Review of GIS Architecture for Environmental Monitoring: from Standalone Monoliths to AI-Ready Systems*

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Abstract

This paper explores the evolution of Geographic Information Systems (GIS) architecture from monolithic desktop systems to distributed, cloud-native solutions, highlighting the transformative impact of artificial intelligence on GIS and spatial mapping. The shift from standalone systems with local storage to networked, client-server GIS and eventually to cloud-based architectures has enabled real-time geospatial processing, automation, and seamless integration with big data frameworks. While core spatial algorithms and data models have remained stable, advancements in storage, computation, and deployment models have significantly reshaped GIS capabilities. The integration of AI-driven techniques has further revolutionized spatial mapping by enhancing predictive analytics, automated feature extraction, and real-time geospatial decision-making. However, challenges remain, including high-throughput processing for large-scale geospatial data, complexities in AI integration, and interoperability between legacy GIS systems and modern cloud-native environments. Future GIS architectures are expected to focus on optimizing AI-powered spatial analytics, enhancing real-time geospatial computing, and leveraging microservices and serverless technologies for increased modularity and scalability. This review provides a comprehensive analysis of GIS architecture evolution and the transformative role of AI in shaping the future of geospatial technologies.

Keywords

GIS, architecture evolution, computational architectures, AI integration in GIS, geospatial data processing, predictive analytics.

1. Introduction

The evolution of GIS software architecture has been driven by the increasing complexity of spatial data and business demands. At the same time, it developed hand in hand with broader advancements in computing and data management. Initially GIS were designed as standalone desktop applications with most of the data being stored, accessed and processed locally [1, 2]. While these systems laid the groundwork for spatial analysis, they were limited in terms of data sharing, scalability, and computational efficiency [3, 4]. These limitations were lifted with the evolution of client-server architecture and introduction of cloud computing resulting in a variety of collaborative, networked solutions [16, 17].

Understanding how GIS software architecture has evolved is essential for both researchers and practitioners, since it provides insights into the challenges and technological shifts that have shaped modern geospatial systems. Examining the evolution of GIS architecture from its early designs to its current state can help us understand the broader landscape. Through the review we can identify

The Second International Conference of Young Scientists on Artificial Intelligence for Sustainable Development (YAISD), May 8-9, 2025, Ternopil, Ukraine

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which components have fundamentally changed and which have simply evolved via technological advancements together with the general software development trends.

Research aims are: systematic integration of knowledge regarding the evolution of GIS and their transformation towards AI-ready systems within the context of environmental monitoring; analysis of the current state and identification of gaps in research on GIS architectures oriented towards AI for environmental monitoring; synthesis of disparate knowledge from the fields of GIS and artificial intelligence within the context of environmental monitoring to form a holistic understanding of future development directions.

Ultimately the goal of this review is to guide developers towards understanding future GIS design and possible areas of improvements to the architecture that will support ongoing trends in GIS domain.

2. Methods

This research employs a literature review methodology to analyze the evolution of Geographic Information Systems (GIS) and changes in their architecture, particularly within the context of environmental monitoring and the transition to systems ready for Artificial Intelligence (AI) utilization.

Scientific databases, digital libraries, and other authoritative sources were utilized to search for articles, conference proceedings, books, and technical reports pertaining to GIS, environmental monitoring, and artificial intelligence. The selection of literature was based on its relevance to the research themes, the quality of the source, and the currency of the information.

The selected sources were analyzed to identify key trends, architectural changes, approaches to AI integration, and challenges in the field of GIS for environmental monitoring. Information from various sources was systematically organized and synthesized to identify common patterns, contradictions, and gaps in existing research. Based on the literature analysis, key stages in the development of GIS were identified, ranging from standalone monolithic systems to modern AI-ready architectures.

The transformation of architectural approaches in GIS was investigated, including the transition to client-server systems, web GIS, cloud GIS, and service-oriented architectures (SOA), with a particular emphasis on their adaptation to the needs of environmental monitoring and integration with AI.

