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Security Challenges and Economic-Geographical Metrics for Analyzing Safety to Achieve Sustainable Protection

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Abstract: In this article, we aim to develop the theoretical background for the possible application of Economic-Geographical metrics in the field of population protection. We deal with various options for analyzing the availability of "safety" for citizens using studied metrics. Among others, we apply well-known metrics such as the Gini coefficient, Hoover index and even establish their generalizations. We develop a theoretical background and evaluate our findings on generated and actual data. We find that the metrics used can have an opposite interpretation depending on the scenario we are considering. We also discover that some scenarios demand a modification to the usual metric. We conclude that Economic-Geographical metrics give valuable tools to address specific security challenges. Metric's generalizations could serve as a potent tool for other authors working in the field of population protection. Nevertheless, we must keep in mind that metrics also have drawbacks.

Keywords: security challenges; economic-geographical metrics; sustainable protection; civil defence; gini coefficient; shelter accessibility; urban security

Citation: Jekl, J; Jánský, J. Security Challenges and Economic-Geographical Metrics for Analyzing Safety to Achieve Sustainable Protection. *Sustainability* **2022**, *14*, 15161. https://doi.org/10.3390/su142215161

Academic Editor: Maria Rosa Trovato

Received: 22 September 2022
Accepted: 12 November 2022
Published: 16 November 2022

1. Introduction

Unfortunately, even in the 21st century, armed conflicts occur across continents and thus threaten people's lives. Populations drawn into conflict must be protected. The Universal Declaration of Human Rights and its Article 3 says that: 'Everyone has the right to life, liberty and security of person' [1]. Nevertheless, the obligation to protect the population stems not only from international conventions but also from a moral obligation. With the development of technology and weapons of mass destruction in the 20th century, it is now easy to kill large numbers of people at once. Moreover, with the continued development of technology, the possibility of protecting the population against these risks seems to be more difficult. In recent years, as a result of the COVID pandemic, we were able to obtain a realistic idea of the potential impact of a viral threat that could be brought about by the deliberate spread of a new virus created in a laboratory. Ugarte et al. in [2] documented the population loss in several countries during the first months of 2020. Similarly, protecting the population or endangering it can play a role in the development of a war conflict, the terrible example of which we, unfortunately, see every day in the news from Ukraine. Other authors highlight this issue as well. Possible threats to civilians are discussed, for instance, by Gosden in the article [3]. Thayer, in [4], discusses the influence of public sentiment on the outcome of the war.

In the event of a war conflict, it may be necessary to move people into a shelter. In some countries, a sufficient number of protective bunkers are built so that almost all the inhabitants can find shelter in them if necessary. Such a case is Switzerland, or Finland [5,6]. In other countries, however, the population is not protected to such an extent. A shelter is often built for only a small part of the population (about 10% in Czech Republic, see ([7], page 198)). In both cases, however, we can and should measure how evenly and effectively this protection occurs. To that end, we will look at ways to measure the distance people need to travel to get to a shelter, which is necessary for achieving sustainable protection by optimizing the situation as much as possible.

The general term distance can represent different entities in the broader context of the discussion. For example, the actual physical distance from point A to point B or the time required to use different means of transport with which the person can get to safety. Moreover, this type of “distance” may not be constant over time. It may depend on the traffic density or the type of danger. On the other hand, we deal with the evaluation of these distances rather than their actual measurement in our article. Emphasis is placed on the calculation of Economic-Geographical metrics, which are applicable in many scientific fields, as was shown by Cai in [8], whose article appeared recently in the scientific journal Nature.

In fact, the aim of this paper is similar in nature and that is to transfer knowledge from one field to another and investigate the theoretical background for possible applications of Economical-Geographical metrics in the field of population protection (a topic of civil defence). We wish to emphasize that transferring knowledge from one field to another is often a source of essential insights. Similar work in a different field with different metrics was conducted recently in [9] by Simone et al.

We develop applications of studied metrics throughout the article based on hypothetical examples. In the process, we use, among others, the Gini coefficient, the Hoover index, and the CEO-to-worker gap ratio. We combine established metrics with standard statistics, such as arithmetic mean or maximum distance, to obtain a more robust analysis. As far as we know, the discussion in literature is usually limited solely to the Gini coefficient, see [10–12], and the introduction of other Economical-Geographical metrics has not been conducted in this field yet. Moreover, we think the discussion about the Gini coefficient lacks acknowledging its drawbacks. On the other hand, the application of Economical-Geographical metrics in the field of population protection is relatively new and is still under development. Therefore, we wish to contribute our results to progress the discussion further. In our article, we find that the interpretation of metrics is highly dependent on the situation in which we are looking for protection and on the intention of the decision-making body that controls the development of the studied area. For example, it is natural that different threats require different protections and solutions. Zibulewsky also illustrates this natural fact in [13], highlighting the qualitative difference between natural and man-made disasters.

The obtained results serve as a theoretical basis for further research and possible applications of the used metrics in population protection. Our conclusions bring the most significant benefit in combination with the results of other authors who have developed another advanced methods for calculating the distance to safety. Therefore, we believe our results could be a beneficial tool for further development in the field. Finally, we wish to emphasize that throughout the article, we use the word safety to indicate places where people seek protection, help or a place to which they escape from danger.

2. Literature Review

In economics and other fields, we use available data and Economical-Geographical metrics to measure the even distribution of a resource. Among the most well-known metrics are the Gini coefficient and the Lorenz curve. They are applied to measure, for example, the distribution of wealth in society [14–16], the equality of access to health care in a region [17], the availability of employment for residents [18], or perhaps also the distribution of individual races across a geopolitical area [19]. These methods were subsequently applied in other areas as well. See, for example, the article [8], which shows how the Gini coefficient is applied to measure the clustering of bacteria, or [20], where the authors use the Gini coefficient to process heart rate measurements.

