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Climate Risk and Vulnerability Assessment of Floods in Austria: Mapping Homogenous Regions, Hotspots and Typologies

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Abstract: This research addresses the need for proactive climate risk management (CRM) by developing and applying a spatial climate risk and vulnerability assessment (CRVA) to flooding under consideration of the socio-economic dimension in Austria. Our research builds on a consolidated risk and vulnerability framework targeting both disaster risk reduction (DRR) and climate change adaptation (CCA) while integrating the consolidated risk approach of the Intergovernmental Panel on Climate Change (IPCC). Furthermore, our research advances current methodologies by applying a spatially explicit and indicator-based approach, which allows the targeted and place-specific identification of intervention options—independent from the spatial bias of administrative units. The flooding CRVA is based on a comprehensive list of 14 primary indicators and 35 socio-economic sub-indicators. Our results indicate that high levels of socio-economic vulnerability related to flooding are concentrated in the northern and eastern regions of Austria. When integrating a climate hazard proxy, statistically significant risk hotspots (>90% confidence) can be identified in central-northern Austria and towards the east. Furthermore, we established a typology of regions following a spatially enabled clustering approach. Finally, our research provides a successful operationalization of the IPCC Fifth Assessment Report (AR5) risk framework in combination with enhanced spatial analysis methods.

Keywords: climate change adaptation; resilience; exposure; regionalization; aggregation; spatial indicators; spatial analysis

1. Introduction

The occurrence of extreme natural events, such as droughts and floods, has increased during the past decades [1] globally as well as in Austria [2]. Moreover, it is likely that extreme natural events will become even more frequent in the future as climate change continues to evolve and socio-economic development further shapes the drivers of risk. Under these conditions, river floods will affect more people worldwide than any other natural hazard [1,3]. In the past, floods have occurred repeatedly and often on a large scale in Austria, often entailing severe social and economic impacts as well as high fiscal stress [4].

With the publication of the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) [1], the focus on the integrative role of risk in responding to climate change increased [4]. Floods are one type of climate-related risk and are traditionally dealt with in the short-term, (often) reactive manner of disaster risk reduction (DRR) rather than in combination with a long-term, foresighted climate change adaptation (CCA) view. To more effectively manage such climate risks, it is necessary to establish a link between DRR and CCA and address those in an integrated

manner. A proactive approach to climate risk management (CRM) is essential for comprehensively addressing climate-related risks and successfully coping with the challenges at the interface of CCA and DRR.

In this research, we developed and applied a spatial climate risk and vulnerability assessment (CRVA) for floods in Austria. Specifically, we developed a risk and vulnerability framework targeting both DRR and CCA, while building on the consolidated AR5 risk approach of the IPCC. Furthermore, our research advances current methodologies by applying a spatially explicit and indicator-based approach, which allows for targeted and place-specific identification of intervention options—independent from the spatial bias of administrative units. To be able to conduct the research independent of the constraints of administrative units, we applied the geons approach [5]. The geons concept of creating "homogenous regions of risk/vulnerability" significantly surpasses other methods, such as the concept of spatial composite indicators or multi-criteria assessment approaches [6–11]. Visualising such homogenous regions encourages decision-makers to reflect on complex issues such as vulnerability and, ultimately, risk. Another benefit of using geons is the ability to categorize the resulting risk/vulnerability regions into their underlying domains. Such a categorisation can help to improve the design of place-specific measures that can strengthen preparedness and mitigation measures [12], thus laying the foundation for a well-targeted, effective and successful CRM. Similar assessments in Austria have either been conducted on the sub-national scale level [6,12] and/or applied a more traditional approach using gridded units [13]. This study, on the other hand, establishes a CRVA for floods at the national scale in Austria and makes use of the novel geons approach, thus improving significantly on the previous studies conducted in the field.

In summary, this paper addresses the following research questions: (i) Which indicators represent the socio-economic drivers determining risk and vulnerability to river floods in Austria?; (ii) which regions in Austria are subjected to higher and which to lower risk and vulnerability?; (iii) in this context, how could a spatial CRVA of river floods in Austria be approached methodologically?; and (iv) how can risk be delineated based on geons, making use of the available quantitative data for Austria and how can such regions be characterized beyond an index approach?

2. Materials and Methods

2.1. Study Area

The study area comprises the entire federal territory of the Republic of Austria, located in central Europe. The country covers an area of 83,879 km^2 and has about 8.9 million inhabitants with a population density of 105 inhabitants per km^2 in the cadastral area and 269 inhabitants per km^2 in the permanent settlement areas. Over 60% of the Austrian federal territory is not occupied by permanent settlements but instead is covered by forests, bodies of water, alpine meadows and the wastelands of high mountain regions.

The precipitation conditions in Austria are highly diverse even on a very small scale, due to the country's varying topography and its location at the intersection of different climatic regimes. The total annual precipitation ranges from about 500 mm in the northeastern areas to more than 2000 mm in Alpine regions. In addition to the influence of the Alps, a west–east divide is also evident in Austria. The continental influence increases and precipitation decreases towards the east [14].

While floods of varying intensity occur every year throughout Austria, major events took place in 2002, 2005, 2013 and 2018. Identifying robust future trends in precipitation is challenging for climate modellers, and an increase in extreme events is expected in the future [15]. Overall, climate projection analysis [16] suggests that the measured flood discharges have increased in recent years, but the increase is still well within the natural flood variability. In the Alps, significantly higher winter runoff is expected in the future [17]. Furthermore, studies on future flood risk propose that an integrated flood risk management approach that focusses on the reduction in vulnerability of the societal system is required [16].

2.2. Conceptual Risk Framework

The IPCC AR5 risk framework serves as the core definition of risk for the CRVA presented in this paper. In the context of climate-related impacts, risk is defined as a combination of three interacting components [1]: climate-related hazards (including hazardous events and trends), vulnerability of human and natural systems and its exposure in places and settings that could be adversely affected. While the hazard component indicators could be derived from impact model results (such as scenarios on future flood extents), the vulnerability and the exposure components require a more explicit definition, as even the IPCC AR5 definition of these sub-components are not entirely clear.

A holistic approach, considering both the natural hazard risks and the threats to human security, must be considered jointly for a successful CRM. As environmental conditions change, societies need to become more resilient by reducing their vulnerability to natural hazards [18].

The MOVE risk framework [18] builds on a similar definition of risk as the IPCC AR5, defining risk as a 'function' of hazard, exposure and vulnerability (MOVE stands for "Methods for the Improvement of Vulnerability Assessment in Europe" and was a research project funded under the EU FP7 research program. The risk and vulnerability framework is an outcome of this project). We took the MOVE framework into consideration in this assessment to specifically define the domains and dimensions of vulnerability, which are not yet clearly laid out in the IPCC reports. Thus, for our CRVA, the MOVE framework was adapted to be consistent with the IPCC framing, as shown in Figure 1. The following modifications have been made to the original MOVE framework:

- For the overall definition of risk, we retain the IPCC definition, which understands exposure as an interlinked component between hazard and risk: 'Under exposed conditions, the levels and types of adverse impacts will be the result of a physical event (or events) interacting with socially constructed conditions denoted as vulnerability' [19]. In the MOVE framework, exposure is understood as a component of vulnerability. While this is not a major modification, it supports the consistent integration of the AR5 risk framing.
- The six thematic dimensions of vulnerability are now used in both domains of susceptibility and lack of resilience, and do not only address "susceptibility" alone. Furthermore, we refrain from using the term fragility—as originally used in the MOVE framework—and only use the term susceptibility, as the difference between the two terms has never been clarified. Thus, in this case, the aim is to simplify the definition by only using the term susceptibility.
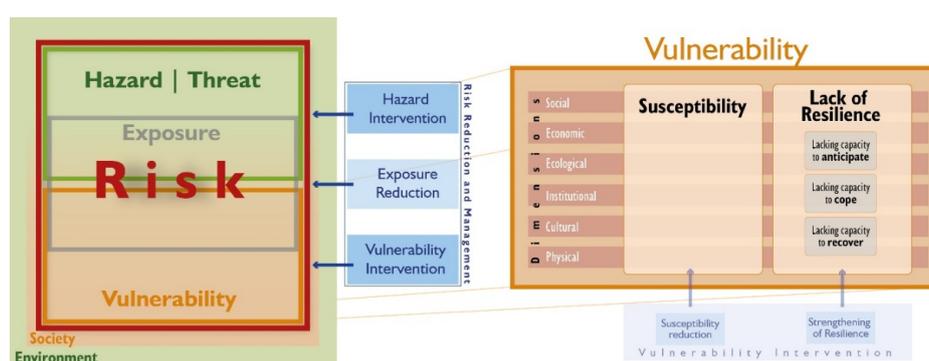

Figure 1. Applied risk and vulnerability framework (adapted from [18]).