3. Evolution of GIS and current state

Like any other software GIS follows an “S” shaped adoption curve. Though due to specifics of application, cost and complexity GIS adoption has spread across decades [1]. Long adoption cycle resulted in a cascade of ongoing changes and improvements due to rapid enhancement of technologies that enabled GIS. These changes in technologies often brough new capabilities and extended GIS beyond professionals and researchers. At the same time each new cycle introduced new challenges for GIS developers to overcome. One of the domain areas that has significantly benefited from GIS development is environmental monitoring [2]. In this article we attempted to link GIS trends, technologies enhancements and its application for environmental monitoring.

We started our review from 1990 because that period marks a critical turning point in the evolution of GIS technology. It was the time of advent of personal computers and the emergence of systems like ESRI's ARC/INFO, early versions of GRASS GIS and others [3]. Most of those products captured a decent portion of the market and still exist today. Overall development of GIS can be outlined in several major phases:

Baseline mapping and early monitoring. During this period, desktop GIS systems were adopted to map environmental resources and hazards. Early remote sensing data integration enabled basic assessments of land cover, and contamination. GIS began its transformation from a niche, mainframe-based tool into desktop applications accessible to a broader range of users. Pioneering systems like ESRI ARC/INFO and GRASS GIS leveraged file-based formats (such as Shapefiles and GeoTIFFs) and basic spatial algorithms to integrate raster and vector data [4;5].

Expanded data integration and multidisciplinary assessments. GIS began to support environmental policy and land-use planning. As well as started playing a vital role in environmental impact assessments, deforestation mapping, and pollution monitoring. This became possible because of satellite imagery and improved spatial indexing and the initial support for spatial databases [6].

Web-based sharing and standardization. This period marks a significant shift as GIS transitioned to web-based data sharing and open architectures. The adoption of OGC standards like as WMS, WFS and GML combined with service-oriented approaches enabled more flexible component-based designs. These developments allowed GIS to integrate multiple data streams broadening its capabilities to monitor water quality, air quality, biodiversity, and climate trends concurrently [7;8].

Mobile near real-time monitoring. Phase characterized by GPS-enabled field data collection facilitated by multiple REST APIs for accessing data from various sources. At this point GIS gained lots of practical meaning for wildfire risk mapping and localized hazard monitoring, although issues like data latency and sensor integration still presented challenges [9;10].

Big data integration and cloud-based processing. Large-scale satellite imagery and citizen science data became central to monitoring environmental changes. Advanced data storage and ETL capabilities made it possible to integrate crowdsourced observations. GIS became capable of managing and processing massive and diverse datasets [11].

AI real-time analytics and immersive visualization. Marks use of IoT devices, advanced 3D visualization frameworks (WebGL and CesiumJS) and machine learning techniques. These improvements allow GIS to provide high-resolution change mapping and 3D visualizations that help better understand dynamic environmental processes. While use of AI allows making decisions on the fly and spot patterns in spacial data and its layers [12;13].

Clearly aforementioned phases were not consequent, some happened in combination and related technologies keep evolving till today. Below is a visualization of how search trends in geographic information systems have evolved over time by Jorge Vinueza-Martinez et al from their recent work "Bibliometric Analysis of the Current Status and Research Trends" (Fig. 1). Over 350 publications were analysed in scope of the review using metadata like author, keywords and thematic mapping to analyze research trends, gaps, and thematic clusters [14].