However, income inequality is often dependent on geographical distribution. As a result, in literature, we often encounter a situation where the evenness of distribution across a region is interpreted together with geographic information. This can be conducted, for example, by dividing the region into individual sub-regions and subsequently comparing these sub-regions with each other. See article [21], where the accessibility of museums to residents is measured similarly. The Gini coefficient is then sometimes used to interpret the region's inequality, where the number of museums across the region serves the same role as income in economic sources. However, whether a museum is accessible to residents is determined not only by how many facilities there are in the area, but also by how far they are from the residents and how long it takes to get to these facilities. Therefore, articles such as [22,23] measure the distance to a public park to interpret the accessibility in the region. This is sometimes done by measurement of Euclidean distances [23] or by the utilization of more sophisticated software tools [24]. Measuring health care services accessibility is sometimes measured with a combination of different tools where the distance is interpreted through sophisticated models [24–26] and the Gini coefficient together with Lorenz curve is sometimes considered to interpret these results [27,28]. Our article deals with distances, or more precisely, with the equal distribution of distances that must be covered for a citizen to get to safety. Accessibility of health care services is usually related to access inequality [27], however when it comes to emergency [29], the situation slightly changes as it is less about inequality and more about survival. The laws of the Czech Republic state the time during which an emergency service vehicle should arrive at any place in the Czech Republic (Act. No 374/2011 Coll., on the Emergency Medical Services, paragraph 5, [30]). However, this is only an upper limit (20 min), but we could also monitor how long it takes for the ambulance or the patient to arrive or how evenly this travel time is spread across the region. In this regard, it can also be one of the components of associated security risk (see [31]).

Not only access to health care and education, but also the protection of the population should ideally be available to the largest possible part of the population. In literature, we do not find many cases where Economic-Geographical metrics are used in relation to the topic of civil protection. In the case of a long-lasting drought, we can include the optimal distribution of water among the topics of civil defence. Such a topic is dealt with through the Gini coefficient in [32]. Urban security is covered in [33], where shelter accessibility is measured. Protection at the time of an earthquake is also considered. However, Ref. [33] focuses on measuring accessibility. An interpretation of these results through Economic-Geographical metrics is offered in relatively recent articles [10–12] which utilize the Gini coefficient. However, none of the other Economic-Geographical metrics was used. Another article that focuses on accessibility, this time concerning fire services, is [34]. In [9] appear metrics different from ours that could be applied to solve other security challenges, where the resilience of a drainage network is considered and proposed metrics are studied on theoretical examples and in an actual case-study. In this way, the aim of the article [9] is similar to ours.

Finally, we emphasize that we often find a statistical interpretation of the measured distances and corresponding values in the literature; see [18,22,34–37]. Methods covered in our article focus more on metrics and their interpretation. Statistical methods could be used in combination with our results as well.

3. Preliminaries

Assume that we are working with a finite ordered set of points $S \subset \mathbb{R}^2$ together with a set of end points $E \subset \mathbb{R}^2$. Consider a sequence of distances

$$x_i = \operatorname{dist}(s_i, E), \tag{1}$$

where s_i is the i-th point of S and $i \in \{1, \ldots, |S|\}$ ($|S|$ is the cardinality of the set S). There are different ways to compute the distance between two points. In our article, we work with the simple Euclidian distance in a plane as well as with the grid-based distance, which is more suitable for urban environment (see also [38]). These distances are an approximation of the distance in the real world. Practical applications of the theory should include more precise distances and consider information about elevation and means of transport, and consider the state of the road and its capacity, etc.

A natural metric for a finite number of distances would be to see the total amount of distances $D(x_n)$, i.e.,

$$T(x_n) = \sum_{i=1}^{|S|} x_i. \tag{2}$$

However, the value (2) loses some information about the sequence x_n and it is difficult to interpret this number without other information. For example, the interpretation of (2) is influenced by the units of x_n and by the information on which scale we are working on. For example, the metric T would be different if the set S contained thousands of points as compared to the case where it would contain only ten points.

Other problems arise when we consider the mean value $\bar{x}$ of x_n

$$\bar{x} = \frac{1}{|S|} \sum_{i=1}^{|S|} x_i. \tag{3}$$

To understand the mean value, we have to know at least whether the units of distances in x_n are kilometers or meters, or something else.

There are metrics which are unitless and work with a fixed scale. For example, when we say 50%, we know immediately what it means even without other information (for more on this, see [39] and references cited therein). We will define such metrics subsequently.

When x_n is a finite sequence, we find a permutation $\sigma(n)$ (for the definition of permutation, see [40]) such that $x_{\sigma(n)}$ is a nondecreasing sequence (generally there can be more than one permutation $\sigma(n)$). Then, the Lorenz function (sequence, curve), as is defined in [14] for a finite sequence x_n is given for $n \in \mathbb{N}, n \leq |S|$ as

$$L\left(\frac{n}{|S|}\right) = \sum_{i=1}^{n} \frac{x_{\sigma(i)}}{T}, \tag{4}$$

together with the fact that $L(0) = 0$. For a better visualization of the Lorenz function (denoted as $L(x_n)$) we will draw $L(x_n)$ together with the set of linear segments connecting neighbouring points, i.e., connecting points $\left[\frac{n}{|S|}, L\left(\frac{n}{|S|}\right)\right]$, $\left[\frac{n+1}{|S|}, L\left(\frac{n+1}{|S|}\right)\right]$.

The Lorenz function $L(x)$ originated in the work of O. Lorenz's dissertation: "The Economic Theory of Railroad Rates" (see [41]) which was recently reprinted as [42]. The classic interpretation of the Lorenz function is the following. If we have a sequence $y_n = x_{\sigma(n)}$ an ordered sequence x_n from the smallest value to the largest, then the value $L\left(\frac{n}{|S|}\right)$ represents how much the values $y_1, y_2, \ldots, y_n$ contribute to the total amount of distances $T(x_n)$. The following definition originated in the work of C. Gini (see [43]) and can be found, for example, in [14].

Definition 1. *The Gini coefficient G is given as*

$$G(x_n) = \frac{\sum_{i=1}^{|S|} \sum_{j=1}^{|S|} |x_i - x_j|}{2|S|(|S|-1)\bar{x}}. \tag{5}$$

In literature, we could also find the definition of the Gini coefficient via a different formula (see [44])

$$\frac{\sum_{i=1}^{|S|} \sum_{j=1}^{|S|} |x_i - x_j|}{2|S|^2\bar{x}}. \tag{6}$$

Nevertheless, Formula (6) differs from Definition 1 only in the terms $|S-1| \cdot |S|$ in the denominator. This is because for large values of $|S|$ is $\frac{|S-1|}{|S|}$ close to the value of one, we can consider this difference only as a rounding error.

There is an equivalent definition of the Gini coefficient via the Lorenz function. Here, the Gini coefficient is defined as an "area" between the Lorenz function $L(x)$ and the line of perfect equity $f(x) = x$. For a discrete sequence x_n it is given through formula (see [14])

$$G(x_n) = 2\sum_{i=1}^{|S|} \frac{i}{|S|} - L\left(\frac{i}{|S|}\right). \tag{7}$$

Nevertheless, formula (7) corresponds to the definition (6). To obtain the formula corresponding to Definition 1 we would have to multiply it by a factor $\frac{|S|}{|S|-1}$.

