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Seeing what is not shown

Combining visualization critique and design to surface the limitations in data

Keywords: critical visualization, critique, urban data, visualization design, data studies

Critical studies of data visualization often highlight how the reductive nature of visualization methods excludes data limitations and qualities that are crucial to understanding those data. This case study explores how a data visualization could express contingent, situated, and contextual facets of data. We examine how such data limitations might be surfaced and represented within visualizations through an interplay between the critique of an existing data visualization and the development of alternative designs. Based on a case study of urban tree data, we interrogate data limitations in relation to four different types of missingness: Incompleteness, Emptiness, Absence, and Nothingness. Our study enables reflections on how data limitations can be investigated using visualizations and considers the development of a critical visualization practice.

1. Background

Among the key concerns of critical visualization research are discrepancies between what a visual design suggests and the characteristics of the visualized data (e.g., D'Ignazio & Klein, 2020; Hall et al., 2015). Such discrepancies can conceal important qualities of the data, such as how, when, and where they might be contingent, incorrect, inconsistent, inaccurate, incomplete, uncertain, relative, contextual, or situated (e.g., D'Ignazio & Klein, 2020; Dörk et al., 2013; Drucker, 2017; Kennedy et al., 2016; Kitchin, 2014; Kosminsky et al., 2019; Loukissas, 2019). These issues have been explored by previous studies, including those looking at sociological perspectives on visualization practices (e.g., Ricker et al., 2020; Simpson, 2020; Van Geenen & Wieringa, 2020), uncertainty visualization and the visualization of missingness (e.g., Fernstad, 2019; Kay et al., 2016; Kinkeldey et al., 2017; McCurdy et al., 2019; McNutt et al., 2020; Skeels et al., 2010; Song & Szafir, 2018), and by work that integrates local and material contexts in visualization practice (e.g., D'Ignazio, 2017; Loukissas, 2016; Offenhuber, 2019). Despite these efforts, re-introducing complexities, qualities, and limitations of data into visualization design remains a challenge as it is not always obvious how this might be achieved.

Our work takes the challenges of integrating the qualities and limitations of data into a design as a starting point for exploring alternatives to an existing visualization. Our case study considers an urban tree map that is part of '*giessdenkiez*' ('water the neighborhood'), a project that aims to inform and provide guidance to the people of Berlin with regard to the need to water public trees. Although a critique of the map's design is central to this study, our aim here is not to produce a critique of the project's goals and usefulness. Likewise, we do not aim to produce a 'better' map for the purposes of the original project. Our aim is to examine the original map as an example of a seamless visualization where the overall cleanliness of a visualization design can disguise the complexities of the data and the phenomenon represented (Hengesbach, 2022). Our critique informs alternative designs that surface and interrogate the limitations of the underlying tree data. This interplay is an example of a critical visualization practice where critical studies of data can inform design and vice versa, facilitating a productive exchange between criticism and design. This approach sees maps as research objects that allow us, as researchers engaging with (critical) data studies and critical visualization, to generate questions and explore answers regarding a data set, the represented phenomenon, and the conventions of visualization/s.

2. Case study: An urban tree map

The '*giessdenkiez*' map provides a bird's eye view of tree locations in Berlin. These are represented by clickable yellow or green dots indicating the recent rainfall. When zoomed out, an even surface of tiny dots covers the map. The distribution of trees can be seen in more detail when zooming in, and the user can access some meta-information about the trees by clicking on a dot (Figure 1). The interface features official logos of the organizations involved, a legend, and data sources. The map uses a reduced color palette: white, blue, and gray to depict landscape and water features, and yellow and green for the trees (Figure 1). The base map omits most of the urban context (e.g., green space, use of space) and all trees are represented with dots of the same size regardless of their real size or species.

