Methodology for Analyzing Climate Criticality of Infrastructure Networks

A Case Study of the Serbian Health Care Network

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Statement of Originality

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Chapter 1

Introduction

Europe is not prepared for future impact of climate change (European Environment Agency, 2024). The temperature over European land areas has risen by 2.1 degrees of Celsius since pre-industrial levels and 2023 will most likely be the hottest year in over one hundred thousand years. Rising temperatures affect the lives of thousands of Europeans in a range of matters. First, Ballester et al. (2023) estimate that heatwaves in 2022 have caused excess deaths of between 60 thousand and 70 thousand European civilians. Such heat also facilitates the spread of huge forest fires, which in turn cause many environmental risks and destruction of infrastructure. Second, rising temperatures cause other extreme weather events like torrential rainfall and cyclones, which can also result in heavy precipitation. Extreme rainfall has caused large-scale damage in multiple areas on the European continent. In Germany, Belgium and the Netherlands flooding led to over 200 casualties and an estimated 44 billion euros in damaged goods in 2021 (Mohr et al., 2022). In 2023 the damage of large floods in Slovenia was estimated to be about 10 billion euros, which is close to 15 percent of the national GDP (Bezak et al., 2023). Extreme weather events in Europe are a huge risk to the society and the economy, because they threaten the health of citizens and countries.

In the event of extreme weather there will be a great amount of people that are in need of help and will look for health care. At the same time do these extreme weather events threaten the actual health care services itself. If there is a storm or a flood roads might not be accessible and hospitals might be damaged, so the health care access of many people is in danger. As stated, Europe is not ready for the impact of such climate hazards. Because temperatures are and will only be rising further in the future, it is essential that public health infrastructure is ready to cope with more extreme weather events. Therefore, this thesis seeks to identify key assets of health infrastructure and analyse the resilience of networks in order for them to become climate-proof in the future.

Analytics for a Better World (ABW) is an institute that uses data analytics to achieve the United Nations Sustainable Development Goals. ABW has designed the Public Infrastructure Service Access Toolkit (PISA) to provide public and private organisations with a clear framework to make data-driven decisions with regards to public infrastructure improvements (Analytics for a

Better World, 2024). The approach focuses around three functionalities: geographical accessibility analysis, digitized road network creation and resilient infrastructure planning. The toolkit uses big data to identify areas that lack access to, for example, health care and ultimately proposes infrastructure upgrades to improve health care access. Currently, the approach does not incorporate the impact of future climate events and thus the criticality of public infrastructures. In order to further improve the PISA this thesis develops a methodology to calculate the criticality of infrastructure with regards to future climate events. Therefore the research question of this thesis is as follows: How do future climate events impact infrastructure networks?

The literature review first provides an overview of existing research on criticality and infrastructure networks. The methodology chapter details the data used and describes the process for calculating criticality and related concepts such as vulnerability, hazard, and exposure. Subsequently, the Serbian health care network is analyzed as a case study, with the criticality of its health care facilities illustrated through various visualizations. The conclusion demonstrates that the proposed methodology is effective, easily applicable to other countries or regions, and adaptable to various infrastructure sectors and extreme weather events, provided the necessary data is available.

The academic relevance of this thesis lies in its contribution to the existing body of research on critical infrastructure and climate change resilience. By developing a methodology to assess the criticality of infrastructure networks in the face of future climate events, this study fills a significant gap in the literature. The integration of concepts such as vulnerability, hazard, and exposure into a cohesive analytical model represents a substantial methodological innovation that can inform future research and policy development. Furthermore, this thesis builds upon the Public Infrastructure Service Access Toolkit (PISA) developed by ABW. By incorporating the impact of future climate events and the criticality of public infrastructures into the PISA framework, this thesis enhances the toolkit's applicability and robustness. This extension of PISA's functionalities represents a notable advancement in the field of infrastructure resilience and climate change adaptation.

From a societal perspective, this thesis addresses a pressing and immediate concern. By identifying the key vulnerabilities within health care networks and proposing strategies to enhance their resilience, this research offers critical insights that can help mitigate the adverse effects of climate change. The findings of this study have the potential to improve decision making that ensures the continuity of health care services during and after extreme weather events. This proactive approach is essential for protecting lives, reducing economic losses, and fostering a resilient society that can withstand the challenges posed by a changing climate. Additionally, the improved PISA toolkit can be used by public and private organizations to enhance the resilience of health care infrastructure globally, ensuring that communities are better prepared for future climate challenges.

Chapter 2

Literature Review

First, the concept of climate-resilient infrastructure is discussed. Afterwards, criticality and related concepts with respect to extreme weather events and infrastructure are discussed. Ultimately, several elements of health care networks are examined.

2.1 Climate-resilient Infrastructure

The EU states that 'critical infrastructure' are assets within systems that are vital to the health, wealth and security (Council of the European Union, 2008). This refers to four different sectors: energy, transport, industry and social infrastructure. Within these sectors there are different types of infrastructure networks. In the transport sector, for example, the rail and road networks are critical. The social sector focuses on education, thus schools, and health, namely hospitals. These infrastructure types can suffer damage or destruction by extreme weather events and to achieve health care accessibility such networks need to be as climate resilient as possible (Handmer et al., 2012). As the case study of this thesis is the health care network of Serbia, the climate resilience of hospitals is investigated.

Infrastructure is climate resilient when it operates in such a way that it can withstand changing climate conditions and still operates as desired (OECD, 2018). Therefore climate-resilient infrastructure reduces the impact of climate-related extreme events such as floods or droughts. The resilience of infrastructure to cope with such weather events is based upon the exposure and vulnerability of the infrastructure (Agard and Schipper, 2014). Later sections describe the concepts exposure and vulnerability. There are multiple ways for infrastructure to become more climate-resilient. First, an asset can be located where it is less prone to the risks of climate events. This means, for example, moving a hospital to a location that cannot be flooded. Second, an asset can be better protected against extreme weather. This is, for example, paving roads such that a flood is no longer capable to destroy the dirt road. The assessment of individual infrastructure should always be viewed with respect to the complete system. Ultimately, the goal is to increase the climate resilience of an entire system and not only individual areas. Therefore, the risks and costs of enhanced climate resilient of the entire area should be considered before the allocation of resources. Climate-resilient infrastructure thus refers to an entire system, such as health care access or energy supply, that is able to cope with the occurrence of extreme weather events.

2.2 Impact Climate Change on Infrastructure

Climate change is caused by increasing concentrations of greenhouse gases in the atmosphere. These gases cause the temperature to rise severely. Current estimations are that temperatures will at least rise with more than two degrees Celsius (IPCC, 2023). These higher average temperatures in turn have an adverse effect on the occurrence of extreme weather phenomena, like heatwaves and heavy precipitation. These events have an effect on both the demand and supply of infrastructure. During a heatwave more people might need to go to the hospital, while a flood is capable of destroying an entire hospital. The effects of climate change on infrastructure are thus various.

Temperature change leads to a multitude of weather phenomena. OECD (2017) describes that either severe heat or severe cold affects the capacity or efficiency, the subsidence and/or desiccation, biological processes, and demand for service. They indicate that severe heat and cold affect roads negatively by altered capacity, demand for service and subsidence. However they do not discuss the effects of temperature changes on health care facilities. OECD (2018) also stresses that road surfaces can melt through temperature changes. They only discuss urban development, which could mean health care facilities, and how temperature changes affect cooling or heating demand. Forzieri et al. (2018) use an expert survey to estimate the sensitivity of weather events on infrastructure types. In the survey, experts are asked to indicate the effects on a scale between, no, low, moderate and high. They find that heat and cold waves have a moderate impact on local roads, roads of national importance and motorways.

Precipitation change can lead to river flooding, pluvial flooding and droughts, which in turn affect capability or efficiency and stability of earthworks and roads (OECD, 2017). Similarly, OECD (2018) indicates that flooding affects transport and urban development. Forzieri et al. (2018) find that floods have a moderate sensitivity on all road types, but a high sensitivity on health care facilities. All different road types have no sensitivity and hospitals have a moderate sensitivity for droughts.

Lastly, storms with heavy wind cause damages to roads and buildings (OECD, 2017, 2018). The sensitivity of roads to windstorms is estimated to be low, while the sensitivity to health care facilities is moderate (Forzieri et al., 2018).

2.3 Risk

Haggag et al. (2021) explain that there are three conditions for a disaster to happen. First, the hazard has to take place. Second, a system needs to be exposed to that hazard. Third, the negative consequences because of the hazard actually actually hit the system. Risk is considered to refer to the adverse effects of extreme weather events. Cardona et al. (2012) propose a risk framework that assesses the impact of extreme weather events through the hazard, exposure and vulnerability. These three concepts together estimate the risk for an infrastructure asset. Forzieri et al. (2017) use a similar approach and describe risk as follows: Risk = Hazard $*$ Exposure $*$ Vulnerability. In the next three section the different components of climate risks are discussed.

Hazard

Hazard refers to the future occurrence of extreme weather events that harm infrastructure. Forzieri et al. (2018) describe the occurrence of such events as the probability they occur within the current climatology. The intensity of an extreme weather events is classified according to the return period. To give a fictional example: a drought of ten days is classified as moderate, because it only occurs once every twenty to fifty years. Forzieri et al. (2018) divide into six different hazard intensities: very high, high, moderate, low, very low and no. The return period for a hazard of very high intensity is once in more than one hundred years. High is between one hundred and fifty years. Moderate intensity is between fifty and twenty years. Low is considered between twenty and ten years. Very low is between ten and two years, while there is no hazard intensity if the return period is less than two years.

Exposure

Cardona et al. (2012) explain that exposure is the set of assets within a given area that is affected, if an extreme weather event occurs. If a population does not live in the place where the flood occurs the exposure for the population is zero. Therefore, exposure is the presence of people, assets, and ecosystems in places where they could be adversely affected by hazards. But whether the extreme weather occurs does not matter for the exposure. However, exposure is a necessary determinant of risk. For Forzieri et al. (2018) this refers to the stock of systems within the energy, transport, industry and social sector. Forzieri et al. (2017) use the population distribution. In this thesis, the exposure refers to the population of Serbia with health care accessibility.

Vulnerability

Vulnerability refers to actual damage or loss of assets when they are adversely affected by hazard events (Cardona et al., 2012). The way damage or loss in incurred is dependent on a multitude of factors. In climate change adaptation, vulnerability often encompasses exposure, sensitivity and adaptive capacity. Exposure has been discussed previously. Sensitivity is the degree to which a system, population, or resource is or might be affected by hazards. Forzieri et al. (2018) use a classification from no to high sensitivity. They use an expert survey to estimate the sensitivity of all infrastructure types and hazards. Adaptive capacity refers to the possibility of human beings and/or institutions to cope with hazard events and absorb the impact. The presence of capacity suggests that impacts will be less severe. In this thesis, the adaptive capacity is the possibility of people to use a different health care location, when the preferred option is not available due to extreme weather. To assess the vulnerability Forzieri et al. (2017) quantify the ratio between the people killed by a climate disaster and the people exposed to such a disaster. Similarly, this thesis uses the ratio of people that lose health care accessibility and the people that are exposed to losing health care access when an event would occur.

2.4 Criticality

Criticality is rather similar to risk in the literature as it also considers the impact of events on the users of a system (Patterson and Apostolakis, 2007; Myers and Sorrentino Jr, 2011; Koonce et al., 2008). This means that criticality is a combination of likelihood of the failure, magnitude of the failure and impact. Katina and Hester (2013) propose several general criticality factors that view criticality in terms of network. First, the level of resilience is a factor. This refers to the capability to withstand a hazardous event. The second factor in criticality is the level of interdependency, which addresses the relationship with the infrastructure among the system it is connected to. The third factor is the dependency, which refers to the usage of the system. The fourth factor is the risk, which is similar to the previous discussion of risk. Criticality and risk in infrastructure literature are thus somewhat different, namely risk a part of criticality. So how can the criticality of infrastructure be defined in a single description that covers these four factors?

