



“Sponge Maps”: Using the Concept of Value by Area Maps for Avoiding the Area Size Bias in Choropleth Maps

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Abstract

A well-known problem with choropleth maps is the cognitively induced effect that larger regions are perceived as more dominant. Consequently, unsatisfactory detection rates for small areas can result, which becomes relevant when important spatial features or patterns are explored (e.g., regions with maximum values). One possible approach to avoiding the area size bias is the use of cartograms. While there is already some work on Equal Area Unit Maps, little or no research has been done on the possibility of applying the concept of Value By Area Maps to transform the reference area maps. One goal of this article is to introduce the concept of so-called “Sponge Maps”, which distort the base maps independently of thematic attributes, but depending on the need to show or emphasize certain areas of interest. The second goal of the article is to answer the overall research question whether Sponge Maps actually reduce the area size bias and improve the detectability of maximum value regions. A user study was able to verify the effectiveness of the Sponge Map approach in particular. However, it also became clear that not only the area size bias plays a role in the detection of important regions—dependencies on the absolute position (top-down bias), compactness or conspicuous shape (shape bias), the familiarity (awareness bias), the color intensity (darkness bias) and not least by the distortions in the Sponge Maps as such (distortion bias) are shown. Furthermore, special aspects of detecting minimum value regions are revealed (including the so-called inverse area size bias).

Keywords Choropleth maps · Reference area maps · Area size bias · Sponge maps · Value by area maps · Equal area unit maps

“Sponge Maps”: Nutzung des Konzepts der Proportionalflächen-Darstellungen zur Vermeidung des Area Size Bias in Choroplethenkarten

Zusammenfassung

Ein bekanntes Problem bei Choroplethenkarten ist der kognitive Effekt, dass größere Regionen als dominanter wahrgenommen werden. Folglich können unbefriedigende Erkennungsraten für kleine Regionen resultieren—dies hat große Relevanz, wenn wichtige räumliche Merkmale oder Muster exploriert werden sollen (z. B. Regionen mit Maximalwerten). Ein möglicher Ansatz zur Vermeidung des Flächengrößen-Effektes (engl.: *area size bias*) ist die Verwendung von Kartogrammen. Während es bereits einige Arbeiten zu Äquiflächen-Darstellungen (engl.: *Equal Area Unit Maps*) gibt, gab es wenig oder gar keine Forschung zu den Möglichkeiten, das Konzept der Proportionalflächen-Darstellungen (engl.: *Value By Area Maps*) zur Transformation der Bezugsflächenkarten anzuwenden. Ein Ziel dieses Artikels ist es, das Konzept der sogenannten „Sponge Maps“ vorzustellen, die die Basiskarten unabhängig von thematischen Attributen verzerren, aber je nach Bedarf der zugrunde liegenden räumlichen Muster bestimmte Interessensgebiete zeigen oder hervorheben. Das zweite Ziel des Artikels ist die Beantwortung der allgemeinen Forschungsfrage, ob Sponge Maps tatsächlich die Flächengrößen-Effekte reduzieren und die Erkennbarkeit von Regionen mit Maximalwerten verbessern. Eine Anwenderstudie konnte insbesondere

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die Wirksamkeit des Sponge-Map-Ansatzes verifizieren. Es wurde aber auch deutlich, dass nicht nur der Flächengrößen-Effekt bei der Erkennung wichtiger Regionen eine Rolle spielt—es werden auch Abhängigkeiten von der absoluten Position (engl.: *top-down bias*), der Kompaktheit oder auffälligen Form (engl.: *shape bias*), der Vertrautheit (engl.: *awareness bias*), der Farbintensität (engl.: *darkness bias*) und nicht zuletzt durch die Verzerrungen in den Sponge Maps als solchen (engl.: *distortion bias*) aufgezeigt. Darüber hinaus werden Besonderheiten bei der Erkennung von Regionen mit Minimalwerten herausgearbeitet (u. a. der sog. *inverse area size bias*).

Schlüsselwörter Choroplethenkarten · Bezugsflächenkarten · Flächengrößen-Effekt · Sponge Maps · Proportionalflächen-Darstellungen · Äquiflächen-Darstellungen

1 Introduction

Thematic maps, especially choropleth maps, are of great importance for communicating spatial statistical data and phenomena. The requirement for fast and reliable interpretability of these maps implies a task-based design that in particular enables an effective and efficient search for regions and spatiotemporal patterns (e.g., of extreme values, hot spots or clusters) (Slocum et al. 2009).

Important choropleth map design elements include, among others, color scheme, data classification or map projection. On the other hand, the geometry of the reference area maps (also often called “base maps”) is rather rarely discussed. Usually the default case is applied: The administrative or geographic regions are depicted in a strict ground plan or a ground plan alike representation, depending on the scale. In the following, for the sake of simplicity, the term of *Ground Plan Alike Maps (GPAM)* is always used—this is done against the background that the majority of thematic maps have scales of 1:50,000 or smaller where a strict ground plan is not achievable.

A well-known problem with choropleth maps is the cognitively induced effect that larger regions are perceived as more dominant. In the case that these have the same color value compared to small regions, different interpretations and wrong decisions might occur. This effect is also known as *area size bias* (Slocum et al. 2009).

One approach to avoiding the area size bias is the use of cartograms, which are generated by transforming and distorting the GPAMs. Dorling (1996) provides an overview of this. The most rigorous option is to use reference areas that are identical in shape and size (*Equal Area Unit Maps, EAUM*; Schiewe 2021). However, the respective distortions within EAUMs normally lead to a more difficult search and localization of regions as well as to a distortion or even violation of topological relationships and spatial patterns.

This contribution proposes a compromised approach between GPAM and EAUM. The approach is built upon the concept of Value By Area Maps (VBAM; Dorling et al.

2006) that usually transform attribute values into area sizes using a proportional assignment. Instead of using existing attribute values as input, various kinds of scaling factors are now introduced to adjust certain reference areas depending on the need to show or emphasize them. With that, at least, small “important areas”—in the following called Areas of Interest (AOIs; such the ones that represent extreme values)—will be enlarged. Optionally, also enlargement or shrinking of other regions is possible. Due to their flexible adjustment depending on map use tasks and on geometries of specific reference areas, these compromised solutions are called “Sponge Maps” in the following.

Goals of this contribution are—

- to introduce the concept of Sponge Maps in more detail, and
- to answer the overall research question whether Sponge Maps are actually able to reduce the area size bias and to improve the detectability of AOIs.

It can be expected that the detectability of AOIs is also affected by other effects. These include, for example, the absolute or relative position or the shape of the important regions as well as the user’s awareness of the entire area. The following empirical study that is concerned with the proposed progress of Sponge Maps will also consider these additional effects. The study focuses on one selected map use task, namely the detection of regions that belong to the class with extreme values (predominantly, maximum values). Furthermore, different options to adjust the area sizes with Sponge Maps methods are compared with respect to improved detectability on the one hand, and undesired distortion effects on the other hand.

The remainder of this paper is structured as follows: Sect. 2 presents previous work on the overall framework of the topic—namely the area size bias problem, limitations of cartograms, and the concept of Value By Area Maps. Section 3 describes the approach of Sponge Maps in more detail, in particular the different options for adjusting the areas. In Sect. 4, the empirical study for testing the overall research question of this contribution is presented, including an in-depth discussion of results. A summary, a discussion of study limitations and an outlook into future research and development complete this article (Sect. 5).

