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Extreme weather exposure identification for road networks in heterogeneous landscapes

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Abstract

Resilient transport infrastructure is essential to the functioning of society and economy. Ensuring network functionality is particularly vital in the case of severe weather events and natural disasters, which pose serious threats to both people's health and the integrity of infrastructure elements. Thus, providing reliable estimates about the frequency and intensity of extreme weather impacts on road infrastructure is of major importance for road maintenance, operation and construction. However, against the background of data scarcity in terms of area-covering, long-term time series, the assessment of extreme weather events is difficult, especially in areas with diverse landscape properties.

In order to account for heterogeneous small-scale topographic conditions, a hot-spot approach based on selected characteristic regions is used in this study. For each region, combinations of different extreme value approaches and fitting methods are compared with respect to their value for assessing the exposure of transport networks to extreme precipitation and temperature impacts. Four parameter estimation methods (maximum likelihood estimation, probability weighted moments, generalized maximum likelihood estimation and Bayesian parameter estimation) are applied to extreme value series obtained via both the block maxima approach (annual maxima series, AMS) and the threshold excess approach (partial duration series, PDS). Their relative performances are compared based on the CRMSE_5, i.e. the conditional root mean square error for observations with a return period exceeding 5 years, which gives much weight to the most extreme events.

The viability of the approach is demonstrated at the example of Austria by analyzing five meteorological indicators related to temperature and precipitation at 26 meteorological stations. These stations have been selected to represent diverse meteorological conditions and different topographic regions. Results show the merits of Bayesian parameter estimation methods as compared to traditional fitting methods. Bayesian estimation of generalized Pareto (GP) distributions fitted to the PDS yielded the best results in 46% of all cases, followed by Bayesian estimation of Generalized Extreme Value (GEV) distributions fitted to AMS, which showed the best performance in 35% of all cases. The study suggests that the concept of meteorological hot spot areas offers a suitable approach for characterizing extreme weather exposure of road networks in heterogeneous landscapes. The presented framework may contribute to a comprehensive climate risk assessment of infrastructure networks.

Keywords: weather extremes; adverse weather; extreme value analysis; road infrastructure; hot spots

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1. Introduction

Road infrastructure networks are one of the major backbones of every society. Many spheres of life depend on reliable transportation systems, be it the distribution of daily goods and services, the accessibility of healthcare facilities or various pastime activities. This system reliability is especially important in case of occurrence of severe weather events, which may in turn trigger natural disasters. Single link failures within the network may already cause serious consequences in terms of restricted reachability of certain areas because of bottleneck effects (Witte et al., 2012). In the worst case, damage to crucial network elements might even cause complete blackouts, cutting off people or important assets from the outside world. Therefore, overall societal loss introduced by infrastructure damage clearly exceeds the mere physical damage to the infrastructure (Masiero and Maggi, 2012). This is particularly critical in landscapes with complex terrains, like the Alpine region, where both rehabilitation work and the use of alternative routes might be associated with considerable efforts and costs. Due to their central location in Europe and their importance to European cross border transit, the design and construction of resilient transport infrastructure thus are of major concern for countries within the Alpine region.

While many influencing factors exist that determine the magnitude of pavement distress (Wistuba, et al., 2001) this study focuses on climate variables, in particular on air temperature and precipitation. Against the background of global climate change (Easterling et al., 2000; APCC, 2014; Vavrus et al. 2015) it is reasonable to assess the vulnerability of the existing road infrastructure with respect to meteorological extremes in order to be prepared for changing circumstances coming along with a changing climate. Albeit climate change research has been on the table for several decades, the analysis of climate change impacts on transportation infrastructure can still be considered to be a relatively uncharted area of research (Eisenack et al., 2011; Doll et al., 2013). Climate change adaptation for road networks has gained center stage in recent years, though, as recent efforts show (Caldwell et al., 2002; Peterson et al., 2008; TRB, 2008; Koetse and Rietveld, 2009; UNECE, 2013; Meyer et al., 2014; Michaelides et al., 2014, Schweikert et al., 2014a, 2014b; Matulla et al., 2017).