Jafino et al. (2020) explain that network criticality can be expressed as the contribution to the performance of the entire network. Based on this contribution the infrastructure can be ranked in terms of criticality. Some of the contributions that can be used are increase in travel cost or travel time or the decrease in the accessibility. Similarly, Chen et al. (2024) use the disruption of commutes as the indication of criticality and García-Palomares et al. (2018) use four different indicators to assess the criticality of road networks: weighted average travel time, potential accessibility, daily accessibility with a three and a four hour limit. In the light of these infrastructure criticality definitions, this thesis criticality defines as the impact of infrastructure on health care accessibility with regards to future climate hazard events. This means that criticality is indicated as the loss of health care accessibility for a proportion of the population.

2.5 Health Care Networks

Since the case study of this thesis focuses on the health care network in Serbia, this section discusses the relationship several aspects of health care networks. The health care access of a population depends on the availability of a medical facility near a population. In essence, there are thus two factors that influence the access: the locations of medical facilities and the location of the population. In order for the population to have the highest health care access possible, it are the quantity and the locations of such medical facilities that determine the health care access of the population. All these health care facilities in a certain area together form a health care network. Such a network should be strategically build to cover the entire area, but the decision to build a hospital in a certain location depends on a wide range of factors that are covered in uncertainty. This means that the supply and demand of a hospital are susceptible to change in the future (Mestre et al., 2015; Farahani et al., 2012).

Therefore, a hospital network needs to be robust for the future. A factor that can influence the demand of a hospital are the demographics of the population. In some area the amount of people can increase due to economic opportunities, which in turn increases the amount of hospital visits and thus the demand for medical services. Similarly, a hospital can be difficult to reach by car, because a road is closed, which would decrease the supply of the hospital. Ideally, all people have health care access within a certain time period, but this would mean that lots of hospitals need to be build and that has enormous costs, which is often not feasible. The strategic planning of such a health care network is essential in the long-term health care access of a population.

The objective of a health care network is thus to cover health care access for as much people as possible, but often these people are constrained. In some research an individual should be served by at least one facility within a given distance, but more often the covering is constrained by the distance between the individual and the facility (Farahani et al., 2012). For example, the travel time of an individual to the nearest health care facility is limited. If the health care is urgent, it might not be sufficient to travel for over an hour to see a doctor. Moreover, if a health care facility is too distant, the population that depends on it might not bother using it in non-emergency cases. It is thus from significant importance that the travel time is not excessive. A travel time of over an hour is deemed excessive as within an hour critical health care in case of emergencies can still be given (Shiomi et al., 2011). Another constraint for individuals to visit a medical facility could be the travel costs.

There are also multiple constraints for the facilities that offer health care service (Shiomi et al., 2011). There can be a maximum amount of facilities. If the facilities are yet supposed to be build, there also is a budget constraint on the building costs for all the facilities. Similarly, there can be a constraint on the costs to ensure that facilities are climate-resilient. Often hospitals also have a maximum capacity for the amount of individuals it can give health care to.

Future climate disasters also are a constraint for hospitals location network. Obviously, a hospital that is built next to a river is more prone to floods than a hospital that is build on a mountain. During a flood a hospital would not be able to provide service and all of its users lose health care access. Therefore spatial planning incorporates the risks that come with climate disasters and tries to minimise them (Caparros-Midwood et al., 2017). In the context of this thesis, the criticality of each facility is calculated to discover which facilities cause the most people to lose health care access due to future climate disasters. Future planning of the infrastructure health care network of Serbia can then minimise the damage to climate events.

PISA Toolkit

The Public Infrastructure Service Access (PISA) Toolkit, developed by Analytics for a Better World (ABW), is designed to optimize the location of facilities, that provide essential services like hospitals or market places, using a data-driven approach (Analytics for a Better World, 2024). It integrates various big data sources, including population data, facility locations, and digitized road networks, to conduct a comprehensive geographical accessibility analysis. PISA assesses physical access to services and thereby identifying regions with insufficient coverage. Ultimately, it proposes new facility locations to increase the the coverage with an efficient use of resources.

In the Timor-Leste case, PISA was used to find the optimal placement of health care facilities (Krishnan, 2023). First, the set of households and existing and possible facility locations are identified. Then, the model takes into account the distances between population centers and facility locations, the current distribution of healthcare services, and the transportation network's efficiency. Potential facility sites are analysed and the optimal locations are found.

The objective of the model is to maximize the number of people that have access to a health care facility. The constraints ensure that households are assigned to a medical facility and that each facility stays within the budget constraints. By solving this optimization problem, PISA provides a set of recommended locations for new healthcare facilities that ensure efficient maximum coverage and accessibility (Krishnan, 2023).

Chapter 3

Methodology

In the methodology chapter, the data is described. Afterwards, the methodology to calculate criticality is explained, which involves using exposure, vulnerability, and hazard. Finally, the calculation from weather events to hazard is detailed.

3.1 Data

The data is collected from five different datasets. First, Global Administrative Areas (2022) is used to locate the administrative area of Serbia. The dataset contains three different administrative bounds. This means the boundaries of entire Serbia, and the provinces and counties of Serbia can be used in the analysis. The dataset uses the coordinates of Serbia to create a framework for spatial analysis in Serbia. Global Administrative Areas (2022) is available for all countries and regions in the world. Second, the population data of Serbia are collected through WorldPop (2018). They estimate the number of people per grid of one square kilometre. Every grid has its own identification number and population count. The total population in 2020 is estimated at 6.98 million, which is close to the official Serbian number of 6.9 million (Statistical Office of the Republic of Serbia, 2021). Third, OpenStreetMap (2017) is used to find hospitals and clinics in Serbia. A hospital is defined as a building that provides in-patient medical treatment and emergency facilities. A clinic is a medium-sized medical facility or health centre. The total number of hospitals and clinics in Serbia is 234. For each hospital and clinic OpenStreetMap provides the name and location as well as the country, district and area type in both the local and English language. Fourth, OpenRouteService (2024) provides isochrones between hospitals and households, indicating that population grids within a certain travel time by car are included in the catchment area of each medical facility. The fifth dataset used in this thesis is from (ESA GPBP, 2023). The ESA has utilised historical climate data to estimate future climate scenarios for specific weather events, like maximum, minimum and average temperature, precipitation and wind speeds. The dataset consists of an approximation of the occurrence of weather events for certain geographical areas from 2015 to 2100. Thus, for example, the dataset predicts the precipitation in July 2050 in Belgrade.

These weather datasets are also available for a wide range of countries.

3.2 Definition of Criticality

Criticality is defined as the impact of infrastructure on health care accessibility with regards to future climate hazard events. This means that criticality is indicated as the loss of health care accessibility for a proportion of the population. As discussed in the literature review there are a couple of components that affect the criticality. First, the exposure of people to health care access. In other words, how many people currently have health care access to a certain facility in Serbia. Second, the vulnerability indicates how many people lose health care access if a facility is no longer capable to provide health care access. The third factor is the hazard: which, where and when does a hazard take place and how does that affect the facilities.

The first indicator, exposure (E), is thus the amount of people that have health care access for each facility. Health care access is defined as living within a certain travel time of a health care facility (Weiss et al., 2020). The amount of people with health care access are thus the total amount of people that live within that time of a health care facility. Weiss et al. (2020) show that 91 percent of the population in the world can reach a health care facility with motorised transport within an hour, while 56 percent can reach a facility within an hour walking. However, Weinhold et al. (2022) show that the accepted travel time differs greatly for parts of the population. The accepted distance depends on the medical speciality, distance, age, health, income and town size and ranges from 24 minutes to 50 minutes. In the results chapter an analysis is done to show the relation between the travel time and health care access in Serbia. Based on this analysis and Krishnan (2023), the choice is made is to set the travel time at 30 minutes. The exposure of a facility thus represents total amount of people with health care access to that facility. However, it could be that people have access to multiple hospitals which would mean that they are counted a multitude of times while they will only visit one facility. Therefore, the exposure of a facility, E_i, is calculated as the total amount of people for which that facility is closest and within the accepted travel time.

The second indicator is the vulnerability of a facility. Vulnerability refers to the number of people affected by a hazard. For each facility, it is calculated how many people lose health care access if that facility is disconnected from the health care system. This assessment checks whether people have multiple options for medical care facilities. Vulnerability is indicated by V and represents the ratio of people that lack health care access with and without a specific health care facility. Therefore, V_i indicates the percentage of people who lose access when health care facility i is unable to provide care.

The impact of an extreme weather event on the vulnerability of facilities is not uniform. There are two forms of vulnerability identified. Maximal vulnerability occurs when no other medical facilities are available. This can happen due to extreme weather events where all facilities are destroyed and people have no other options. Conversely, minimal vulnerability assumes that every medical facility is available if one is unable to provide care. This scenario assumes that if two facilities are in the same neighborhood and one is affected by a flood, the other can still provide care. While neither scenario perfectly reflects reality, using both extremes helps determine an interval within which the actual vulnerability lies.

The third indicator is the hazard of extreme weather events. The weather data is available for temperature, precipitation and wind speeds, but in the analysis only temperature and precipitation effects on health care accessibility are considered (ESA GPBP, 2023). This is mainly due to difficulty to predict the effects of wind speeds (Mao et al., 2022). The data on the weather consists of daily predictions of the values until 2100. Therefore, the days with extreme weather can be found. The thresholds for extreme weather are from the Risk Threshold Database (Geospatial Planning and Budgeting Platform, 2024). For precipitation extreme weather occurs when the rain is over 60 millimeters per day. Similarly, temperature values are considered extreme when they exceed 40 °C.

It is assumed that during such events, a facility cannot provide health care. The objective is to determine how often each facility will encounter extreme weather over the next century. The hazard, indicated by T, represents the ratio of time a facility is unable to serve its customers due to extreme weather over the next century. The hazard is consists of two components: the duration of the weather event itself, during which the facility is unable to provide health care, and the recovery time required for the facility to resume full operations after the event. Currently, due to a lack of data, the recovery time is assumed to be zero. Thus, T_{ij} is calculated as the number of days of extreme precipitation or temperature divided by the total number of days between 2015 and 2100. Ultimately, T_{ij} indicates the ratio of time that facility i will be unable to provide health care due to weather event j.

These tree indicators together form criticality, which is defined as the number of people that lose health care as a result of the incapacity of a facility due to extreme weather events. In order to estimate the criticality of health care facility i the following equation is used:

$$\text{Criticality}_i = \sum_j \mathrm{E}_i * \ \mathrm{V}_i * \ \mathrm{T}_{ij}, \tag{3.1}$$

where i indicates facility i in the set of facilities I and j indicates weather event j in the set of weather events J. If, for example, four million people in Serbia have health care access to a hospital in Belgrade and it will not be able to provide health care for two years in the period between 2020 and 2100 due to extreme weather events and ten percent of this population depends solely on this hospital, the criticality of this hospital in the case of extreme weather events is as follows:

$$\text{Criticality}_{\text{Belgrade}} = 4 * 10^6 * 0.1 * \frac{2}{80} = 10000. \tag{3.2}$$

This means that 10,000 will people lose health care access for the entire period due to extreme weather and because they depend on this facility in Belgrade. As the minimal and maximal vulnerability are calculated, the analysis also includes a minimal and maximal criticality.

