International Cartographic Association
Association Cartographique Internationale

The effects of line simplification on planform geometry

Ethan Shavers [a,*], Lawrence Stanislawski [a], Barry J. Kronenfeld [b], Barbara P. Buttenfield [c]

[a] *U.S. Geological Survey, Center of Excellence for Geospatial Information Science, eshavers@usgs.gov, lstan@usgs.gov*
[b] *Eastern Illinois University, bjkronenfeld@eiu.edu*
[c] *University of Colorado-Boulder, babs@colorado.edu*

* Corresponding author

Keywords: sinuosity, streams, planform, simplification, fractal

Abstract:

Data on maps should retain accuracy regardless of scale. Yet, as cartographic lines are generalized, there can be impacts on properties such as topology, density, and planform geometry. Here, we investigate the use of the Scale Specific Sinuosity (S3) metric (Stanislawski et al., 2023) to evaluate the effects of line simplification on planform geometry, which is the bends of streams in map view. We employ an open-source Python S3 workflow to characterize the geometry of five diverse stream channels in the United States. The original data are extracted from the U.S. Geological Survey National Hydrography Dataset 1:24,000-scale vector data (U.S. Geological Survey, 2000) (Table 1), and the simplification is done using the Visvalingam and Whyatt method (2017) with a simplification tolerance of 0.5, 1.0, 1.5, and 2.0 km. The S3 analysis is calculated at each level of simplification and S3 derivatives are generated. Derivatives include measures of sinuosity, fractal dimension, and the dominant bend wavelength. The findings show that the change in planform geometry is scale-dependent, though simplification will have little effect on straighter lines. The change becomes more apparent in complex lines as the degree of simplification aligns with the scale of the dominant bend geometries. These logical conclusions are evidence that the S3 is a useful metric for automated characterization of bend geometry regardless of line complexity.

Name	Length (km)	Points per km	Conventional sinuosity	S3 sinuosity
Cannonball River	362	85	2.8	2.7
Licking River	311	13	2.1	2.1
Mississippi River	166	27	1.4	1.3
San Cristobal Wash	121	16	1.1	1
Osage River	132	10	1.8	1.8

Table 1. This study tested the line characteristics of 1:24,000-scale National Hydrography Dataset (NHD) vector polyline representations of five river systems. Conventional sinuosity is the ratio of total path length over the end-to-end distance. S3 sinuosity is calculated as base ten with an exponent of the area under the S3 curve. S3 sinuosity is not an exact measure because the analysis is limited to step lengths between 0.1-100 km and 200 step length increments.

Recent increases in remote sensing coverage and resolution offer great opportunities for automated mapping of the Earth's surface. The increased spatial and temporal resolution allows the capture of fine-scale features and their dynamics. Yet, as datasets become more detailed, line simplification becomes more challenging and may be required in near-real-time applications. Artificial intelligence algorithms and other advanced applications are being tested for these substantial challenges (Du et al., 2022; Yan and Yang, 2024). However, little work has been published about evaluating simplification strategies, much less in a standardized, repeatable way.

Here, we test the recently developed S3 metric as a tool to evaluate how the planform geometry and general complexity of line features change with varying degrees of simplification. Planform geometry is an important landscape characteristic that can be a function of a landscape's geometry, ecology, anthropogenic activity, and hydrology (Poff et al., 2006). It is proposed here that the S3 can serve as a metric to characterize and record the complex geometry of original lines and to evaluate how best and to what degree simplification should adjust line features for multi-scale mapping.

Of note in this analysis is the pattern revealed among the S3 sinuosity and fractal dimension values (Figure 1). As Stanislawski et al. (2023) show, the area under the S3 curve approximates sinuosity, and the fractal dimension equals one plus the mean S3 value. Whereas all the sinuosity and fractal dimension values decline with simplification, the effects are very small on lines dominated by large bends: Osage River, Mississippi River, and San Cristobal Wash.

https://doi.org/10.5194/ica-abs-10-259-2025

Conversely, the geometry of the Cannonball and Licking Rivers includes many small bends, with substantial decreases in sinuosity and fractal dimension with increasing simplification tolerance.

