

# Information Distortion and Cartographic Quality in AI-Generated Thematic Maps

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## Abstract:

The possibilities of generative artificial intelligence are rapidly growing, also in the field of cartography. The AI-supported tools with rule-based design are developed for various aspects of map makers' work, e.g. color choice (N. Yang et al., 2025), layout design (J. Yang et al., 2025), creating thematic map elements (Wang et al., 2025), and even generating the whole maps (Zhang et al., 2025).

Despite the scope of such tools growing rapidly, popular general-purpose multimodal large language models (MLLMs) are still a common choice for lay users with no professional training. As MLLMs are not purposely trained on specific geospatial data nor implement cartographic rule-based design, the quality of map images generated can be far from perfect and may result in information distortion on such maps. The aim of the study is the identification, description, and classification of information distortions in thematic maps generated by popular MLLMs, as well as the assessment of their frequency. This approach aims to revise observations that AI-generated maps often diverge from established cartographic design principles and introduce new forms of information distortion (Affolter et al., 2025, Zhang et al., 2023). The achieved findings provide a basis for further empirical studies on how specific distortions influence users' perception of and trust in contemporary cartographic products. Previous cartographic research has shown that even subtle design decisions may significantly affect map interpretation and credibility (Muehlenhaus, 2012; Monmonier, 2018). The analysis therefore examines which map elements are most susceptible to distortion in MLLM-generated maps and whether these distortions form recurring patterns that allow the identification of distinct quality profiles of AI-generated maps.

The research material comprised 704 (88 maps per tool) maps generated (Fig. 1) using eight popular and publicly available tools based on large language models capable of producing images from textual prompts, namely ChatGPT, Gemini, Grok, Ideogram, Leonardo, Microsoft Designer, MidJourney, and Wan. The tools were selected on the basis of popularity in 2023–2025 (Liu & Wang, 2026; Moore, 2026), technological diversity, and differences in visual characteristics (Affolter et al., 2025; Joynt et al., 2024) such as emphasis on aesthetics or text legibility. Because text-only prompting provides limited control over a map's spatial composition and semantic layout, we standardized prompts and explicitly constrained key cartographic requirements to reduce uncontrolled variability across generated outputs. Each prompt specified the map topic, spatial extent, map type, an appropriate color scale, a requirement for high contrast, and the inclusion of essential map elements (title, legend, labels, and borderlines).

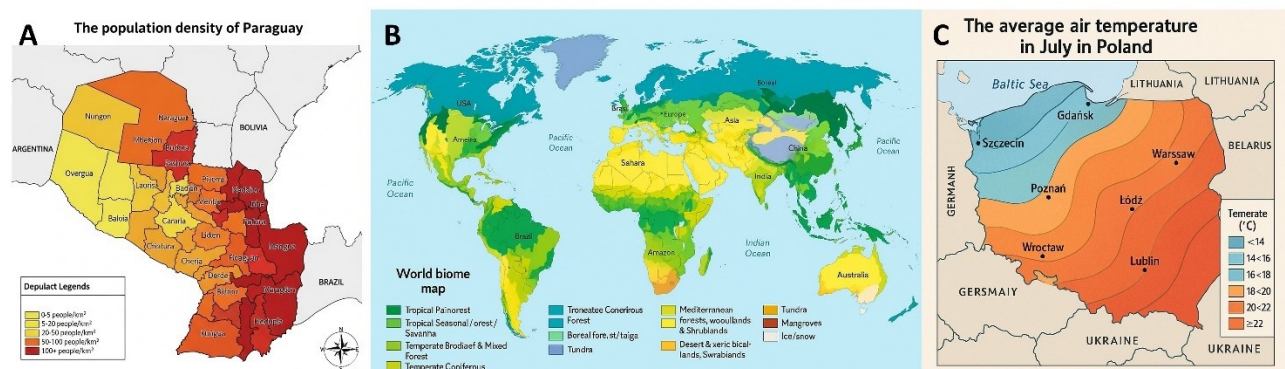


Figure 1. Examples of maps that achieved a high map quality index. A – population density of Paraguay (choropleth method); B – world biomes (qualitative area map); C – average air temperature in July in Poland (isoline map).

Stimulus variability was controlled through combinations of 4 topics (average temperature in July, population density, political/administrative map, and biomes), 4 map types (isoline maps, heatmaps, choropleth maps, and qualitative area maps), 11 spatial extents (from the global level to second-level administrative units), and 8 MLLMs. Map quality and information distortions were assessed using a set of criteria drawn from cartographic literature. Criterion weights were assigned using an expert-based approach to reflect their importance for cartographic correctness and message credibility (Prestby, 2024). The findings show substantial variation in the quality of the analyzed map elements. Compositional and descriptive features (e.g., title, style and layout) and map coverage received the highest scores, whereas elements crucial for the semantics of cartographic communication—especially thematic data, geographical names, and borderlines—were rated the lowest. Hierarchical cluster analysis identified four coherent groups of criteria: (1) informational features, (2) structural and spatial features, (3) compositional and descriptive elements, and (4) map coverage as a distinct dimension. This is consistent with earlier claims that map credibility depends on multiple, partly independent dimensions rather than a single visual factor (Muehlenhaus, 2013). Comparative analyses show that the generating tool is the strongest factor differentiating quality assessments, followed by spatial extent.

The conclusions highlight the need to develop evaluation tools and benchmarking frameworks for generative mapping systems, e.g. implementing a connection to authoritative geospatial data services as well as to advance research on trust in maps under conditions of widespread GenAI adoption. The relatively lower quality of semantic and informational elements may be partly explained by the greater variability of geographic features, differences in cartographic generalization, and the absence of direct connections to reliable geospatial data sources. The proposed structure of criterion clusters will provide a foundation for the next stage of research aimed at identifying which distortions undermine perceived map credibility.

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