Despite these earlier findings seem to be also valid for the Alpine region, this area is unique with respect to its topographic and climatic conditions which lead to small-scale analyses clusters. This attribute vastly impedes a detailed and comprehensive nationwide extreme weather impact assessment, since area-covering gridded data sets like e.g. the E-OBS data (Haylock et al., 2008) are not sufficiently capable of accounting for local effects in complex terrains. While sophisticated methods such as downscaling, data assimilation and reanalysis, which could provide estimates of meteorological conditions at higher resolution (Steinacker et al., 2005; Haiden et al., 2011), are mainly used for applications like nowcasting, computation of hindcasts spanning time periods required for extreme value analysis (i.e. at least 30 years) is associated with tremendous efforts.

An approach based on spatially reprehensive regions featuring certain meteorological exposure (henceforth termed “hot spots”) thus seems to be suitable for describing selected aspects of interest in this complex natural region for multiple reasons. First of all, observed values measured at standardized meteorological measuring stations can be used. Consequently, the associated uncertainty is relatively small, since only measurement errors have to be considered, while modelling errors do not come into play in terms of observed data. Secondly, results derived at certain selected areas can be considered as a valuable basis for providing a profound impression of possible impact scenarios that may occur along the whole road network. Thirdly, this approach allows gaining some insight into which kind of weather exposure (hazard) is prevailing in what region. It has to be noted that sensitivity and adaptive capacity are not taken into account. Fourthly, using selected hot spot regions for demonstration purposes is computationally efficient. A similar approach has been taken for instance by Doll et al. (2013), who present two specific case studies for adapting rail and road networks to weather extremes in southern Germany and Austria, focusing on economic consequences extreme weather conditions. While this approach is not capable of delivering area-covering results, it is useful to provide a range of expected impacts as well as to foster general understanding of the underlying processes.

In order to assess the impact of adverse weather on road infrastructure, extreme value analysis of direct meteorological measurements can provide viable information to contribute to a comprehensive climate risk assessment of infrastructure networks (Schlögl and Laaha, 2017). This study aims at providing a quantitative basis for assessing the extreme weather exposure of infrastructure by implementing a systematic data-based assessment over a range of most relevant categories of indicators. Special emphasis is put on applying such an assessment in heterogeneous regions like the Alpine area. Using the example of Austria, various methods of extreme value analysis are applied for modelling extreme weather events at 26 selected hot spots located along the Austrian primary road network. The best fitting methods are eventually selected based on the $CRMSE_5$ (Schlögl and Laaha, 2017). The main objective of this work is to establish a practicable and generalizable methodology for a quantitative assessment of the impacts of several meteorological indicators.

2. Setting and data

2.1. Climate

Basically, the northern and western parts of Austria are characterized by oceanic influences, which often emerge in the form of humid westerly winds. In the eastern lowlands, however, the continental Pannonian climate prevails, bringing along low precipitation amounts, hot summers and cold winters. Finally, the actual Alpine region which features both deeply incised valleys and peaks of up to 3800 m has to be mentioned. These areas typically exhibit high precipitation amounts, short summers and cold winters. The influence of Mediterranean low-pressure areas, which bring along high precipitation, manifests itself especially in the Southern Alps (Auer et al., 2001, 2007; Hiebl et al., 2011).

While the overall climatic conditions in Austria thus can essentially be classified as part of the moderate temperate (nemoral) zone, there are in fact considerable regional differences, as the regional climate in Austria is heavily influenced by Alpine topography. Various mountain ranges serve as climatic divides, most notably the main chain of the Alps. This entails that substantial climatic differences may occur within short distances, and that both horizontally and vertically (i.e. height above sea level). With increasing altitude, the nemoral zone gradually transitions into the boreal zone and eventually into Alpine Tundra climate. At the highest peaks there are polar climate conditions (Kottek et al., 2006).

As a matter of fact, the superimposition of the regional climate by effects grounded in the Alpine topography leads to a high diversity of seemingly contrastive climatic conditions: within close distance, sunny alpine valleys characterized by warm Foehn winds (e.g. Inn Valley) exist next to basins wreathed in dense fog (e.g. Klagenfurt Basin); and foothills with high precipitation (e.g. Bregenz Forest) exist alongside inner-alpine dry valleys (e.g. Ötztal, Pitztal) and dry lowlands with continental climate conditions (e.g. Vienna Basin, East Styrian Hills) (Auer et al., 2001a; Hiebl et al., 2011).

