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Using AI to Generate Accessibility Descriptions for Maps

Anthony C. Robinson [a,*], Amy L. Griffin [b]

[a] GeoGraphics Lab, Department of Geography, The Pennsylvania State University - arobinson@psu.edu
[b] Geospatial Sciences, School of Science, RMIT University - amy.griffin@rmit.edu.au

* Corresponding author

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Abstract:

While much progress has been made to expand the populations who participate in map making and map sharing, there remain major challenges for ensuring that maps are accessible to diverse audiences with varying physical and cognitive abilities. One contemporary cartographic accessibility challenge is to ensure that useful text descriptions exist to support screen-readers for blind and visually impaired (B/VI) users (Hennig, Zobl, and Wasserburger 2017). Sophisticated large-language model (LLM) artificial intelligence (AI) tools provide a potential opportunity to automate what is currently a manual process to caption map images. Here we review common guidelines that have been used to make accessibility descriptions for maps and evaluate those models using several map types and two common LLM AI platforms.

Several frameworks exist for guiding the development of accessibility descriptions for images. General guidelines are published by W3C[1], but these do not anticipate descriptions of maps specifically. The National Center for Accessible Media (NCAM) in the United States has published a widely adopted set of guidelines for describing STEM images that encourages descriptions to focus on *brevity*, *data* (focusing on content versus extraneous visual elements), *clarity* (straightforward and concise writing), *drill-down organization* (brief descriptions followed by more extensive details), using linear *narrative description* communicated via properly formatted HTML that supports efficient *navigational control* (Gould, O'Connell, and Freed 2008). NCAM also provides specific guidance for images that include tables, process diagrams, and mathematical formulas, but does not specify what to do with maps. The DIAGRAM Center extended the NCAM guidelines with a brief set of principles for describing maps, although these guidelines pertain only to basic locator and political maps[2] and don't provide guidance on more complex maps.

Recent work by Lundgard and Satyanarayan (2022) proposes a four-level semantic content model for accessibility descriptions that can be readily operationalized by users and that can also be utilized for empirical evaluations of the quality of accessibility descriptions. The four levels they propose describe visual representations, statistics and quantitative relationships, perceptual and cognitive elements including patterns, and the social and political context for an image. An image description using this model may include one or two sentences explaining each level.

Few of these existing frameworks are readily translatable into explicit instructions either for people writing descriptions or LLMs. Most provide general guidelines and principles to follow (e.g., NCAM suggests that *Brevity* is a key feature in an effective STEM image description, but it does not say exactly what that entails in terms of specific length limits). Therefore, in order to support an evaluation, we have translated guidelines into prompts that can be followed either by people or AI tools (Figure 1). We evaluated four types of AI prompts in this research; 1) NCAM Stem image guidelines, 2) the 4-level model by Lundgard and Satyanarayan, 3) a naïve prompt as written by a user without guidelines, and 4) a naïve prompt that includes a length constraint. The latter two types are what we might expect many end-users to employ in the absence of specific guidance for writing image accessibility descriptions.

NCAM STEM Images	Using the following guidelines, write an accessibility description for this image.
	One sentence that briefly describes the data represented in the image.
	One sentence that briefly summarizes the content provided in the image.
	Two sentences that provide a linear, narrative description of the content represented in the image.
4-Level Model	Using the following guidelines, write an accessibility description for this image.

[1] https://www.w3.org/TR/WCAG22/
[2] https://diagramcenter.org/specific-guidelines-e-2.html