These features produce a sleek, professional, and trustworthy appearance, and a map that appears effortless and seamless, and whose visual design reduces the

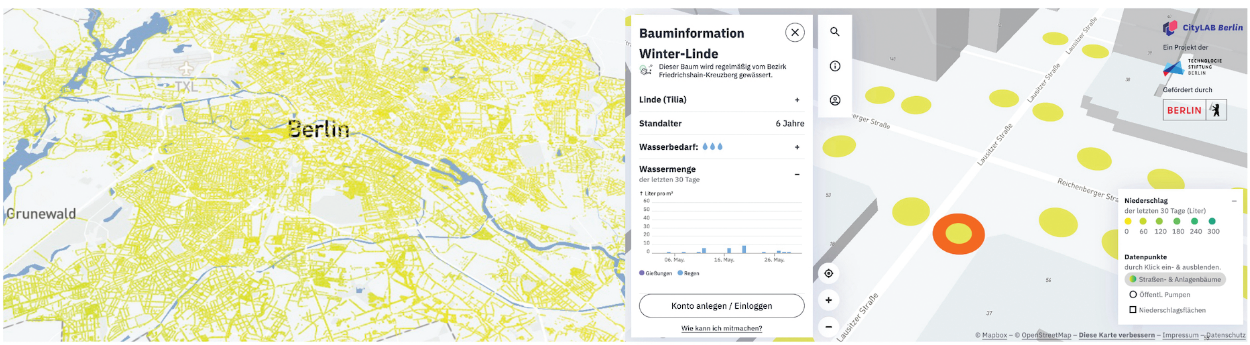

Figure 1. Screenshots of the original map from the project website (giessdenkiez.de). Left: Zoomed-out map of Berlin. Right: Zoomed-in map showing details of the interface, such as information about a specific tree (circled red), a legend showing the color coding for the dots based on the recent rainfall amounts, and logos of the organizations involved in the project

apparent complexity of the data. The map design seems to suggest that every tree in Berlin can be seen. There is no indication that this is not the case. Likewise, there is no suggestion that the data, provided by Berlin's administration, are anything other than correct and concise. It was the apparent completeness of the data that has led us to explore *missingness* through alternative map designs.

3. Methodology

We began by closely engaging with the original visualization, interrogating the limitations of the map and the data, and questioning what may be missing. This initial critique was followed by design experiments whereby alternative designs allowed us to explore different dimensions of the missingness in these data: Incompleteness, Emptiness, Absence, and Nothingness (Table 1). These types of missingness consider how the data relate to the trees and encourage the exploration of missingness within and beyond the data set. Although we conducted this study from a distance, we drew on local knowledge of places on the map, which helped us identify questions about missingness.

Our exploration of alternative designs began with the reproduction of the original map in *R* (R Core Team, 2021). From this, our critical reflections directed the generation of alternative designs by changing colors, encodings, symbols, and base maps using *RStudio* and appropriate code packages (Bivand et al., 2021; Dowle & Srinivasan, 2021; Hijmans, 2020, 2021; Urbanek, 2013; Wickham, 2016; Wickham et al., 2021; Wilke, 2020; Zeileis et al., 2020). The tree data are available as open data (GeoPortal Berlin, n.d.a; n.d.b). The satellite imagery in Figures 8–10 is from *Google Maps* and was edited with *Affinity Designer*. Our maps focus on the Friedrichshain-Kreuzberg district (Figure 2). Throughout our study we chose color scales with different hues instead of tone, shade, or tint. This was to enable greater differentiation between colors when the maps were of a small size and when there were many data points.

Table 1. Types of missingness as defined by the presence or absence of data when trees are present or absent. The four quadrants of this matrix produce four routes for questioning the data through the visualization design.
(i) In/completeness: The data that are present describe the trees that are (supposedly) present in the urban space, how in/complete are these data?;
(ii) Emptiness: What do the data suggest about areas without any trees?;
(iii) Absence: What are the areas where trees are present but data are absent?;
(iv) Nothingness: What are the areas where both data and trees are absent?

		Data: Yes	**Data: No**
Tree	**Yes**	In/completeness	Absence
	No	Emptiness	Nothingness

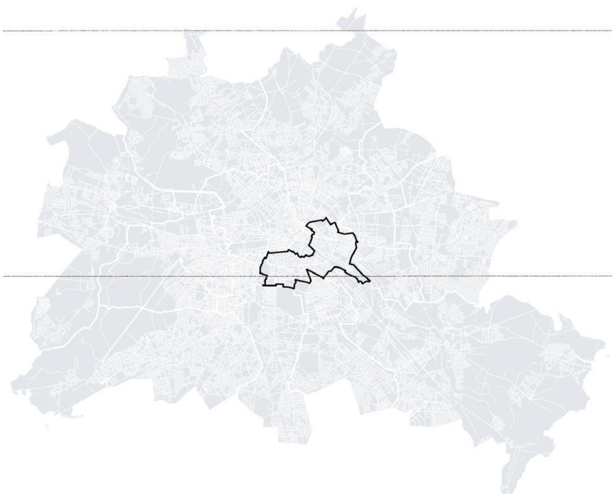

Figure 2. Map of Berlin highlighting the district of Friedrichshain-Kreuzberg, which is the focus of this case study

4. Exploring missingness

In this section we explore missingness through alternative map designs and briefly discuss each one of the dimensions. In/completeness, Emptiness, and Absence are represented with two maps, and Nothingness with one.