The MOVE concept emphasizes that the hazard component of risk is linked to natural or socio-natural events, whereas vulnerability mainly results from societal conditions and processes, which reflect the understanding of the IPCC AR5 thinking. Generally, the framework includes domains (or key factors) of vulnerability and distinguishes between the different thematic dimensions of vulnerability ([18]). For this study, we addressed the socio-economic (combining social and economic) dimension. Because the social and the economic dimensions appeared to be frequently interlinked, they were merged into one socio-economic dimension.

2.3. Risk Drivers, Indicators/Proxies and Related Data

In general, the indicator selection process must be primarily driven by the relevance of the indicators, rather than simply using whatever data are available. Lange [20] argues that indicators should be chosen on the basis of their analytical suitability, measurability, spatial coverage, relevance to the phenomenon of assessment as well as their relationship to one another. Thus, we selected the indicators based on their relevance for the national flood hazard assessment for Austria and their applicability to the vulnerability domain (and dimension). This ensures that indicators are context-specific. However, in reality, the final choice of indicators is also data-driven, meaning that the availability of data also determines the choice of indicators to a certain extent [21]. In our case, suitable data had to be accessible and (except for the census data, which are provided by Statistik Austria (StatAT) for a fee) had to be open access, which did not affect the final choice of indicators. A further criterion for the choice of appropriate indicators was that data are available nationwide and based on a 1 km^2 regular grid or could be aggregated to it.

Based on the recommendation of a context-driven indicator selection process, we took the results of a literature review as the starting point. However, the authors' expert knowledge (including individual expert consultation) and the availability of the datasets determined the final choice of the indicators. Furthermore, previous vulnerability assessments [6,12] on sub-national scale—including "validated" indicators—additionally informed the selection of the indicators.

Table 1 presents the refined and final list of indicators used for the risk assessment, distinguished by the three different components of risk–hazard, exposure and vulnerability—and, in the case of vulnerability, by its subordinate dimensions (in this case, socio-economic). In most cases, sub-indices were developed to better integrate and weight sub-indicators [12]. The weights were assigned by the authors based on their expert judgement and informed by previous studies [6,12]. Appendix A discusses in detail the indicator framework with the relevant data used for each risk component, its justification, and the literature references for each indicator.

Table 1. Overview of the indicators used to assess the socio-economic dimension of risk to floods in Austria in the context of climate change.

		Indicator	Sub-indicator	Sign	Data Source	Weight	Date
HAZARD		maximum 5 day precipitation	(RCP4.5, RCP8.5; 19712000, 2071–2100)		ÖKS15		2016
EXPOSURE		Perm. Settlement Area			StatAT		2011
VULNERBAILITY	Susceptibility	Transport infrastructure	Highways	+	GIP	0.25	2017
			Primary Roads	+	GIP	0.25	2017
			Secondary Roads	+	GIP	0.25	2017
			Railway	+	GIP	0.25	2017
		Employment by sectors	Emp. in primary sector	+	StatAT	0.5	2015
			Emp. in secondary sector	+	StatAT	0.35	2015
			Emp in tertiary sector	+	StatAT	0.15	2015
		Age	Population under 20 years	+	StatAT	0.4	2016
			Pop. between 20 and 64 years	+	StatAT	0.2	2016
			Pop. over 64 years	+	StatAT	0.4	2016
		Ecosystem services	Food production	+	CLC	0.3	2012
			Disturbance regulation	–	CLC	0.25	2012
			Recreation	+	CLC	0.2	2012
			Cultural [1]	+	CLC	-	2012
			Raw materials	+	CLC	0.25	2012

Table 1. *Cont.*

			Indicator	Sub-indicator	Sign	Data Source	Weight	Date
VULNERBAILITY	Susceptibility		Land use	Cropland	+	CLC	0.2	2012
				Pasture	+	CLC	0.2	2012
				Woodland/forest	+	CLC	0.1	2012
				Industrial/commercial	+	CLC	0.25	2012
				Urban	+	CLC	0.25	2012
			Urbanization		+	CadENV	1	2006–2012
	Lack of Resilience	LcA[2]	Early warning system (EWS)	EWS for river	–	BMNT	0.75	2018
				EWS for catchment	+	BMNT	0.25	2018
		Lacking capacity to cope	Origin	Origin Austria	+	StatAT	0.275	2016
				EU/Northern America/AUS	+	StatAT	0.325	2016
				MEDCs [3]/LEDSs [4]/unknown	+	StatAT	0.4	2016
			Education	Academic degree	–	StatAT	0.23	2015
				Higher school certificate	–	StatAT	0.23	2015
				Apprenticeship	–	StatAT	0.23	2015
				Compulsory school certificate	–	StatAT	0.3	2015
			Accessibility	Access to health services	–	StatAT	0.5	2014
				Access to security services	–	StatAT	0.25	2014
				Access to retail services	–	StatAT	0.25	2014
			Unemployment		+	StatAT	1	2015
			Size of companies	Micro-enterprises	+	StatAT	0.4	2011
				Small enterprises	+	StatAT	0.3	2011
				Medium-sized enterprises	+	StatAT	0.2	2011
				Large enterprises	+	StatAT	0.1	2011

[1] Indicator was removed due to high correlations; [2] lacking capacity to anticipate; [3] more economically developed countries; [4] less economically developed countries.

2.4. Data Preprocessing, Correlation Analysis and Corrections

To combine the different vulnerability data with the CRVA (Figure 2), they were aggregated on a regular grid/reference basis [6]. Statistik Austria offers a nationwide, regional statistical 1 km^2 grid based on the ETRS LAEA projection following the EU Infrastructure for Spatial Information in the European Community (INSPIRE) directive [22].

Before continuing with the index calculation, possible corrections to the indicator values must be considered, such as the identification of missing values or outliers [23]. Subsequently, descriptive statistics, including missing values, the minimum and maximum and standard deviation, were calculated for each vulnerability indicator [23,24]. The descriptive statistics showed that missing values were not a problem. This can be attributed to the diverse datasets and, consequently, different value ranges used. In this case of spatially explicit data, skewness and kurtosis were excluded from the descriptive statistics. The reason is that—aside from using example data with administrative boundaries as a basis—this spatially explicit grid-based approach results in higher skewness and kurtosis: a high number of grid cells tend to take a value of zero. Extreme outliers were detected for the following indicators: small enterprises and medium-sized enterprises. To avoid the extreme outliers, we used the method of winsorization, with which the extreme outlier values were assigned the next best value [23,24]. The last adjustment to the data was the assignment of the corresponding signs, as shown in Table 1, which indicate whether an indicator increases or decreases the vulnerability/risk.