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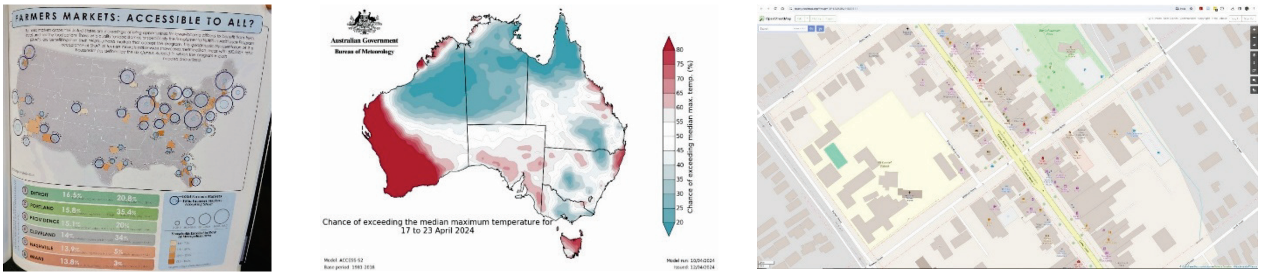
	One sentence that describes the visual components of the image.
	One sentence that describes the relationships between data observations in the image.
	One sentence that describes the perceptual and cognitive phenomena appearing in the image.
	One sentence that describes the context and domain-specific insights that can be gained from the image.
Naïve	Write an accessibility description for this image.
Naïve with Length Limit	Write an accessibility description for this image. Limit the description to four sentences.

Figure 1. Prompts used to evaluate AI accessibility descriptions.

To evaluate the potential for AI-generated map accessibility descriptions, we used three example maps from a range of map types and formats, including a phone-captured image of a thematic map printed in a book, a web-published meteorological map from a government agency, and a large-scale reference map of a rural town from OpenStreetMap (Figure 2). There are of course many other types of maps and map image formats that could also be tested, so we began with these examples with the knowledge that they may be broadly representative but are by no means exhaustive.



(Guerrilla Cartography 2013) (Bureau of Meteorology 2024) (OpenStreetMap 2024)

Figure 2. Map images used to evaluate AI accessibility descriptions.

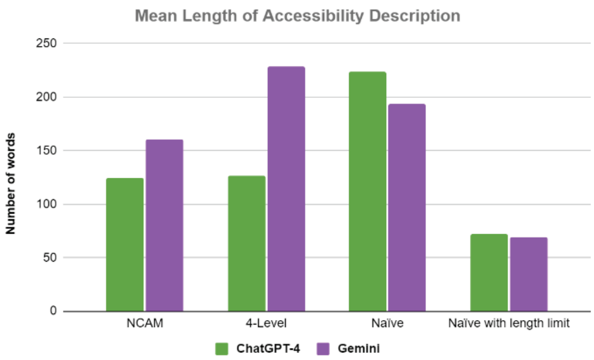


Figure 3. Length comparison of AI-generated map accessibility descriptions. Gemini also sometimes repeated parts of the prompt in its answer. These statements were excluded in our word count analysis.

We find that AI tools may in fact provide useful means of automatically generating accessibility descriptions for a variety of map types. Such captioning is however very sensitive to different types of prompt guidance (Fig. 3). In reading the resulting captions, many appear to be useful, but we still find instances in which factual errors are evident in AI image descriptions. In future work, we will compare AI-generated captions to those made by human experts. If it appears that automated captioning can provide comparable quality, a key advantage associated with AI-enabled captioning would be that it can be deployed in near-real time and directed by B/VI users themselves, who could immediately ask follow-up questions and be able then to iteratively engage with map contents in a way that has been heretofore difficult to accomplish without a sighted collaborator.

References

A. Lundgard and A. Satyanarayan. 2022. “Accessible Visualization via Natural Language Descriptions: A Four-Level Model of Semantic Content.” IEEE Transactions on Visualization and Computer Graphics 28 (1): 1073–1083. doi:10.1109/TVCG.2021.3114770.

Gould, B., T. O’Connell, and G. Freed. 2008. Effective Practices for Description of Science Content within Digital Talking Books. https://www.wgbh.org/foundation/ncam/guidelines/effective-practices-for-description-of-science-content-within-digital-talking-books.

Hennig, Sabine, Fritz Zobl, and Wolfgang W. Wasserburger. 2017. “Accessible Web Maps for Visually Impaired Users: Recommendations and Example Solutions.” Cartographic Perspectives 88: 6–27. doi:10.14714/CP88.1391.

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