4.1 In/completeness

This type of missingness is perhaps the most common and has to do with what attributes of the tree data are in/complete. We focus on the attributes that describe the trees' age, size, and species, considering nine attributes in total.

To explore in/completeness each attribute was encoded into a color that represents the total amount of missing attributes in each data point (Figure 3), ranging from one to a total of nine missing attributes. To further examine the incompleteness, each missing attribute in a data point was encoded to circle diameter and hue. By stacking these attributes (circle and hue) on top of each other for each data point/tree, the patterns of in/completeness are, to some extent, revealed (Figure 4). This way, we can see how many and which attributes are missing for each tree, as well as something of the local

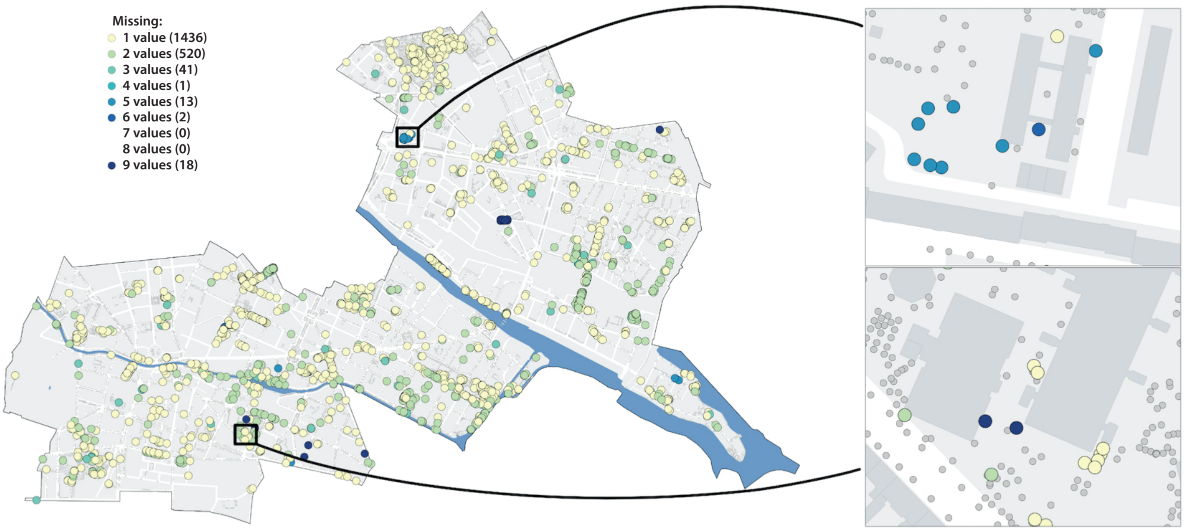

Figure 3. The number of missing attributes for each tree is color encoded in this map to emphasize the in/completeness of the tree data. The trees with complete data are plotted in smaller gray dots. The incompleteness shown in this map (and in the map in Figure 4) refers to the attributes in the data set that describe the tree's immediate characteristics (year of plantation, age, crown diameter, trunk circumference, height, botanical species name, common species name (German), genus name in Latin, common genus name (German)) and omits data attributes that contain details of a tree's location and details of identification (e.g., street name, identification number)