2 Previous Work

In the following, previous work on core aspects of this research work will be briefly summarized—the area size bias (together with other effects that influence an effective and efficient map reading), Equal Area Unit Maps (EAUMs) as an alternative, and Value by area maps as fundament of the Sponge Map solution within this paper.

Ground plan-like reference area maps have the disadvantage that small regions can easily be overlooked or not seen at all. In the event that these have the same hue, intensity or saturation value compared to large regions, this can lead to misinterpretations and wrong decisions. This effect—also known as **area size bias** (Slocum et al. 2009)—does not include any problems that arise from using an inappropriate map projections (i.e., non-area preserving projections for choropleth maps).

Robinson et al. (1984) and Forbes (1984) confirmed the area size bias. They found that reference areas that are too small lead to difficulties in perceiving characteristic elements or relevant patterns. Own empirical studies (Schiewe 2019) have confirmed that the detection rates in the order of 60% for local extreme values in small areas are significantly worse than in large areas (approx. 90%).

When treating the areas size bias, however, it should not be forgotten that there are **other possible effects** that can also influence the detectability of important regions (AOIs) in choropleth maps, in particular:

- *Top-down or left–right bias*: Due to the typical reading directions (in western cultures), it can happen that regions in the top or left come first and other regions may no longer be recognized due to reduced attention. An F-shaped pattern (Nielsen 2016) is known for reading web pages (i.e., first from left to right, then down); however, the transfer to map reading has not yet been investigated in detail.
- *Local contrast bias*: In addition to the aforementioned absolute position, the relative position of an AOI also plays an important role: If a dark area (representing a maximum value, for example) is surrounded by many very bright areas, then this is more noticeable than one area surrounded by other dark areas due to the lower contrast (Slocum et al. 2009).
- *Shape bias*: It is known from perceptual psychology that both compact shapes and very conspicuous shapes are more likely to be perceived than others and are therefore detected more frequently (Goldstein 2002).
- *Darkness bias*: Darker ("denser") colors are also more noticeable, so that corresponding regions are potentially detected more often than brighter regions (Slocum et al. 2009).

The most rigorous solution to avoid the area size bias is the use of **Equal Area Unit Maps** (EAUMs) in which each spatial unit has the same area size and often the same shape (e.g., squares or hexagons) (Schiewe 2021). There is no uniform terminology for this type of map in the literature—some authors speak of "equal-area cartogram" (Brath 2015; Ordnance Survey 2020), "tile map" (McNeill and Hale 2017) or "grid map" (Eppstein et al. 2015). The generation of the EAUMs can be understood as an assignment problem from graph theory: The usual algorithm for the necessary weighted matching in bi-partite graphs is the Hungarian method, also known as the Kuhn–Munkres algorithm (Kuhn 1955; Munkres 1957).

The geometric distortions of EAUMs lead to distortions or even violations in topological relationships and spatial patterns, and consequently to a more difficult search and localization of regions. Only a few empirical studies have been carried with EAUMs. With regard to pattern identification, it could be shown that EAUMs can increase the detectability rates for local extreme values. On the other hand, global lateral gradients (north–south or west–east) or hot spots often get blurred or even get lost (Schiewe 2021). EAUMs are often labeled with the names of the administrative regions or the values—this can improve searches but not pattern recognition (Korycka-Skorupa and Golebiowska 2020). Wood and Dykes (2008) suggested equal-area cartograms that can interactively switched forth and back (and eventually also morphed) with choropleth maps to also show correct geographical and topological relationships, too. However, this approach is not feasible for quick and easy perception in static (for example, media) maps.

Value By Area Maps (VBAMs) scale the area sizes of spatial units according to a numerical attribute value (Dent 1975). This type of map belongs to the class of contiguous cartograms, in which the shape of the spatial units is distorted, but the topology of all direct neighborhoods is preserved. On the *Worldmapper* platform (Dorling et al. 2006), topics of global interest are regularly visualized by this type of representation. The original method for computer-aided generation was described by Dorling (1996). Gastner and Newman (2004) presented a diffusion method that allowed a faster computation. Gastner et al. (2018) published a further development based on a continuous transformation, which will be used in the further course of this project. To create contiguous cartograms, Keim et al. (2004) presented an objective function that also included global and local shape preservation.

The usability of Value By Area Maps was already an issue for Dent (1975) and was later taken up by other authors (e.g., Duncan et al. 2020). The maps are generally considered unusual and attractive (Parlapiano 2016), but also difficult to read because the memorability of administrative spatial units is missing. Another disadvantage is the fact

that the geometric distortion also has a negative effect on the preservation of spatial patterns.

VBAMs are similar to but not to be confused with maps that have undergone mono- or poly-focal distortion (Hake et al. 2002): A magnifying glass effect (also: fish-eye view) is created from one or more geometrically defined focal points over the entire map—with that an individual consideration of given administrative regions does not take place—in contrast to VBAMs.

Roth et al. (2010) summarized the characteristics of the different cartograms in a *Cartogram Cube*. This takes into account the preservation of shape and topology as well as the visual equalization effect. Figure 1 shows the classification of the aforementioned GPAMs, EAUMs and VBAMs within this cube. Markowska and Dukaczweski (2022) also consider and define possible deviations from the discrete positions within the cube.

3 Concept of Sponge Maps

3.1 General Approach

Value By Area Maps build the fundament of the proposed Sponge Maps solution. They scale area sizes of spatial units according to associated numerical attribute values. The corresponding Gastner algorithm (Gastner et al. 2018) determines area sizes using weighting factors w_i for each i -th spatial unit ($i = 1, \dots, n$; n : number of spatial units in the data set). An unchanged area size (i.e., a GPAM) is achieved with $w_i = 1$ (for all i), whereas all spatial units are of equal size (i.e., EAUM) with $w_i = \frac{\sum_{k=1}^n A_k}{nA_i}$ (for all i ; with A : area sizes).

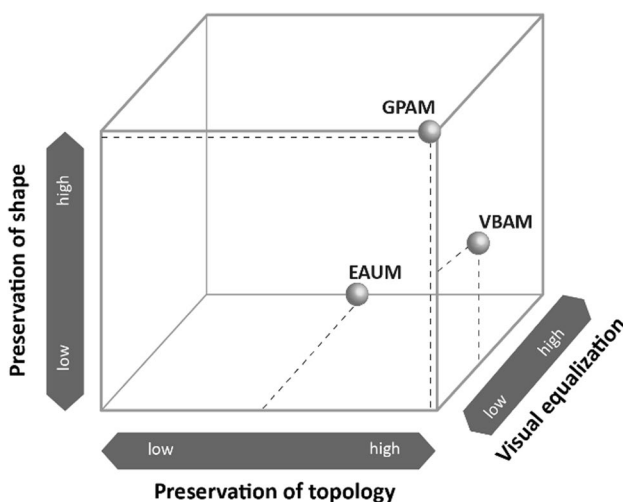


Fig. 1 *Cartogram Cube* according to Roth et al. (2010)—with placement of Ground Plane Alike Maps (GPAM), Equal Area Unit Maps (EAUM) and Value By Area Maps (VBAM)

The map examples in the following are created using the go-cart-tool (<https://go-cart.io/>), which is based on the Gastner algorithm.

In the following, the weighting will no longer take place via a user-selected thematic attribute. Instead, various target-based scaling options are introduced that adjust area sizes for a better perception, in particular, for enlarging very small areas so that the area size bias can be reduced or even avoided. Apart from this, also areas of other sizes can be resized optionally.