Chapter 4

Analysis

This chapter presents the analysis of the health care access network in Serbia. First, I assess the spatial distribution of households and medical facilities. Next, the health care access for multiple travel time periods is shown, afterwards the distribution of health care access for a travel time of 30 minutes is shown and the exposure for each facility is calculated. Second, the vulnerability of the medical facilities is derived and shown. Third, future extreme weather events in Serbia are found, connected to hospital locations and the hazard is calculated for each hospital. Ultimately, exposure, vulnerability and hazard are combined to find the criticality of each medical facility. The facilities and areas with the highest criticality are highlighted such that these are prioritised for improvements in health care infrastructure.

4.1 Health Care Access

Figure 4.1 shows the household locations in Serbia according to WorldPop. The household locations are color coded from green, yellow and orange to red based on the estimated quantity of people living on those locations. The red areas on the map thus depict locations with a high population density. Similarly, the green ares indicate areas where relatively not a lot of people are living. Figure 4.1 shows that especially the centre of the country the population density is highest. This is expected as Belgrade is in the centre of Serbia and the capital is with a population count of almost 1.4 million by far the biggest city of Serbia (Statistical Office of the Republic of Serbia, 2022). The second greatest city in Serbia in terms of population is Novi Sad, which is in the north of Serbia in the region Vojvodina, with nearly 350 thousand inhabitants. The third biggest city is Niš with a population of almost 250 thousand in the Southeast of Serbia. Most other regional cities are either in North or Central Serbia which is clearly depicted in Figure 4.1.

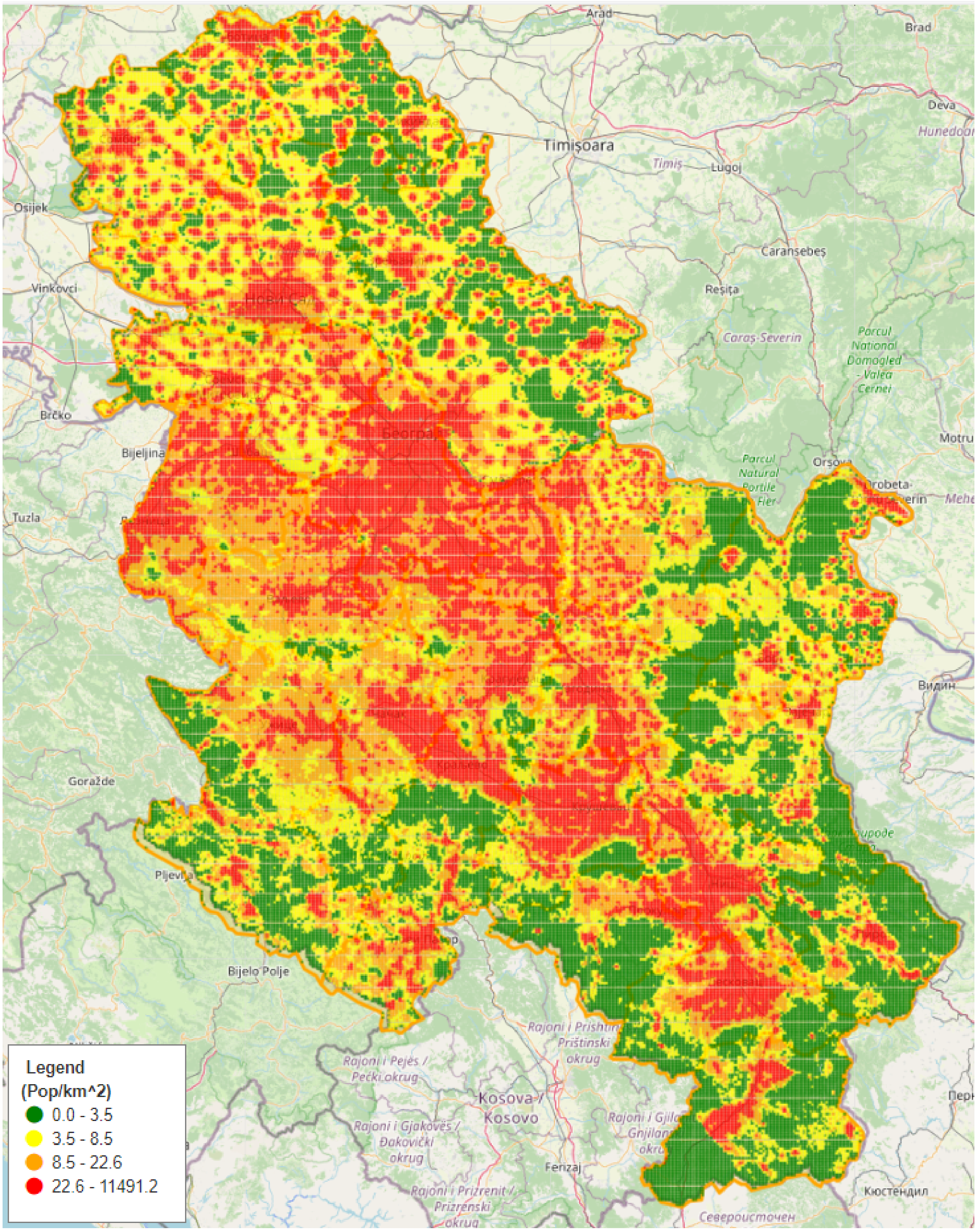

Figure 4.1: Population density in Serbia. The color gradient from red to green represents population density, with red areas indicating the most densely populated regions and green areas indicating the least densely populated regions.

Figure 4.2 depicts all medical facilities in Serbia according to available data. In total, there are 234 medical facilities. Similar to figure 4.1, the difference in hospital density between Belgrade and the rest of Serbia is significant. As most people live in Belgrade it is logical that the demand for health care in Belgrade is much greater than anywhere else in the country and most medical facilities are thus located in the city. Other cities with a variety of medical facilities are Novi

Sad, Niš and Subotica located in the northern part of the country. Again, the northern province Vojvodina has medical facilities well spread around the region, but in the southern less populated areas of Serbia some regions do not even have one medical facility. Other regions only have a handful.

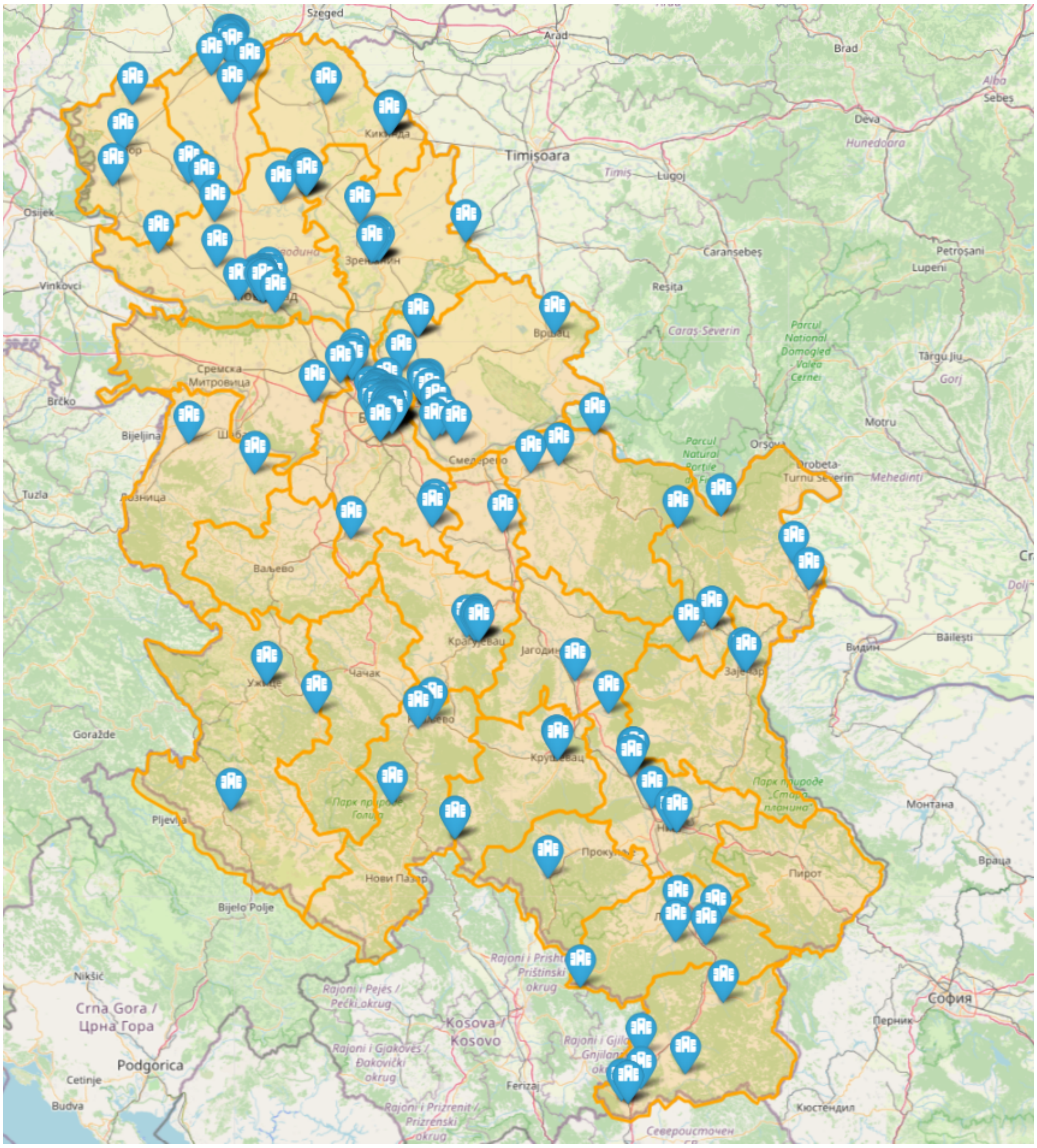

Figure 4.2: Map of hospital locations in Serbia. This map illustrates the geographical distribution of hospitals across Serbia. Each blue marker represents a hospital, indicating its specific location within the country's administrative boundaries. The boundaries of the administrative regions are highlighted in orange, providing a clear demarcation of the different areas.

Exposure

In order to assess the health care infrastructure of the population of Serbia the access to a medical facility is calculated for a multitude of travel times, which is considered the driving time by car to a facility. In figure 4.3 the relation between travel time and accessibility is depicted. The shortest travel time is 5 minutes, while the longest travel time is set at 60 minutes or one hour. This is often regarded as the longest accepted travel time to a medical facility, because in case of an emergency health care within one hour greatly influences the chance of survival (Shiomi et al., 2011). For a travel time of five minutes 27 percent of the population has health care access, while with a travel time of one hour 95 percent has access. Within 30 minutes 72 percent already has health care access and within 45 minutes almost 90 percent, so initially there is a rapid increase of health care accessibility, while after 30 minutes the increase gradually becomes less significant. For further analysis a travel time of 30 minutes is taken, as the accepted travel time differs from less than 30 minutes for elderly people to over 50 minutes for young patients (Weinhold et al., 2022). The health care access for a travel time of 30 minutes is 72 percent.