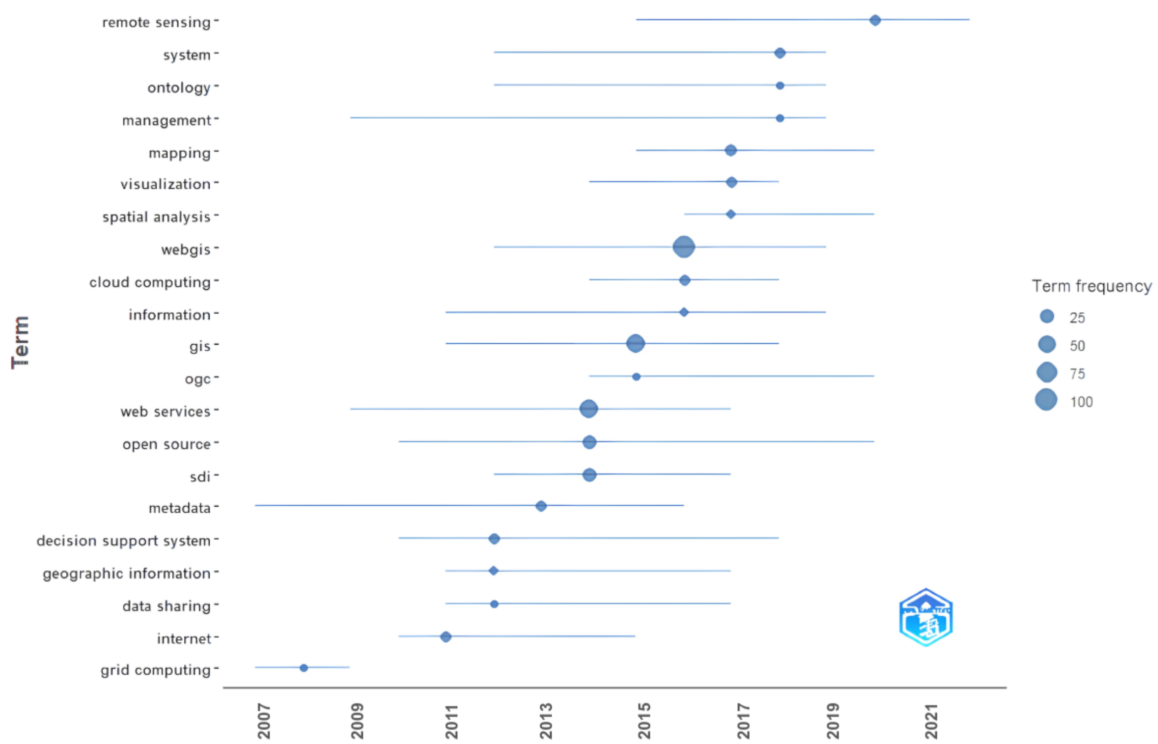

Figure 1: GIS trend themes over years [14]

4. Results and discussion

The research may, for the first time, clearly identify and analyze precisely which changes in GIS architecture (for example, the transition to cloud technologies, service-oriented architectures) are most crucial for the effective application of artificial intelligence methods in environmental monitoring tasks. The review may reveal underexplored aspects or problematic areas in existing architectures that hinder the effective implementation of AI in environmental monitoring practice, thereby defining directions for future research.

4.1. Early Desktop GIS

Before mass-adoption, GIS architecture was primarily monolithic and on-premises with limited scalability. Clients were mostly desktop-based with local storage with little to none network connectivity. GIS services were basic and worked with static data through tightly coupled map and feature services (see Fig. 2).

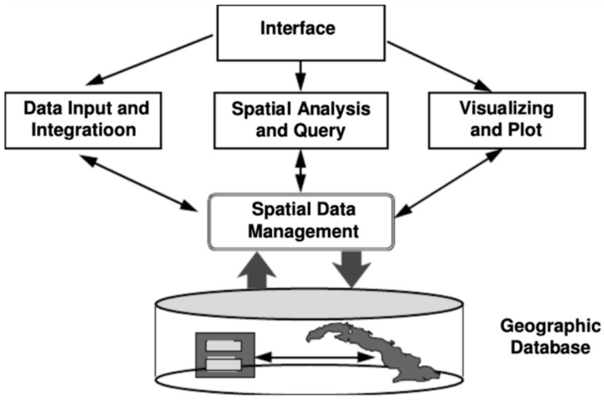

Figure 2: Client-server architecture of marine environment surveillance GIS [15]

Data processing involved simple batch processing and manual imports, while storage was a simple two-tier system using spatial databases and file systems. Data sources were limited to vector data, remote sensing, and tabular data, with communication relying on SOAP/XML for synchronous operations [15].

3.2 Client-Server GIS

With advancements in communication technology and the growing need for multi-user access, GIS architectures evolved into Client-Server GIS, enabling remote accessibility.