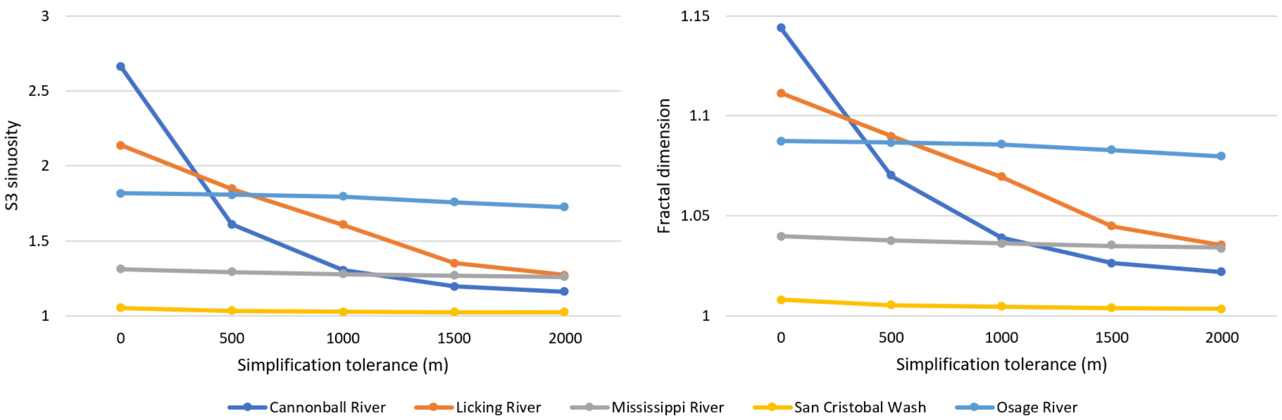

Figure 1. Plots of the S3 derivatives sinuosity and fractal dimension for the five 1:24,000-scale National Hydrography Dataset polylines with degrees of simplification tolerance ranging from 0 (no simplification) to 2000 m.

It is of note that this analysis shows that the effects of simplification are not solely dictated by initial sinuosity or fractal dimension values. The three rivers that show little change in geometry with simplification have a range of initial metric values. The Osage River has the closest initial values to the Licking River, yet the respective deltas are very different, as seen in Figure 1. This provides strong evidence that sinuosity alone is insufficient to characterize planform geometry. Also indicated here is that the S3 metric can show how lines change with simplification and could be used to determine which lines should be simplified and with what tolerance. The S3 values can capture the complex planform geometry of lines across scales and detail the effects of simplification (figure 2).

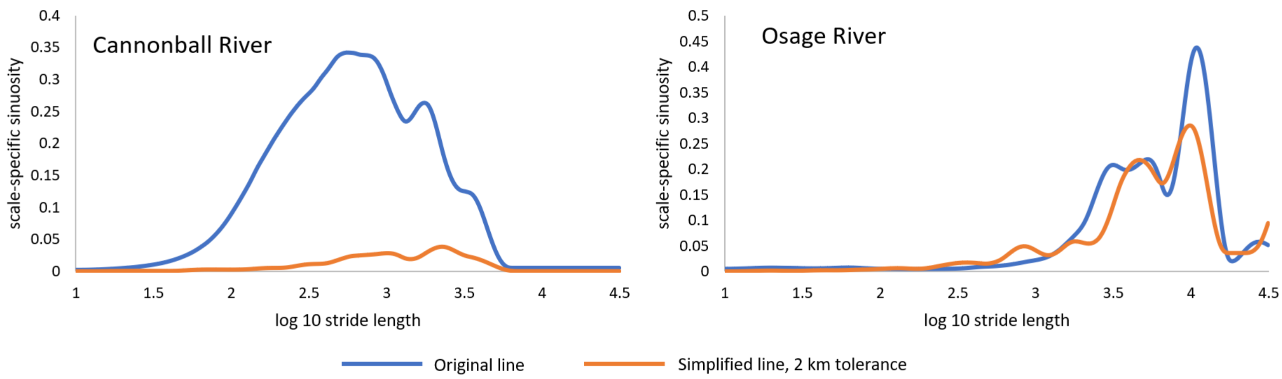

Figure 2. Examples of the S3 values for the original line (blue lines) and the lines simplified with the 2.0 km tolerance (orange lines) for the Cannonball and Osage Rivers.

Disclaimer

Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

References

Du, J., Wu, F., Yin, J., Liu, C. and Gong, X., 2022. Polyline simplification based on the artificial neural network with constraints of generalization knowledge. *Cartography and Geographic Information Science*, *49*(4), pp.313-337.

Poff, N.L., Bledsoe, B.P. and Cuhaciyan, C.O., 2006. Hydrologic variation with land use across the contiguous United States: geomorphic and ecological consequences for stream ecosystems. *Geomorphology*, *79*(3-4), pp.264-285.

Stanislawski, L.V., Kronenfeld, B.J., Buttenfield, B.P. and Shavers, E.J., 2023. At what scales does a river meander? Scale-specific sinuosity (S3) metric for quantifying stream meander size distribution. *Geomorphology*, 436, p.108734.

https://doi.org/10.5194/ica-abs-10-259-2025

U.S. Geological Survey, 2000. The National Hydrography Dataset: Concepts and Contents. www.usgs.gov/national-hydrography/national-hydrography-dataset, last accessed 05 May 2025.

Visvalingam, M. and Whyatt, J.D., 2017. Line generalization by repeated elimination of points. *In Landmarks in Mapping* (pp. 144-155). Routledge.

Yan, X. and Yang, M., 2024. A deep learning approach for polyline and building simplification based on graph autoencoder with flexible constraints. *Cartography and Geographic Information Science*, 51(1), pp.79-96.

Abstracts of the International Cartographic Association, 10, 259, 2025
32nd International Cartographic Conference (ICC 2025), 17–22 August 2025, Vancouver, Canada.
https://doi.org/10.5194/ica-abs-10-259-2025