Another metric for measuring inequality which can be derived from the Lorenz function is the Hoover index. The Hoover index is applied in different fields under different names (see [45]).

Definition 2. *The Hoover index H is defined as*

$$H(x) = \frac{1}{2}\frac{\sum_{i=1}^{|S|} |x_i - \bar{x}|}{T}. \tag{8}$$

The Hoover index is a simple metric that shows how many distances we need to redistribute to obtain total equality, i.e., so that the sequence x_n would be a constant sequence. The Hoover index is usually considered with respect to the redistribution of wealth from rich to poor. Thus it is also known as the Robin Hood index (see [45]).

Notice that when the distances in x_n are the same, then $x_i = \bar{x}$, for all i, and hence $H = 0$. It is possible to obtain the value of the Hoover index as a maximum distance between the perfect equity line $f(x) = x$ and the Lorenz function (see [14]), i.e., for a discrete sequence x_n it is

$$H(x_n) = \max_{n\in\mathbb{N}\cap[1,|S|]} \frac{n}{|S|} - L\left(\frac{n}{|S|}\right). \tag{9}$$

The Gini and Hoover indices can both be traced to the Lorenz function $L(x)$. The following metric is independent of the Lorenz function and is based on the ratio between the salary of a CEO and the salary of an average worker (see [46]).

Definition 3. *The Gap score Ga is given as*

$$Ga(x_n) = \frac{\max x_n}{\hat{x}}, \tag{10}$$

where $\hat{x}$ is the median of the sequence x_n.

The Gap score works nicely when the values of x_n are unbounded from above. In this way, we observe how many times the largest distance is bigger than an average distance. On the other hand, when we assume that the values of x_n are positive and arbitrarily close to zero, then it would also be possible to consider the value

$$\frac{\hat{x}}{\min x_n}. \tag{11}$$

However, distances arbitrarily close to zero are not natural. Another problem could easily arise in the denominator because it can be that $\min x_n = 0$.

The above-mentioned indices provide a value that can be assigned to a set of distances. The information aggregated in these numbers tells us useful facts about the system. However, they are even more useful when we compare two or more systems together. On the other hand, the Lorenz function $L(x)$ may give us a potent visualization tool for better understanding of the situation. Such a visualization of the investigated problem is often times desired.

The Gini coefficient aims for an equal distribution. To avoid complete equality and to better asses the safety of the system, we could consider a modification of the Gini coefficient. Higher-order Gini coefficients G_n are defined for example in [47] (see also [48]) so that a larger focus is placed on the extremely poor people (in our context on the people with the shortest distances).

$$G_n = n(n+1)\sum_{i=1}^{|S|}\left(\frac{i}{|S|} - L\left(\frac{i}{|S|}\right)\right)\left(1-\frac{i}{|S|}\right)^{n-1}. \tag{12}$$

Of course, G_1 is the usual Gini coefficient (corresponding to the definition (7) and (6)), which we obtain by integrating the difference $x - L(x)$, i.e., we have an area between the line of perfect equity and between the Lorenz function. In the formula for higher order Ginis, we multiply the difference $x - L(x)$ by a weight function $(1-x)^n$, which puts more weight on shorter distances in x_n and they are more represented in the coefficient. Formula 12 is then just a discrete version of this integral.

Hence, the same inequality is expressed as a larger number for the higher n in G_n. Let us consider, as an example, the fixed Lorenz function $L(x) = x^2$. We can find that they are $G_1 = \frac{1}{3}$, $G_2 = \frac{1}{2}$, $G_3 = \frac{3}{5}$, $G_4 = \frac{2}{3}$, ... Nevertheless, it still holds $G_n \in [0,1]$ and $G_n = 0$ if and only if $L(x) = x$.

There are some natural drawbacks to the Gini and Hoover indices. Such drawbacks are well known in the field of measuring distribution inequality, and we would like to illustrate at least one of them.

Example 1. *Consider as an example Figure 1, created from modeled data and two different Lorenz functions L_1, L_2 that describe two different distributions of wealth. However, the area between L_1, L_2 and the line of perfect equity $f(x) = x$ is visibly the same. Hence, both distributions have the same Gini coefficient. We can interpret Figure 1 in the following manner. The blue line describes the situation where around 50% of distances (for values $x \in [0, 0.5]$ on the x-axis) are relatively small and represent 10% of the total sum T (for values $y \in [0, 0.1]$ on the y-axis). On the other hand, the red line describes the situation where around 10% of the distances (for values $x \in [0.9, 1]$ on the x-axis) represent 50% of the total sum T (for values $y \in [0.5, 1]$ on the y-axis).*

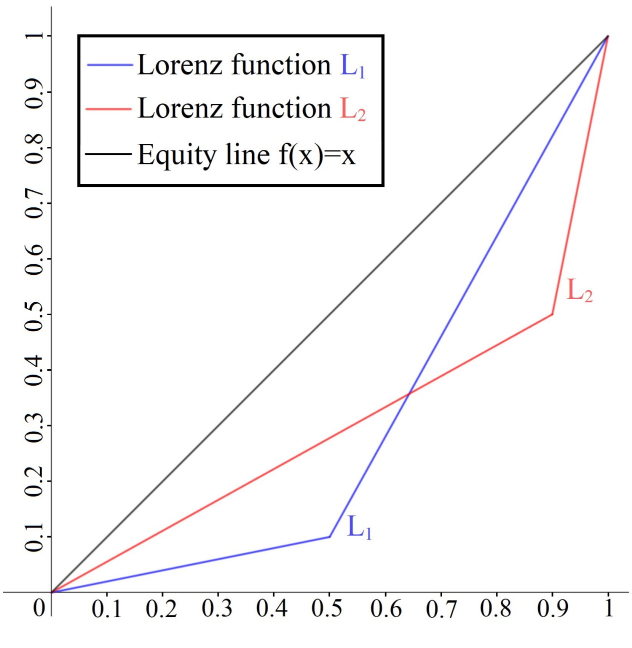

Figure 1. Two Lorenz functions with the same Gini coefficient.

Because of the symmetry between functions L_1 and L_2, we can observe that the maximal distance between Lorenz functions L_i and the line of perfect equity $f(x) = x$ satisfies

$$\max_{n \in \mathbb{N} \cap [1,|S|]} \frac{n}{|S|} - L_1\left(\frac{n}{|S|}\right) = \max_{n \in \mathbb{N} \cap [1,|S|]} \frac{n}{|S|} - L_2\left(\frac{n}{|S|}\right). \tag{13}$$

Hence, the Hoover index is the same for both distributions as well. Still, the functions L_1 and L_2 have a different Gap score as well as a different total sum of distances T.