Following the recommendations of OECD and Saisana [23,24], the indicators were evaluated for multi-collinearities. For this purpose, we used the Pearson correlation coefficient, which is the most

reliable correlation measure for metric data [20]. Highly collinear sub-indicators (r > 0.92) contributing to the same composite indicator had to be treated according to Saisana [24] either by eliminating one of the two or counting them as a single indicator. Otherwise, they would have influenced the later results and dominated the sub-index values of the respective indicators.
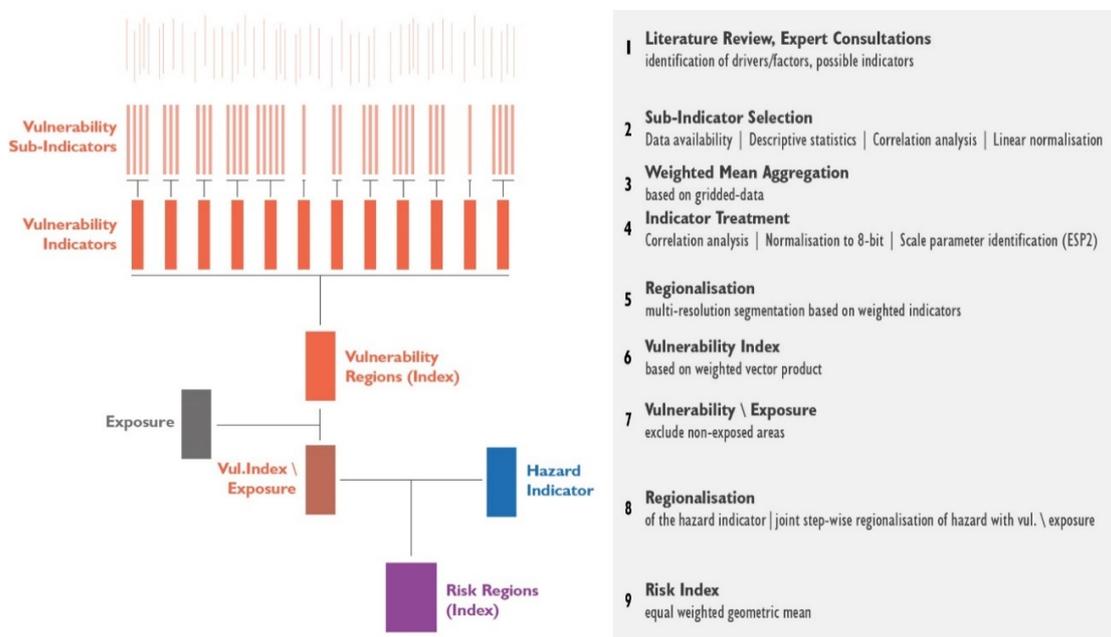

Figure 2. Conceptual design and assessment workflow.

All sub-indicators of the composite indicator age distribution were highly correlated (population under 20 years and population between 20 and 64 years with r = 0.98, population under 20 years and population over 64 years with r = 0.95 as well as population between 20 and 64 years and population between 20 and 64 years with r = 0.95). Nevertheless, eliminating one of the sub-indicators was not an option as all of them were considered relevant. Rather, they were weighted to account for the different ways in which they influence flood vulnerability. The sub-indicators disturbance regulation and cultural also displayed a high correlation (r = 0.94). This is probably because of overlaps in the input data (CORINE Land Cover—CLC). We decided to eliminate the sub-indicator cultural because disturbance regulation can be assumed to have a higher significance with regard to floods. Additionally, the sub-indicators origin Europe/Northern America/Australia and origin 'more economically developed countries' (MEDCs)/'less economically developed countries' (LEDSs)/unknown showed an extremely high correlation (r = 0.99). It could be presumed that people of an origin other than Austria generally live in certain areas, for example, bigger cities due to job opportunities. We decided to keep both of these sub-indicators as they are, and to instead apply weights (Table 1) in the next step (Figure 2).

Furthermore, the sub-indicators academic degree and matura or other higher school certificate (r = 0.97) as well as apprenticeship and compulsory school certificate (r = 0.95), all contributing to the composite indicator education level, were correlated on a level above the critical threshold. Since those sub-indicators were to be integrated into one composite indicator anyway and eliminating certain ones was not considered a good option, they were kept for further index construction, but we applied different weightings. Finally, the sub-indicators access to health services and access to retail services (r = 0.95) showed a correlation exceeding the critical threshold. This is most likely because health services are often present in similar areas as retail services, for example, urban centres. As counting those two as a single indicator would not have made sense due to their different thematic context and they appeared to both be too significant to eliminate, they were both kept for the index construction. In the next step of aggregation, those sub-indicators were summed up to a respective composite indicator. This step was—to some extent—used to balance out certain inconsistencies through weighting.

2.5. Normalization, Aggregation and Regionalisation of Indicators

Before weighting and aggregating the sub-indicators to sub-indices (composite indicators), the input variables needed to be normalized as they had different units of measurement and value ranges. To render data comparable, the different datasets were normalized using a linear min–max normalization. In a min–max normalization, the initial values are transformed to a value range between zero (minimum of the initial values x_{min}) and one (maximum of the initial values x_{max}) [6,12,20,24,25]. We decided to determine the weights for the sub-indicators normatively based on the considerations outlined above: When there were clear reasons to weight a sub-indicator higher or lower than the others, we did. When this was not the case, we applied equal weights to the sub-indicators. The chosen weights are presented in Table 1. The sub-indicators of the vulnerability indicators were aggregated using weighted arithmetic means (Figure 2). Subsequently, the datasets were converted to TIFF-files and normalised to an 8-bit scale range (to make use of the full "radiometric" spectrum of raster datasets) and integrated into the Trimble eCognition software environment to carry out the regionalisation and aggregation of composite indicators and risk components to the vulnerability and risk indices.

Exposure—represented by the permanent settlement area—was integrated into the vulnerability domain by deducting non-settlement areas. Thus, no weighting was performed. Only areas irrelevant to the vulnerability component were eliminated from further integration towards risk and vulnerability. This ensured that geons were formed on the basis of the exposed area only. As a result, the vulnerability layers for the socio-economic dimension were spatially limited to the permanent settlement area in Austria. This task was carried out in eCognition, where the area of regionalisation was limited to the exposed area only.

The vulnerability regions were derived from the (weighted) vulnerability indicators (Figure 2). A multiresolution segmentation algorithm was applied [26] to delineate homogeneous regions (geons) of vulnerability and risk. This segmentation algorithm allows the establishment of highly homogeneous regions of any resolution from different types of data. Multiresolution segmentation enables [26] an even growth of image objects over the analysis extent and balances regions of high and low data variance [6,10]. The assignment of weights to each vulnerability indicator and the choice of shape values (compactness versus smoothness) and a scale parameter can influence the size and shape of the final homogeneous units as well as the final index value itself. In the absence of justifiable weights, we chose to apply equal weighting to combine the composite indicators. We used the ESP2 tool to identify the scale parameter [27], which provides an algorithm to create local variance (LV) and rate of change (ROC) graphs automatically based on certain input data layers. Thus, based on the interpretation of the LV and ROC graphs, a scale parameter of 12 was selected for the socio-economic vulnerability index (flood). The shape index for two-dimensional regions is defined as the border length feature of the object divided by four times the square root of its area. The smoother the region border, the lower the shape index of this object. Consequently, the shape index can be generally described as representing the smoothness of an object border, balancing out the smoothness of an object against its compactness. Thus, the generated spatial regions can be compact or have smooth outlines [6,28]. Both the shape and compactness criteria were set to a relatively low value of 0.1, because for the delineation of vulnerability or risk regions, there is no need for units to be as compact and smooth as possible.

Thus, by carrying out the multiresolution segmentation using the parameter values as specified above, we delineated vulnerability and risk regions (as integrated geons) that share a commonality regarding their underlying indicator values and a spatial constraint. Subsequently, a vulnerability index was determined, calculating the weighted vector magnitude—the length of the vector for each region—considering the different composite vulnerability indicators in the multidimensional indicator space [6]. As a final step in the delineation of vulnerability regions, the outlines of the geons were smoothed using a smoothing algorithm, namely the polynomial approximation with an exponential kernel algorithm (with the tolerance parameter set to 3000 m) [7,8].