The rescaling of spatial units leads to a distortion of reference area maps. To restrict distortions to “important” areas (Areas of Interest, AOI) only, it is possible to adjust only these. AOIs are regions of relevance that could be affected by the area size bias; for example, areas that contain extreme values or that are of particular thematic interest (e.g., in news stories about a specific State). To express the flexibility of adjusting the spatial units depending on AOI, the term “Sponge Maps” is used for the following reference area map concept.

3.2 Adjustment of Area Sizes

Given are the area sizes A_i of all n areas in a choropleth map (with $i = 1, \dots, n$) and the Areas of Interest (AOI; depending on a specific application; e.g., regions with maximum value class). Required are adjusted areas sizes adj_A_i (either of all areas, of all AOIs only or selected AOIs only).

In principle, there is an infinity of possibilities for area adjustments. From these, the following four basic options are selected (see also Fig. 2 for examples):

- *Linear global adjustment (LG)*: The range of area sizes in the data set between minimum and maximum values is reduced around the average value \bar{A} in a linear manner, using a scaling factor c (with $0 \leq c \leq 1$):

$$adj_A_i = \bar{A} + c \cdot (A_i - \bar{A})$$

This results in a shrinkage of larger and an enlargement of smaller regions (with the mean area size as border between “large” and “small”).

- *Linear AOI adjustment (LA)*: Because the global adjustment distorts all regions (and with that possibly the overall impression), only AOIs can be changed. Applying the same principle as before, a scaling factor f (with $0 \leq f \leq 1$) is introduced to shrink larger AOI and enlarge smaller AOI (related to the mean area size), by leaving non-AOI areas sizes as they are:

$$adj_AOI_i = \bar{A} + f \cdot (AOI_i - \bar{A})$$

- *Equal AOI adjustment (EA)*: The linear AOI adjustment still leads to AOIs of different size, which might be con-

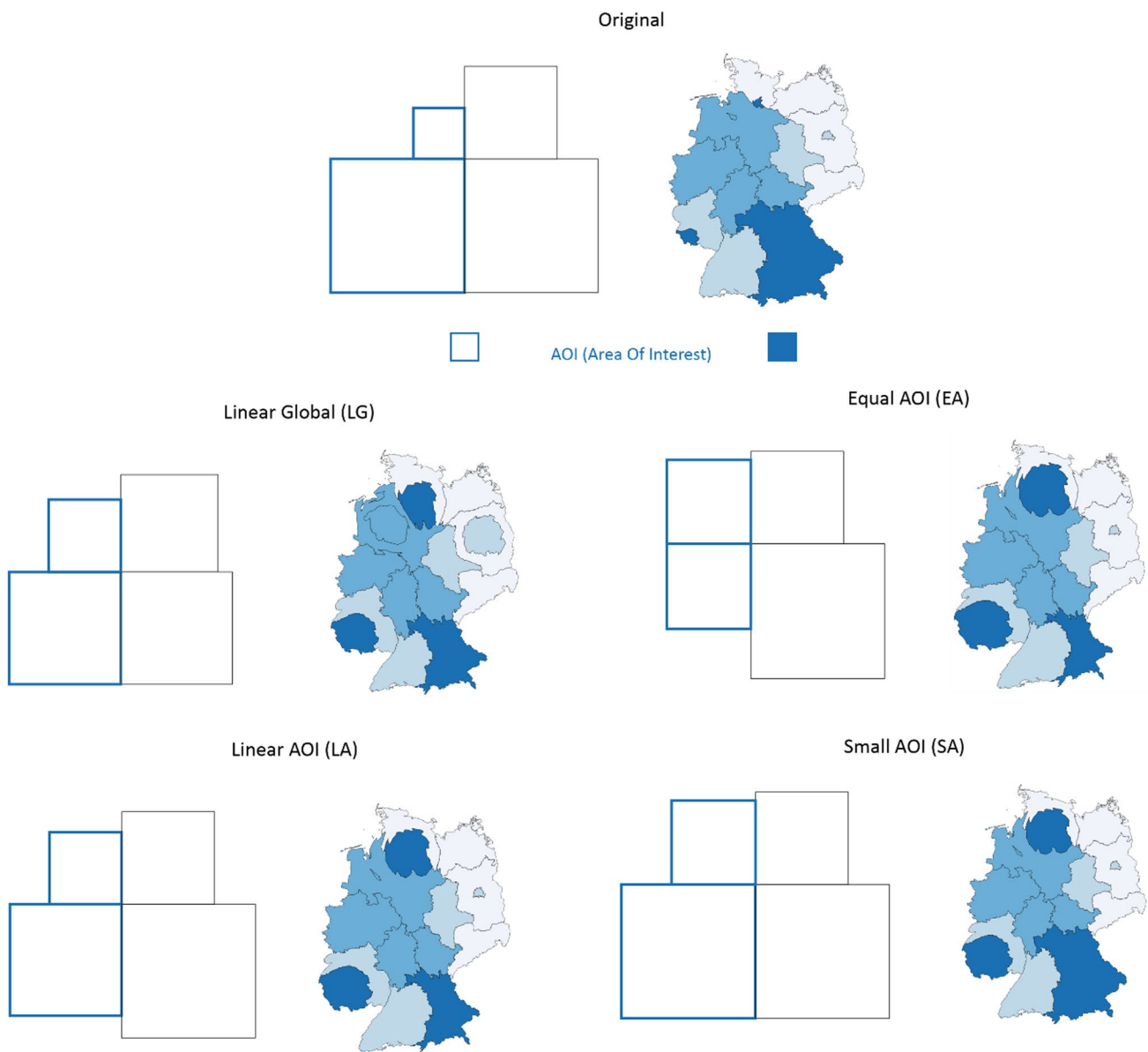


Fig. 2 Options for area or AOI area adjustments—for a simple geometric example and a real world example (States of Germany)

fusing because they represent the same attribute value (or class of attribute values). Alternatively, all AOI areas can be transformed to one common value (e.g., to the maximum AOI area size or to the mean AOI area size \overline{AOI}), by leaving non-AOI areas sizes as they are:

$$adj_AOI_i = Max(AOI_i).OR.adj_AOI_i = \overline{AOI}$$

- *Small AOI enlargement (SA)*: A further reduction of distorted areas can be accomplished when only small AOI are enlarged and all other areas (large area AOIs and all non-AOIs) are not modified. “Small AOI” can be defined in a different manner, for example (as shown below) as areas that are smaller than the mean area

size. Also the transformed value adj_A_i can be defined in a different manner, for example using the mean AOI area size \overline{AOI} :

$$adj_AOI_i = \overline{AOI} \text{ if } AOI_i < \overline{A}$$

4 Empirical Study

4.1 Research Question and Hypotheses

The following empirical study is essentially intended to answer the overarching **research question** of whether

Sponge Maps can reduce the area size bias, and with that to improve the detectability of AOIs (here: maximum value regions).

The following **hypotheses** are examined in detail:

[H1] The area size bias can be verified for the given GPAM examples.

The original GPAMs are used for comparison purposes with the new Sponge Maps. To be able to describe changes or the degree of changes caused by Sponge Maps, the GPAMs have to be examined in more detail with regard to the area size bias.

[H2] Apart from the area size bias, the detectability of AOIs is also influenced by other factors.

These other possible factors—as already outlined in Sect. 2—include the absolute location (top-down bias; left–right bias), relative location (local contrast bias), compact or conspicuous shapes (shape bias), or color lightness (darkness bias).

[H3] The detectability of AOIs with minimum values is less effective in GPAMs and Sponge Maps than for AOIs with maximum values.

