	2.6	44.7	y	1
Q1	urban	Q1urban8	152567	35.56365435	*7938.85*	*1.00*	3897.5	*0.91*	0.9	0.8	0.2	0.0	0.1	0.0	4.1	145.6	y	1
Q2	urban	Q2urban1	76064	32.40653695	*24752.97*	*0.75*	3272.7	*0.31*	1.0	0.7	0.0	0.0	0.0	0.0	1.8	59.9	y	1
Q2	urban	Q2urban2	18528	26.22625035	*26740.87*	*0.72*	3254.3	*0.28*	1.0	0.8	0.0	1.0	1.0	0.0	2.0	51.6	y	3
Q2	urban	Q2urban3	24864	29.19451642	*27119.61*	*0.71*	3595.7	*0.32*	0.9	0.8	0.0	0.0	1.0	0.0	1.9	55.0	y	1
Q2	urban	Q2urban4	43706	34.95543491	*22807.35*	*0.78*	4383.2	*0.91*	0.9	0.9	0.0	1.0	0.2	0.1	3.8	132.9	y	3
Q2	urban	Q2urban5	152053	28.81116244	*27840.82*	*0.70*	3437.1	*0.29*	0.9	0.8	1.0	0.0	0.0	0.0	3.7	107.8	y	4
Q2	urban	Q2urban6	48701	28.07887056	*22793.03*	*0.78*	2789.0	*0.27*	1.0	0.8	0.0	1.0	0.0	0.1	2.1	59.3	y	3
Q2	urban	Q2urban7	109419	17.66847672	*24607.83*	*0.75*	2393.9	*0.22*	1.0	0.8	0.1	0.1	0.1	0.0	2.0	35.9	n	0
Q2	urban	Q2urban8	155717	35.38301909	*23588.67*	*0.76*	3970.3	*0.93*	0.9	0.9	0.2	0.0	0.1	0.0	3.4	120.9	y	1
Q3	urban	Q3urban1	32971	35.5877001	*26682.63*	*0.72*	2666.1	*1.00*	0.9	1.0	0.0	0.0	0.2	0.0	2.4	86.6	y	6
Q3	urban	Q3urban2	37591	23.54391083	*28240.19*	*0.69*	2702.8	*0.25*	0.9	0.8	0.0	0.7	1.0	0.0	1.1	26.8	n	0
Q3	urban	Q3urban3	89989	35.37592873	*27645.26*	*0.70*	4588.1	*0.86*	0.9	0.9	1.0	0.0	0.0	0.0	4.4	155.5	y	5
Q3	urban	Q3urban4	33512	27.95536201	*26652.08*	*0.72*	2730.5	*0.27*	1.0	0.8	0.0	1.0	0.0	0.0	1.2	34.8	n	0
Q3	urban	Q3urban5	67158	31.9141477	*29288.54*	*0.68*	2569.2	*0.27*	1.0	0.7	0.0	0.0	0.2	0.0	1.0	31.8	n	0
Q3	urban	Q3urban6	35751	34.97593584	*27061.03*	*0.71*	4617.7	*0.91*	0.9	1.0	0.0	1.0	0.2	0.2	2.9	101.2	y	6
Q3	urban	Q3urban7	192353	28.13928986	*28328.14*	*0.69*	2581.3	*0.25*	1.0	0.6	1.0	0.0	0.0	0.0	2.8	79.3	y	5
Q3	urban	Q3urban8	42205	35.43861238	*29998.35*	*0.67*	2675.8	*0.71*	1.0	0.8	0.0	0.0	0.2	0.0	1.6	55.0	y	6
Q3	urban	Q3urban9	93593	17.21418807	*28741.99*	*0.69*	2438.4	*0.22*	1.0	0.7	0.1	0.1	0.1	0.0	1.2	20.8	n	0
Q4	urban	Q4urban1	62136	33.16542356	*57370.43*	*0.25*	3664.9	*0.36*	0.9	0.8	0.0	0.0	0.0	0.1	0.6	20.7	n	0
Q4	urban	Q4urban2	28110	32.14223113	*58053.82*	*0.24*	2649.9	*0.26*	1.0	0.7	0.0	0.1	1.0	0.0	0.5	15.2	n	0
Q4	urban	Q4urban3	128874	33.32192285	*54670.51*	*0.29*	4658.3	*0.39*	1.0	0.7	1.0	0.0	0.0	0.0	2.2	72.1	y	5
Q4	urban	Q4urban4	18537	35.4546935	*61544.54*	*0.19*	4489.6	*0.85*	0.9	0.8	0.0	0.0	1.0	0.0	1.1	38.3	n	0