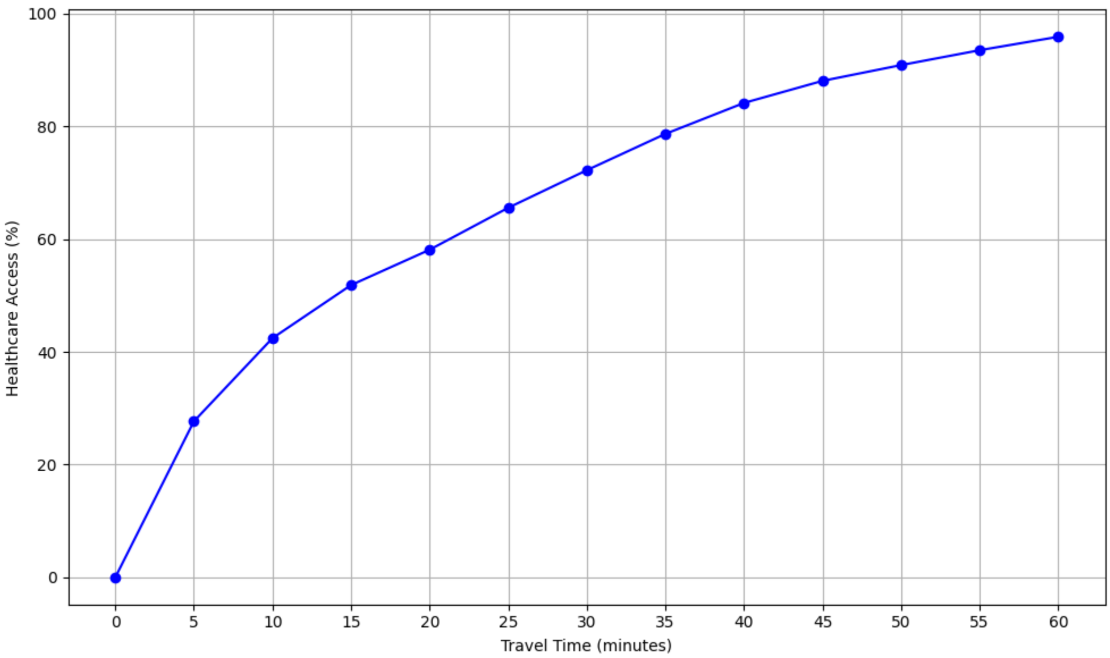

Figure 4.3: Health access for different travel times.

Figure 4.4 shows which parts of the population in Serbia have health care access with a travel time of 30 minutes. With a ratio of 72 percent more than 5 million people have health care access and almost 2 million people lack access. The red parts of the figure are households that do not have health care access, while the green parts represent households that do have health care access. Both colors have reduced opacity for less densely populated areas. The blue markers show the locations of the medical facilities. Although great parts of the map are red, most people do have health care access. Most red areas are less opaque and thus represent sparsely populated areas, like the southeast and southwestern parts of Serbia. Most of the north of Serbia up to Belgrade does have health care access, but below Belgrade only inhabitants of regional cities appear to have access. This suggests that especially for these parts of the country the travel time is greater than 30 minutes. The rural and less densely populated areas are thus somewhat underserved.

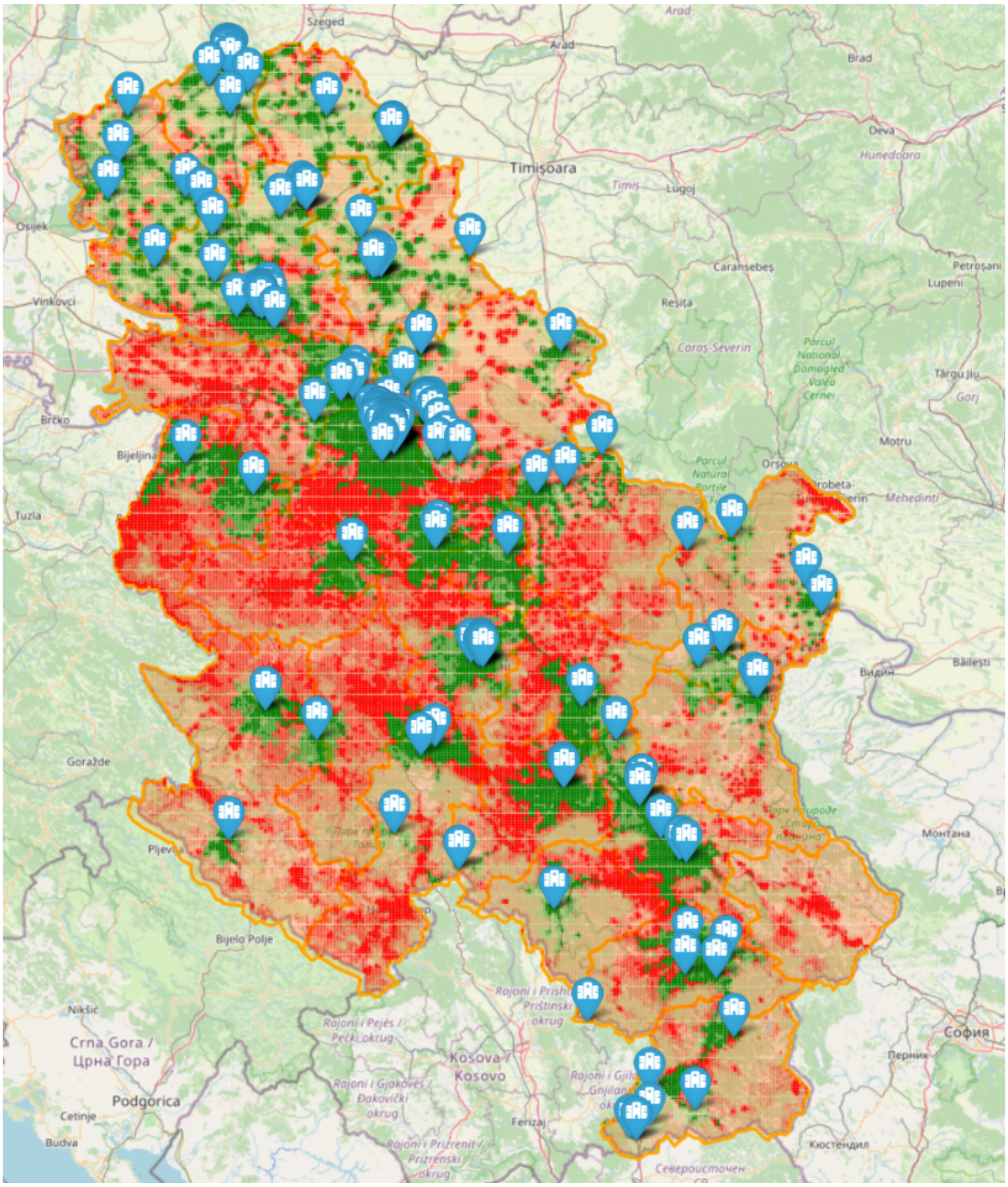

Figure 4.4: Map of population with healthcare access within 30 Minutes in Serbia. This map illustrates the accessibility of healthcare facilities in Serbia, highlighting areas where the population can reach a hospital within 30 minutes. The blue markers represent hospital locations, providing specific positions within the country's administrative boundaries, outlined in orange. The underlying color gradient from green to red indicates health care access, with green representing population with access and red representing population without health care access within 30 minutes driving.

The exposure of a facility is defined as the number of people for which that facility is nearest and within accepted travel time. This definition is chosen, because just using access leads to counting households multiple times. The descriptive statistics and thus the difference between exposure and access values are shown in Table 4.1. The mean exposure of a facility is 21,552, while the mean amount of people that have access to a facility is almost 560,000, a value 25 times as great. The minimal exposure is 0 and the maximal is 183,202. The highest access value is just shy of 1.45 million. The difference between access and exposure is very significant.

Table 4.1: Descriptive Statistics Exposure and Access.

Statistic	Exposure	Access
Count	233	233
Mean	21,552.8	559,196.6
Std	31,032.3	565,815.2
Min	0.0	215.0
25%	3,416.8	96,705.0
50%	10,561.2	280,584.0
75%	25,216.9	1,333,597
Max	183,202.7	1,435,831

Vulnerability

Vulnerability is defined as the percentage of people that lose access when a health care facility is not able to provide health care. As discussed in the methodology chapter, vulnerability is bounded between minimal and maximal vulnerability. The descriptive statistics of both vulnerabilities are described in Table 4.2. The maximal vulnerability is by definition 1 for all data points. This means the mean is also 1 and the standard deviation is 0. The minimal vulnerability has a mean of only 0.08 and half of the data points have a minimal vulnerability at least smaller than 0.005. Only the upper 25 percent of the range of hospitals have a minimal vulnerability value above 0.01. However, the standard deviation is 0.23 and there are hospitals with a minimal vulnerability equal to 1. Facilities in cities probably have a lower minimal vulnerability as they are closer together due to higher demand in densely populated areas. The facilities that have a minimal vulnerability of 0 are probably located in the cities.

Table 4.2: Descriptive Statistics Vulnerability.

Statistic	Min Vulnerability	Max Vulnerability
Count	234	234
Mean	0.08	1.00
Std	0.23	0.00
Min	0.00	1.00
25%	0.00	1.00
50%	0.00	1.00
75%	0.01	1.00
Max	1.00	1.00

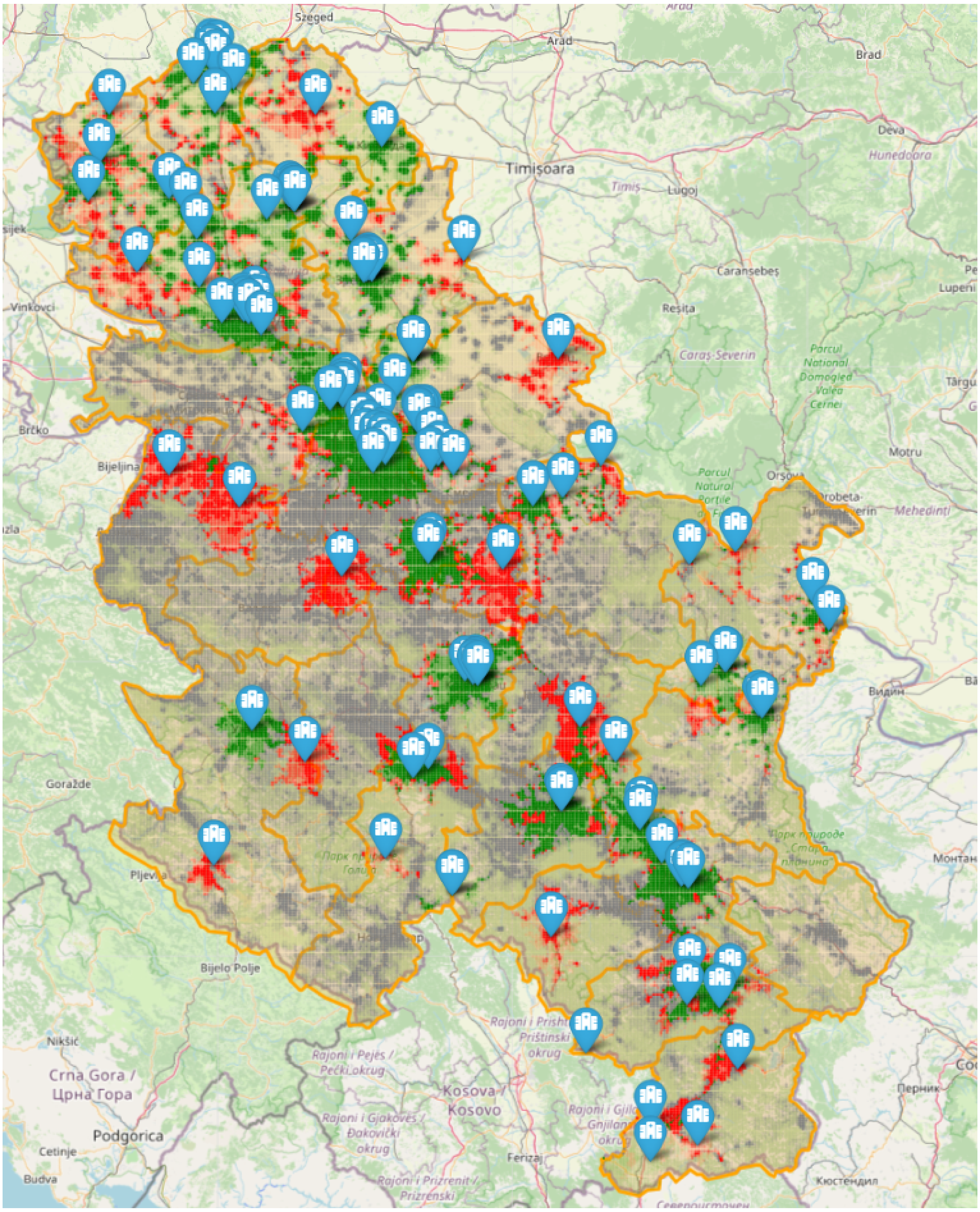

Figure 4.5: Map of vulnerability of the Serbian population. The green areas represent regions where the population has access to multiple healthcare facilities, indicating reduced vulnerability. In contrast, the red areas depict households with only one available medical facility, highlighting regions of higher vulnerability due to limited healthcare access. The grey areas on the map indicate parts of the population that do not have any healthcare access, emphasizing the most vulnerable segments. The blue markers represent healthcare facilities, specifically those where a portion of their visitors are entirely dependent on that particular facility.