Earlier investigations have shown that due to the lighter and thus less dominant coloring, regions with minimum values are less detectable than those with maximum values and darker appearance (Schiewe 2019). It is investigated whether this effect can be confirmed, also applies to Sponge Maps and can alternatively be eliminated using a bi-polar color scheme.

[H4] Using Sponge Maps methods, it is generally possible to improve the detectability of maximum value AOIs and to reduce the area size bias.

This hypothesis deals with the core topic of these investigations—the proposed added value of Sponge Maps. A distinction is made between the different methods for generating Sponge Maps (Sect. 3.2).

[H5] There are options or parameter settings for Sponge Maps for which distortions are subjectively perceived as not disturbing.

Sponge Maps inevitably show distortions that can have a negative impact on the effectiveness and efficiency of map usage tasks (*distortion bias*). The subjective impression is examined to find first clues for compromises between good detectability and less distortion in future work.

4.2 Study Design

The purpose of the study is to assess the overall effectiveness of Sponge Maps—it's not about uncovering blunders or understanding why some solutions work better than others. For this reason, a quantitative empirical design was chosen. The study was web-based to get as many participants as possible. Both an English and a German version were offered to participants.

After a short introduction into the survey, some questions related to cartographic skills (self-assessment between expert, school knowledge, layman), and origin (Germany, Europe, others) were asked. The main block consisted of 25 map-based questions (named “cases” in the following). Finally, free comments were possible.

Two different base maps were used for the map-based questions—the federal states of Germany (known to most users) and the departments of Paraguay (unknown to most users). To answer the questions, the individual regions were marked with letters. The default data classification used four classes in the case of a sequential color scheme and five classes in the case of a bi-polar color scheme. All color scheme were designed according to the *Colorbrewer* recommendations (Harrower and Brewer 2003). Legends were intentionally not shown to test intuitiveness. Nevertheless, the dark-is-more bias was pointed out in the question (“the darker, the larger the value”). The maps also did not contain an explicit theme to rule out any thematic or knowledge influence.

The tasks are shown in Figs. 3, 4, 5, 6, 7—here sorted according to the five associated hypotheses (Sect. 4.1). In the study, however, the tasks were presented in unsorted order to avoid learning effects and effects of boredom. The tasks shown in Figs. 3, 4, 5, 6 consisted of determining regions with maximum or minimum or simply “dominant” impressions. Finally, there were two tasks (Fig. 7) that were supposed to describe the subjective impression of the distortions between different Sponge Map variants.

4.3 Results

In total, 219 persons participated in the study. 80% of them were German. The self-assessment revealed that 81.7% ranked themselves as “experts”, 16.9% as people with “school knowledge” and 1.4% as “laymen”. The high proportion of Germans and experts is probably due to the use of E-mail distribution lists for advertising the study, which primarily addressed colleagues and experts in Germany. Unfortunately, the small number of people in other groups does not allow any statistical significance statements on differences between the given groups.

Table 1 summarizes the detection rates for hypotheses [H1] to [H4] (referring to the case descriptions in Figs. 3, 4, 5, 6), whereas Table 2 reflects the subjective impressions of the users concerning the distortion of maps in use (Fig. 7).

4.4 Interpretation and Discussion

In the following, several results of statistical tests on significant differences between detected AOIs or cases are

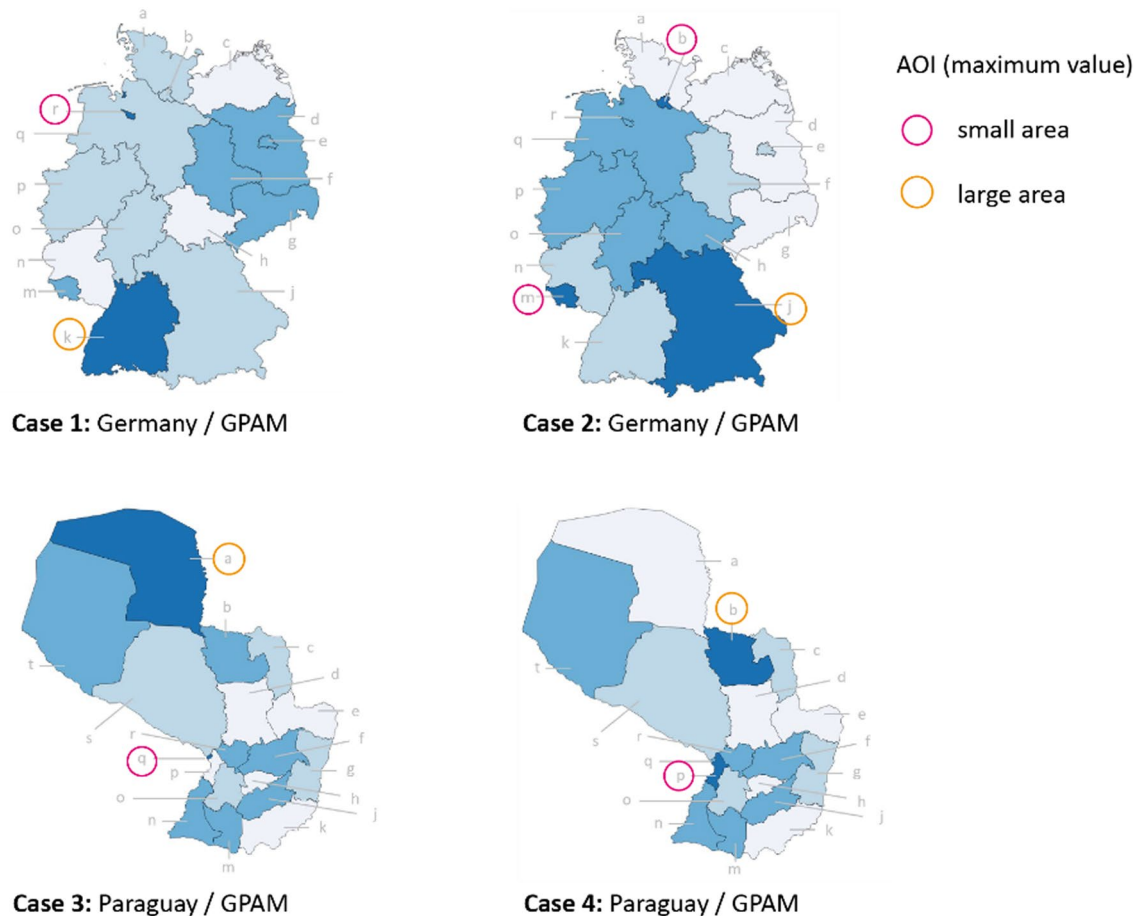


Fig. 3 Analysis of area size bias in GPAMs (belonging to [H1])—circles point to required solutions

reported. For this purpose, the χ^2 -test for two independent variables has been applied. The significance based on p-values is categorized as follows: “significant” ($*p < 0.05$), “very significant” ($**p < 0.01$) and “highly significant” ($***p < 0.001$). In the following, the results are interpreted and discussed w.r.t. the five hypotheses.

[H1] The area size bias can be verified for the given GPAM examples.

In the study, four different cases for the detection of very small AOI regions with maximum values were examined. At first glance, the results were different:

- In case 1, there was no significant difference in the detection of small versus large areas (here: states of Bremen (r) 82.6% vs. Baden–Württemberg (k) 84.9%; $p = 0.389$). Reasons for this may be the location of Bremen (in the north, recorded first) and the conspicuousness of the divided federal state. Also the fact that Bremen is well known to most users (*awareness bias*) certainly led to this result.
- In contrast, case 2 shows after all a “significant” difference in recognition between the small regions of Ham-

burg (78.5%) and Saarland (77.6%) to the large region of Bavaria (85.8%; $p = 0.046*$ for Hamburg, $p = 0.026*$ for Saarland).