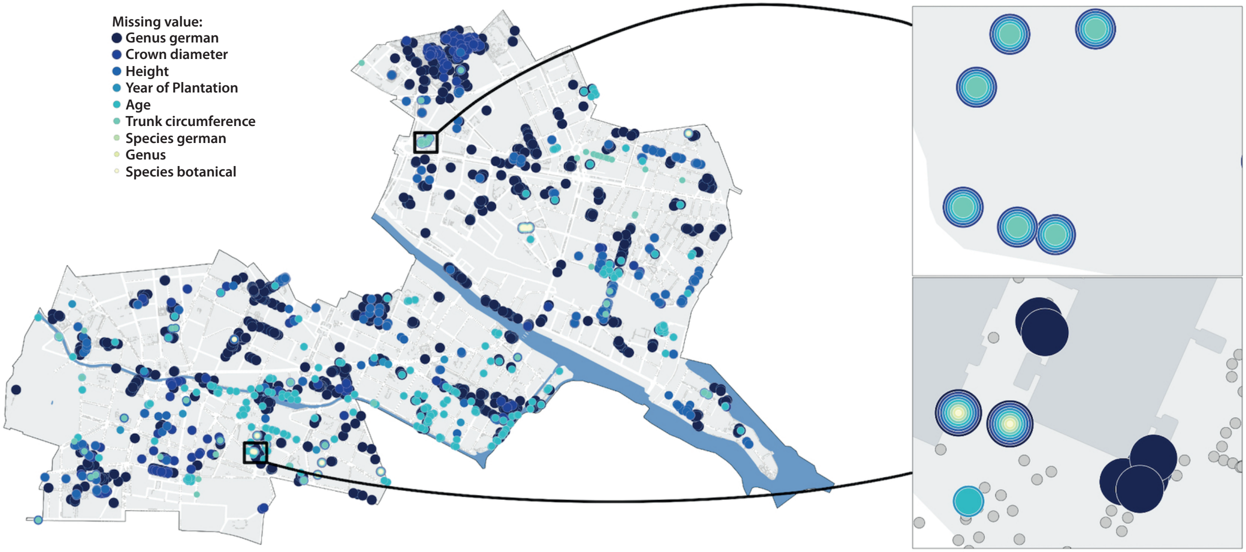

Figure 4. In this map the incompleteness is represented by using a circle of different diameter and hue for each missing attribute of a data point (i.e., tree) plotted on top of each other. This produces a set of stacked circles for trees that have more than one attribute missing. The trees with complete data are plotted in smaller gray dots

patterns in missing attributes. While the map in Figure 3 may be read more easily and quickly, the map in Figure 4 allows for a richer understanding of the incompleteness of the data.

Trees that are close to each other sometimes have the same combination of missing attributes. Some data attributes seem to be missing due to the physical inaccessibility of a tree or a group of trees, e.g., if they were in backyards. Other data seem to be missing due to gaps in cross-referencing, e.g., the Latin species name is included but the common species name (German) is missing. The ability to examine and view in/completeness enabled some further critical reflections on how data were recorded, which generated insights that a seamless design could not.

4.2 Emptiness

By displaying the location of the trees, the visualization also seems to indicate the places where no trees are present. We can emphasize this emptiness in the design by removing the base map (Figure 5), which highlights the presence and absence of trees and reveals aspects of the relationship between trees and the structures of the built environment. The emptiness can be encoded into the symbols by displaying distances between trees and their nearest neighbors (Figure 6). Compared to the map in Figure 5, this version makes it easier to locate more isolated trees. Emptiness can help understand the context of trees' occurrence (e.g., potential competition between trees or habitat availability) as well as the

Figure 5. The pattern of the tree distribution is emphasized in this map by showing the location of the trees with same-sized black dots on a white background, highlighting the areas where, according to the data, (public) trees are absent