Figure 4.5 shows the vulnerability of the population of Serbia. The green areas depict the population that has multiple health care facility options, while the red areas are households that only have one medical facility to go to. The grey areas are the part of the population without health care access. On the map only those facilities for which a part of their visitors is completely dependent on this facility are shown. These are thus facilities with a minimal vulnerability greater than 0. In total, there are 120 such facilities. Similar to the healthcare access map, the areas around Belgrade and north of the capital are less vulnerable if a healthcare facility is unable to provide a service due to the higher concentration of medical facilities and better infrastructure in these regions. However, in some areas in the south near, for example, Niš, but also in other regional cities do people have multiple health care facility options.

4.2 Weather Analysis

The next section some weather phenomena in Serbia are discussed. For precipitation the daily cumulative sum from the last century is compared to the next century. Moreover are the yearly maximum, minimum and average for each year of the next century compared. Ultimately, the amount of (consecutive) days with precipitation over 60 millimeter are counted for every grid. A similar analysis is done for the temperature. The historical dataset contains daily weather events from 1981 until 2023 and the future dataset contains projections from 2015 until 2100.

Precipitation

Firstly, historical and future rainfall are compared with each other. In Figure 4.6 the daily cumulative sum of precipitation for each day of the year in the past and for the future is depicted. The dashed lines represent the maximum precipitation for both the future and the past, while the solid lines are the average. Figure 4.6 clearly shows that the maximum precipitation for each day of the year is much lower in the future than in the past. This difference is quite significant, while historical precipitation relatively often reached over 25,000 millimeter per day, future daily cumulative precipitation will barely reach over 5,000 millimeter per day. Interestingly, there is not such a great difference in the average cumulative precipitation per day between the future and the past. Both of these hover around 2,500 millimeter per day. The maximum and average precipitation in the future are also very much alike. From Figure 4.6 I conclude that average rain will be equal to the past, but the maximum precipitation in the past was much greater, thus the chance of floods relative to the past should decrease in the future.

The fact that extreme precipitation levels are less likely in the future does not mean that they will not occur. Figure 4.7 shows the average precipitation for every year from 2023 until 2100. The green line is almost 0 for the entirety of the future period. The red line depicts the maximum daily precipitation for each year. The maximum is around 100 millimeter for almost every year. It is quite often the case that one year precipitation is just above and another it is just below. There are years where the maximum is less than 80 or more than 120, but this occurs barely. The blue bars in Figure 4.7 represent the number of days where precipitation is over 60 millimeter in that year on any location. These show the greatest differences over the years. There is not a real upward or downward sloping trend, but the differences between the years can be huge. For example, in 2070 the number of days with precipitation over 60 millimeter is only 30 which is one of the lowest in

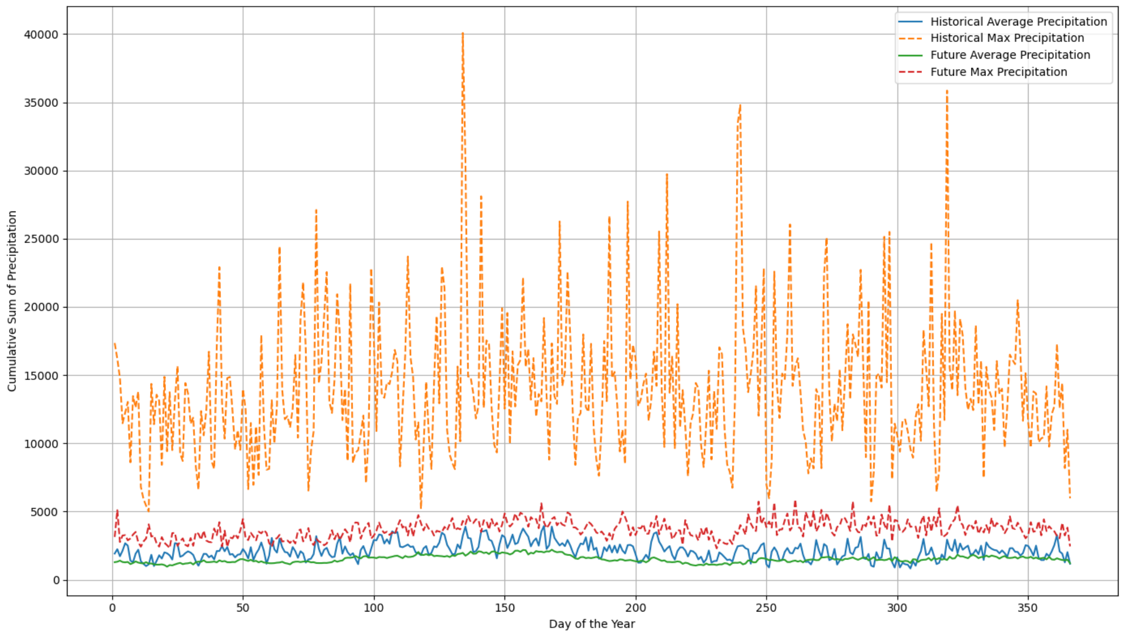

Figure 4.6: The historical and future cumulative sum of precipitation for every day of the year in Serbia.

the entire period. However, in 2071, only a year later, the number of days is the second highest of the entire period with 83 days with precipitation over 60 millimeter. So while the average rainfall is almost equal between the years, the days with a lot of precipitation differ greatly over the years and the days with precipitation with over 60 millimeter are omnipresent and the hazard of floods is still great.

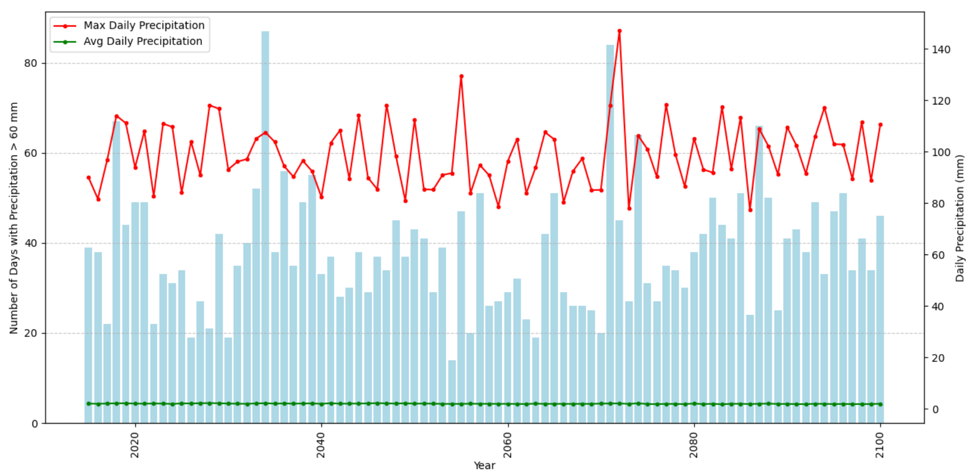

Figure 4.7: Future precipitation trends in Serbia. The blue bars represent the number of days each year with precipitation above 60 millimeters. The red line represents the maximum daily precipitation (in millimeters) recorded each year, while the green line represents the average daily precipitation (in millimeters) for each year.

The previous two figures have shown temperature data for the entirety of Serbia, but it is also very important to see where the precipitation in Serbia actually will occur. The weather data are 52 data points in Serbia, so we grid the data such that every data point now represents the area surrounding it as well. Then for every grid the days with extreme precipitation are counted and displayed in figure 4.8. Purple grids represent the areas with the most days of extreme rain, while light blue color indicates grids with relatively few days of extreme precipitation. Figure 4.8 shows that the south western part of Serbia will face much more extreme precipitation compared to the rest of the country. The northern regions of Serbia will have almost no extreme rain, while the densely populated Belgrade area will have quite some days with extreme precipitation.

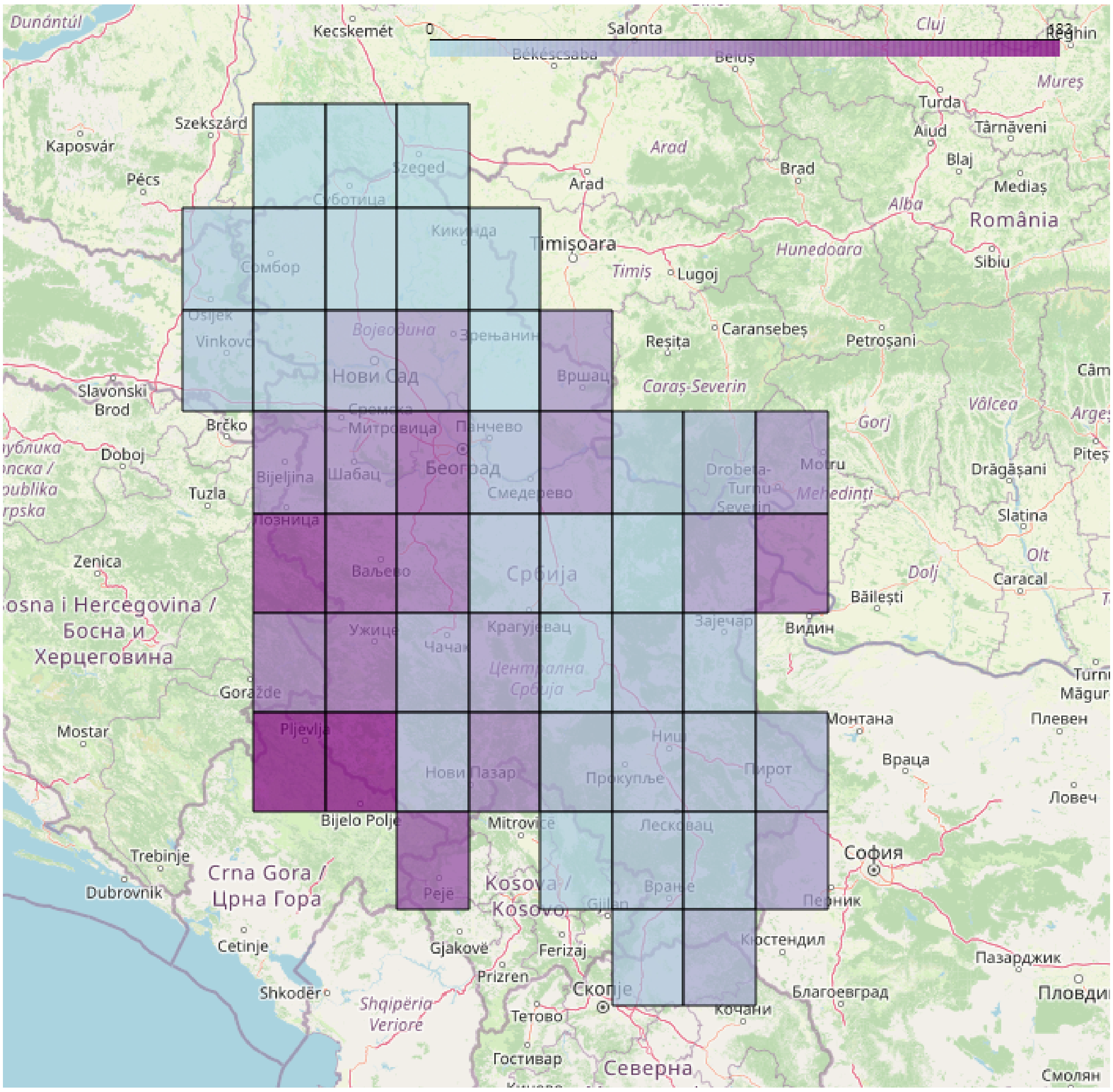

Figure 4.8: Spatial distribution of days with extreme precipitation in Serbia. Each grid cell on the map represents a specific geographic area where the days with extreme precipitation have been tallied. The color gradient, ranging from light blue to deep purple, indicates the frequency of extreme precipitation events.