Given the availability of long-term observational time series of various climatic parameters collected within a relatively dense network of observation stations (Barry 1994), research related to the climate of the Greater Alpine Region, including a special focus on its spatio-temporal variability and its long-term changes has been popular in recent years (e.g. Haeberli and Beniston, 1998; Schär et al., 1998; Stefanicki et al., 1998; Böhm et al., 2001; Beniston and Jungo, 2002; Beniston, 2005; Brunetti et al., 2006; Raible et al., 2006; Auer et al., 2007; Matulla et al., 2007; Brunetti et al., 2009; Chimani et al., 2011, Chimani et al., 2012; Frei, 2013). In addition, the influence of the Alpine climate on various natural and socio-economic sectors has been – and still is – of great scientific interest (e.g. OECD, 2007; Schönhart et al., 2016). However, studies specifically investigating weather effects on infrastructure in the Alpine region, which is particularly exposed to natural hazards, are rare.

This is somehow surprising, since the diversity and variability of weather conditions, which result from the complex small-scale topography of Alpine areas like Austria, pose substantial challenges to both scientists and practitioners like road operators. Regional situations caused by the effects of e.g. orographic precipitation, basin locations or cold air pools may be difficult to account for.

Studies assessing the impacts of climate change in the European Alps show that precipitation and temperature extremes are expected to intensify. In addition, seasonal shifts in precipitation are expected (Frei et al., 2006; Gobiet et al., 2011; APCC, 2014). This cumbers the assessment of both current and future weather effects and emphasizes the importance of formally establishing a quantitative assessment of potential extreme weather exposure of road networks in order to be prepared for changing weather impacts on roads.

2.2. Primary road network

As of 2015, the Austrian primary road network consists of 18 motorways and 13 expressways with a total length of 2,208 km (of which 1,719 km motorway and 489 km expressway). 167 tunnels and galleries with a total tube length of 383.8 km and 5,166 bridges are operated on this network (bmvit, 2016).

Several principal crossings of the main Alpine chain are part of the Austrian primary road network: Brenner Pass (A13), Arlberg Tunnel (S16), Tauern Road Tunnel (A10), Bosruck Tunnel / Gleinalm Tunnel (A9), Semmering Tunnel (S6), Wechsel Pass (A2) and Pack Saddle (A2) are essential for trans-Alpine freight and passenger traffic. Interruptions of such bottlenecks may have tremendous economic consequences (Pfurtscheller 2014; Witte et al., 2012).

Given the topographic diversity in Austria, the different segments of the primary road network are located in regions which exhibit various topographic situations, ranging from flat lowland areas to mountainous terrain. In conjunction with the aforementioned climatic diversity this entails different foci regarding construction, operation and maintenance.

2.3. Meteorological indicators

Meteorological indicators analyzed in this study are related to two major meteorological quantities, namely precipitation and temperature. Regarding precipitation, both storm rainfall events and incessant rainfall events are considered in this study. Firstly, daily precipitation sums are considered for assessing rainfall events on the basis of daily extremes. While it is obvious that sudden and intense downpour becomes blurred to some extent when using daily data, storm rainfall is still recognizable. Even though a higher temporal resolution would shed more light on the intensity of heavy rainfall, long-term data sets containing temporal high resolution precipitation data are scarce and hardly available. This is due to the fact that the majority of automatic weather stations in Austria have not been installed before the mid-1990s. Secondly, continuous rainfall is assessed by considering the precipitation sums of five consecutive days. The term “continuous rainfall” used within this study thus denotes the amount of precipitation that has fallen within the period of five subsequent days. Since this definition is not congruent with the term “wet spell” which is usually defined as the number of consecutive rainy days (Ratan and Venugopal, 2013) or as periods of heavy rainfall (Singh et al., 2014), the term “wet spell” is not used in order to avoid misunderstandings. Heavy precipitation does not only cause damage through direct effects like flooding or erosion, but may also trigger secondary processes like mudslides and other gravitational natural hazards (Guzzetti et al., 2008). Three quantities derived from daily temperature measurements are considered in this study for characterizing extreme temperature impacts on roads, i.e, daily temperature maxima (T_{max}), daily temperature minima (T_{min}) and maximum daily temperature difference ($T_{\Delta} = T_{max} - T_{min}$).