- For the example in the unknown area (Paraguay), there are even highly significant differences in the detection of very small vs. large regions (case 3: 60.7% vs. 94.1%; $p < 0.001***$; case 4: 76.2% vs. 93.6%; $p < 0.001***$).

In summary, it can be stated that in principle, the area size bias could be confirmed (i.e., [H1] could be verified). Detection rates for maximum value regions in the order of 60% to 80% for the small regions are unsatisfactory and need improvement—which supports the general idea of this article. However, it was also shown that other influences play a role and can increase or (as in case 1) weaken the area size bias.

[H2] Apart from the area size bias, the detectability of AOI is also influenced by other factors.

With cases 5 to 9, the aforementioned assumed additional influences are examined in more detail. For this purpose, the occurrence of an area size bias was ruled out: The AOIs no

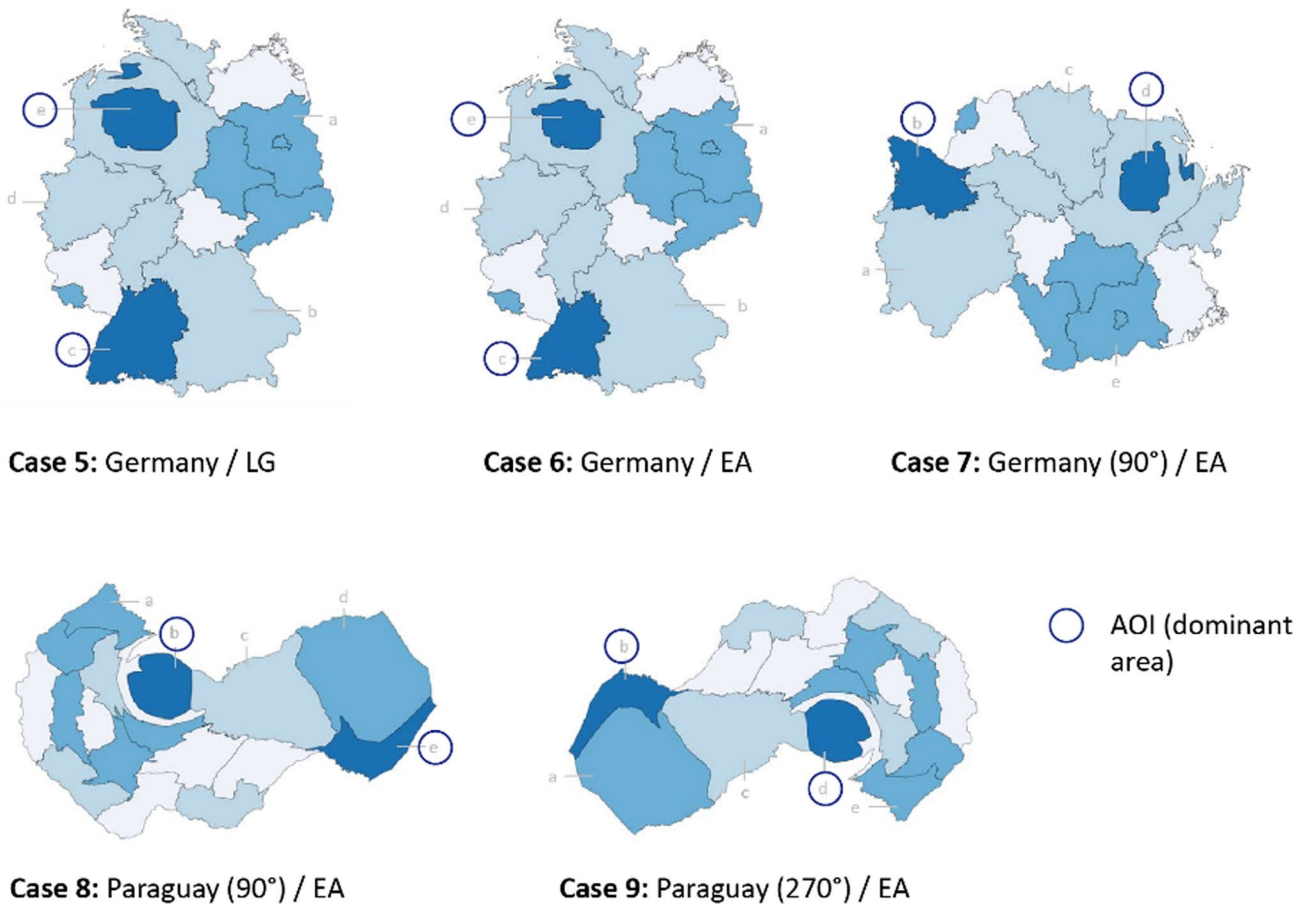


Fig. 4 Analysis of further effects (belonging to [H2])—circles point to required solutions

longer appeared as very small but as similarly sized areas. Instead, they now differed in terms of absolute position (top-down, left–right) and shape (i.e., compactness). It was explicitly no longer asked about extreme values, but about "visually dominant regions". The possible AOIs were uniformly coded with the darkest tone. The relative position (local contrast bias) was not explicitly examined, as there are too many possible combinations that would have gone beyond the scope of the study.

Cases 5 and 6 show that the regions in the top are recognized highly significantly more frequently than those in the bottom part of the map (90.9% vs. 63.0%; $p < 0.001^{***}$; 83.6% vs. 59.4%, $p < 0.001^{***}$), although they are even slightly smaller (case 5) or of the same size (case 6). This confirms the top-down bias.

Case 7 shows very similar detection rates for regions of the same size that lie roughly on a horizontal line (72.6% vs. 74.4%; $p = 0.467$)—a left–right bias could therefore not be observed. In contrast, in cases 8 and 9, clearly different detection rates were achieved (81.7% vs. 63.0% with $p < 0.001^{***}$; 85.8% vs. 53.0% with $p < 0.001^{***}$), although the AOIs are again on a horizontal line. Since the left region

dominated in one case and the right region in the other (after rotating the map by 180°), a left–right bias can again be ruled out. Instead, the clearly greater compactness of the more frequently recognized areas can be given as a reason here.

In all cases 5 to 9, it was also shown that there were also larger regions than the searched and darkly coded regions, but the area size as such was obviously less important in the assessment of dominance. In summary, [H2] can be confirmed with regard to top-down bias and shape bias. A left–right bias, on the other hand, was not visible.

[H3] The detectability of AOIs with minimum values is less effective in GPAMs and Sponge Maps than for AOIs with maximum values.

The search for minimum values is fundamentally difficult, since the color scheme (now low color brightness) is no longer dominant by definition.