Such architecture mitigated limitations of standalone desktop GIS, introducing centralized spatial data management and at least partial server-side processing [16]. These architectures relied on GIS servers handling spatial processing and database management, while web-based or desktop clients acted as front-end interfaces for users. Technologies such as ArcGIS Server, OpenLayers, PostGIS, and MapServer enabled organizations to serve geospatial data over networks, improving collaboration and data consistency.

However, these systems often faced performance bottlenecks, complex maintenance, and early challenges in distributed processing. A notable example from this period is the web-based GIS for marine environment surveillance and monitoring presented in Kulawiak et al (2009) [17]. The architecture of the system is depicted on Fig. 3.

This system followed a client-server model where a central GIS server processed real-time marine sensor data and satellite imagery, with results visualized through a web-based interface. While it demonstrated the advantages of web-based GIS for environmental monitoring, it remained constrained by the traditional client-server paradigm, and limitations of server side computing features at that time.

Another example is GIS architecture presented by Frank Kühnlenz and Ingmar Eveslage (2008) for their research project for SAFER project, which at that time was co-funded by the European Commission [18]. The project itself was focused on developing methodologies of detection and analysis of seismic events through GIS. The architecture diagram is displayed on Fig 4.

While this system already presented somewhat decentralized architecture by using component based software design it can't be considered fully modular and decentralized by modern standards [19].

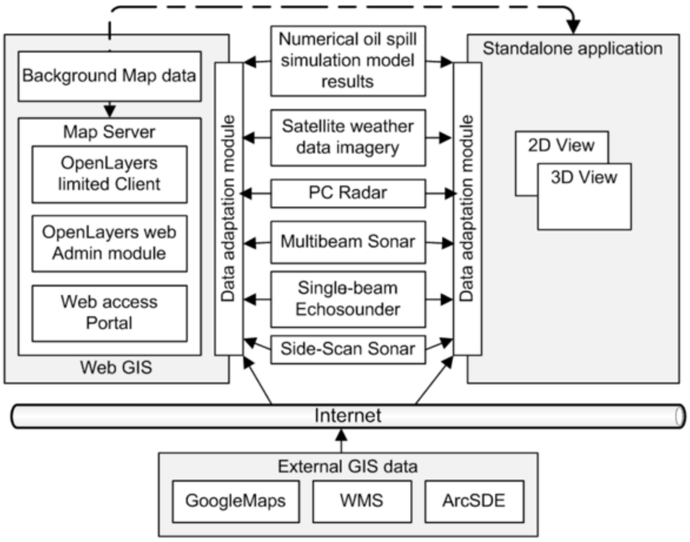

Figure 3: Client-server architecture of marine environment surveillance GIS [17]

Despite having some distributed characteristics it lacks the flexibility of a modern microservices or API-driven architecture. Specifically it has no clear API-driven approach and has tight component coupling - they are embedded within each node rather than being independent services that nodes can call when needed. And of course cloud and edge computing was not widely available at the time of publication. At the same time this work clearly shows the direction of GIS architecture advancements.

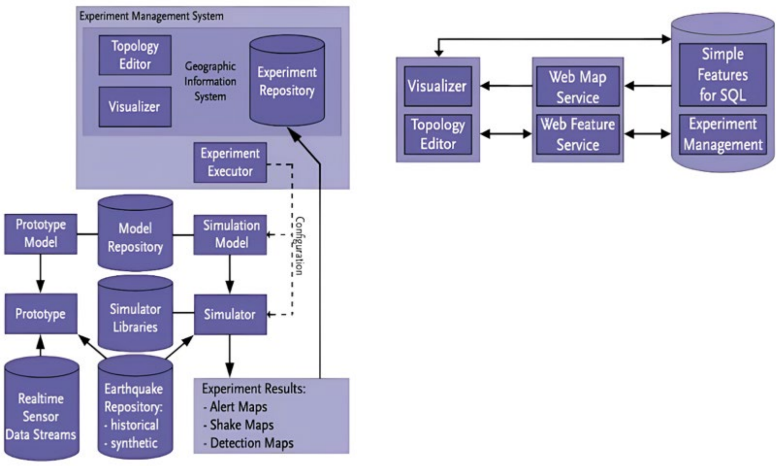

Figure 4: GIS architecture by Frank Kühnlenz and Ingmar Eveslage [18]