2.4. Selection of exposure hot spots

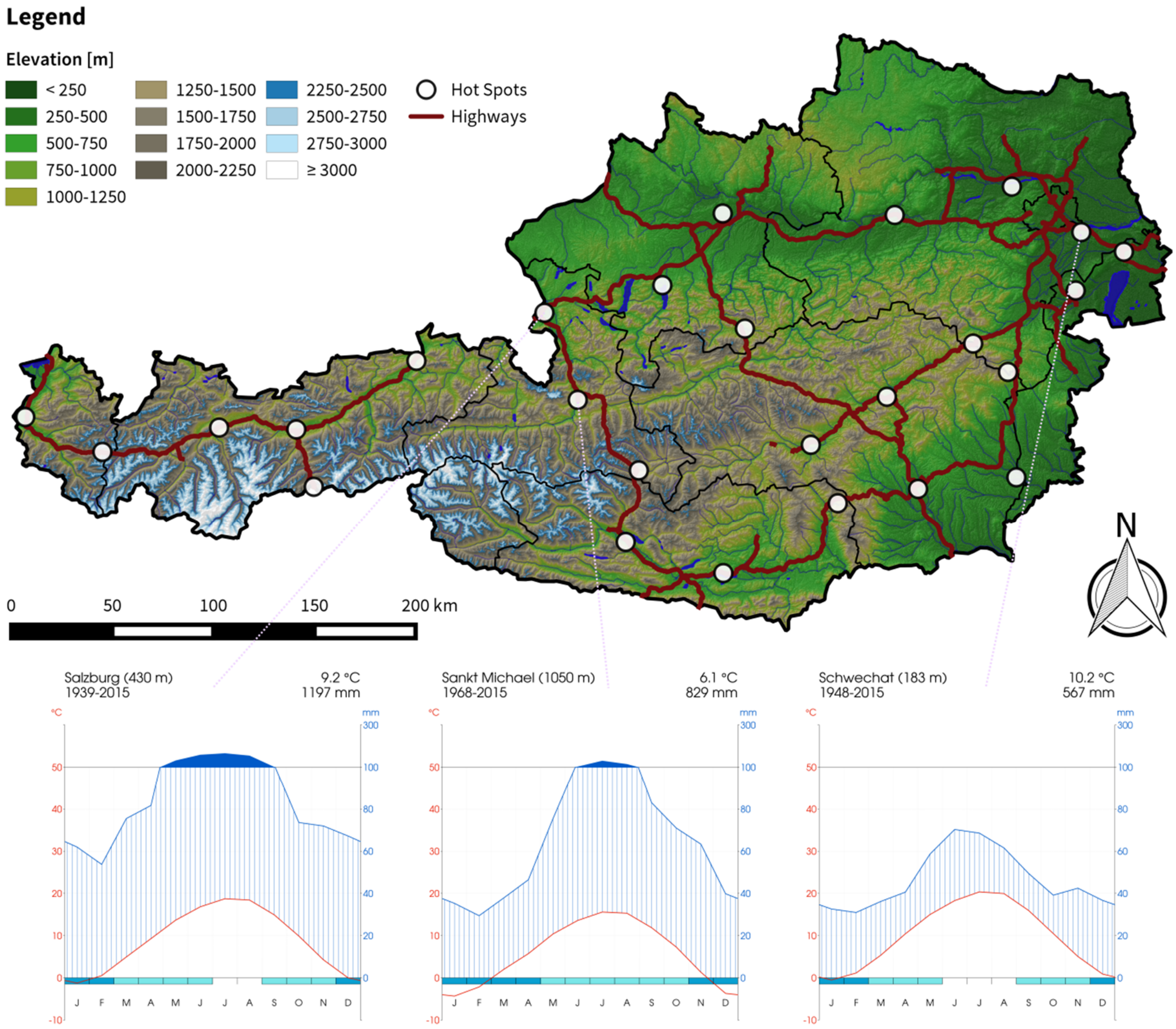

Figure 1: Overview of (a) the location of the selected exposure hot spots, and climographs for (b) the north-western area (Salzburg), (c) the alpine region (Sankt Michael im Lungau) and (d) the eastern area (Schweachat).