To conclude the climate risk assessment workflow (Figure 2), the indicator maximum five-day precipitation amount (rx5) was used as a hazard proxy (deriving from the ÖKS15-datasets [15]).

rx5 is the largest precipitation sum over a continuous period of five days [15]. The RCP4.5 and RCP8.5 scenarios for the climate period representing the climate period at the end of the century (~2100) were used. The respective rx5 indicator for the present-day conditions was generalised using the segmentation algorithm to derive geons with normalised rx5 values to the standard scale of 0–100. The two geon datasets, hazard and socio-economic flood vulnerability (including the exposure component), were then merged (intersect) in a first step. An additional segmentation, based on the intersected regions, was conducted to merge regions of similar values in the different indicators towards new homogenous regions of similar risk (see approach developed by [11]). This stepwise integration approach preserves "strong" region borders of the hazard proxy and vulnerability regions to ease the comprehensive analysis of the resulting maps. Finally, a risk index value was calculated using the geometric mean, to account for zero values, e.g., for zero hazard values that also result in zero risk values. Due to the non-availability of any socio-economic vulnerability indicator for future scenarios on the required spatial scale level, we did not develop any future risk indices. However, the change in the hazard proxy (rx5) was visually overlaid over the risk assessment and indicates increases/decreases in rx5 for the given scenarios.

The final index scores were normalized to a zero to 100 range for visualisation. The results were visualized following best practice [29] with an unclassed colour gradient with a continuous colour scheme of orange for socio-economic vulnerability (Figure 3) and violet for risk (Figure 4). For transparency reasons, the roughly associated histogram of the index values is presented along with the legend on the maps [11]. Furthermore, the contributing factors (inter alia indicator values) per geon are shown as bar charts for the three selected regions (see Figure 3).
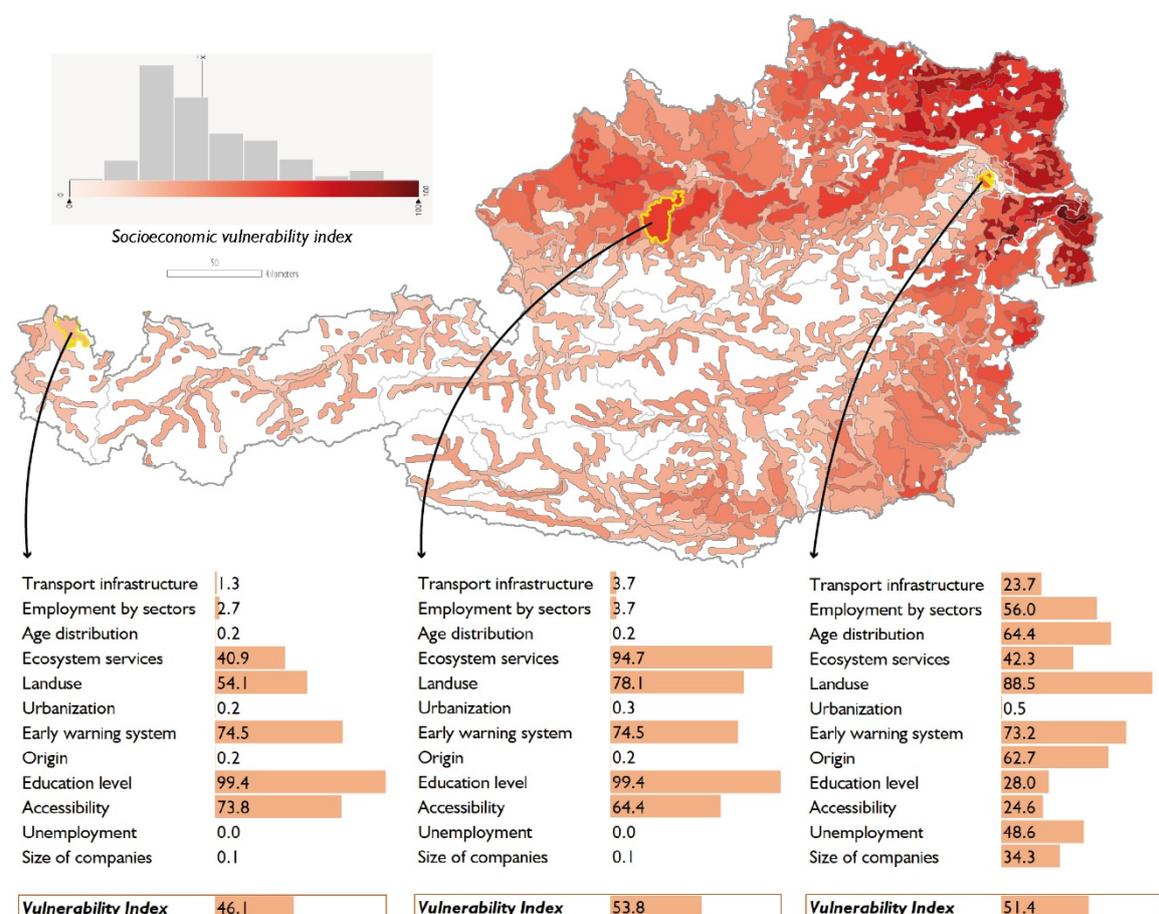

Figure 3. Socio-economic vulnerability (and exposure) to floods in Austria. Contributing vulnerability indicators are shown for the three selected vulnerability regions.
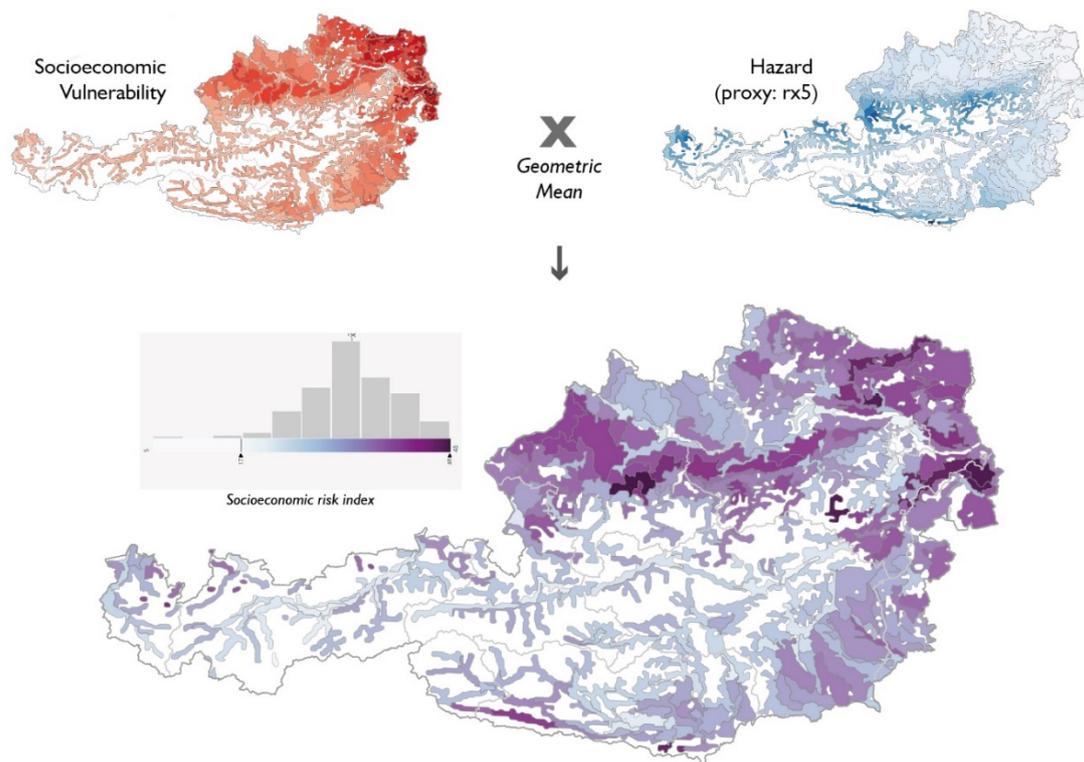
Figure 4. Socio-economic risk posed by flooding in Austria and together with its sub-components of socio-economic vulnerability (incl. exposure) and the hazard proxy.