Q4	urban	Q4urban5	50815	31.09446766	*74109.79*	*0.00*	2624.5	*0.23*	1.4	0.0	0.1	0.0	0.0	0.0	0.1	4.0	n	0
Q4	urban	Q4urban6	118895	20.50756795	*53338.03*	*0.31*	2387.2	*0.22*	1.0	0.7	1.0	0.0	0.0	0.0	2.0	41.2	n	0
Q4	urban	Q4urban7	34080	18.25953445	*53626.84*	*0.31*	2257.9	*0.21*	1.0	0.8	0.0	0.3	1.0	0.0	0.5	9.8	n	0
Q4	urban	Q4urban8	124627	35.57852896	*59067.71*	*0.23*	3498.2	*0.93*	0.9	0.8	0.2	0.0	0.0	0.0	1.6	55.8	y	6
Q4	urban	Q4urban9	64035	19.89064644	*60706.73*	*0.20*	2421.5	*0.23*	1.0	0.7	0.0	0.0	0.0	0.1	0.4	8.0	n	0
Q1	suburban	Q1suburban1	52491	22.13880432	*9663.91*	*0.97*	244.0	*0.09*	1.1	0.6	0.0	0.1	0.2	0.0	2.1	45.7	y	2
Q1	suburban	Q1suburban2	51972	31.36781223	*10536.91*	*0.96*	258.4	*0.05*	1.1	0.6	0.1	0.1	0.2	0.0	2.2	70.1	y	2
Q1	suburban	Q1suburban3	24448	18.06719963	*11739.34*	*0.94*	284.1	*0.08*	1.0	0.7	0.0	0.7	0.8	0.0	2.0	36.8	n	0
Q1	suburban	Q1suburban4	84353	21.44520855	*11237.72*	*0.95*	278.0	*0.09*	1.1	0.6	1.0	0.0	0.0	0.0	4.0	85.9	y	4
Q1	suburban	Q1suburban5	23601	17.29480386	*9924.27*	*0.97*	233.7	*0.05*	1.0	0.7	0.0	1.0	0.3	0.1	2.1	36.0	n	0
Q1	suburban	Q1suburban6	57554	15.25764899	*10051.82*	*0.97*	250.7	*0.05*	1.0	0.7	0.0	0.0	0.2	0.0	2.0	30.6	n	0
Q1	suburban	Q1suburban7	96790	17.14190739	*10725.20*	*0.96*	240.2	*0.05*	1.0	0.7	1.0	0.0	0.0	0.0	4.0	68.2	y	4
Q1	rural	Q1rural1	62578	29.36258603	*10489.68*	*0.96*	150.6	*0.02*	1.0	0.6	0.2	0.1	0.2	0.0	2.4	70.7	y	2
Q1	rural	Q1rural2	57616	12.27354636	*9815.85*	*0.97*	147.1	*0.00*	0.9	0.8	1.0	0.0	0.0	0.0	3.9	48.1	y	4
Q1	rural	Q1rural3	28284	15.77579261	*11880.91*	*0.94*	161.9	*0.01*	1.0	0.7	0.0	0.7	0.9	0.0	1.9	30.2	n	0
Q1	rural	Q1rural4	20032	9.280662357	*9577.67*	*0.98*	120.0	*0.00*	0.9	0.8	0.0	0.0	0.2	0.0	2.0	18.1	n	0
Q1	rural	Q1rural5	15547	11.03193253	*9169.42*	*0.98*	124.1	*0.00*	0.9	0.8		1.0	0.3	0.1	2.0	22.0	n	0
Q1	rural	Q1rural6	62742	27.38404614	*10180.18*	*0.97*	122.5	*0.00*	1.0	0.7	0.1	0.1	0.2	0.0	2.2	60.3	y	2
Q1	rural	Q1rural7	36032	12.61631906	*10054.94*	*0.97*	145.2	*0.02*	1.0	0.7	0.2	0.1	0.2	0.0	2.4	30.4	n	0
Q2	suburban	Q2suburban1	42038	21.10148654	*26559.63*	*0.72*	270.2	*0.09*	1.0	0.7	0.0	0.0	0.2	0.0	1.5	32.5	n	0
Q2	suburban	Q2suburban2	17790	19.34583307	*26522.29*	*0.72*	250.4	*0.06*	1.0	0.7	0.0	0.8	0.8	0.0	1.6	30.0	n	0