All meteorological measuring stations in Austria operated by the Central Institution for Meteorology and Geodynamics (ZAMG) as well as the hydrological measuring stations operated by the hydrographic central bureau (HZB) of Austria served as a starting point. Ensuing from this initial data basis, the selection of representative hot spots was carried out in a stepwise procedure with respect to the following considerations: First of all, the spatial proximity of available measuring stations to the highway network was considered. All stations with a distance greater than 10 kilometers were excluded from the dataset. Secondly, data availability and data quality were evaluated in several ways. Given the assumption of sufficiently long time series as a prerequisite for reliable return level estimation, stations which did not date back until at least 1 January 1985 (i.e. resulting in a time-series duration of less than 30 years) or where data availability was below 95 % were also dropped. Finally, topographic conditions and regional peculiarities were also taken into account by consulting the Austrian climate maps for 1971–2000 (Hiebl et al., 2011) and the digital hydrological atlas of Austria (BMLFUW, 2007; Fürst et al., 2009) under the premise that the stations are evenly spread throughout Austria. The final dataset consists of 26 hot spots representing small homogeneous areas within Austria (Figure 1).

Station measurements of precipitation [mm/d] and air temperature [°C] are used in this study. Since the hydrographic services of Austria do not measure air temperature, temperature analyses are carried out at only 25 of the 26 stations under investigation.

3. Methodology

Extreme value theory provides a suitable framework for analysing weather extremes with respect to their return levels and return periods (Coles, 2001; Katz et al., 2002; Katz, 2010; Chavez-Demoulin and Davison, 2012; Cheng et al., 2014). Based on long historical time series of meteorological data, both the block maxima approach and the threshold excess approach are applied for deriving annual and partial extreme value series. Both of these methods are widely applied in studying climatic extreme events (Smith, 1989; Davison and Smith, 1990; Parey et al., 2010; Villarini et al., 2011; Papalexiou and Koutsoyiannis, 2013; Gilleland and Katz, 2016; Schlögl and Laaha, 2017).

Firstly, block maxima (or minima) series consist of the most extreme values observed within time blocks of equal length. If the block size is defined to cover a time period of one calendar year, resulting extreme value series are referred to as annual maxima (or minima) series (AMS). Secondly, partial duration series (PDS) consisting of values exceeding a certain threshold are analyzed by means of the threshold excess approach. While this approach may be considered to be more efficient than the block maxima method if complete (time) series without gaps are available – as all values exceeding a certain threshold can serve as a basis for model fitting (Coles 2001) – the choice of thresholds might be cumbersome. Several approaches for threshold selection have been proposed by various authors, ranging from graphical diagnostics via fixed quantile rules to automated threshold selection methods (Coles, 2001; Scarrott and MacDonald, 2012; Northrop and Coleman, 2014). In this study, the square root rule $k = \sqrt{n}$ is employed as a standardized method for determining the tail fraction, using the k^{th} upper order statistic – which is related to the time series length n – as a threshold. This rule satisfies the intermediate order statistic convergence property (Leadbetter et al., 1983), but may not properly account for threshold uncertainty on subsequent inferences (Scarrot and MacDonald, 2012). The pre-selected thresholds obtained via the square-root criterion have subsequently been validated by means of graphical diagnostics for bias and parameter stability (Coles, 2001). Eventually, according to the type of extreme value series, either generalized extreme value (GEV) distributions or generalized Pareto (GP) distributions are fitted to the underlying extreme value series.

Four different parameter estimation methods are applied for each of the two approaches. Besides maximum likelihood estimation (MLE; Coles, 2001) and the more robust probability weighted moments (PWM) estimators (Hosking, 1990), generalized maximum likelihood estimation (GMLE; Martins and Stedinger, 2000, 2001) and Bayesian parameter estimation (BPE; Coles, 2001; Gilleland and Katz, 2016) are used for estimating parameters for both GEV and GP distributions.