2.6. Mapping Hotspots and Clusters of Socio-Economic Vulnerability

High risk scores are of interest but do not necessarily represent a statistically significant hotspot [30]. Therefore, we applied the Getis-Ord Gi* statistic [31,32] to identify cold and hotspots of socio-economic risk to floods in Austria. Using the present-day risk scores per geon as an input, the method highlights statistically significant spatial clusters of high (i.e., hotspots) and low vulnerability index values (i.e., cold spots) for 90% (p-value < 0.1), 95% (p-value < 0.05) and 99% (p-value < 0.01) confidence levels. The resulting hot/cold spot map (Figure 5) shows hot and cold spots based on the different confidence levels.

For the vulnerability component, the vulnerability index scores together with the bar charts (Figure 3) allow for an individual and geon-specific interpretation of contributing factors for each region. However, to provide and establish a general typology of the geons based on their contributing factors, we applied a multivariate clustering analysis based on the k-means algorithm [33]. The k-means algorithm aims to separate the objects so that the differences between the objects in a cluster—across all clusters—are minimized. A classification into five different cluster types seemed to be the most appropriate most appropriate to reflect the vulnerability landscape of Austria (Figure 5). Accompanying box plots provide details on both the characteristics of each cluster and each indicator used.
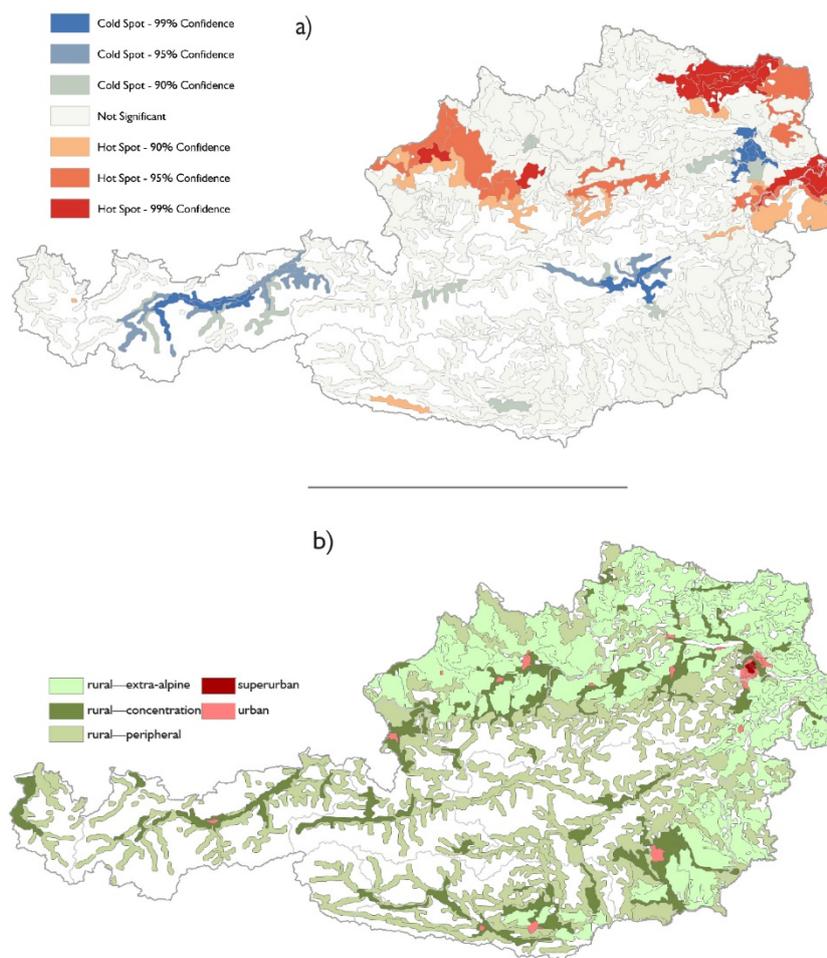
Figure 5. (**a**) Socio-economic risk hotspots with confidence intervals; (**b**) typology of vulnerability regions based on a k-means cluster analysis (see Appendix B for the accompanying multivariate clustering box plots).

3. Results

The map in Figure 3 shows that the socio-economic vulnerability regions coincide with the major settlement characteristics. Especially striking are some parts of eastern Austria, where high levels of vulnerability seem to be prevalent, most likely related to the rural, peripheral and agricultural characteristics of the area. Apart from that, the urban centres represent socio-economic vulnerability hotspots as well. For instance, locations in Vienna, Salzburg, Graz and Linz are characterized by higher vulnerability, which seems plausible since urban centres can be social flashpoints. The areas in the north and southeast of Austria partly reach somewhat lower vulnerability levels. The peripheral and mountainous regions of central and western Austria tend to show lower vulnerability values. For three selected geons, the contributing vulnerability indicators are shown in the bar charts. The three selected regions also represent different vulnerability characteristics, with varying contributions of the individual indicators.

In the present-day climate risk assessment (Figure 4), distinctive socio-economic risk regions also appear. High-risk values can be observed in the northern centre of Austria (southeast of the city of Linz), reflecting both higher values in vulnerability/exposure and hazard. The hotspots in the east, representing high vulnerability values, are the result of a lack of early warning systems (Leitha catchment). A few isolated hotspots also occur in the south and in northern alpine regions towards the west (Tyrol and Vorarlberg).

Possible future climate change scenarios have not been directly implemented into a scenario-based risk index. Figure 6 shows recent changes in rx5 (2010–1986 to 1985–1961) in the southern parts of the Alps and a decrease in rx5 days can be observed in inner alpine areas. However, the future scenarios until 2100 RCP4.5 and RCP8.5 suggest an increase in rx5 days. While for RCP4.5 the increase in rx5 days is strongest in the east, in the RCP8.5 scenario the areas in central-northern Austria (northern Salzburg and Upper Austria) show a stronger increase. When interpreting the results, it is important to consider uncertainties in precipitation projections for the future.
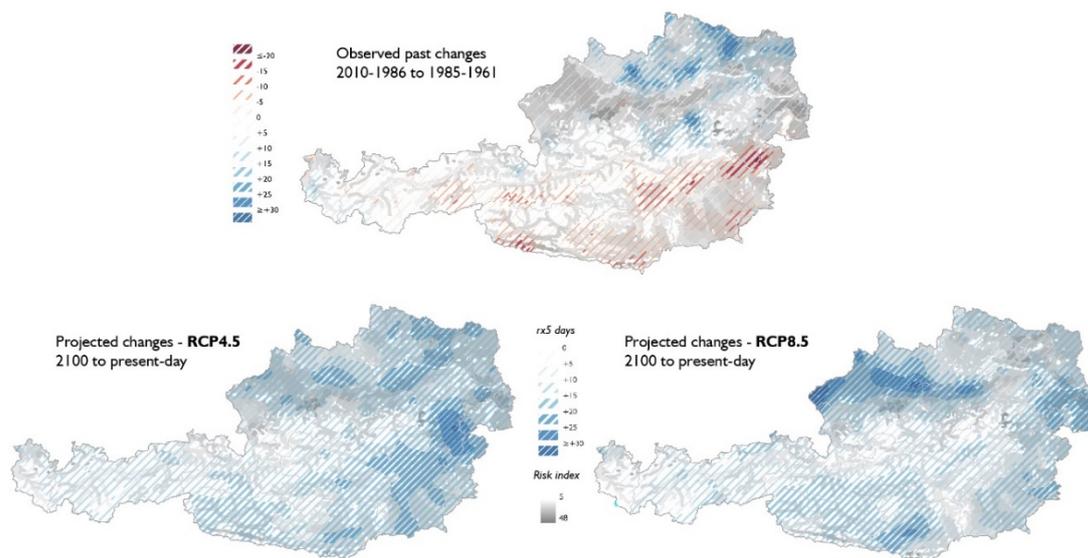

Figure 6. Past changes as well as future projections of rx5 for Austria. The changes are presented as overlays over the socio-economic risk regions.