The Lorenz function $L(x)$ is obtained as a cumulative sum of the ordered sequence x_n. Therefore, to better understand the Lorenz function, we can visualize the data that gave rise to Figure 1 by observing the ordered sequence x_n in Figure 2.

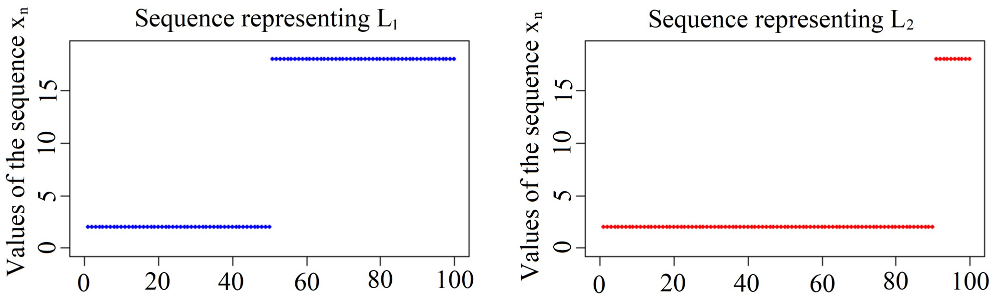

Figure 2. Ordered sequences x_n giving rise to Lorenz functions L_1 and L_2.

4. Methods and Materials

As stated above, the aim of this paper is to investigate the theoretical background for possible applications of Economical-Geographical metrics. This was achieved with a two step approach. Step 1: Investigation of the possible security challenges and a development of possible scenarios in which people seek safety. We investigated the applicability of said metrics based on these scenarios and their metric's generalizations were developed when necessary. Step 2: Generate or procure geographical data for the investigation of the defined scenarios. We have used software tools to simulate illustrative data and developed a simple custom code to create a mathematical graph from a map. We calculated all metrics based on these datasets and interpreted the metrics.

4.1. Generalized Metrics

To assess the overall safety of the region, we can utilize, when appropriate, the modifications of the Gap score and the Hoover index. Assume that we know that distance z to the evacuation border is safe with a high probability, i.e., the standard distance which people could cover in a reasonable amount of time with a reasonable probability. Such a distance can be specified by an expert, an experiment, or by other means. This distance depends on many variables and as such is highly situation-dependent. It may be a part of an evacuation zone where the risk is relatively small.

Next, let I be the set of indices of x_n such that $i \in I$ if and only if $x_i > z$. Then, we propose the Modified Gap score and the Modified Hoover index as

$$\begin{aligned} MGa &= \frac{\max x}{z}, \\ MH &= \frac{\sum_{n \in I}(x_n - z)}{\sum_{n \in I} x_n}. \end{aligned} \tag{14}$$

The interpretation of these indices is that MGa shows how many times bigger the maximal distance is compared to the safe distance z. Of course, when $MGa < 1$, that means that everyone lives in this reasonable distance. The MH index, on the other hand, shows which portion of the overall distances consists of distances above the safe distance z.

The weight function in G_n gives higher priority to poorer people (people who are close to safety). If we wish to represent richer people (people with larger distances), we can utilize when appropriate similar coefficients:

$$\overline{G}_n = n(n+1)\sum_{i=1}^{|S|}\left(\frac{i}{|S|} - L\left(\frac{i}{|S|}\right)\right)\left(\frac{i}{|S|}\right)^{n-1}. \quad (15)$$

4.2. Generated Data

We have generated a set of hundred points inside a circular area representing a city in the mathematical software R [49]. All elements of this set represent a location of a house where one person lives. Another point was later situated inside the circle to represent the safety location. All locations are represented as a set of coordinates. The distance was calculated by the software as a length of the shortest path connecting these two points. As there were no obstacles inside this circular area, the shortest path was a segment connecting the house with the safety.

Points were generated via the Continuous uniform distribution with a combination of fixed seed for reproducibility. Uniform distribution generated elements of two random sequences ρ_n, θ_n and we have calculated the coordinates for an n-th house $[x_n, y_n]$ with a combination of polar coordinates as

$$\begin{aligned} x_n &= \sqrt{\rho_n}\cos\theta_n, \\ y_n &= \sqrt{\rho_n}\sin\theta_n. \end{aligned} \quad (16)$$

Furthermore, we have added a denser cluster of points to simulate a city center more precisely in the same manner with just a smaller starting circle.

4.3. Map-Based Data

We have created a simple custom code to create a mathematical graph from a map with the tools of the mathematical software Matlab [50]. For that, we have used a background map from the service [51]. We have created a set of points manually at an approximate location of each house appearing in the map. These locations represent a set of nodes of a mathematical graph. We have added another set of nodes to represent street intersections. We have also manually added edges to the graph as a set of lines connecting nodes that were next to each other in the map. The length of the line representing the edge gave the weight to the edge, i.e., we have assigned each edge its physical distance. We have added later other nodes to the graph to represent locations of the safety. Matlab software offers built-in tools to work with graphs and algorithms to calculate the shortest path in the graph between two nodes and we have used these tools to calculate the distance from each house to the safety.

The chosen location is situated in the city of Brno, with which we are familiar and because we know that it is close to a military site. The area is demarcated by Zemědělská, Martinkova, Fišova, Schodová, Černopolní, Tomanova, and Lesnická streets. The location is part of an older development area full of smaller villas and houses and with smaller city blocks and narrower (but not too narrow) streets. Urban environment poses different security challenges than the situation in the countryside and we reflect this with the studied scenario.

5. Results

The following section is divided into two parts to separate the generated and real-world map-based data.

5.1. Model Scenarios and Their Interpretations with Metrics on Generated Data

The following part considers several scenarios for the modelled data and discusses different interpretations of the obtained coefficients. In this way, we would like to illustrate their possible applications.

Scenario 1: As was already said, Figure 3 shows a model situation where we have a set of points dispersed throughout the circular area, representing houses dispersed in a region. The scenario assumes that we would like to build a new hospital in the region and consider two different locations for the new hospital. They are marked in Figure 3 as red and blue circles. One should look at the situation from different angles in the decision process to choose the location. Here, we would like to present the hospital's accessibility point of view. We think that it should be clear that to build a safe and sustainable environment, we should construct hospitals accessible to everyone as much as is realistic.