3.3 Cloud and Web GIS

The shift toward cloud computing in the 2010s further evolved GIS architectures, addressing scalability and interoperability limitations inherent in client-server models [20]. GIS architecture has evolved from traditional client-server models to cloud-native, web-based platforms. This shift has been driven by the need to process and visualize large, complex spatial datasets in real time and be scalable to accommodate increased user demands. Such design leveraged scalable distributed processing, RESTful APIs, and open standards and some GIS-specific tooling like OGC protocols, GDAL and others. Cloud computing opened the way towards using big data tools like Hadoop and Spark for storing and processing large volumes of geospatial data [21].

Major platforms like ESRI ArcGIS also moved into cloud, this provides both cost optimization and more flexibility to the customers who are now able to deploy and maintain their application by themselves [22]. Below is an example of the architecture of a cloud-native GIS architecture by Reza Nourjou and Joel Thomas – Fig. 5 [23].

This design leverages real-time data streaming and integration with distributed IoT devices to enhance geospatial analysis. Proposed architecture makes use of modern web services and APIs to integrate external data sources for near real time data collection. The cloud-based processing layer facilitates computational analysis and can be scaled due to the nature of cloud components.

As for data storage and processing Big Data became another possible option for the applications with large-scale data processing requirements [24]. It plays a vital role in the organization of comprehensive GIS solutions due to the need to process a high variety of data formats - imagery, audio, sensory and geospatial data [25].

When transitioning from traditional file-based spatial databases to a Big Data storage architecture, the approach shifts from centralized systems to distributed, scalable solutions designed to handle large and complex geospatial datasets. Hadoop Distributed File System (HDFS) replaces conventional file storage formats like Shapefiles and GeoTIFF, providing fault-tolerant, parallelized storage that improves data accessibility and reliability [26]. At the same time, NoSQL databases such as HBase and Accumulo offer a more efficient alternative to relational spatial databases like PostGIS and Oracle Spatial by enabling faster indexing and distributed querying [27;28].

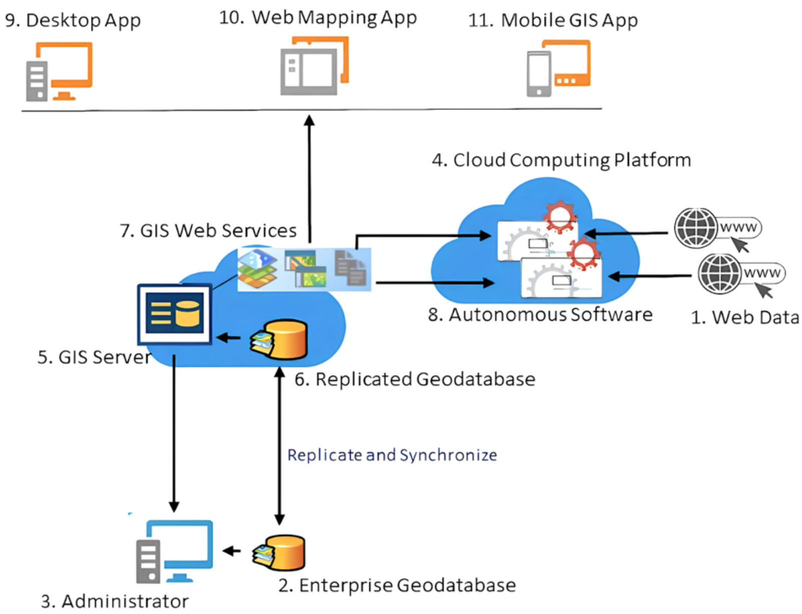

Figure 5: System architecture of cloud-based web GIS with 3rd party APIs

Instead of relying on a single database server, modern GIS systems use distributed query engines like Hive and Impala, which allow parallel spatial processing across multiple computing nodes [29]. Raster data, previously stored in relational databases or standalone files, is now managed through HDFS or cloud-based object storage, ensuring more efficient storage and faster processing. Additionally, spatial indexing methods have evolved from traditional QuadTree and R-Tree structures to distributed indexing frameworks such as GeoMesa and GeoSpark, allowing faster spatial queries on large-scale datasets [30].