The hotspot analysis (Getis-Ord Gi*) shown in Figure 5a shows hotspots (>90% confidence) in the pre-alpine areas of central-northern Austria (Salzburg, Upper Austria), northeastern Austria, in the south (Gailtal) as well as in the east (Leitha catchment), where the early warning system is not yet available. Cold spots (> 90% confidence) include eastern areas (Wiener Wald area), and the valleys in the west (Inn valley), as well as some areas in the southeast (central Styria).

The multivariate cluster analysis resulted in five geon types (Figure 5b) that can be categorised into three rural and two urban types. The rural geon types include the clusters rural—extra-alpine, rural—concentration and rural—peripheral. Rural—concentration mainly encompasses areas with high population dynamics close to regional centres. Interestingly, the clusters rural—extra-alpine and rural—peripheral also reflect the physical morphology of Austria to a certain extent. The cluster superurban is only present in Vienna (east), which is the only major urban agglomeration in Austria. Its singularity compared to the other clusters is clearly reflected in the accompanying box plots in Figure A2. The cluster urban includes other relevant urban areas in Austria.

4. Discussion

We successfully developed an indicator framework based on a literature review to assess the current state-of-the-art and indicators used in previously conducted CRVAs. This was structured following a combination of the IPCC AR5 risk framework and the MOVE framework [18]. In the scope of the indicator selection process, the relevant indicators for the assessment of flood occurrence and the associated socio-economic dimension were identified. To appropriately assess the complex phenomenon of flood risk, well-approved methodologies in combination with novel representations were used to construct risk and vulnerability indices. Subsequently, regionalizing areas of homogenous vulnerability and risk levels resulted in integrated geons.

In general, the flood risk and vulnerability maps reflect the topography, as risk and vulnerability decrease or disappear towards the mountainous terrain of the Alps. Furthermore, flood risk and vulnerability tend to concentrate around settlement and transport axes across the country. Urban centres, as well as rural and agricultural areas, were shown to be at higher risk.

We were able to conduct an assessment on a fine-scale, thus, differences can already be seen within a town on a spatial scale of 1 km^2 (for the vulnerability data). The assessment was carried out on a national scale, making a nationwide image possible. Thus, the CRVA undertaken as part of this study can serve as a basis to identify appropriate and relevant place-based intervention measures [12] with the aim of reducing flood risk in Austria. However, it should be noted that the risk maps present potential scenarios and not precise predictions or probabilities [11]. To make results publicly available, the design of a web-tool visualizing the risk and vulnerability maps and respective diagrams in an interactive way would be helpful and is recommended to be part of future developments.

The presented approach for a CRVA for floods can be transferred to assess risk in other countries or regions. However, the respective indicators and methodologies should always be checked and (slightly) modified depending on the intended use. This ensures a proper assessment of the concept being measured. In general, it is important to keep in mind that there is a scale gap between vulnerability, exposure, and hazard data. As a national-scaled assessment of flood risk and vulnerability was the aim, an abstraction to a 1 km^2 spatial resolution can already be considered fine-scale. However, the hazard component was included based on continuous data derived from climate change models and can serve as a proxy only to reflect flooding conditions. Hydrologically-based probability data (e.g., future HQ$_{30}$, HQ$_{100}$ etc.) would be ideal, but are currently not available for Austria.

The absence of a risk index value equating to 100 or even getting close to that might serve as proof for the diversity of indicators. This can be seen as a positive characteristic of the conducted CRVA: it is natural that one region does not reach the highest values for the entire set of different indicators. Furthermore, it should be kept in mind that the use of the vector magnitude makes changes in the larger indicator values impact the index more intensely than changes in smaller values [11].

The spatial structures and distributions of different risk levels seem to be in fair agreement with the underlying indicator value distributions. The resulting patterns appear plausible and correspond with topographic characteristics, population patterns, socio-economic as well as physical factors and hazard zonings. The risk maps provide a possibility to visualise spatially explicit information and integrate several factors related to floods. Thus, an overview of various risk factors is given in an integrated manner. This not only enables exploration of the different factors, but also the quality of risk can be examined by evaluating the risk units and the respective factors contributing to and characterizing these regions.

In addition, the conducted CRVA proves the operationalization of the geon concept and related methodology (see research question 3) for successfully regionalizing spatially explicit data into risk and vulnerability units. Thus, innovative techniques from the field of remote sensing analysis, combined with index construction approaches for the assessment of complex phenomena such as risk and vulnerability, succeed in mapping risk and vulnerability on a national level, independent of administrative boundaries, in contrast to similar studies which have been limited by administrative boundaries [13]. Working independently of the administrative boundaries reduces unit-related biases, such as the modifiable areal unit problem [34], as well as the related effect of ecological fallacy [12]. Furthermore, we explored options to characterise the regions more "qualitatively", by applying a spatially enabled clustering approach (see also research question 4). As such, similar types of regions could be identified, which helps to generalise potential intervention measures for these specific typologies. Besides this statistically driven approach, further opportunities—such as threshold-based approaches, including classifications—should be explored in the future.

Apart from identifying hotspot areas, as a core objective, the derived regions of equal risk and vulnerability can serve as a basis to develop place-specific climate change adaptation and intervention measures to combat the impacts of floods in the future. For instance, such measures might be river

basin management and flood risk management plans; the empowerment of community actions; the development of different adapted prevention; protection and preparedness actions; or generally more informed technical, financial, and political decisions. A region can be examined and visualized in terms of the underlying indicators. This enables the choice of the appropriate measures for each region as adequate intervention measures may differ from one region to another. Finally, a number of challenges and difficulties are constituted in the assessment of risk and vulnerability in combination with the geon approach, for instance, those related to data availability [12] or scale gaps between different data sources.

5. Conclusions

Overall, we conclude that we have proven the successful implementation of the IPCC AR5 risk framework while expanding and clarifying the definition of vulnerability. Furthermore, we applied the geon approach for a CRVA in Austria and significantly expanded on the scope of previous studies [6,12] through the identification of regional typologies. A challenge remains the validation of the results, which is, to a certain extent, questionable, if such latent potentials can be validated at all. Furthermore, it is required to integrate such assessment approaches in a strong stakeholder dialogue to be able to untangle and clearly "appreciate" complexity as well as uncertainties deriving from concepts, used data and applied methods. However, this study contributes to the continuous advancement of knowledge to successfully address climate change risks through informed and evidence-based decision-making.

Appendix A

In the following, we provide an overview of the indicators used and their justification based on the relevant literature. A visual overview of the exposure, hazard and vulnerability indicators is provided in Figure A1.

For the socio-economic dimension, transport infrastructure, which includes highways, primary roads, secondary roads and railways, was chosen as an indicator. According to Cutter et al. [35], the loss of infrastructure may place an insurmountable financial burden, especially on smaller communities lacking the financial resources for rebuilding (data from GIP—Grapheninteyrations-Plattform). Within the socio-economic context, the lack of transport infrastructure can mean that people cannot get to the destinations they usually go to. This can interfere with their social or economic activities, such as driving to work.