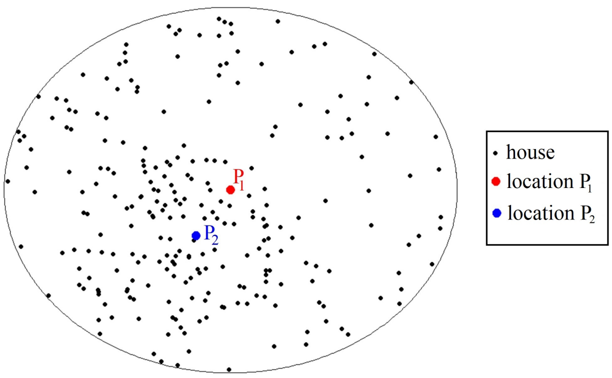

Figure 3. Possible locations for a new hospital—the red dot represents the first location P_1 and the blue dot represents the second location P_2. The black points represent houses.

The first point P_1 corresponds to a sequence of distances x_n^1, and the second point P_2 corresponds to a sequence of distances x_n^2. The system analysis starts by observing Figure 3 for a better understanding of the studied situation. Location P_1 lies in the middle of the circle, whereas location P_2 lies to the side. There is a denser cluster of houses around location P_2. Location P_2 is closer than P_1 to this denser cluster. However, it is also further from the border points in the circle's other half. Visual analysis is possible for points in a plane from Figure 3. Nevertheless, a grid network would not allow such a precise image to be drawn.

In Table 1, we can find a list of basic metrics. Notice that by these metrics, it seems that the second location P_2 is more optimal than location $P1$. It has a smaller mean and median distance, meaning the average house would be closer to the hospital. Similarly, the sum of distance T is smaller, which means that the hospital would be closer overall. However, we see this is for the cost of the increased maximal distance. Table 1 does not show whether the maximal distance changes only for one house or several. Nevertheless, we can see in Figure 3 that the maximal distances are longer for more than one house.

Table 1. Table with natural metrics.

Sequence	T	$\bar{x}$	$\hat{x}$	$\max x$
x^1	301.44	1.21	1.24	1.98
x^2	288.33	1.15	1.01	2.53

For each of the sequences x^1, x^2 was calculated: Total amount of distances T, mean distance $\bar{x}$, median distance $\hat{x}$ and maximal distance $\max x$. Software R [49] was used for calculations.

However, the Gini coefficient, Gap score, as well as Hoover index show a different situation. All the metrics in Table 2 prefer the first position P_1. Different metrics show that the first position P_1 offers more equal access to the location. In fact, the second position

P_2 is more advantageous for a certain group of houses at the cost of a longer distance for another group of people. This disparity sums into smaller average and median distances, which we see in Table 1. This is probably because the group of disadvantaged people is smaller than those of privileged people. To see the Lorenz functions of the situation, see Figure 4.

Table 2. The table of equality metrics for locations P_1 and P_2.

Sequence	G	Ga	H
x^1	0.241	1.6	0.18
x^2	0.309	2.5	0.19

The values of G, Ga, H were calculated using (7), (8), (10), respectively. All values were calculated using a software R [49].

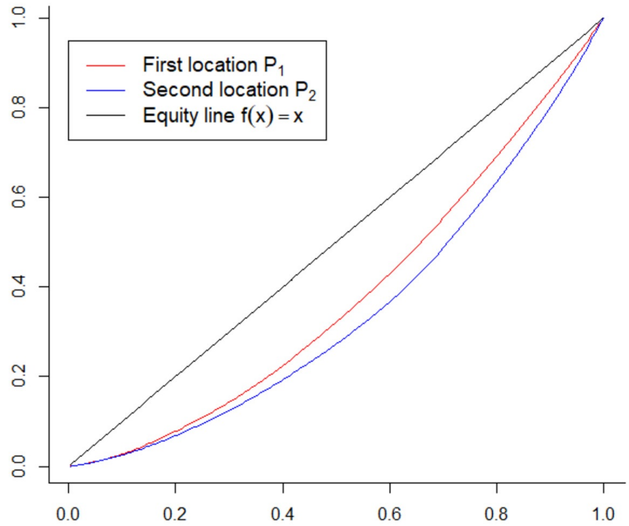

Figure 4. Lorenz function for the possible hospital locations P_1 and P_2.

In Table 2, we can observe that the biggest difference is between the Gap scores for locations P_1 and P_2. There are two reasons for this, and we can see them in Table 1. First of all, the maximal distance is smaller for the first location P_1, i.e., $\max x_1 < \max x_2$. The second reason is that the second location P_2 has a smaller median distance than the location P_1, i.e., $\widehat{x_1} > \widehat{x_2}$.

Regarding public property, it seems natural that the commodity should be distributed as equally as possible. Furthermore, we think hospitals should naturally be built so that we do not exclude any group and everyone can reach the hospital in a certain amount of time. Such a result is achieved better by the first location. On the other hand, we still need to optimize the location to achieve sustainable security and avoid losing resources.

Notice that in Table 1, the mean distance of P_2 decreased a lot less than the increase of the maximal distance. Here, we have to consider the phenomenon of diminishing returns. A diminishing return occurs when the change becomes so tiny at a certain point that it is negligible. Hence, we have to decide whether the change in mean distance here is worth the change in the maximal distance. For example, the increase in the mean distance represents the change in average distance for the majority, and it will take most people longer to get to the hospital. However, this could be perhaps a change of several seconds. We see in Table 1 that the maximal distance changed ten times as much as the mean distance, i.e., the change for a minority, which is ten times larger than the change for the majority. Therefore, a change of several seconds for the majority can result in a change of several minutes for the minority. Ultimately, we must decide what to prefer and which compromise is more reasonable by considering every consequence of our decision. Our viewpoint is only one side of a more complex problem.

Scenario 2: Imagine that the points P_1 and P_2 represent, at this time, possible locations for building a new protective shelter. In the shelter, people will seek protection from danger in their time of need. Such danger may arrive quickly or more slowly. In addition, such a shelter can have a limited capacity or it may accommodate all the people in the area; see [7].

The interpretation of the Gini coefficient G remains in this new scenario the same. The difference here is that we may want different outcomes. The small value of G means that the shelter would be equal distance from the houses. All the people would need a similar amount of time to get to the shelter, and they would arrive probably at a similar time. This could cause a problem, especially when the capacity of the shelter entrance would be limited. Furthermore, the other drawback of the Gini coefficient is that it only measures how equally a resource is distributed. We may have small G even when the shelter would be very far from the houses. For example, a shelter built on the other side of the planet is equally distanced from everyone in the area because their distance is, at this scale, negligible.

On the other hand, G close to 1 means in this scenario that most houses are situated relatively closer to the shelter and that only a minority of houses are significantly farther. In some situations, that can be a desired situation, as in some cases, we may want to favour a majority. For example, a limited budget or limited resources may give rise to such compromises.