Q2	suburban	Q2suburban3	41196	31.31638032	*26297.36*	*0.72*	247.8	*0.05*	1.0	0.7	0.1	0.2	0.1	0.1	1.8	55.0	y	2
Q2	suburban	Q2suburban4	22958	20.86963669	*23742.60*	*0.76*	315.2	*0.09*	1.0	0.7	0.0	1.0	0.2	0.1	1.7	35.4	n	0
Q2	suburban	Q2suburban5	63784	20.83522523	*27199.32*	*0.71*	280.8	*0.09*	1.0	0.7	1.0	0.0	0.0	0.0	3.3	68.6	y	4
Q2	suburban	Q2suburban6	50007	14.2119562	*25505.21*	*0.73*	229.7	*0.05*	1.0	0.7	0.0	0.2	0.1	0.1	1.5	21.9	n	0
Q2	suburban	Q2suburban7	81904	16.61549493	*26412.78*	*0.72*	237.9	*0.05*	1.0	0.7	1.0	0.0	0.0	0.0	3.3	54.2	y	4
Q2	rural	Q2rural1	189958	17.69181728	*25979.23*	*0.73*	139.9	*0.02*	1.0	0.7	0.2	0.2	0.2	0.0	1.9	33.4	n	0
Q2	rural	Q2rural2	114360	8.720049567	*24566.91*	*0.75*	119.7	*0.00*	0.9	0.8	0.0	0.1	0.1	0.0	1.5	13.1	n	0
Q2	rural	Q2rural3	50390	15.23625785	*24653.85*	*0.75*	150.0	*0.00*	1.0	0.8	0.0	0.7	0.9	0.0	1.5	22.9	n	0
Q2	rural	Q2rural4	305075	12.20019714	*24680.32*	*0.75*	141.2	*0.00*	0.9	0.9	1.0	0.0	0.0	0.0	3.2	39.6	n	0
Q2	rural	Q2rural5	25472	11.89713396	*23371.55*	*0.77*	162.6	*0.01*	1.0	0.8	0.0	0.9	0.0	0.6	1.5	18.4	n	0
Q2	rural	Q2rural6	119164	28.30749602	*25555.08*	*0.73*	154.3	*0.01*	1.0	0.7	0.2	0.1	0.1	0.0	1.8	50.4	y	2
Q3	suburban	Q3suburban1	56279	21.61075911	*28858.58*	*0.68*	253.3	*0.09*	1.0	0.6	0.0	0.2	0.3	0.1	0.8	17.2	n	0
Q3	suburban	Q3suburban2	39093	17.2771321	*28005.67*	*0.70*	326.6	*0.06*	1.0	0.7	0.0	0.8	0.8	0.1	0.8	14.6	n	0
Q3	suburban	Q3suburban3	80092	21.96540122	*27854.40*	*0.70*	278.5	0.09	1.1	0.6	1.0	0.0	0.0	0.0	2.5	55.7	y	5
Q3	suburban	Q3suburban4	50415	15.09053823	*28904.51*	*0.68*	228.8	0.05	1.0	0.7	0.0	0.2	0.2	0.1	0.7	11.3	n	0
Q3	suburban	Q3suburban5	91865	17.47423503	*27155.99*	*0.71*	241.5	0.05	1.0	0.6	1.0	0.0	0.0	0.0	2.5	43.8	y	5
Q3	suburban	Q3suburban6	50496	31.25967702	*28569.64*	*0.69*	257.2	0.05	1.1	0.6	0.1	0.2	0.2	0.1	1.0	31.0	n	0
Q3	rural	Q3rural1	106915	12.55519702	*28694.32*	*0.69*	152.8	0.02	1.0	0.7	0.1	0.1	0.2	0.1	0.9	11.9	n	0
Q3	rural	Q3rural2	66906	14.04111401	*28412.51*	*0.69*	126.3	0.00	1.0	0.8	0.0	0.8	1.0	0.0	0.7	9.7	n	0
Q3	rural	Q3rural3	101604	27.93023051	*28720.37*	*0.69*	138.9	0.00	1.0	0.7	0.1	0.1	0.2	0.0	0.9	24.9	n	0
Q3	rural	Q3rural4	43436	21.43138044	*28144.39*	*0.69*	153.4	0.02	1.0	0.7	0.0	0.7	0.8	0.1	0.8	16.4	n	0
Q3	rural	Q3rural5	218889	12.71558993	*27850.83*	*0.70*	136.7	0.00	1.0	0.8	1.0	0.0	0.0	0.0	2.4	30.5	n	0