Another indicator of the socio-economic dimension is employment by sectors, composed of the sub-indicators employment in primary sector, employment in secondary sector and employment in tertiary sector. As exemplified in other studies, for example by Kienberger et al. [12], the economic sector of the workplace can play a significant role in the level of vulnerability. We chose to distinguish the economic sectors as it is common in geographic literature, which defines three main economic sectors: the primary sector, which includes all facilities of initial production, namely agriculture, forestry, fishery, hunting, mining and the extraction of stone and earth; the secondary sector, which comprises the transformation of primary products through processing by industry, and the crafts; and the tertiary sector, which holds all service activities in the broader sense, from public administration over retail, wholesale, banking and insurance up to the more differentiated personal services, such as legal advice, auditing and healthcare [36]. Therefore, we required census data with information about

the sector in which people work with their place of residence as reference. Fekete [37] considered employment groups as one of the variables between the socio-economic factors in the validation of the social vulnerability index in the context of river floods in Germany. For the socio-economic dimension, the employment status is important as some occupations may be overly impacted by hazards, especially those that involve resource extraction [35]. For instance, floods may reduce the demand for labour in the agricultural sector if they destroy the crops with which people work [38]. The service sector is usually less affected [35]. The possible loss of employment after a disaster exacerbates the unemployment numbers in a community. This contributes to a slower recovery from the hazardous event [35].

The next indicator of the socio-economic dimension is age distribution with its sub-indicators of population under 20 years, population between 20 and 64 years and population over 64 years. Here, population statistics census data from Statistik Austria were employed. Other studies about flood risk and vulnerability, as for example, that carried out by Kienberger et al. [12], already made use of an indicator of population age because different age groups show different levels of (social) vulnerability. Children and the elderly population are usually more susceptible than the other age groups due to the weakness of their physical and sometimes mental conditions [12]. Fekete [37] also applied age-specific indicators for social vulnerability in the context of river floods in Germany. Extremes of the age spectrum generally increase vulnerability because this factor affects the movement of people out of harm's way due to mobility restrictions [35,39]. This makes it necessary to assess the vulnerability of these groups to provide a basis on which to develop policies to improve their conditions. In a pre-impact recovery plan, they are also considered as a distinct group to enable appropriate management of their requirements [12]. The elderly are especially vulnerable since they may have mobility constraints or mobility concerns, which increases the burden of care and lack of resilience [35]. The presence of children might delay families from evacuating until all family members are accounted for [39]. In addition, parents may lose time and money when day care facilities are damaged. People aged 20 to 64 years are assumed not to be characterized by higher vulnerability [35] since they are the age group of adults, yet not elders, which is mobile without help and usually does not face any kind of mental or physical limitations.

The indicator, ecosystem services—with its sub-indicators food production, disturbance regulation, recreation, cultural as well as raw materials—is based on the concept of ecosystem services introduced by Costanza et al. [40]. Ecosystem functions represent the habitat, biological or system properties or processes of ecosystems. Ecosystem services refer to '[...] the benefits human populations derive, directly or indirectly, from ecosystem functions' [40,41]. Various functions and services are included and grouped into 17 categories. Importantly, ecosystem services and functions do not necessarily correspond one-to-one. Furthermore, a minimum level of ecosystem infrastructure needs to be present to allow the production of the range of services described by Costanza et al. [40]. Each biome or land-use type is assigned an average global value (on a per hectare basis) of annual ecosystem services. Constanza et al. [41] updated the global values of ecosystem services in 2014, including updates in unit ecosystem service values as well as land-use change estimates between 1997 and 2014. In the scope of a weighting process at a stakeholder workshop, the most significant ecosystem services in Austria were identified as food production, most importantly dairy farming, and the sourcing of raw materials, mainly through forestry [12]. If the land cover relevant to certain ecosystem services is affected by floods, these services can no longer be provided (to the full extent for a certain period). Table A1 summarizes the ecosystem services relevant to socio-economic vulnerability and their values corresponding to the different land-use types in Austria, retrieved from Costanza et al. [41]. Other land-use classes are not listed either because they do not occur, are known to be negligible or due to a lack of available data. The values from Table A1 were multiplied with the relevant land-use class values based on the latest CLC dataset and transferred to the 1 km^2 grid.
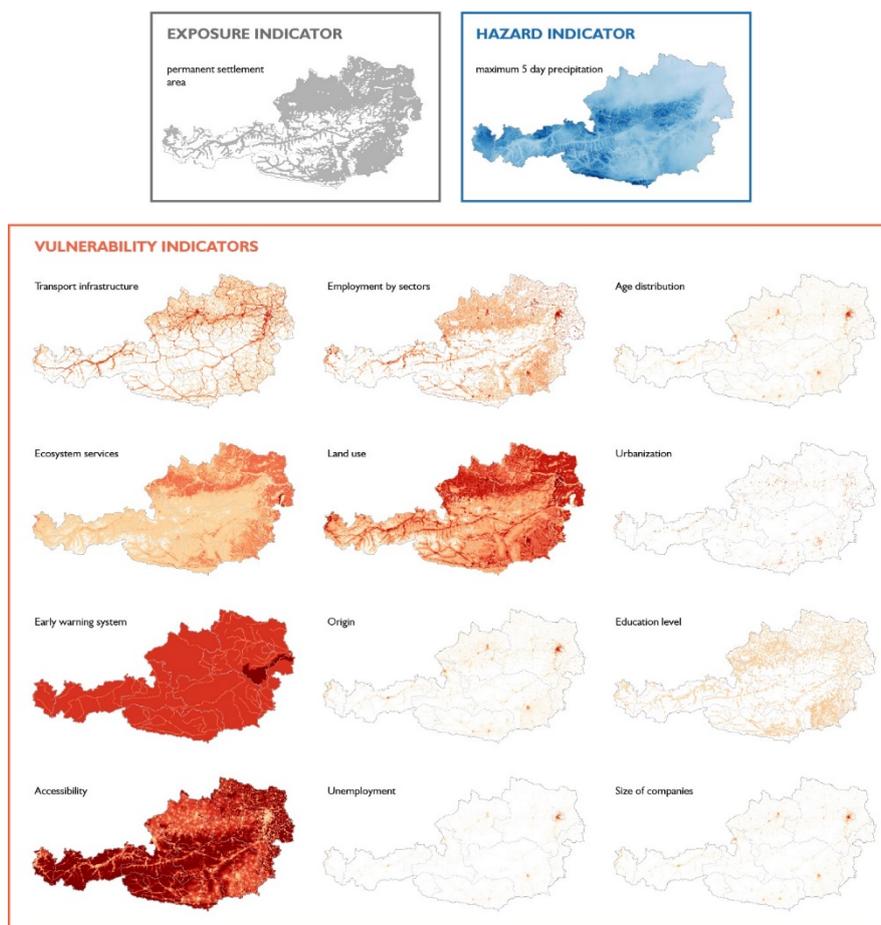
Figure A1. Visual representation of the hazard, exposure and socio-economic vulnerability indicators used in the assessment.

Table A1. Ecosystem service values in 2007 USD per ha per year (left columns) and 2007 USD per m^2 per year (right columns) (after [41]).

	Food Production		Disturbance Regulation		Recreation		Cultural		Raw Materials	
Forest (Temperate)	299	0.0299			989	0.0989	1	0.0001	181	0.0181
Grass/Rangeland	1.192	0.1192			26	0.0026	167	0.0167	54	0.0054
Wetlands (Swamps/Floodplains)	614	0.0614	2.986	0.2986	2.211	0.2211	1.992	0.1992	539	0.0539
Lakes/Rivers	106	0.0106			2.166	0.2166				
Cropland	2.323	2.323			82	0.0082			219	0.0219
Urban					5.740	0.5740				

The ecosystem service of food production refers to [40] the share of gross primary production extractable as food. Examples are the production of fish, game, crops, nuts and fruits by hunting, gathering, subsistence farming or fishing. The ecosystem service of disturbance regulation refers to the '[c]apacitance, damping and integrity of ecosystem response to environmental fluctuations' [40]. Examples are storm protection, flood control, drought recovery and other aspects of habitat response to environmental variability mainly controlled by vegetation. The ecosystem service of recreation refers to the provision of opportunities for recreational activities. For instance, this includes eco-tourism, sport fishing and other outdoor recreational activities. The cultural ecosystem service refers to the provision of opportunities for non-commercial uses, for example, aesthetic, artistic, educational,

spiritual or scientific values of ecosystems. The ecosystem service of raw materials represents the share of gross primary production extractable as raw materials. It includes, for instance, the production of lumber, fuel and fodder [40].