Figure 4.9 shows the number of days with precipitation over 60 millimeter on the y-axis and the x-axis measures maximum of consecutive days with precipitation over 60 millimeters. For every grid the population is counted and represent by the blue data points in figure 4.9. So the bigger the blue data points, the greater the population is that has to deal with the precipitation events. As some grids represent multiple regions all the regions that correspond to the hospital inside the grid are stated in the plot. It could be the case that households have the options to go hospitals in two different regions and are therefore counted double, but the results do not suggest that there are extreme errors. Figure 4.9 shows that there is only one region, Mačva, where the maximum amount of consecutive days with rain over 60 millimeters per day is 4. Mačva is the region west of Belgrade between the Sava and Drina rivers which both go through the capital. However, the population count of Mačva is rather small and heavy precipitation would have a relatively low impact compared to other regions. There are some regions that will experience a maximum of three consecutive days with over 60 millimeters of rain. These are Belgrade, Srem, South Banat and Braničevo. Especially, the first three district represent an large size of the population. It seems as if the Belgrade district and the districts surrounding the capital will face the most precipitation in the future, while also representing the greatest part of the population. Zlatibor will experience the most days with extreme rainfall with over 175 days, but this is in the southwestern part of the country where not many people live.

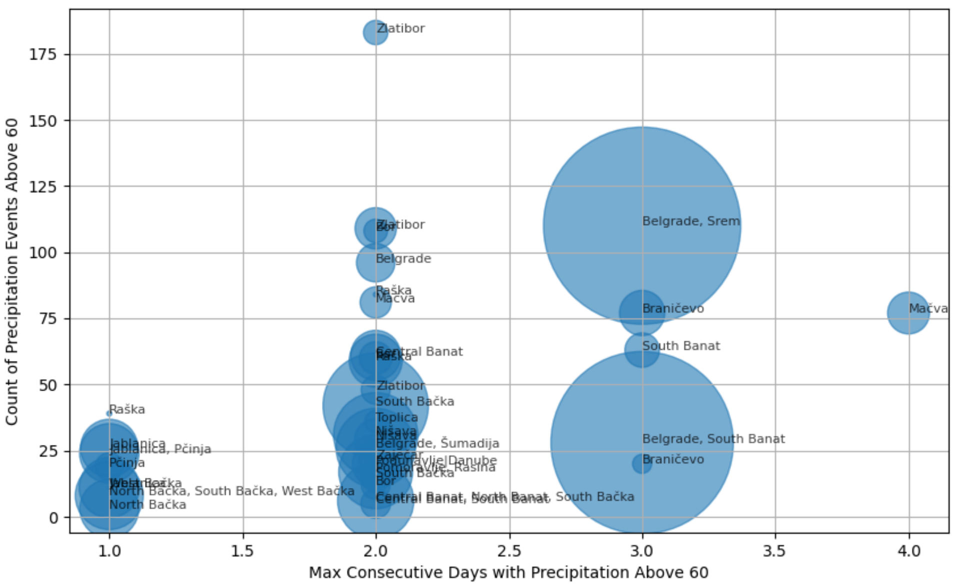

Figure 4.9: Count of days with precipitation over 60 millimeters for different regions and populations. Each blue data point represents a specific grid area, with the size of the data points corresponding to the population inside that grid and thus affected by these extreme precipitation events.

Temperature

Similar to the analysis for precipitation are historical and future temperature occurrences compared. Afterwards a closer look is taken into the temperature developments in the future. Finally the temperature phenomena are shown on the map of Serbia and for the population.

Figure 4.10 shows the historical and future development of temperature for every day of the year. The figures show the maximum, minimum and average temperature for each day. The dashed lines are the past, while the solid the lines depict the temperatures in the future. The minimum temperature in the past and future are almost equal through the entire year. Only near the end of the year the future minimum temperature reaches far more extreme values than in the past. The temperature averages in the future is greater than the past with a difference of around 3 °C over the entire year. The maximum temperatures show the greatest difference between the future and the past. During the beginning and end of the year, so during winter, the maximum temperatures show a similar difference to the average temperature increase of three percent. However, during the middle of the year, summer, the maximum temperature in the future can increase by at least 10 °C. It is clear that there is a large increase in temperature in Serbia in the future.

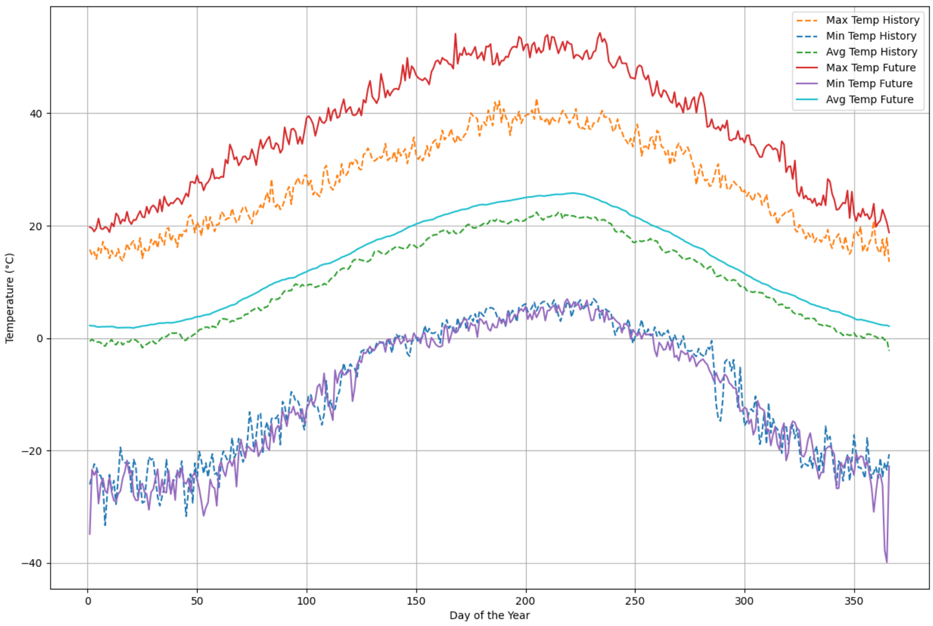

Figure 4.10: The historical and future daily temperature for every day of the year in Serbia. The plot shows the minimal, average and maximal daily temperature.

In Figure 4.11 a more detailed description of temperature developments in the future is given. The minimum temperature in 2015 is close to minus 30 °C and in 2100 it is closer minus 20 °C. Some years it already reaches above minus 20 °C, but this occurs rarely. However, the conclusion can be drawn that minimum temperature gradually increases. A similar conclusion can be drawn for the average temperatures in the future. The increase is very gradually from just above 10 °C in 2015 to more than 15 °C in 2100. The maximum temperatures show a similar pattern to the average and minimum, but the increase of maximum temperature is somewhat greater from around 45 °C in 2015 to close to 55 °C in 2100. Figure 4.11 also shows the number of days above 40 °C for each of the year. While for the first decade the number of days above 40 degrees is between 20 and 30, this increases very rapidly. From 2060 on there is almost no year with less than 80 days of temperatures above 40 degrees and by 2100 over 120 days with temperature over 40 degrees is not rare.

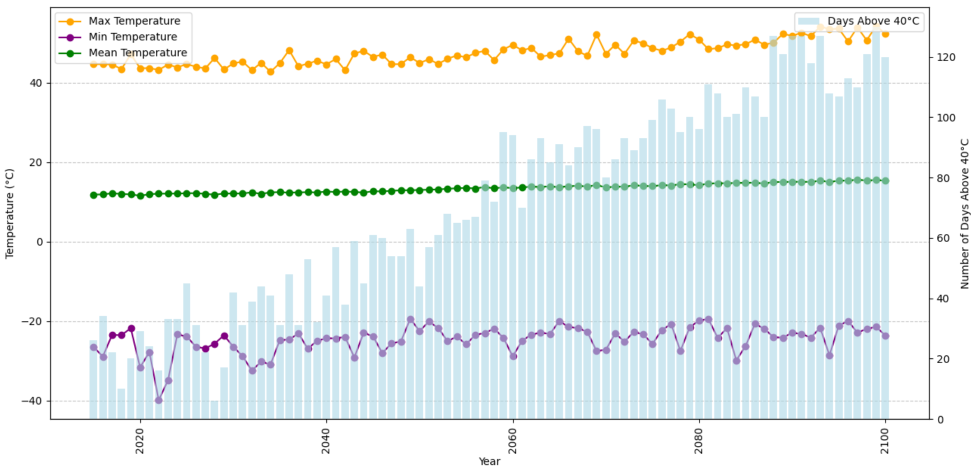

Figure 4.11: Temperature and extreme heat days in Serbia. The blue bars represent the number of days each year with maximum temperatures above 40 °C, indicating the frequency of extreme heat days. The orange line represents the maximum daily temperature (°C) recorded each year, the green line represents the mean daily temperature (°C), and the purple line represents the minimum daily temperature (°C) for each year.

The distribution of extreme heat days over Serbia is not equal. In figure 4.12 the number of extreme heat days are displayed for every grid. The red grids represent areas with a lot of days of extreme heat, while yellow and to a lesser extent orange areas represent the grids with the least days of extreme heat. The north of Serbia faces much more extreme heat days than the south of Serbia. In the Belgrade area and north of it the number of extreme heat days in the next century is over 5000, while in some southern parts of the country as little as 250 days of extreme heat days will occur. The differences within parts of the country are thus enormous.