Case 10 shows that the smaller area was detected highly significantly more frequently than the larger area (87.2% vs. 57.6%; $p < 0.001^{***}$), although the larger area is also located in the top region. Rotating this example by 180° (case 11), the small area appears in the top and is still

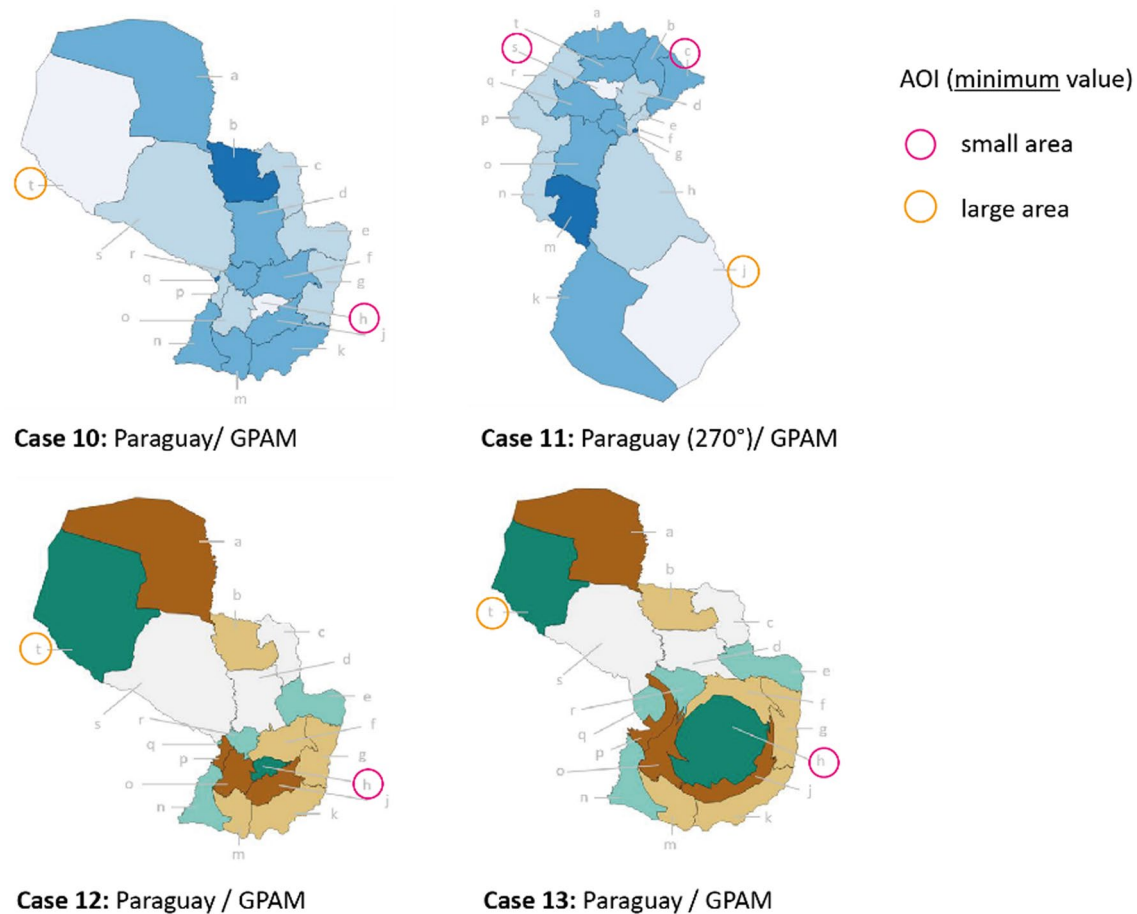


Fig. 5 Analysis of AOIs with minimum values (belonging to [H3])—circles point to required solutions

recognized more frequently than the large area (90.9% vs. 63.5%; $p < 0.001^{***}$). However, the slightly increased rate in the small area (90.9% vs. 87.2%) through the top position is not significantly different ($p = 0.204$). This leads to the conclusion that top-down location has less of an impact than area size for the detection of minimum value areas.

In general, the detectability of small minimum areas is of the same order of magnitude as for maximum value areas. On the other hand, large areas with small values are now recognized clearly less frequently than small areas. One can therefore speak of an *inverse area size bias*: the intuitive association with small values occurs primarily via the area size, and only then via the (no longer dominant) color brightness.

An alternative to the sequential color scheme is the bipolar scheme, in which also the minimum values have a dominant (i.e., low) color brightness. However, cases 12 and 13 show very unsatisfactory detectability rates for the minimum areas between 50.2% (GPAM) and 67.6% (Sponge Map). Of course, these rates can be greatly improved by introducing a legend, but the intuitively poor response performance of the lesser known bi-polar schemes remains.

In summary, it can be stated that smaller (in any case not to be overlooked) minimum value AOI regions are in principle well detected—with similar detection rates as maximum value regions, which contradicts hypothesis [H3]. On the other hand, large areas with small values are clearly detected less frequently than small areas (inverse area size bias).

[H4] Using Sponge Maps methods, it is generally possible to improve the detectability of maximum value AOIs and with that to reduce the area size bias.

Table 3 summarizes the changes in detection rates between GPAMs and different Sponge Maps.

It can be observed that there were no significant changes by recognizing the (formerly) large regions (four right columns in Table 1). However, for small regions in nine out of 14 cases, the application of a Sponge Map method led to a highly significant improvement in the detectability rate, in one case to a very significant improvement. The four exceptional cases are as follows:

- Case 14 shows that with the Sponge Map method (LG) only a slight and not significantly improved detection of the small AOI can be achieved (from 82.6% to 87.7%;