Nevertheless, we think the best application of a Gini coefficient here lies in identifying potential problems. The Gini coefficient together with the Lorenz function can help us to see whether there is a group with a greater need of help. Take, for example, Figure 1 and its Lorenz function L_2. There, we saw a group of about 10% people who were much farther than the rest of the population. Hence, we may identify potential problems in the region.

We have calculated the higher-order Gini coefficients in Table 3. We observe that the values increase with increasing order. We think this approach is also applicable for the comparison of different regions. Based on assumptions, we would calculate, for example, G_3 instead of G_1, where we wish to emphasize different conditions in the model. In fact, it is natural that urban security faces different challenges than the countryside.

Table 3. Higher order Gini coefficients for locations P_1 and P_2.

Distances	G_1	G_2	G_3	G_6
x^1	0.241	0.371	0.455	0.513
x^2	0.309	0.448	0.527	0.579

The values were calculated using (12) where we put n=1, 2, 3, 6. All values were calculated using software R [49].

Scenario 3: Finally, imagine that Figure 3 represents an evacuation zone around certain causes of risk we want to manage. The border would mark the zone from which we may need to evacuate people from their houses. The point P_1 in the middle of the circle could represent, in this scenario, a nuclear power plant or a chemical plant.

In Figure 5, we observe a situation where we try to add four new houses at a specified location. We can observe how a new house changes the Gini coefficient G. While it was initially G = 0.366, it is now G = 0.369. We can conclude that the houses would only slightly increase the Gini coefficient. The change does not seem significant at this moment and probably does not cause a risky situation. Nevertheless, we see that the Gini coefficient with this change increases; thus, houses at this location are farther than houses in an equal distance distribution (if the distance is similar to other distances, then the Gini coefficient would stay the same or even go down). Moreover, if we continue adding houses to this location, we could create a risky group.

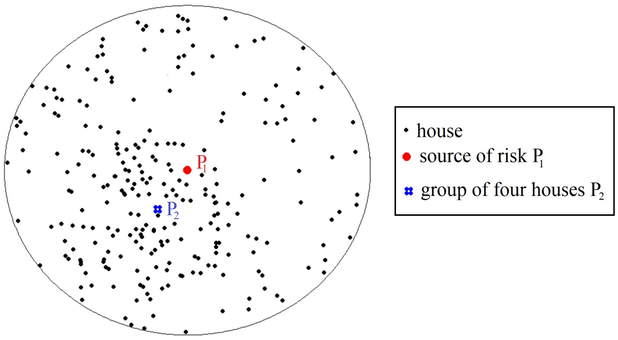

Figure 5. We see a set of black points representing houses inside a circular evacuation zone. We investigate the situation where we intend to add a group of four houses P_2 marked in blue.

In Figure 3, we arbitrarily set z as one-third of the evacuation radius. For such a z, we obtain $MGa = 2.78$ and $MH = 0.429$. Therefore, we see that people living farther away from the area's border than the safe distance z spend about 40% of their distance out of the zone. In combination with other information, this could mean that people inside this circle might need to take other precautionary steps when managing the risk of living in the location. The value of MGa is unsurprising, since we consider the circular evacuation zone here, and z is one-third of its radius. Proposed metrics are not limited solely to an evacuation from a circular area. However, they could also serve as a tool to interpret other scenarios, for example, an evacuation from a region along the river in case of a flood. See also [52] and its discussion of the threat of floods.

5.2. Model Scenario Based on the Actual World Map

The previous section looked at the theoretical implementation of the metrics used. However, we have randomly generated the second section's map. Therefore, we present the following scenario based on the actual world's system of roads.

Figure 6 illustrates part of the city, where we have obtained the background map from [51]. We see several blocks of the city of Brno situated in the Czech Republic. We have created a grid connecting the houses (indicated by red squares) through the city streets (we have marked road intersections as small blue circles). We have connected houses to the intersections at the ends of their streets, and we have connected intersections through connections representing actual roads. Thus we have a graph where the nodes represent an actual system of intersections and houses, and the graph's edges represent an existing system of roads. Finally, the pink squares represent possible pick-up locations for the evacuation (more on the scenario later), to which we will refer solely as locations A, B, or C.

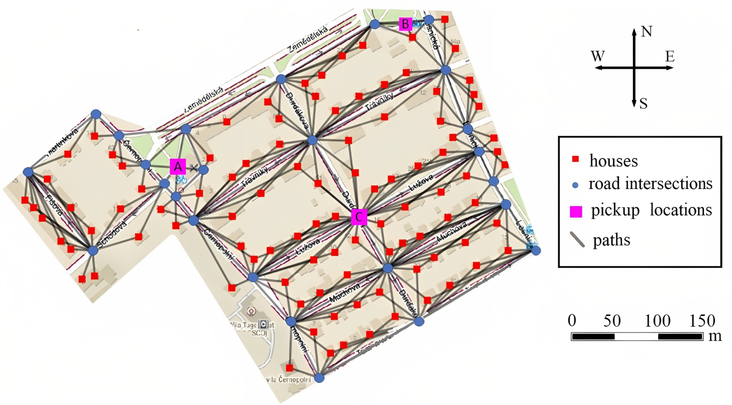

Figure 6. Map of several blocks of the city of Brno [53]. Red squares represent the houses, blue circles represent road intersections, and pink squares represent possible pick-up locations for the evacuation. The image was created in Matlab, which could retrieve the necessary coordinates and perform all the calculations. Source: own.

We have also calculated the length of each edge connecting nodes, and therefore we can calculate the shortest distance between two nodes. In view of the fact that red squares represent houses and pink squares represent pick-up locations, we cannot travel through the graph via red nodes. Hence, in the computation of the distance, we allow travelling merely through blue roads and intersections.

Sometimes when there are not enough protective shelters for everyone, it might be necessary to evacuate people. Hence, the scenario this time is to find the best location to pick people up in case of a sudden evacuation from that area (in fact, the chosen location is close to the military area situated in the city). We would pick up people by buses and find the best place to set up as a meeting point. Figure 6 contains three different locations. However, in each scenario, only one location is considered for the pick up of evacuees, and the rest of the locations then serve as an intersection only. We have computed the shortest distance through the grid via Matlab [50], and for these distances, we have evaluated the metrics considered in our article. The results appear in Table 4. If the metric has a unit, we have used meters. Nevertheless, several metrics here are unitless.

Table 4. Different metrics for locations A, B, and C.