Figure 4.13 displays the number of days with a temperature above 40 degrees and the maximum amount of consecutive days with temperature above 40 °C for different grids in Serbia. The size of the points depends on the population in the grid. The Belgrade and Šumadija region have the most consecutive days with temperature above 40 °C with 27 consecutive days. This grid is located to south of Belgrade. It represent a sizeable part of the population but by no means a great part. The other region with over 20 consecutive days of extreme temperatures are the Banat and Bačka region which are both in North-Serbia. The most densely populated regions of Serbia: Belgrade,

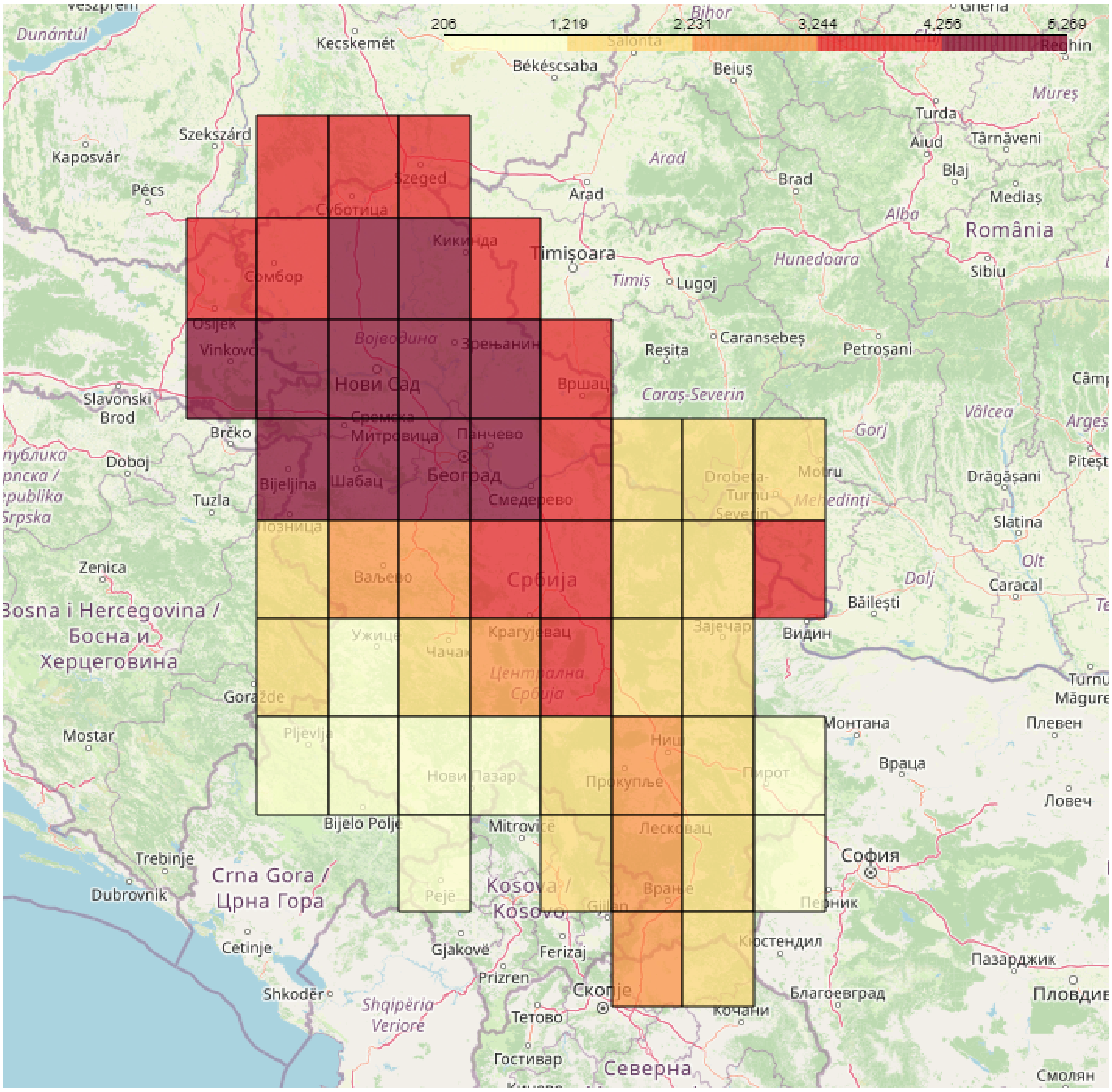

Figure 4.12: Spatial distribution of extreme heat days in Serbia. Each grid cell represents a specific geographic area where the number of days with temperatures exceeding 40 °C has been tallied. The color gradient, ranging from yellow to deep red, indicates the frequency of extreme heat events, with yellow representing fewer days and deep red representing the highest number of days with extreme heat.

Srem and South-Banat do experience a lot of days with temperatures above 40 °C, but this will not happen that consecutive relative to other areas in Serbia. That being said, these regions will face the most problems with extreme temperature as they are most populated. Southern regions in Serbia are less populated and will experience less extreme temperatures.

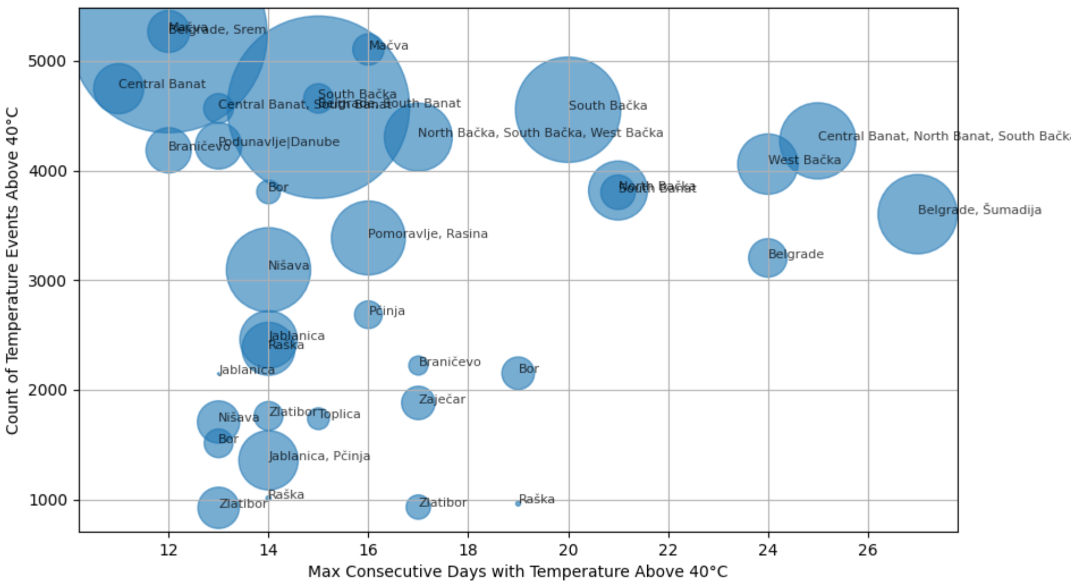

Figure 4.13: Count of days with temperatures exceeding 40 °C for different regions and populations. Each blue data point represents a specific grid area, with the size of the data points corresponding to the population inside that grid and thus affected by days of extreme heat.

Hazard

As explained in the methodology, the hazard is calculated by dividing the number of days of extreme weather by the total number of days. Table 4.3 shows the descriptive statistics for the hazard and the extreme weather events across the 52 grids. The mean number of days with extreme precipitation is almost 63, while extreme heat occurs on average for 2,820 days. Some regions have almost no days with extreme precipitation, while all regions experience at least 206 days of extreme temperatures. The regions with the most days of precipitation still experience six times fewer extreme weather days compared to regions with extreme heat. The hazard thus combines both extreme precipitation and heat. The mean hazard is 0.09, which means that, on average, nine percent of the days in a region will experience extreme weather. This equates to almost three times per month. The minimum value of the hazard is 0.01 and the maximum is 0.17, indicating significant differences between the regions.

Table 4.3: Descriptive Statistics for Hazard.

Statistic	Precipitation Days	Temperature Days	Hazard
Count	52	52	52
Mean	62.98	2,820.48	0.09
Std	113.88	1,447.08	0.05
Min	2.00	206.00	0.01
25%	17.75	1,515.75	0.05
50%	34.00	2,572.00	0.08
75%	77.00	4,090.50	0.13
Max	812.00	5,269.00	0.17

4.3 Criticality

With the exposure, vulnerability and hazard the criticality can be calculated according to (3.1). As explained before, the vulnerability can be calculated in two ways and therefore there are also two values of criticality for each medical facility. In Table 4.4 the descriptive statistics for the minimal and maximal criticality are displayed. As expected, the values for the minimal criticality are smaller than the maximal criticality. The mean minimal criticality is 381 and the mean maximal criticality 2,848, so the difference is quite significant. Also more than 50 percent of the medical facilities has a minimal criticality of 0.0, for 75 percent the minimal criticality is smaller than 15.2. The maximum value of minimal criticality is 16,597. This means that for that facility the amount of people that will lose health care access completely until 2100 equals 16,597. The minimal value of maximal criticality is 0.0, but the median is already 1,304 and the maximum is 31,226. This means that for the medical facility with the the maximum value of maximal criticality more than 31,000 lose health care access for the next century due to the extreme weather.

Table 4.4: Descriptive Statistics for Criticality.

Statistic	Min Criticality	Max Criticality
Count	233	233
Mean	381	2848
Std	1686	4404
Min	0.0	0.0
25%	0.0	378.4
50%	0.0	1,304.7
75%	15.2	3,214.1
Max	16,597.1	31,226.9

Figure 4.14 shows the minimal criticality for the population with health care access. The green households all have a criticality of 0. This means that for every extreme weather event they will not lose health care access. The green areas are mostly in the areas Belgrade, Novi Sad and in the most northern parts of the country. The reason that these households have a criticality of 0 is because they have multiple medical facilities they can visit. The other areas with health care access have also been color coded based on their values. So areas that are colored red relatively have the highest criticality, followed by orange and yellow. As previous, the grey shaded areas represent the population that does not have health care access. There is no clear pattern for the minimal criticality visible. In the northern part of Serbia all four colors are present. In the south of Serbia there are no big green regions, but the red, orange and yellow regions are often next to each other. Only south of Belgrade it seems as if the criticality is relatively higher. This could be due to the fact that lots of the heavy precipitation occurs there.

The maximal criticality for the facilities is displayed in Figure 4.15. As the maximal vulnerability always equals 1, there are no maximal criticality values of 0 and thus are there no green areas in in Figure 4.15. Besides that both Figure 4.14 and 4.15 look quite similar. Most areas with health care directly south of Belgrade and in the northwest of the country are red. Belgrade itself