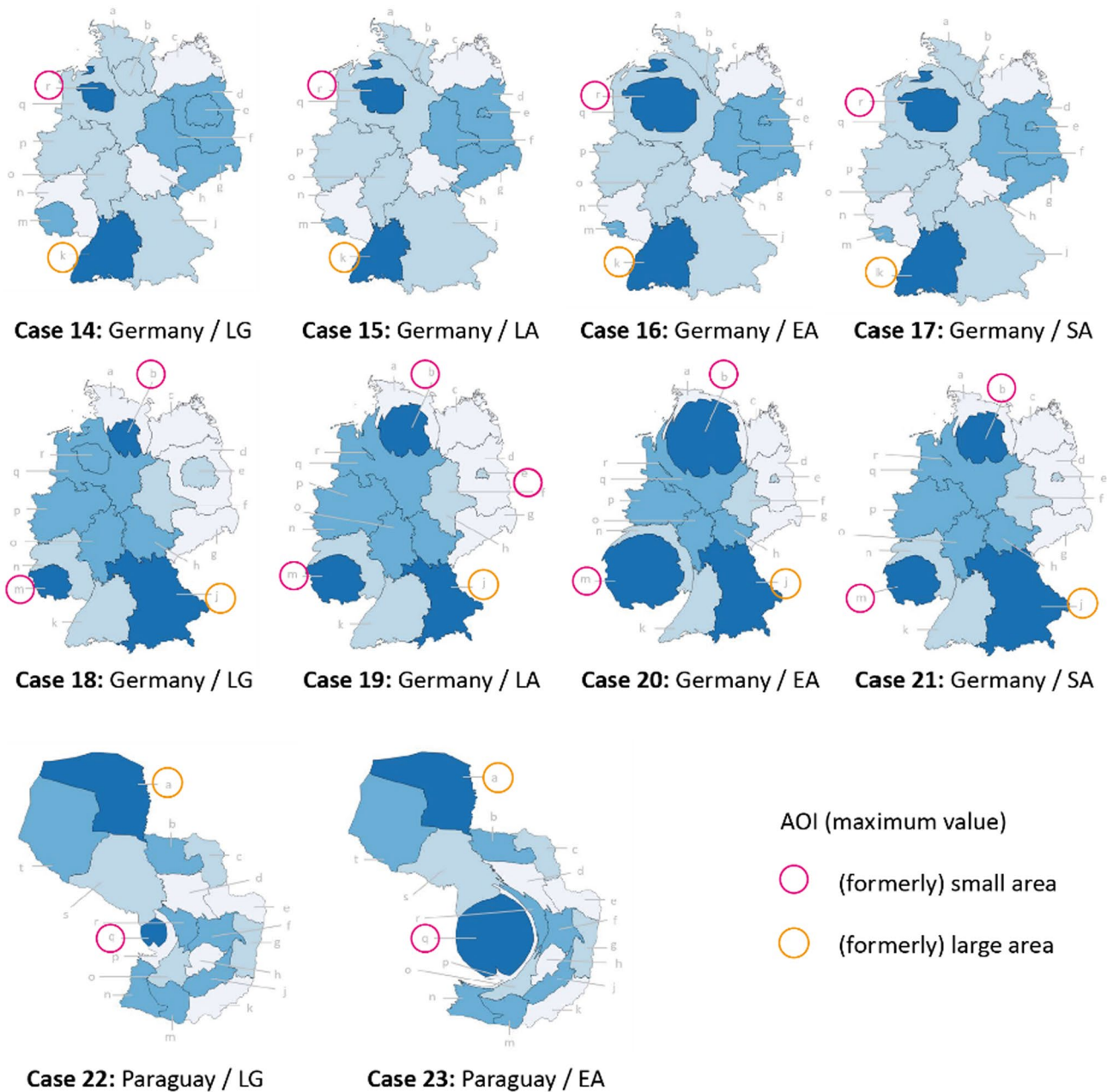


Fig. 6 Analysis of effects of Sponge Maps (belonging to [H4])—circles point to required solutions

$p = 0.103$)—this is mainly due the already mentioned, good detectability in the GPAM (compare with case 1).

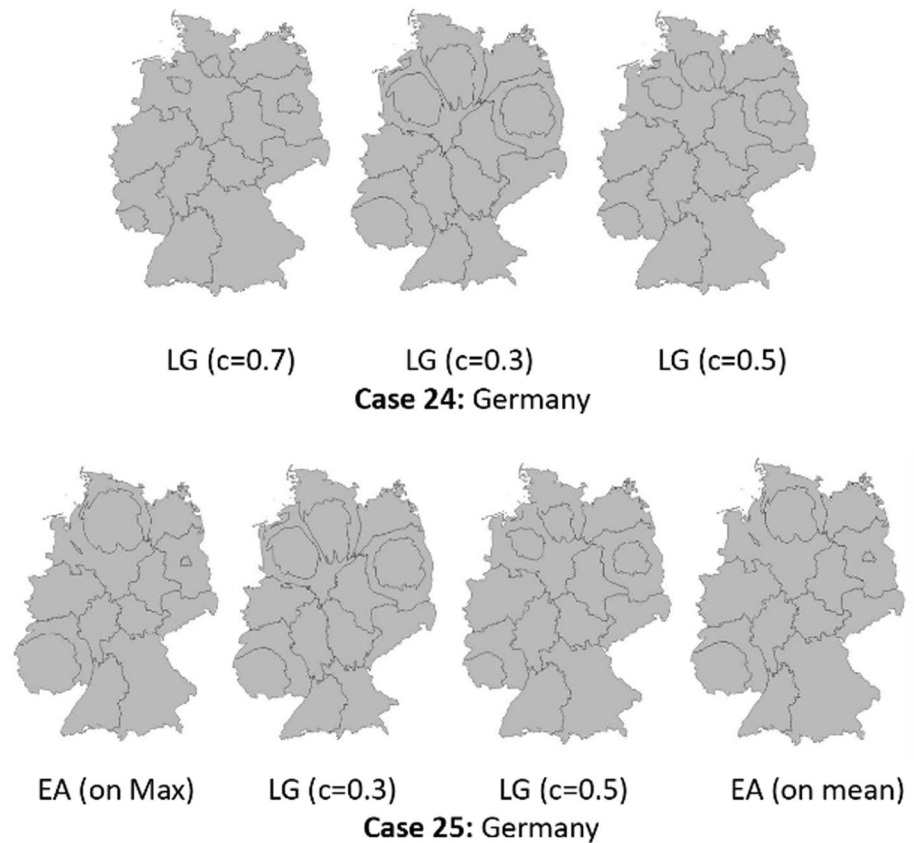
- In cases 18, 19 and 21, the detection rates for the small AOI at the bottom (m: Saarland) increase slightly for all methods. From the consistently better rates for the other (formerly) small AOI (b: Hamburg), it can be deduced that the top-down bias is also at work here.

After using the Sponge Map method, in eight of the 14 cases, previously smaller areas are detected even better than the previously large areas. This can be explained in seven

cases with the northerly location, but possibly also with the conspicuousness of the distortion as such (*distortion bias*).

If one compares the Sponge Map methods with each other, the EA method (same area sizes for all maximum value areas) consistently achieves the best detection rates. However, compared to other methods these are at best statistically significant ($p < 0.05$; *). A more profound statement cannot be derived because other influences such as top-down, awareness or shape biases have to be taken into account.

Fig. 7 Analysis of subjective impression of distortions (belonging to [H5])—for each map the degree of distortion could be categorized with “very strong”, “still ok”, “no problem”



In summary, it can be stated that the application of the Sponge Map methods can fundamentally increase the maximum value AOI detection—the central hypothesis [H4] can thus be verified. Deviations from this can be justified by other, case-specific effects. Although equating the area sizes of all AOIs produces the best detection rates, this statement still requires further investigation. A ranking of the various methods (LG, etc.) does not yet appear possible given the small number of cases examined and the numerous influencing factors.

[H5] There are variants or parameter settings for Sponge Maps for which distortions are subjectively perceived as not disturbing.

In case 24, different factors (see Sect. 3.2) were tested for the LG method. It turned out that the smallest offered distortion ($c=0.7$) was either not a problem or classified as “still OK” for most users (97.7%). The strongest distortion ($c=0.3$), on the other hand, was classified as too strong by 83.1%. 40.0% rated the “compromise” ($c=0.5$) as too distorted.

In case 25, LG and EA methods were compared. The assessments for the LG methods are similar to those from the previous case (79.5% of the users find LG with $c=0.3$ and 32.0% LG with $c=0.5$ to be too distorted). Looking at the EA method, in which the uniform area size is equated to the maximum AOI area size, 65.3% find this as being too

distorted. If, on the other hand, the average area size of all AOIs is used for all new common area sizes, this value is reduced to 52.5%.

In summary, it can be stated that Sponge Map methods often lead to subjectively highly distorted map images. In principle, however, this is tolerable as long as the subjective distortion bias does not become too strong and does not lead to distractions and superimpositions on all other effects (confirmation of [H5]). In this context, it has to be mentioned that some study participants explicitly stated that they essentially do not accept cartograms.

5 Summary and Outlook

5.1 Summary of Results

To overcome the area size bias in choropleth maps, this contribution examined the transformation of Ground Plan Alike reference area maps (GPAMs) using the principle of Value By Area Maps (VBAM). Instead of using attribute values for area scaling, various kinds of scaling factors are introduced to adjust the reference area sizes for specific needs. This leads to distorted reference maps (“Sponge Maps”), in which at least small “important areas” (AOIs) will be enlarged.