Location	T	$\bar{x}$	$\hat{x}$	$\max x$	G	Ga	H
Location A	28,688	290	280	558	0.259	1.995	0.189
Location B	35,323	357	371	607	0.246	1.637	0.178
Location C	20,697	209	191	495	0.321	2.592	0.226

All locations A, B, and C are considered separately, and for each location is generated a sequence of distances x_n from Figure 6. The values in columns $T, \bar{x}, G, Ga, H$ were calculated using the relations (2), (3), (1), (8), (10), respectively. The value $\hat{x}$ is the median of the sequence x_n and $\max x$ is its maximum. Note, the values in the columns $T, \bar{x}, \hat{x}, \max x$ are in meters. The values in the columns G, Ga, H are unitless. All values were calculated using the software Matlab [50].

Location B has the largest T as well as the median and mean distances. Therefore, we observe that location B is, in a sense, the farthest. On the other hand, we also see that the Gini coefficient is the smallest. It may be because the distances to location B are generally large for everyone. Notice that location B is generally far from houses in the west corner of the area in Figure 6.

Location A offers improvements in T, $\bar{x}$ and $\hat{x}$, as compared to location B. The Gini coefficient increased slightly as compared to location B. This increase indicated an increase in inequality for location A. Nevertheless, this could also be a good thing because we can notice that location A is still further from the corner houses on the east side of the area, and yet it is closer to many more houses than location B. Hence, it is far away from some houses. However, the number is smaller than with location B. Additionally, the increase in the Gini coefficient is also relatively small. We wish to point out that the maximal distance decreased as well, and thus based on Table 4. We can say that location A is probably better than location B.

Furthermore, we observe even better improvements to the metrics for location C. The maximal distance is the smallest, together with mean and median distances. These facts indicate that location C is closer to the average house as well as to the houses farther from the pick-up location. It is not that surprising, as location C lies in the centre of the area. On the other hand, the Gini coefficient is the largest here. We assume this is caused by the location' C improvement over locations A and B, which is more prominent for some people than others, even when the overall situation improved. Hence, location C is probably better than locations A and B. However, here the situation is also a lot more unequal.

Finally, we again remark that the calculated metrics do not describe the whole picture. For example, the metrics do not consider the accessibility of locations A, B, and C. It seems easier to access location B because it is located in a park next to a broad road. On the other hand, due to the historical development of the area and the resulting curly roads, it is not as easy to access location A as the other locations. Perhaps it would be necessary to reach location A via the road connecting locations A and B. Therefore, the buses might travel longer to location A than B.

Similarly, location C is centralized in the middle of the area. Therefore, the buses could be hindered by evacuees travelling to the meeting point. At the same time, locations A and B might not suffer as much because the locations lie on the border of the considered area and next to the public parks, where there is more room to organize evacuees. Based on previous observations, we would like to suggest another location on the corner between locations A and C. See location D in Figure 7 as well as its metrics evaluated in Table 5.

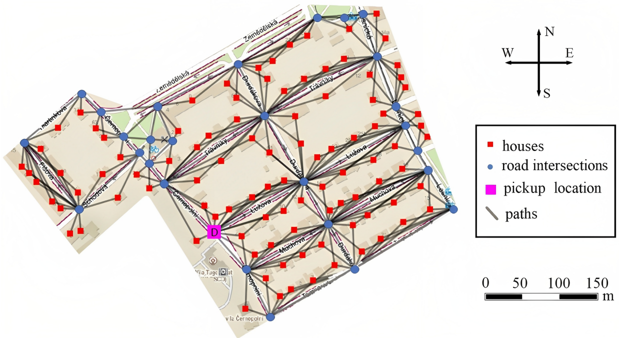

Figure 7. The map from Figure 6 in which pickup locations A, B, and C have been removed, and a new pickup location D is being considered. Location D lies on the corner between locations A and C. Source: own.

Table 5. Metrics of the location D.

Location	T	$\bar{x}$	$\hat{x}$	max x	G	Ga	H
Location D	23,971	242	250	457	0.25	1.829	0.182

We have calculated all the necessary values using the same procedure as in Table 4 based on distances x_n from Figure 7. It then calculated all the necessary values using the same procedure as in Table 4. All values were calculated using the software Matlab [50].

Location D still seems relatively in the centre and closer to the block of houses west of the area. If we look at Figure 7, we observe that the mean distance of location D is between the mean distances of locations A and C. Nevertheless, notice that the Gini coefficient here is smaller than for location A. Hence, we assume that distances are distributed relatively fairly for location D. Furthermore, notice that the maximal distance is the smallest for location D. Therefore, we would argue that location D is the best of the investigated locations if we base our opinion solely on the metrics. It is closer to an average person as well as to the person farthest away.

Figure 8 shows Lorenz curves and cumulative sums of ordered distances for each location. Notice that the Lorenz curves for locations B and D are almost identical, even if they describe a very different situation. On the other hand, the cumulative sum of distances for location C shows that the total amount of distances rises more sharply at its end (we see a change in slope). Hence, we see a group of people for whom location C is qualitatively further away.

Finally, we wish to emphasize several drawbacks of the proposed scenario. For example, we look only at the houses, not the number of people living in each house. Therefore, we disadvantage people living in flats and apartment buildings. Similarly, we connect the houses with intersections directly. Hence, the calculated distance is not completely precise, as the house has some size, and we treat them as points in a plane. In reality, it may take some time to get out of the house, and for bigger houses, this time may be considerable. Nevertheless, here we offer just the modelled situation, and we understand that the actual application would have to deal with such issues. Moreover, similar drawbacks appear in other models as well. See the discussion in [29].

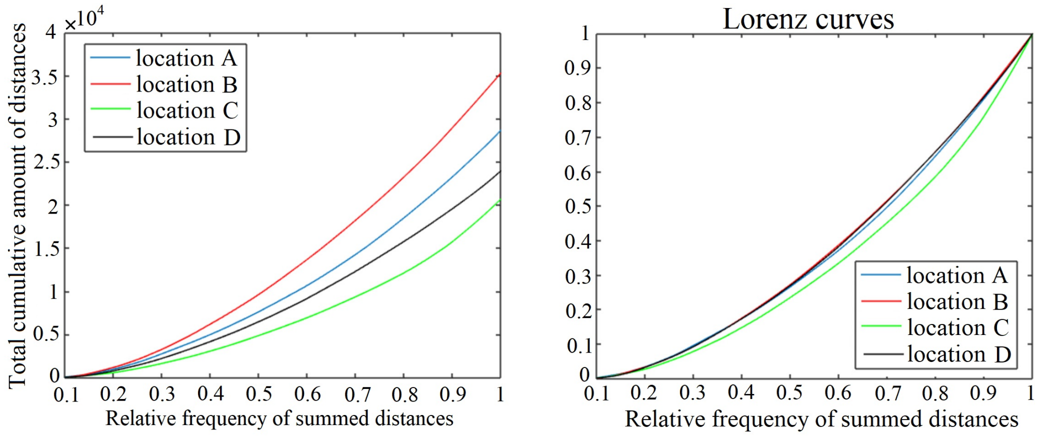

Figure 8. Lorenz curves and cumulative sums of distances.