This approach thus results in eight different models which returned different outcomes and exhibited a different goodness of fit. For each of the four models, the 2, 5, 10, 20, 50 and 100 year return levels are calculated. Based on the approach proposed in Schlögl and Laaha (2017), the best fitting model is determined according to the CRMSE_5, which is defined as the conditional root-mean-squared error (RMSE) calculated for all data points that feature return levels exceeding the 5-year recurrence interval when using Weibull plotting positions. This metric is particularly suitable for assessing the goodness-of-fit for the upper tail of the fitted distributions, thus specifically addressing higher return periods. In addition, the CRMSE_5 is particularly suitable in this case, where an automated assessment of different functions fitted to numerous data series is required.

Two major conditions have to be fulfilled in order to perform an accurate analysis of climate indices: data are required to be independent and identically distributed (Coles, 2011; Katz, 2010; Katz, 2013; Cheng et al., 2014). These prerequisites have to be assessed separately for each of the four classes of climate variables, as there are slightly different implications for each of these groups of indicators.

Taking into account an anticipated climate change, all analyses include a trend-correction for these meteorological indicators – if necessary. Trends are assessed using the Mann-Kendall trend test (Mann, 1945; Kendall, 1976; Gilbert, 1987) at a significance level of 0.05 (Zhang et al., 2004).

As far as the annual maxima series are concerned, independence of data is only a minor issue, as only one value per year is considered. Regarding the threshold excess method, both the occurrence of threshold exceedances on consecutive days and seasonality are issues that violate the assumption of independence of the time series. Dependent values in the peak over threshold series are taken into account by implementing a straightforward declustering procedure. This is employed by removing depended threshold exceedances within the autocorrelation length of both sides of the local maxima (Jarušková and Hanek, 2006). It is argued that the size of the autocorrelation window has to be selected with respect to the meteorological characteristic considered. For instance, while heavy rainfalls are short-term events occurring on a local scale, temperature impacts are much more related to the general (long-term) weather situation. Based on the autocorrelation functions of the time series under consideration, a lag size of 5 days has been found suitable for temperature indicators, while a lag size of 3 is proposed for precipitation data. Concerning incessant rainfall, however, lag size is influenced by the size of the pooling window of consecutive days. Using five-day precipitation aggregates entails extending the lag size to five days, too, in order to avoid overlapping events.

4. Results and discussion

Results show the merits of Bayesian parameter estimation methods as compared to traditional fitting methods. Bayesian parameter estimation of GP distributions fitted to the PDS yielded the best results in 46% of all cases, followed by Bayesian estimation of GEV distributions fitted to AMS, which showed the best performance in 35% of all cases (Table 1).

Table 1: Summary of the best extreme value models for five selected climate indices. The table indicates the number of times the respective combination of parameter estimation method and approach/distribution has been identified as best fitting method based on the $CRMSE_5$.

		parameter estimation method				
meteorological indicator	approach / distribution	BPE	GMLE	MLE	PWM	sum
T_Δ	AMS/GEV	14	0	0	1	15
	PDS/GP	8	1	0	1	10
T_{max}	AMS/GEV	7	0	0	0	7
	PDS/GP	15	0	3	0	18
T_{min}	AMS/GEV	7	1	0	1	9
	PDS/GP	16	0	0	0	16
precipitation	AMS/GEV	10	5	1	0	16
	PDS/GP	7	2	0	1	10
incessant rainfall	AMS/GEV	7	0	1	0	8
	PDS/GP	13	4	1	0	18
sum		104	13	6	4	127

The estimate derived from the thusly selected extreme value model can be visualized to indicate the variability of the extreme weather exposure for a certain meteorological indicator. This is exemplarily illustrated for incessant rainfall in Figure 2. Several possible risks are related to the indicator of continuous rainfall. Most importantly, the risk of flooding of the road surface due to lack of water absorption capacity in saturated soils as well as erosive effects caused by large water amounts with high flow velocity (e.g. bridge scour, washouts at embankments) are increased by perpetual rainfall. In addition, incessant rainfall can be considered as a proxy for exposure to mass wasting processes. It has been shown that continuous rainfall strongly affects the occurrence of mud slides and debris flows. As Guzzetti et al. (2007) have illustrated, the minimum average intensity which is likely to trigger shallow slope failures decreases linearly with increased rainfall duration.