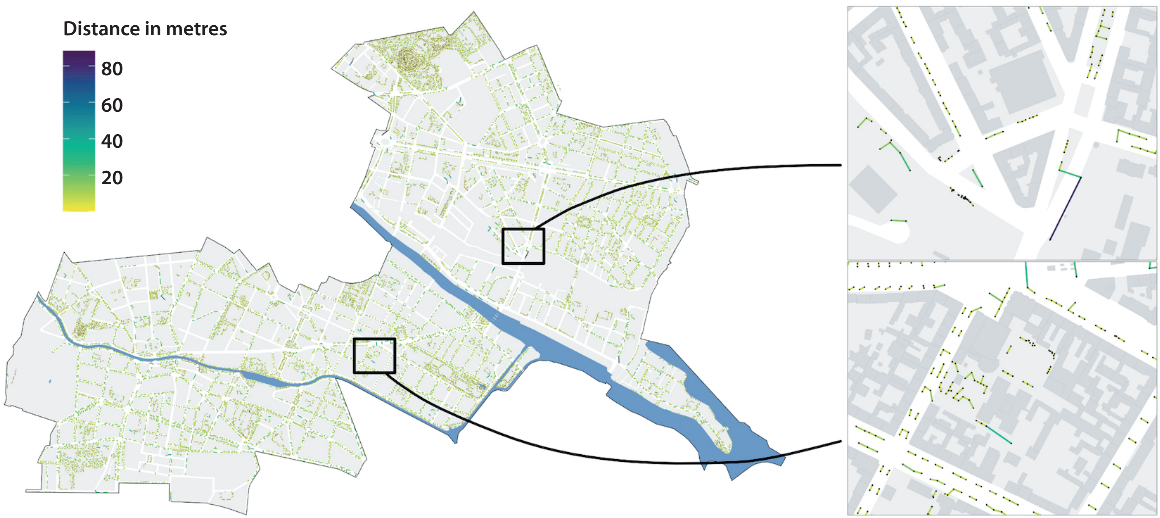

Figure 6. The distance between each tree and its nearest neighbor is represented in this map. Longer distances are indicated by darker hues and shorter distances by lighter hues, emphasizing the absence of nearby trees

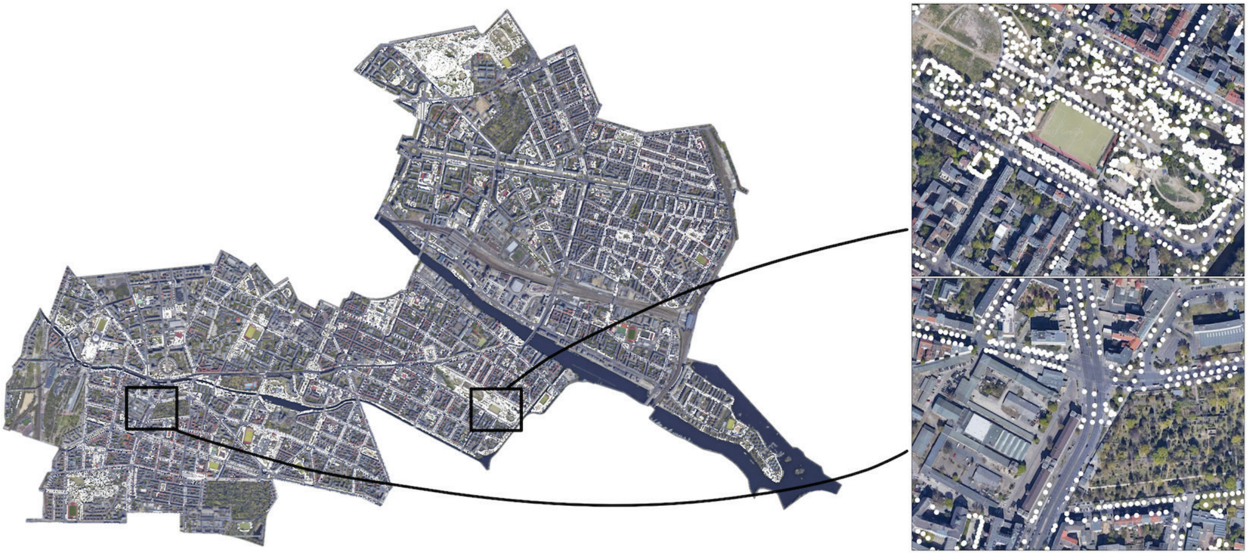

Figure 7. The absences of trees in the data are surfaced in this map by encoding trees in the data with same-sized white dots, making visible the trees that are not recorded in the data but are visible in the satellite imagery. Satellite imagery from Google maps ©2022 CNES / Airbus, GeoBasis-DE/BKG, GeoContent, Maxar Technologies, Map data ©2022

potential distribution of trees' impact (e.g., amenity value and ecosystem services).

4.3 Absence

Large amounts of local context, such as the environment and green space surrounding the trees, are eliminated from the original map and from the maps in Figures 3–6. In contrast, the maps in Figures 7 and 8 show the tree data plotted onto satellite imagery. Despite the transient accuracy and historical context of satellite imagery (e.g., Kurgan, 2013), its inclusion enables some reference to the current local context. With these maps we can identify areas where trees appear in the satellite imagery but not in the data (Figure 7). While these maps highlight what is not present in the data, it remains unclear whether an absent tree is an unrecorded public tree, a private tree, or a plant that resembles a tree. When encoding the crown size into the symbol size, we can explore how, according to the data, the trees occupy space (Figure 8). These maps raise questions about the limitations of data collection and the boundaries of private and public areas. These maps also make us question whether trees are always observable from satellite imagery, e.g., the trees might only be visible when the satellite imagery displays recordings from seasons where the trees carry leaves.