Fig. 6 depicts an architecture of GIS application developed by Zhibo Sun and Liqiang Wang using Hadoop and HBase [36]. Despite advancements in Big Data that make GIS more scalable, resilient, and capable of handling high-volume real-time geospatial analysis in cloud environments, its adoption should be justified by actual needs to prevent data redundancy and unnecessary financial costs.

3.2 Advanced AI and Real-Time GIS

High-volume geospatial and sensorics data created demand for effective ways of data analysis and patterns recognition. This led towards use of Machine Learning and Artificial Intelligence for real-time decision making and forecasting capabilities.

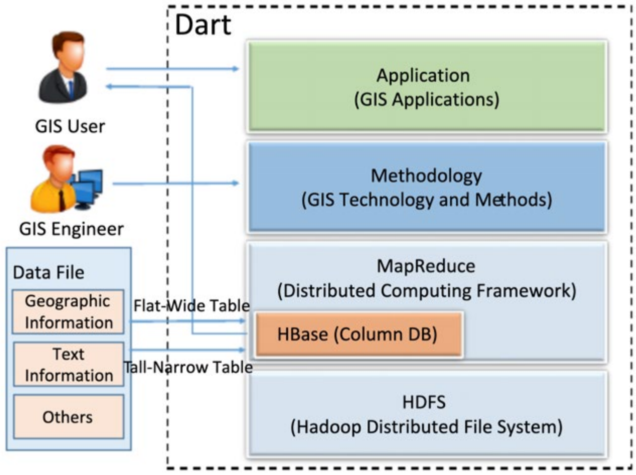

Figure 6: A Geographic Information System on Hadoop [36]

The field of spatial data interpretation and process modeling is the most promising for applying ML and AI in GIS. Machine learning is used in various GIS applications such as the classification of satellite imagery and patterns identification [31]. AI-based forecasting models also allow for the prediction of natural disasters, optimization of resource allocation, and analysis of climate change, which turns GIS into a proactive tool for strategic decision-making [32]. An example of GIS architecture with an integrated Machine Learning module is shown in Fig 7.

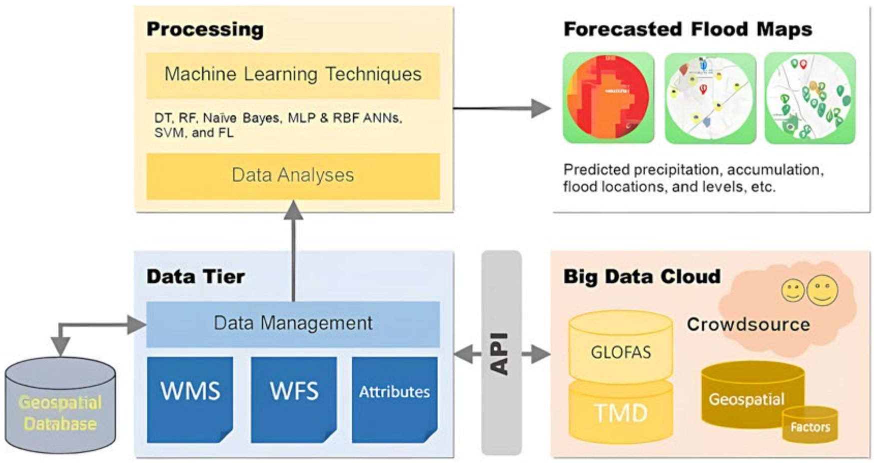

Figure 7: GIS architecture with an integrated Machine Learning module [32]

This system enhances flood forecasting by leveraging crowdsourced data, remote sensing, and weather station inputs. ML models, trained on historical flood data, continuously refine predictions by integrating real-time observations. Data processing is performed using Big Data frameworks such as Hadoop and Spark, enabling scalable spatial analysis. The architecture includes a GIS-based simulation layer for generating flood risk maps and a web-based GIS dashboard for visualization and decision support. This AI-driven approach improves flood prediction accuracy, supporting real-time risk assessment in cloud-based environments [33]. While this is an excellent example of how ML and AI can enhance decision making, there still remain difficulties in integrating AI with complex spatial datasets, ensuring model transparency and correctness, and managing high computational demands [34]. But it's obvious that the growth in AI power will further strengthen its role in GIS through process automation. This will improve the accuracy of analysis, especially when working with large volumes of geospatial data.