6. Discussion

It is possible to look at various parts of the population protection as with human factors in article [54], or the financial side of disaster mitigation in [55]. We have focused only on a small part of the complex problem. The primary purpose of our article was to present possible ways of using different metrics to improve the safety of everyday people. The contribution of our article lies in a new way of interpreting economic coefficients for population protection from the perspective of distance to safety. On the other hand, article [41] looks at the problem from an economic perspective through similar tools. See the chapter [56] and various discussed threats that may impact the development of communities. We expect that the metrics studied in our article could play a role in protecting against other threats.

6.1. Findings and Their Implications

The discussion about population protection concerning measuring physical distance seemed to focus recently on obtaining the data and measuring the physical distance via modern tools. See articles [17,22]. Whereas, our article focuses more on the interpretation of the measured distance. Obtained data are often times in the literature interpreted as a graphical output together with Moran's I [24–26], or through statistical models [18,22,34–37]. Our article offers other tools and metrics that could be implemented, for example, in [24–26,29,33,34] to better interpret the obtained results. The Gini coefficient allows aggregated interpretation of results, and as such, it is being used in the literature from different backgrounds [8,15]. However, it also appears in the investigation of geographical inequality [21,22,57].

Moreover, articles [27,28] measure access to healthcare services and therefore utilize the Gini coefficient, as they have social inequality in mind. On the other hand, we did not find a situation where other Economic-Geographical metrics would be used for measuring inequality. Furthermore, we have demonstrated that the interpretation of Economic-Geographical metrics can change depending on the studied scenario. We have also proposed modifications to studied metrics to suit better these metrics for population protection and the studied scenario. On the other hand, the question is usually formulated as an inequality question in the literature and then the classic Gini coefficient is used [10–12]. However, the same is true when we leave the field of population protection. Articles [21,22,57] could also use our theoretical results to further their study.

We have used the metrics to interpret the distances. It is also possible to use metrics to interpret other values as well. Articles [10–12] measure shelter accessibility in an urban environment and interpret the results through the Gini coefficient. In this way, they highlight the inherently dangerous situation when people do not have access to protection. Nevertheless, article [12] shows a highly unequal situation, and we can question how to interpret these results. We have demonstrated that a highly unequal situation can have meaning when discussing shelter access. It might be, for example, possible that the situation in [12] would be widely different if we focus on a smaller part of the investigated region. Including other metrics could also reinterpret the situation, for example, by considering the higher-order Gini coefficient we have used. The proposed metrics are not perfect and have some drawbacks, as is well known in the field of economics and as illustrated by Example 1. Therefore, we must be cautious when using them.

The studied metrics only look at the situation from a certain point of view and should, therefore, only serve as part of a complex decision-making process. Similar to, for example, the decision model created in [58], which tracks several values to analyze the risk of flooding or to aid with the investigation to propose new measures for the development of an area [59–61]. See also [62], where the discussion focuses on a more complex model for assessing urban security.

6.2. Limitations and Opportunities for Future Research

As was said, we have focused on metrics and their interpretation for different scenarios. However, we believe better results would be obtained if we could calculate the distances with better precision. The same issue appears in article [23]. GIS software tools could be implemented, such as (ArcGIS [63], or QGIS [64]) as was conducted, for example, in [24,33]. Similarly, we have considered all locations as simple points. However, it takes longer to leave a larger building than a small house. Therefore, we should consider each location's shape, as was conducted, for example, in [29]. Nevertheless, the number of floors in each building also should be considered. Moreover, the travel times when disaster comes are inherently uncertain, as usual assumptions are unusable, see [65]. Therefore, the model implementing the travel time uncertainty in [66] could also be applied.

We have studied several scenarios to illustrate possible applications of studied metrics. Recent articles [10–12] investigate the population protection against earthquakes, where public parks and playgrounds serve as a source of protection. Such shelters do not disappear in an emergency. On the other hand, there are also man-made disasters, see [67], and thus in some scenarios, a shelter can even disappear, e.g., because of an attack. In one scenario, we investigated a change resulting from an addition of a new house. A system's resilience could be investigated by looking at the impact of the shelter's disappearance. The study of system resilience is also significant in population protection. See article [68] that discusses the reliability of water distribution networks.

From a purely mathematical point of view, it would be helpful to find an algorithm which would calculate for a predefined set of points S a point E such that the Gini coefficient G for distances $\mathrm{dist}(x_i, E)$ is the smallest. We conjecture that the Least square method could serve as a tool to find the point with the smallest total amount of distances T. It is unclear whether this method could yield results in the investigation of the Gini coefficient G. Such an algorithm could then serve as a tool for optimizing shelter location [67].

7. Conclusions

The main aim of our paper was to investigate theoretical applications of Economic-Geographical metrics in population protection based on different scenarios. We have discovered that the metrics cannot be mindlessly translated and need to be considered in the context of the studied scenario. We have also observed that some scenarios demand a modification to the metric. The obtained tools are applicable to promote other related fields further and could serve as a tool in the decision process across different fields where population protection is considered. Other scholars should consider our conclusions when applying Economic-Geographical metrics in their research.

Author Contributions: Conceptualization, J.J. (Jan Jekl); Methodology, J.J. (Jan Jekl); Software, J.J. (Jan Jekl) and J.J. (Jiří Jánský); Validation, J.J. (Jan Jekl) and J.J. (Jiří Jánský); Formal analysis, J.J. (Jan Jekl) and J.J. (Jiří Jánský); Writing—original draft preparation, J.J. (Jan Jekl); Writing—review and editing, J.J. (Jan Jekl) and J.J. (Jiří Jánský); Visualization, J.J. (Jan Jekl); Project administration, J.J. (Jan Jekl). All authors have read and agreed to the published version of the manuscript.

Funding: This research work was supported by the Project for the Development of the Organization 'DZRO Military autonomous and robotic systems'.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors would like to express their gratitude to Š. Hošková-Mayerová for her help with the manuscript.

Conflicts of Interest: The author Jan Jekl declares that he is also associated with the Masaryk University in Brno, Czech Republic.

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