Q3	rural	Q3rural6	97387	8.714387653	*28439.49*	*0.69*	116.2	0.00	1.0	0.8	0.0	0.1	0.2	0.0	0.7	6.0	n	0
Q3	rural	Q3rural7	29617	13.50839642	*28641.64*	*0.69*	163.1	0.01	1.0	0.8	0.0	0.9	0.0	0.8	0.7	9.4	n	0
Q3	rural	Q3rural8	104995	27.53770333	*28211.95*	*0.69*	155.3	0.02	1.1	0.6	0.7	0.0	0.0	0.0	1.9	51.4	y	5
Q4	suburban	Q4suburban1	57397	22.3270767	*64735.69*	*0.14*	246.6	0.09	1.1	0.5	0.0	0.0	0.2	0.0	0.2	4.4	n	0
Q4	suburban	Q4suburban2	45415	15.34363058	*63403.38*	*0.16*	260.3	0.05	1.1	0.6	0.0	0.0	0.0	0.0	0.2	3.0	n	0
Q4	suburban	Q4suburban3	36014	17.22802343	*56622.60*	*0.26*	254.7	0.05	1.0	0.7	0.0	0.2	1.0	0.0	0.3	5.4	n	0
Q4	suburban	Q4suburban4	94684	17.61224578	*49615.81*	*0.37*	238.1	0.05	1.1	0.6	1.0	0.0	0.0	0.0	1.8	31.9	n	0
Q4	suburban	Q4suburban5	4935	18.84775349	*45682.09*	*0.43*	325.8	0.06	1.0	0.7	0.0	0.8	0.0	1.0	0.5	9.5	n	0
Q4	suburban	Q4suburban6	51610	31.43838623	*62161.83*	*0.18*	259.2	0.05	1.1	0.5	0.1	0.0	0.2	0.0	0.3	10.9	n	0
Q4	suburban	Q4suburban7	84127	21.37035269	*52876.84*	*0.32*	277.2	0.09	1.1	0.5	1.0	0.0	0.0	0.0	1.8	37.4	n	0
Q4	suburban	Q4suburban8	16942	17.40712637	*48123.51*	*0.39*	285.2	0.08	1.0	0.7	0.0	0.6	1.0	0.0	0.5	8.5	n	0
Q4	rural	Q4rural1	92700	29.12605355	*57245.12*	*0.25*	146.6	0.02	1.1	0.6	0.2	0.1	0.3	0.1	0.5	15.2	n	0
Q4	rural	Q4rural2	136904	12.92571107	*58332.52*	*0.24*	139.7	0.02	1.1	0.6	0.2	0.1	0.3	0.0	0.5	6.1	n	0
Q4	rural	Q4rural3	96953	13.05942347	*55045.90*	*0.29*	150.1	0.00	1.0	0.7	0.0	0.3	1.0	0.0	0.3	3.8	n	0
Q4	rural	Q4rural4	95766	10.20847826	*58559.29*	*0.24*	126.3	0.00	1.0	0.7	0.0	0.0	0.0	0.0	0.2	2.4	n	0
Q4	rural	Q4rural5	14278	13.44319263	*47382.27*	*0.40*	163.4	0.01	1.0	0.8	0.0	0.7	0.0	0.9	0.4	5.5	n	0
Q4	rural	Q4rural6	92633	28.6665117	*56983.80*	*0.26*	126.3	0.00	1.0	0.6	0.1	0.0	0.2	0.1	0.4	11.7	n	0
Q4	rural	Q4rural7	175556	13.67542313	*47416.31*	*0.40*	159.0	0.00	1.0	0.7	1.0	0.0	0.0	0.0	1.8	24.8	n	0

TOTAL population	6567373.17	
Population in profile 1	583789.2826	20%
Population in profile 2	390144.2309	14%
Population in profile 3	219806.6334	8%
Population in profile 4	717594.1638	25%
Population in profile 5	688168.2537	24%
Population in profile n/a	269491.7838	9%
Total high-risk population	2868994.348	
Share of high-risk population	44%	

PERCENTILE 0.75 in reference period	43.4	y...	high-risk cluster
		n...	cluster not considered high-risk