The hot spots most exposed to intense continuous precipitation are located in the north-western parts of Austria around the region Salzkammergut-Salzburg. 5-year return levels of between 150 and 170 mm precipitation in five consecutive days have to be expected to occur in these regions. Regarding rare events with a return period of 100 years, precipitation amounts of more than 250 mm have to be expected. Concerning continuous rainfall, the 5-year return levels in dryer regions range between 80 to 90 mm precipitation, while 100 year events show rainfall amounts around 140 mm within five days.

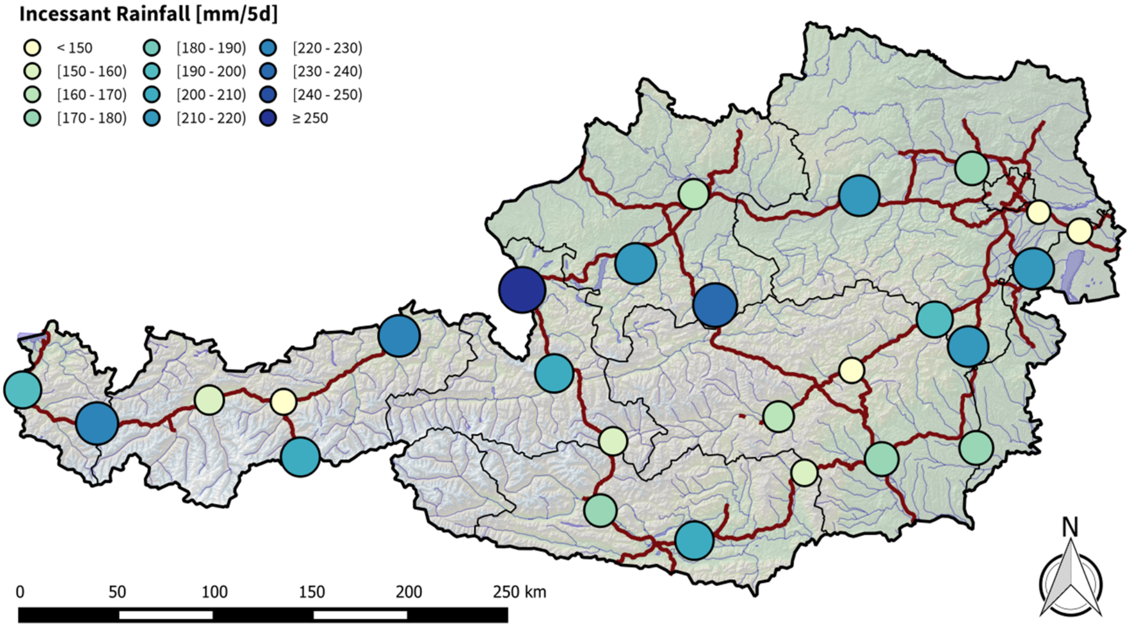

Figure 2: Overview of the 100-year return levels of incessant precipitation extremes at selected hot spots in Austria.

5. Conclusion

The hot spot approach applied in this study is shown to be suitable for spanning up an overall bandwidth of possible outcomes of various extreme weather events. Results obtained via the proposed methodology can prove advantageous for supporting stakeholders such as road authorities in construction and maintenance works in terms of adaptation planning. While providing insight into the general probability and magnitude of occurrence of severe weather events at a state level, this approach is also capable of reflecting regional characteristics.

Arguably, road segments where no meteorological time series are available may be attributed to a representative hot spot based on proximity and similarity of topographic and climatic features (derived from general meteorological maps and expert knowledge). The authors advocate that these locally available return levels of meteorological indicators provide a wealth of information for an improved management of road networks which takes extreme weather exposure of road segments into account.

In this study we have presented a framework for performing a systematic data-based assessment of a range of most relevant climate indices. In order to account for small-scale topographic conditions, we have illustrated that road networks in heterogeneous study areas can be assessed by using representative hot spot stations, which are homogeneous regions in terms of climate and landscape properties. Results show consistent and plausible estimates of locally available return levels of several climate indices related to temperature and precipitation events at certain selected hot spot regions. The uncertainty related to these estimated can be assessed by confidence intervals, which are calculated alongside the estimates for all stations.

Findings show that such specific impact models can be applied to estimate relevant parameters for sustainable transportation planning at appropriate scales. Results provide valuable guidelines for resilient, region-specific transport infrastructure adaption planning with respect to changing climate conditions.

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