Impact Statement of "GeoSpark: A Cluster Computing Framework for Processing Large-Scale Spatial Data"

Jia Yu Wherobots jiayu@wherobots.com Jinxuan Wu Two Sigma jinxuanw@apache.org Mo Sarwat Wherobots mo@wherobots.com

1 Introduction

Over the past decade, GeoSpark has played a foundational role in advancing large-scale spatial data processing. Its impact spans academic research, industrial adoption, open-source ecosystems, and global usage. In what follows, we outline its contributions in accordance with the award selection criteria. Notably, the GeoSpark project was donated to the Apache Software Foundation in 2020 and was subsequently renamed Apache Sedona [1]. While many references now cite Sedona, they all trace their technical lineage back to the original GeoSpark paper.

2 Utility and impact on research

GeoSpark introduced the first distributed in-memory computing framework for large-scale spatial data. It pioneered the concept of spatial distributed datasets, spatial partitioning, and distributed spatial indexing, providing a scalable foundation for spatial analytics. It has been cited over 500 times [2], with nearly 800 citations across all related papers, including ICDE'16 [3], and Geoinformatica'19 [4]. The work is frequently referenced in top venues such as VLDB, ICDE, SIGMOD, and SIGSPATIAL.

The framework has been independently evaluated by researchers around the world. A SIGMOD 2020 paper [5] compared several spatial systems and found that GeoSpark's distance join significantly outperformed Simba, another Spark-based spatial computing system. Another PVLDB 2018 benchmarking paper concluded that GeoSpark was one of the most performant and complete distributed spatial analytics frameworks [6].

GeoSpark has been foundational for subsequent research on distributed geospatial processing, influencing many highly-cited research articles like Simba [7], LocationSpark [8], SparkGIS [9], ST-Hadoop [10], DITA [11], and JUST [12]. The paper is also central to the academic lineage of Apache Sedona (formerly GeoSpark), which is widely used in systems research, spatial machine learning, and spatiotemporal data analytics.

3 Practical impact and scientific reach

GeoSpark's scalable architecture has enabled practical adoption in a wide range of real-world applications involving spatial data. It supports fundamental operations such as spatial joins, nearest neighbor queries, distance joins, and trajectory analysis at distributed scale, which are essential across numerous domains:

(1) <u>Urban computing</u>: Used in traffic analysis [13], and traffic demand prediction [14], GeoSpark powers large-scale processing of GPS data in city-scale applications. (2) Climate science: GeoSpark

have been used to join raster and vector datasets (e.g., zonal statistics over satellite imagery), enabling scalable climate and environmental analysis [15–17]. (3) <u>Public health:</u> During COVID-19, researchers employed GeoSpark to correlate anonymized mobility data with infection rates at regional levels, requiring high-throughput spatial joins [18, 19]. (4) <u>Telecom and energy infra: Service providers in the telecom and energy sectors leverage GeoSpark to optimize infrastructure placement, coverage, and risk mitigation. Applications include cell tower coverage analysis [20] and facility management [21].</u>

GeoSpark is highly attractive for interdisciplinary research, and it has been cited in venues across computer systems [5–8, 11–13], geoinformatics [9, 10, 14], remote sensing [16, 17], and communication & networks [15, 18].

4 Utility in industry

GeoSpark has had a substantial and lasting impact on industrial data infrastructure for spatial analytics. In 2020, we donated the open-source implementation of GeoSpark to the Apache Software Foundation, where it was renamed Apache Sedona [1, 22] and later graduated as a Top-Level Project. Today, GeoSpark (i.e., Apache Sedona) is the most widely adopted open-source distributed spatial processing engine in industry.

The Apache Sedona project has gained significant traction in the open-source and industrial communities, with over 2,000 GitHub stars and contributions from more than 130 developers worldwide. It has been downloaded over 50 million times across Maven Central and PyPI [23, 24], and is used by more than 10,000 organizations (see Figure 2) spanning logistics, e-commerce, financial services, agriculture, and cloud infrastructure sectors.

Each month, users launch more than 5 million Sedona-based clusters across all major cloud platforms, including AWS, Azure, Google Cloud, Databricks, and Snowflake. The project's official website receives over 10,000 monthly page views, with global traffic spanning all major countries across the Americas, Europe, Asia, and many parts of Africa, as illustrated in Figure 1.

Notable users of Apache Sedona include Amazon, which integrates it into daily last-mile delivery route planning; Allstate, which uses it to analyze traffic accident patterns; and Land O'Lakes, which applies it to large-scale agricultural analytics. Adoption has also been reported in organizations such as Mercedes-Benz, Shopee, SpaceX, JB Hunt, JPMorgan Chase, Capital One, HERE Technologies, and Mapbox, supporting use cases including routing optimization, asset tracking, and spatial risk modeling.

The technology introduced in GeoSpark continues to evolve through Wherobots [25], a company founded by the original authors of this paper. Wherobots offers a commercial geospatial lakehouse platform built on Apache Sedona's query engine, enabling



Figure 1: Geographic distribution of Sedona website traffic

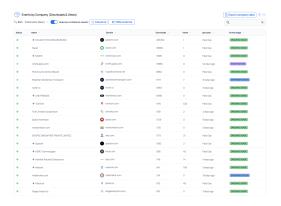


Figure 2: Top 20 most active Sedona users in May 2025

high-speed spatial analytics and geospatial AI at enterprise scale. In the past 3 years, the company has raised 27 million dollars in two funding rounds (Seed and Series A) from world-renowned venture capital firms, including Felicis, Wing VC, Clear Ventures, Prosperity7, and JetBlue Ventures. Today, Wherobots has close to 40 employees and operates offices in San Francisco and Seattle, serving many customers across industries. In particular, these include the Overture Maps Foundation [26], one of the largest open map data providers, founded by Amazon, Meta, Microsoft, and TomTom.

5 Geographic diversity impact

GeoSpark and its successor, Apache Sedona, have demonstrated wide-reaching geographic impact across both academia and open-source adoption.

On the research side, the original GeoSpark paper has been cited by scholars affiliated with institutions in North America, Europe, Asia, and Africa, based on Google Scholar [2]. Notable citation activity comes from the United States [5, 7], Germany [6, 19], China [11], Tunisia [15], Turkey [16], Italy [18], Austria [20], and Sweden [17] with publications in areas such as geoinformatics, transportation, environmental modeling, and distributed systems.

On the open-source front, Apache Sedona enjoys global developer participation and production usage. The project's GitHub repository includes contributors from many countries, with frequent commits and issue activity from the U.S., Europe and Asia

(see Sedona's GitHub [1]). The Sedona website receives more than 10,000 page views per month from users in tens of countries, spanning nearly all regions of the Americas, Europe, Asia, and many countries in Africa (see Figure 1).

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