Land use has been proven to be a relevant indicator when assessing the vulnerability to floods [6,7,12]. Different land-use classes can be vulnerable in different ways and to different degrees. For instance, the author of [8] found the land-use classes pasture, crops and woodland/forest to be especially significant for flood vulnerability. Fekete [37] stated that urban residents are more vulnerable to river floods than those living in rural areas. Possible reasons are, among others, the differences in population and housing density. Thus, the fifth indicator for the socio-economic domain is land use, which is composed of the following sub-indicators: cropland, pasture, woodland/forest, industrial/commercial and urban. The CLC dataset from 2012, already mentioned above, was used as input data. It classifies different land-use classes based on satellite imagery.

Another indicator used is urbanization. As mentioned above, Fekete [37] in his study about the social vulnerability to river floods in Germany, made use of an urbanity indicator. Based on his statements, dynamic regions underlying urbanization processes can be assumed to be more vulnerable. Thus, this indicator measures whether an area is subject to urban growth (urbanization) since it can be assumed that this results in a higher level of vulnerability due to an increase in population and housing density. The indicator is fed with data from CadasterENV (CadENV). The dataset compares two land-use datasets from 2006 and 2012 and classifies the detected changes. Of the different change classes, the land-use change classes of new urban and forest to urban, both attributable to an urbanization process, were used.

Early warning systems are part of a catalogue of measures that can be used to prepare for floods. They can provide enough forewarning to prepare, warn and evacuate people and minimize economic damage and loss of human lives by allowing for specific flood protection measures [12]. The efficiency of an early warning system not only depends on the technical aspects but also on the level of preparedness in the community and the ability of decision-makers to make the right choices [42]. The sub-indicators forecasting model presence on river level and forecasting model presence on catchment level separately indicate whether there are early warning systems available for the river of concern and the subordinate catchment. The reason for using these two sub-indictors is that even though some river segments might not have explicit early warning systems, if there is one for the subordinate catchment, flood warnings can still be derived from that data. The data used were provided by the BMNT (former: Federal Ministry for Sustainability and Tourism).

Origin: Cutter et al. [35] include "race and ethnicity" in their social vulnerability index because it imposes language and cultural barriers. These affect the access that immigrants have to some services in the pre-disaster phase and funding in the post-disaster phase. Jones and Andrey [39] also consider indicators like people without Canadian citizenship, people with no knowledge of English, people new to the area as well as the number of non-white residents for assessing vulnerability for Vancouver as these indicate limited access to aid and difficulties in understanding evacuation warnings. Fekete [37] also includes new residents and foreigners as indicators for his social vulnerability index. Furthermore, Cannon [38] considers the issue of migrants who do not speak the native language. There are particularly vulnerable population groups, such as immigrants, who are more susceptible due to ethnic issues, language problems, income-earning capacity and prejudices, which might reduce their capacity to be able to live in safe buildings or safe areas. Additionally, legal status, language impediments and unfamiliarity with the region influence the access to government resources [39]. Consequently, the sub-indicators were grouped to origin Austria, origin Europe/Northern America/Australia as well as origin MEDCs/LEDCs/unknown. The group of people originating from Austria were assumed to be the least vulnerable as they do not face any of the outlined barriers. People from Europe, North America and Australia were assumed not to have certain difference based on their cultural background, but to not always have the same information and experiences as people from Austria. People from MEDCs (more economically developed countries) or LEDCs (less economically developed countries) face

several barriers, such as language or culture, and thus were considered the most vulnerable group. Population data provided by Statistik Austria were used to feed all of these sub-indicators.

The education level includes the sub-indicators academic degree, "matura" or other higher school certificate, apprenticeship and compulsory school certificate. Cutter et al. [35] included people with high (indicating lower vulnerability) and little (indicating higher vulnerability) education in their social vulnerability index. According to them, a low level of education reduces the ability to understand warning information and access information in the recovery phase. Additionally, education is related to socio-economic status because higher educational attainment generally results in higher lifetime earnings [35]. Fekete [37] distinguishes three variables in relation to education for his vulnerability indicators: graduates without basic education (more vulnerable), graduates with high school graduation (more capacities) and university students (more capacities). Jones and Andrey [39] in their vulnerability index construction, considered little formal education as an indicator for limited access to personal resources: They assumed formal education and the propensity to seek additional information for making informed decisions to be linked. The input data were again retrieved from census data.

Accessibility can be defined as '[. . .] the ease with which a good or service can be reached by the resident population' [43]. In the respective study by Statistik Austria, this was measured by the distance (shortest travel time) along the road network, using a private car from an origin (resident population) to the nearest facility (infrastructure). Demographic and infrastructure data were combined with road network data for calculating the distances. Those distances to different infrastructure facilities were then aggregated to indicators of accessibility in a principal component analyses. This was done on a 1 km² grid for the entire area of Austria. The reference date for data used in the calculations is October 2014. The following five main topics were identified as relevant to producing reasonably clear indicators of accessibility: retail sale (local supply), education, health, security and leisure. Then, contents of the datasets were selected and consolidated to data layers, which in turn were allocated to relevant topics. Except for security, which only comprises the data layer police due to a lack of other data with sufficient quality, multiple data layers were allocated to each topic. All in all, 90,248 infrastructure facilities were selected and grouped into 21 data layers belonging to five main topics [43]. Overall, accessibility is understood to decrease vulnerability because it facilitates the general reachability and approachability of certain services relevant to people's socio-economic sphere of life.

Unemployment is an indicator considered in several vulnerability indices. According to Cannon [38], poor people have less job security after a flood and usually fewer savings to buffer them against the event. Unemployment is also one of the variables of the socio-economic factors considered by Fekete [37] in his vulnerability index, indicating a higher vulnerability. Unemployment means low income, which, according to Jones and Andrey [39] results in a higher potential to be limited in mobility, for example, because of the lack of a car. In the rebuilding phase, access to financial resources plays a critical role in the speed of people's recovery. For this indicator, the census data provided by Statistik Austria also contained appropriate data.

The last indicator measures the size of companies, which has, in a number of studies [6,12,37], been proven to be relevant to the vulnerability of a community. Businesses, in general, are especially vulnerable to floods. This applies especially to small and young businesses, which show an even higher level of vulnerability [44]. For example, after Hurricane Katrina, such companies were more likely to close permanently than the average company [45]. Small companies are significant because they are the lifeblood of many communities and are central to broader national economies [44]. Start-ups, which are usually small, for example, are a critical factor to economic growth [46]. In a survey of businesses after Hurricane Sandy, Collier et al. [44] found that such a natural hazard imposes a financial challenge for many businesses, with small and young companies bearing the costs disproportionately. For instance, especially young and small firms were insured at much lower rates. However, of all businesses surveyed, only about two-thirds had insurance at all [44]. Additionally, 74% of companies with property insurance, 52% of firms with business interruption insurance and 52% of those insured

against flood reported none of their losses having been covered. Larger businesses were more likely to receive credit after the event to be able to cope with damages [44]. To classify companies by size in the available Statistik Austria dataset, we made use of the categorization of the Austrian Economic Chambers (WKO 2017, n. p.), which states that there is, in general, no binding definition for the different size categories of companies. Nevertheless, the EU recommends a classification following four criteria, namely, the number of employees, the revenue or the balance sheet total as well as the degree of autonomy. Ideally, all of these characteristics are available for assigning a company to a size category. This is hardly ever the case in statistics due to a lack of data. Thus, in statistical practice, the number of employees plays a predominant role for differentiating companies into size categories. Micro-enterprises are those with nine or fewer employees, small companies have ten to 49 employees, medium-sized enterprises have 50 to 249 employees and large companies employ 250 or more people [47]. This classification coincided well with the categorization Statistik Austria uses in their census data, which made it possible to apply it one-to-one.

Appendix B

Figure A2. Multivariate clustering box plots for the typology of vulnerability regions based on a k-means cluster analysis (see Figure 5).

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