As expected, the architecture of GIS has significantly evolved reflecting advancements in technology and user needs. Modern GIS are distributed and cloud-native, allowing for horizontal scalability. Another big advancement is support of multiple clients, including web, mobile, and desktop applications. Beck-ends are modular following commonly adopted software architectural patterns like microservices, with each service specialized for various GIS functions. A conceptual difference between legacy and modern GIS designs is shown on the Fig. 8.

Data processing has advanced to include real-time stream processing, batch processing for large datasets, and AI/ML integration. In addition to cloud hosting, storage evolved into a multi-tiered system that consists of spatial databases, object storage, distributed caches, and a time series storage. This enables efficient storage, transformation and extraction of data used in geoinformation systems. Data sources have expanded to include real-time sensors, third-party APIs, and streaming data. Communication uses REST/GraphQL APIs for both synchronous and asynchronous operations, and real-time processing capabilities have significantly improved.

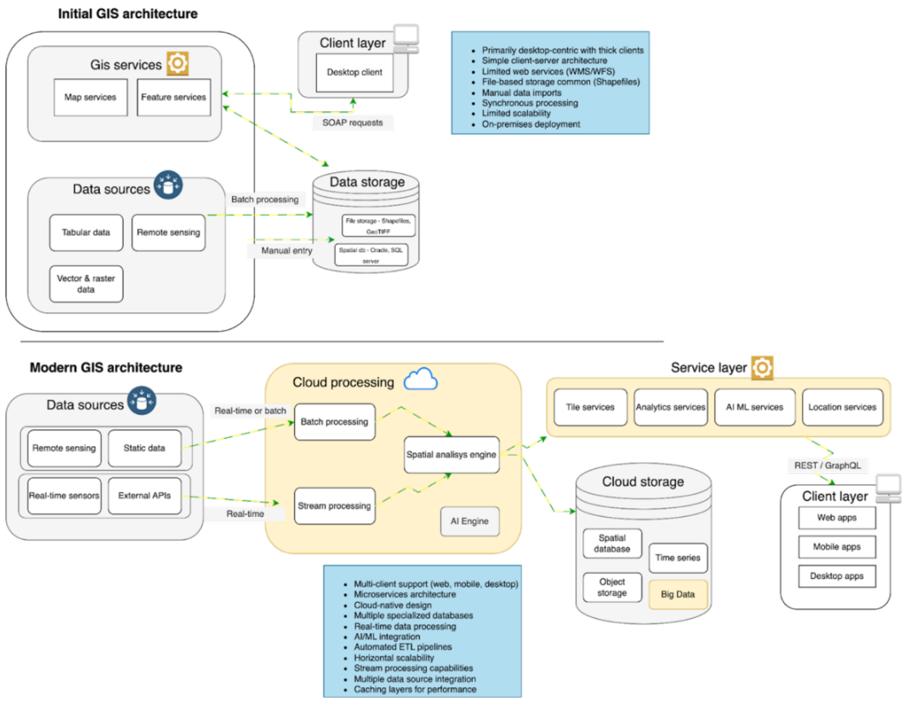

Figure 8: GIS architecture changes overview

Before we only reviewed technology agnostic designs that presented main components and their organization. Fig. 9 displays is how ArcGIS suggests deploying their application on Amazon Web Services [35]. Given schema is technology specific but similar architecture can be implemented using any major cloud provider, it shows modern design with a specific hosting solution. Process modeling is given in [37-39].