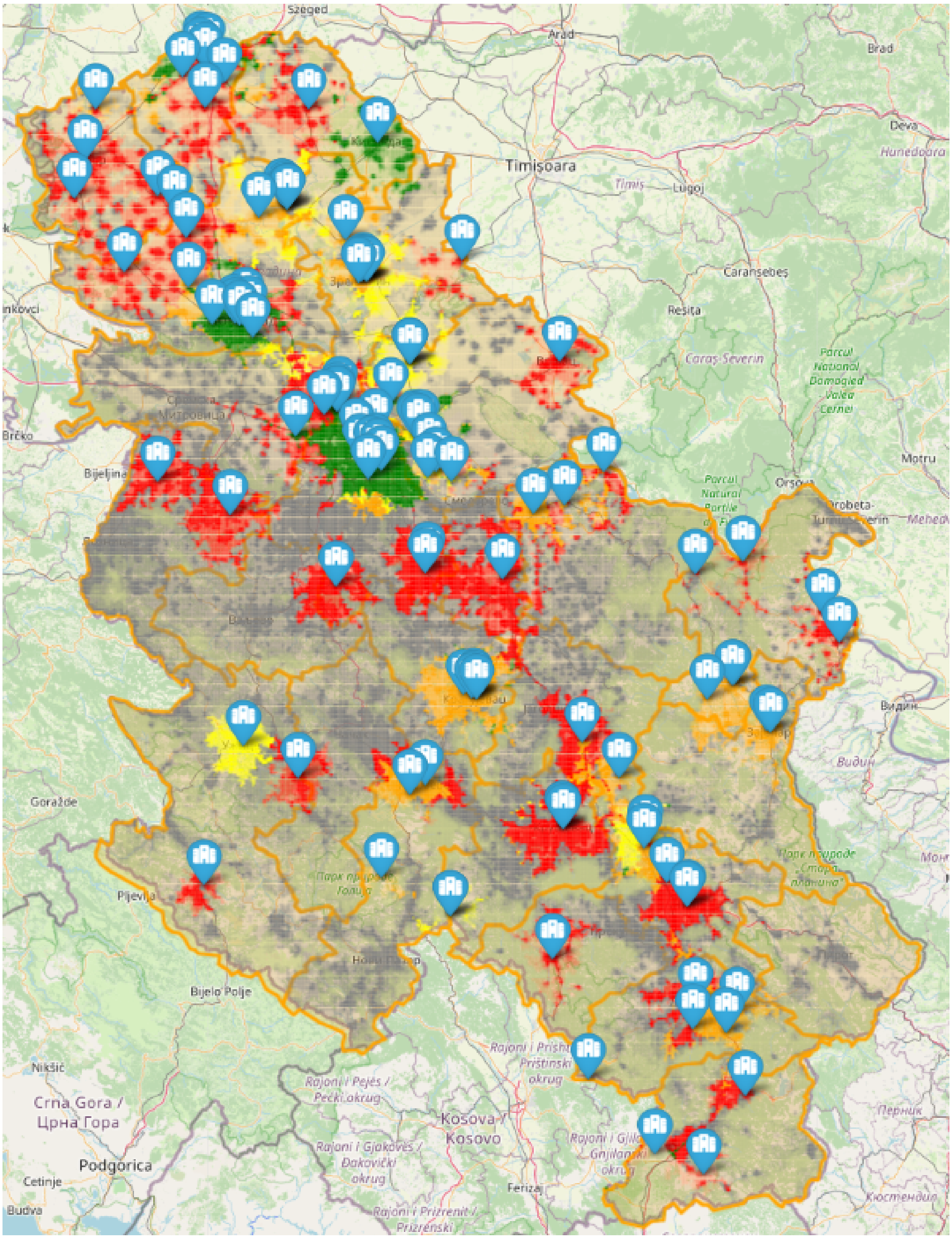

Figure 4.14: Map of minimal criticality of the Serbian population. The green areas represent regions where the population has a criticality of 0. The red, orange and yellow areas depict households with the higher minimal criticality with red areas having the highest minimal criticality. The grey areas on the map indicate parts of the population that do not have any healthcare access. The blue markers represent healthcare facilities for which the minimal criticality is greater than 0.

contains red, orange and yellow parts. Other cities with a relatively great population like Novi Sad in the north and Niš in the south have an orange criticality. Less densely densely populated areas in both the south and the north are yellow, but in general there is not an extremely clear pattern visible in Figure 4.15.

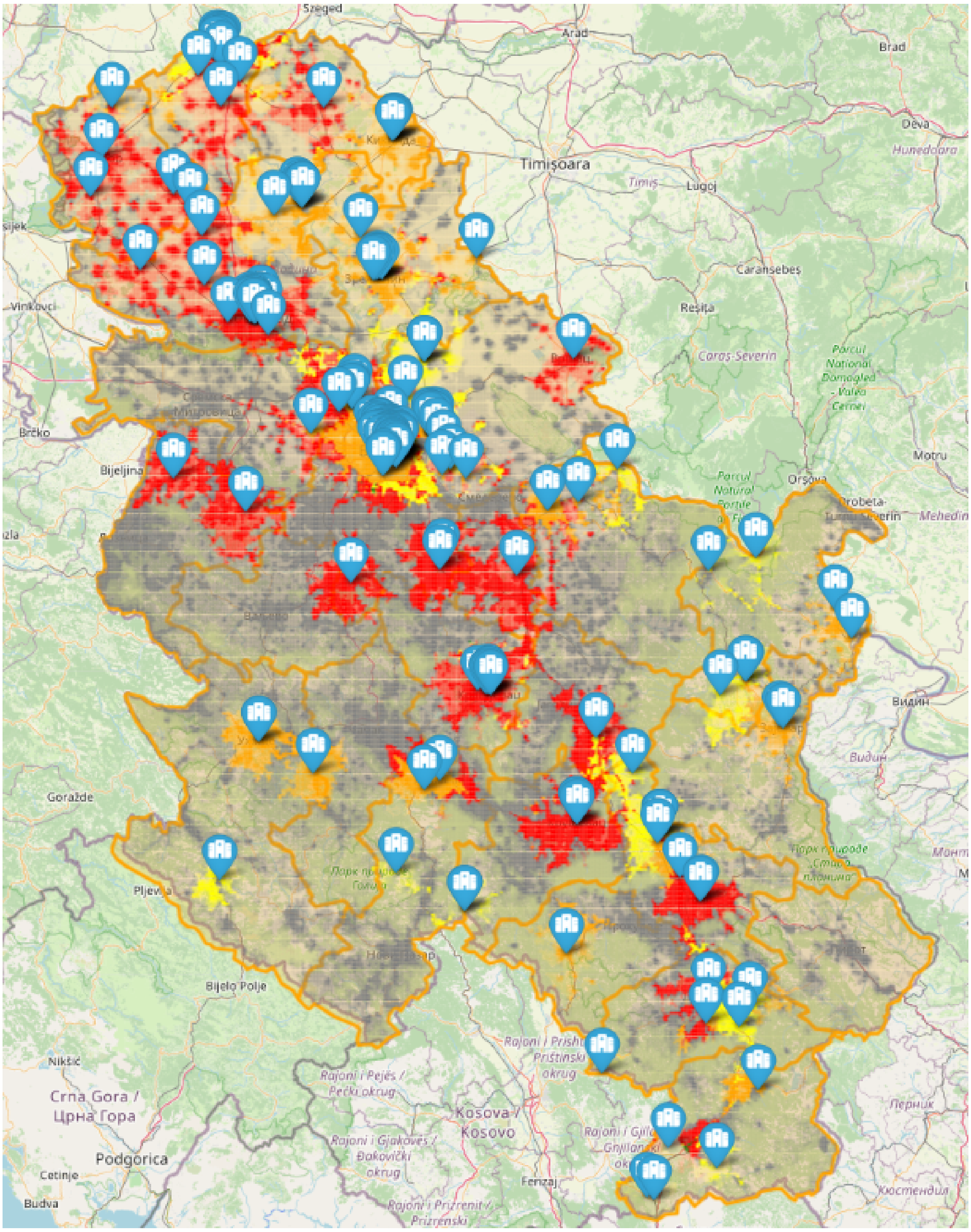

Figure 4.15: Map of maximal criticality of the Serbian population. The red, orange and yellow areas depict households with the different values of maximal criticality with red areas having the highest minimal criticality and yellow areas the lowest value of maximal criticality. The grey areas on the map indicate parts of the population that do not have any healthcare access. The blue markers represent healthcare facilities for which the maximal criticality is greater than 0.

Chapter 5

Conclusion

This thesis sets out to create a methodology to analyze the impact of climate change on infrastructure networks, with a specific focus on health care access in Serbia. The primary goal of this research is to develop a framework that integrates future climate risks into strategic infrastructure planning, thereby enhancing resilience and ensuring the continuity of essential services. The central research question guiding this study is: How do future climate events impact infrastructure networks?

The methodology proposes a comprehensive formulation of the criticality of infrastructure networks by integrating various concepts, like exposure, vulnerability and hazard. The approach is applicable in all countries as long as the data for those countries is available. Moreover, the methodology can be adapted fairly easily to fit a wide range of sectors, weather events and thresholds for extreme weather.

The case study for this study is the health care network in Serbia. The analysis revealed significant disparities in health care access across different regions of Serbia, emphasizing the critical nature of strategic infrastructure planning. Regions with higher population densities, such as Belgrade and Novi Sad, have better health care accessibility and multiple medical facilities, reducing their vulnerability. Conversely, rural and less populated areas face higher risks due to fewer health care facilities and longer travel times.

However, future projections of climate data underscore the necessity for urgent action. The next century some areas in Serbia will face a lot of days with extreme weather. Although the initial health care access in regions like Belgrade and surrounding areas is good, these regions are projected to face the most significant challenges due to high extreme weather. The criticality in these regions is high and the need for the health care network in that area to become climate-resilient is therefore the greatest.

A notable aspect of this thesis is the exploration of the current definition of vulnerability, which presents two interpretations: maximal and minimal vulnerability. On the one hand maximal vulnerability assumes that an extreme weather event will completely incapacitate all health care facilities, leaving the affected population without any alternatives. Minimal vulnerability, on the other hand, assumes the availability of all alternative facilities. This dichotomy highlights the need for a more nuanced approach. One potential solution is to group hospitals and health care facilities that are likely to be impacted simultaneously by an extreme weather event. By considering clusters of facilities rather than individual ones, we can achieve a more accurate assessment of vulnerability and better prepare for scenarios where multiple facilities are affected concurrently. These clusters can be based on the geographical landscape of a country: are two hospitals, for example, in the same valley or river delta which would ensure a flood will leave both hospitals unable to provide health care.

These examples highlight a limitation of the current approach to calculating extreme weather events. Presently, the calculation of hazard only focuses on the occurrence of heavy rain or high temperatures. However, events like floods also depend on, for example, groundwater levels. Similarly, high temperatures do not necessarily cause a hospital to fail in providing healthcare. It is the consequences of prolonged extreme heat, such as fires, that can damage hospitals or roads leading to them, thus impairing their ability to provide healthcare. However, the simplicity of the current approach for extreme weather are easily adjustable, making the methodology highly flexible such that it can be adapted to various weather phenomena. This flexibility allows researchers to refine their models to account for different types of extreme weather events beyond just heavy rain or high temperatures. For example, it can be modified to include parameters for droughts, snowstorms, or hurricanes, making it a versatile tool in predicting and analyzing a wide range of weather-related impacts. The choice that needs to be made is thus between a simple and widely applicable approach or a difficult but very granular approach.

Another limitation of the weather dataset is its lack of sensitivity. The data only provides specific points, which necessitates assumptions about the uniformity of weather conditions over larger regions. This approach can lead to inaccuracies, as weather can vary dramatically within short distances due to local geographic and atmospheric conditions. This variability can significantly affect the accuracy analyses, especially because a hospital is relatively small compared to the grids in the case study.

A final limitation is the need to integrate the road network with the healthcare network in our analysis. This integration is crucial because accessibility to healthcare facilities is heavily dependent on the transportation infrastructure. In emergency scenarios, such as during extreme weather events, damaged or obstructed roads can prevent patients from reaching hospitals, thereby impeding access to essential medical services. Including road networks in the analysis would provide a more comprehensive understanding of the resilience and vulnerabilities of the healthcare system. It would also help in planning and prioritizing infrastructure improvements to ensure that healthcare facilities remain accessible during and after extreme weather events. Without considering transportation, any assessment of the healthcare network's effectiveness remains incomplete, as the ability to deliver timely healthcare services is directly linked to the condition and availability of roads.

Ultimately, this thesis builds upon the PISA Toolkit developed by ABW. By incorporating the impact of future climate events and the criticality of public infrastructures into the PISA framework, this thesis enhances the toolkit's applicability and robustness. The adapted PISA framework would maximise the number of people who can access a climate-resilient facility instead of maximising the number of people that have health care access. The two key decision variables are also changed slightly: whether to build a new facility would become the decision to upgrade a facility to be climate resilient or not. The second decision variable would be whether households have access to an upgraded facility or not and instead of whether a household is connected any medical facility. hospital. The criticality values of each facility show how many people would be able to have health care access to climate-resilient medical facility. By optimizing these variables, the PISA Toolkit can ensure that more people are served by resilient health care facilities, enhancing overall preparedness for future climate impacts.

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