Table 1 Rates for correct detection of AOI

Case	Base map (rotation, if applied)	Distortion	Search for	Detection of small area AOI	Detection of large area AOI	Detection of AOI
<i>re [H1]: Verification and analysis of Area Size Bias</i>						
1	Germany	none (GPAM)	Max. value	r: 82.6%	k: 84.9%	
2				b: 78.5%	j: 85.8%	
3	Paraguay			q: 60.7%	a: 94.1%	
4				p: 76.2%	b: 93.6%	
<i>re [H2]: Further influencing factors</i>						
5	Germany	LG	Dominant area			c: 63.0%
6		EA				e: 90.9%
7	Germany (90°)	EA				c: 59.4%
8	Paraguay (90°)	EA				e: 83.6%
9	Paraguay (270°)	EA				b: 72.6%
						d: 74.4%
						b: 63.0%
						d: 81.7%
						b: 85.8%
						e: 53.0%
<i>re [H3]: Detection of minimum value AOI</i>						
10	Paraguay	none (GPAM)	Min. value	h: 87.2%	t: 57.5%	
11	Paraguay (270°)			s: 90.9%	j: 66.7%	
12	Paraguay			h: 50.2%	t: 57.5%	
13		EA		h: 53.0%	j: 67.6%	
<i>re [H4]: Influence of Sponge Maps on Area Size Bias</i>						
14	Germany	LG (c=0.7)	Max. value	r: 87.7%	k: 88.1%	
15		LA		r: 91.3%	k: 87.8%	
16		EA		r: 94.1%	k: 84.5%	
17		SA		r: 94.1%	k: 87.7%	
18		LG (c=0.7)		b: 92.2%	j: 90.0%	
19		LA		m: 81.7%		
				b: 95.0%	j: 84.5%	
				m: 84.5%		
20		EA		b: 96.8%	j: 85.8%	
				m: 88.6%		
21		SA		b: 90.4%	j: 86.8%	
				m: 82.2%		
22	Paraguay	LG		q: 86.8%	a: 93.6%	
23		EA		q: 88.6%	a: 91.8%	

To test the proposed effect of Sponge Maps, five hypotheses have been tackled in a web-based study. The respective results will be briefly summarized in the following.

Regarding hypothesis [H1], the study confirmed that in principle, the area size bias could be observed. Detection rates for regions with maximum values in the order of 60% to 80% for the small regions are unsatisfactory and need improvement.

As these results vary for different maps, it was concluded that there are also other effects that influence the detectability of AOIs (hypothesis [H2]). The study verified the

top-down, shape and darkness biases, whereas the left–right bias was not observable.

The search for minimum value regions is fundamentally difficult, since the color scheme (now low color brightness) is no longer dominant by definition. The study revealed that these AOIs are in principle well detected—with similar detection rates as maximum value regions, which contradicts hypothesis [H3]. On the other hand, large areas with small values are detected less frequently than small areas (*inverse area size bias*).

Table 2 Classification of disturbing effects through distortions in Sponge Maps

Case	Base map	Distortion	Disturbing effect of distortion		
			Very strong	Still ok	No problem
<i>re [H5]: Subjective impression of distortions</i>					
24	Germany	LG ($c=0.7$)	2.3%	14.6%	83.1%
		LG ($c=0.3$)	83.1%	10.0%	6.9%
		LG ($c=0.5$)	40.0%	49.3%	13.7%
25		EA (on max. value)	65.3%	28.3%	6.4%
		LG ($c=0.3$)	79.5%	13.2%	7.3%
		LG ($c=0.5$)	32.0%	42.9%	25.1%
		EA (on mean value)	52.5%	31.5%	16.0%

After applying the different Sponge Map methods, in most cases, a statistically highly significant increase in the detection of maximum value AOIs could be observed—the central hypothesis [H4] can thus be verified. Comparing the different Sponge Map methods, the EA (equating the area sizes of all AOIs) produced best results; however, a statistically profound comparison to other methods was not possible due to the limited number of test cases and other influencing factors.

Sponge Map methods lead to distorted and unfamiliar base maps. The study has shown that certain parameter settings (e.g., $c \geq 0.7$ for LG method) were found as acceptable for most users. Obviously, there is a conflict between distortion tolerance and AOI detectability (which was best with EA methods).

All in all, the overarching research question—of whether Sponge Maps can reduce the area size bias and improve the

detectability of maximum value AOIs—can be answered in a positive manner.

5.2 Limitations of Study

The core research question of this study could be answered in a statistically profound way. However, there are various aspects that could not be tackled due to complexity reasons. For example, not all influencing effects (such as top-down bias) could be investigated in sufficient detail or even at all (such as local contrast bias). Also a profound comparison of Sponge Map options and parameter settings needs more study questions. In Sect. 5.3, possible continuations of the current study are outlined.

As mentioned in Sect. 4.3, a high proportions of Germans and experts (of about 80%, each) took part in the study. Due to the small number of people of other groups, any statistical significance statements on differences between the groups were not possible. However, even for experts, the central hypotheses of this contribution could be confirmed—leading to the expectation that these are also (and eventually even stronger) valid for laymen.

Due to complexity reasons, the study had to restrict itself to the task of detecting maximum value AOIs and to a limited number of map examples. With that, very similar questions were asked during the study. Although the tasks were presented in unsorted order, some user comments revealed that learning effects and effects of boredom appeared.

5.3 Outlook

The current study is to be seen as a first step toward the general applicability of Sponge Maps. In particular, due to

Table 3 Changes in detection rates between GPAM and different Sponge Map methods (for case numbering, see Figs. 3, 4, 5, 6)

Region	Case	Sponge map method	(formerly) small AOI				(formerly) large AOI			
			AOI	GPAM	Sponge	<i>p</i>	AOI	GPAM	Sponge	<i>p</i>
Germany	14	LG	<i>r</i>	82.6%	87.7%	.103	k	84.9%	88.1%	.281
	15	LA			91.3%	**			87.8%	.330
	16	EA			94.1%	***			84.5%	.495
	17	SA			94.1%	***			87.7%	.330
	18	LG	<i>b</i>	78.5%	92.2%	***	j	85.8%	90.0%	.176
			<i>m</i>	77.6%	81.7%	.251				
	19	LA	<i>b</i>	78.5%	95.0%	***			85.8%	.500
			<i>m</i>	77.6%	84.5%	.067				
	20	EA	<i>b</i>	78.5%	96.8%	***			84.5%	.454
			<i>m</i>	77.6%	88.6%	***				
21	SA	<i>b</i>	78.5%	90.4%	***			86.8	.477	
		<i>m</i>	77.6%	82.2%	.213					
Paraguay	22	LG	<i>q</i>	60.7%	86.8%	***	a	94.1%	93.6%	.488
	23	EA			88.6%	***			91.8%	.297

the aforementioned complexity reasons, a couple of continuations are conceivable, for example:

- The area size bias cannot be treated in an isolated manner. Some additional effects (such as top-down, shape, awareness, darkness, or distortion biases) could be clearly observed; however, a possible ranking or an interplay between these factors (which is possibly user and task dependent) need more investigations.
- Of course, the way how AOIs are principally identified should be considered in the context of a successful Sponge Map design. However, this is complex issue going beyond the scope of this contribution—here, several parameters have to be taken into account (e.g., geometrical parameters, such as area size, shape, orientation, but also perceptual aspects).
- Only some methods and parameter settings for generating Sponge Maps could be tested. To come up with recommendations or even default settings (as function of input data and detectable patterns), more combinations have to be tested. In this context, it should be investigated whether the aforementioned additional effects could also be handled by Sponge Map distortions.
- This study concentrated on maximum value regions as AOIs. In fact, other important spatial patterns (such as minimum value regions, hot/cold spots, and clusters) have to be taken into account in future.
- In the context of finding recommendations, more testing is necessary to find feasible compromises between distortion acceptance and AOI detectability.
- In addition to the pure concept of Sponge Maps, also possible interplays with other static or interactive displays (such as GPAMs or diagrams) should be considered to improve the usability.

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Data availability The raw and processed data required to reproduce the above findings cannot be shared at this time due to technical and time limitations.

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