This system takes advantage of cloud-native services like AWS EC2, S3, RDS, and DynamoDB to support scalable, distributed spatial analysis and geospatial data management. By combining dynamic image services, raster analytics, and real-time data processing it demonstrates how modern GIS platforms leverage cloud infrastructure to improve performance, reliability, and computational power. This architecture is a real-world example of how present-day GIS solutions apply modern principles and technology. It utilizes elastic computing, distributed storage, and automated service orchestration to streamline geospatial workflows and handle large-scale data processing efficiently.

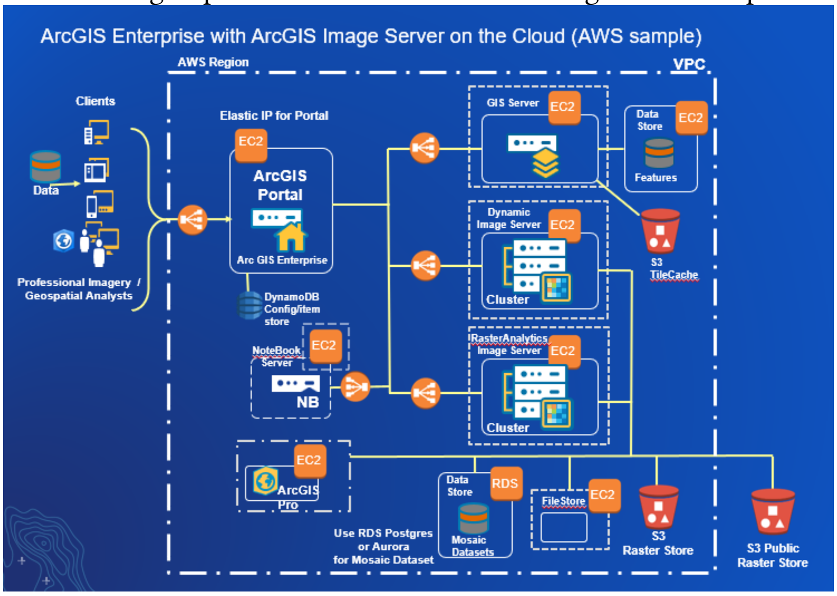

Figure 9: Recommended architecture for deploying ArcGIS software

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

Conclusions

The evolution of GIS architecture reflects both intentional advancements in spatial data management and broader shifts in software design. Early monolithic desktop GIS relied on local storage and standalone processing limiting scalability and collaboration. The transition to client-server GIS introduced centralized databases and networked processing addressing multi-user access but still facing performance bottlenecks. With the development of cloud computing, GIS architectures became distributed, API-driven and highly scalable. This enabled real-time spatial processing, automation and integration with big data frameworks.

Our review shows that some architectural components have changed significantly, while others have evolved mainly due to technological trends. Core spatial algorithms and data models remained relatively stable while storage, computation, and deployment architectures had major transformations. The shift from single-server relational databases to cloud-native storage (HDFS, NoSQL, object storage) and from standalone processing to distributed computing (Hadoop, Spark, Kubernetes based GIS workloads and etc) was primarily driven by general software advancements rather than GIS-specific needs. However, the rise of geospatial web services, AI-enhanced GIS architectures, and geoAPIs was deliberate GIS-driven evolution and enabled interoperability, automation and predictive analytics.

Despite these advancements GIS architecture still faces challenges. Specifically, there are few common bottlenecks: Many distributed GIS solutions struggle with high throughput for geospatial data streams, AI integrations introduce computational, spatial data standardization and model explainability complexities Moreover ensuring seamless interoperability between traditional GIS architectures and modern cloud-native environments remains a priority for future development.

The next phase of GIS architectural evolution will likely focus on enhancing real-time geospatial computing, optimizing AI-powered GIS architectures, and improving modularity through microservices and serverless GIS frameworks. As AI continues to advance, its integration into GIS will become increasingly pivotal, enabling more sophisticated spatial analysis and predictive modeling. These advancements will define how future GIS platforms scale, integrate, and support intelligent spatial decision-making. By leveraging AI, GIS can automate complex data processing tasks, identify patterns and trends more efficiently, and provide actionable insights in real-time. This evolution will open new applications of GIS in environmental monitoring where timely and accurate spatial data is crucial.

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