Figure 8. Based on Figure 7, this map surfaces the absences of trees in the data by representing trees as white circles that are now sized relatively to the crown size recorded in the data. Although not highlighting an absence, this encoding makes it possible to spot tree crowns that seem excessively big (displaying probable errors in the data), which was not possible with uniformly sized dots. Satellite imagery from Google maps ©2022 CNES / Airbus, GeoBasis-DE/BKG, GeoContent, Maxar Technologies, Map data ©2022

Figure 9. The built environment in the district is highlighted in this map by changing green colors in the satellite imagery to white and by locating the tree data with white dots sized relatively to the crown size that is recorded in the data. Satellite imagery from Google maps ©2022 CNES / Airbus, GeoBasis-DE/BKG, GeoContent, Maxar Technologies, Map data ©2022

4.4 Nothingness

Whereas *emptiness* focuses on gaps in the distribution of trees, *nothingness* focuses on what is found where trees are not present. Nothingness thus looks at areas where both tree data and physical trees (and other green space) are absent. To achieve this, the green hues in the satellite imagery were replaced with white, over which the tree data were plotted as white dots (Figure 9). Whilst drawing attention to the overall presence and absence of green space, and emphasizing the built environment in Berlin, the map now serves as a critique of the data veracity when compared to the one in Figure 7 which includes green spaces.

5. Conclusion

While the importance of critical studies of data and visualization is now increasingly acknowledged, these new perspectives rarely influence the design of visualizations. This might be because it is no small task to account for these critiques by developing improved approaches to visualization. Works that have explicitly experimented with aspects of these critiques may require additional data or measurements (Drucker, 2011). Moreover, such works could be considered radical rather than being able to feedback into mainstream visualization (Davila, 2019), or focus on data collection or on the structure of the design team (D'Ignazio & Klein, 2016). Our aim in this case study was to move towards a critical visualization practice that visually surfaces limitations in data to enable a richer representation of data. The maps we have created are the result of a critical interrogation of data. They are also a critical tool for interrogating data, which generates new reflections on visualizations (see McInerny, 2018) and on the involved processes and practices.

The integration of different perspectives is essential for critical visualization. It will take us beyond a visualization with multiple views (e.g., Roberts, 2007; Windhager et al., 2018) and towards visualizations with multiple perspectives. This could emerge from a consideration of pluralism (D'Ignazio & Klein, 2020), abundance (Meyer & Dykes, 2019), plurality (Dörk et al., 2013), and/or multiple presentations (Loukissas, 2016).

While the maps in this study emerge from one data set, they each refer to the trees in a different way and can offer a plurality of perspectives on both the data and the phenomenon represented. Although these alternative perspectives are not definite, fixed, or complete, the maps, taken individually or together, provide depictions of what we miss when looking at data from a single, and seamless, perspective. Therefore, this approach makes it possible to critically explore and reverse the reductiveness of visualization (e.g., Hall et al., 2015; Lockton et al., 2017; Offenhuber, 2019) by moving from the seamless to the 'seamful' (Hengesbach, 2022), to reveal the messiness and complexities of data.

The critique and the data limitations we surfaced were influenced by subjectivity relating to our perspectives and backgrounds. A similar study by other researchers would likely surface different limitations, for example, data accuracy or provenance. Moreover, local people were likely to address completely different limitations of the map and the data. Similarly, at a different time, different limitations might surface as neither the trees nor the data are static. Our alternative maps surface substantially different perspectives on the data by minimal changes in the design. More profound, or radical, design changes could change the perspective being 'from above' to being street-level views, more akin to human scale and our experience of trees in-situ. These street-level views could include a change in interactive features, introduce accessibility features, or support a broader range of tasks, and in so doing, account for different uses, users, and experiences of the visualization and the trees. For example, the visualization might show the density of the trees to locate areas of shade, show young trees and those that are particularly prone to drying out, or show trees that carry edible (or poisonous) fruits.

While this study focused on offering a plurality of perspectives on urban tree data, exploring the directions we highlighted could demonstrate how other approaches to multiple perspectives can become part of (critical) visualizations. We explored the original visualization and data set from afar, thus a next step could be to empirically engage with the data in the physical space they refer to and alongside the entities that the data represent. Such an approach might enable further understanding of data limitations and provide ways in which to surface these limitations with, in, and within a visualization.

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