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AI Integrated Framework for Intelligent Geospatial Handling and Robust Operation in MultiGIS Applications (AI4MultiGIS)

Topic: Multidimensional Geographic Information Systems (MultiGIS)

AI4MultiGIS

D2.1

Analysis of Technology and Solutions for MultiGIS

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Executive Summary

The AI4MutiGIS project aims to offer an integrated framework for Multidimensional Geographical Information System (MultiGIS) data generation and management, aiming to enhance the overall GIS capabilities for optimised processing chain of MultiGIS applications. This deliverable, D2.1, encompasses a comprehensive analysis of the state-of-the-art with the areas that are within the scope of the project.

The deliverable outlines the current landscape of MultiGIS and tools that are used to enhance the overall GIS capabilities in terms of data collection, generation, storage, and real-time processing from a set of diverse heterogeneous sources.

The deliverable also investigates the adoption of Artificial Intelligence (AI) and their potential for the MultiGIS application. Specifically, AI is already widely considered to support various capabilities of GIS, including spatial data analysis, predictive modelling, automation of mapping processes, image classification, pattern recognition, and enhancing decision-making through advanced analytics. However, there are challenges associated with the responsible use of AI-enabled applications in the MultiGIS domain. Finally, the document outlines these challenges and suggests future research directions.

Document History

Version	Date	Author(s)	Comments
0.1	15/01/2025	Shareeful Islam	ToC is added with main sections and related sub-sections
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Acronyms and Abbreviations

AI	Artificial Intelligence
AHP	Analytical Hierarchy Process
ANP	Analytic Network Process
BN	Bayesian Network
BP	Bathymetric Projection
CNN	Convolutional Neural Networks
DEM	Digital Elevation Model
DE	Digital Earth
DPS	Distributed Problem-Solving
XAI	Explainable AI
EWS	Early Warning Systems
EO	Earth Observation
FAHP	Fuzzy AHP
FME	Feature Manipulation Engine
GDAL	Geospatial Data Abstraction Library
GDPR	General Data Protection Regulation
GIS	Geographic Information System
GIFAHP	Group Intuitionistic Fuzzy AHP
GEE	Google Earth Engine
Grad-CAM	Gradient-weighted Class Activation Mapping
GAI	Geospatial AI
GPAI	General-Purpose AI
HITL	Human-in-the-Loop
HOTL	Human-on-the-Loop
IoT	Internet of Things
JSON	Java Script Object Notation
LCA	Life Cycle Assessment
LLM	Large Language Models
LIME	Local Interpretable Model-Agnostic Explanations
MAS	Multi-Agent Systems
MRA	Multiresolution Analysis
LPWAN	Low-Power Wide-Area Network
NFIS	Neural-Fuzzy Inference System

MCDM	Multi-Criteria Decision-Making
MCDA	Multi-Criteria Decision Analysis
MultiGIS	Multidimensional Geographical Information System
ML	Machine Learning
MLP	Multi-Layer Perceptrons
MOS	Multispectral and Optical Satellite
NFIS	Neural-Fuzzy Inference System
OGC	Open Geospatial Consortium
OWS	Open Web Service
OWA	Ordered Weighted Averaging
PSO	Particle Swarm Optimisation
RAI	Responsible AI
RDF	Resource Description Framework
RF	Random Forest
RF	Random Forest
SHAP	Shapley Additive Explanations
SAR	Synthetic Aperture Radar
SDI	Spatial Data Infrastructure
SOS	Sensor Observation Service
SHAP	Shapley Additive Explanations
SVM	Support Vector Machine
TAI	Trustworthy AI
UAV	Unmanned Aerial Vehicle
WCS	Web Coverage Service
WFS	Web Feature Service
WMS	Web Map Service
W3C	World Wide Web Consortium

1 Introduction

1.1 Purpose and Scope

The vision of AI4MultiGIS is to deliver an integrated framework which aims to optimise the processing chain of MultiGIS data to support robust operation of GIS-enabled applications and services through the development of methods and techniques. It also aims to ensure RAI practice for the AI-enabled MultiGIS application. The deliverable D2.1 reviews the state of the art within the scope of the project.

1.2 Contribution to other Deliverables

The deliverable D2.1 provides a comprehensive state-of-the-art analysis of the works which are relevant to AI4MultiGIS including MultiGIS application, data processing, AI-enabled GIS, TAI and RAI. This review also identifies the challenges and gaps which are necessary to consider for the development of method under the MultiGIS project. Therefore, D2.1 provides the foundation for development of novel methods and techniques in WP3 -WP5 of AI4MultiGIS. Moreover, the characteristics related to the RAI investigated by D2.1 will ensure that AI-enabled GIS applications developed by WP4 are in compliance with these characteristics and will provide a roadmap for the policy development and best practice guidelines in WP5 and WP6.

1.3 Structure of the Document

The structure of this deliverable is as follows:

- **Section 2** provides an overview of GIS applications, including data collection methods, current GIS applications, and identified research gaps.
- **Section 3** offers insights into spatiotemporal data processing and management techniques, evaluating their strengths and weaknesses.
- **Section 4** reviews the state-of-the-art in AI-enabled GIS applications, with a specific focus on TAI and RAI. This section also discusses research gaps and suggests future directions for adopting RAI in AI-enabled applications.
- **Section 5** presents a review of existing relevant standards within the context of AI4MultiGIS.
- **Finally**, the deliverable concludes with a summary and references.

2 Overview of the MultiGIS Environment

2.1 Introduction to MultiGIS

MultiGIS is a system that analyses spatial data across multiple dimensions. Traditional mapping techniques are no longer effective and efficient for complex data visualisation needs, specially when we deal with multiple dimensions of information for analysis and decision-making. Hence, MultiGIS extends conventional GIS by integrating data that varies across multiple dimensions, including temporal dimension (i.e., time), spatial dimension (2D & 3D), vertical dimension (depth/height), spectral dimension (e.g., information captured by remote sensing, such as satellite imagery and LiDAR), attribute dimension (e.g., population density, temperature, pollution levels) and scale dimension (from local to global levels). This capability allows for a more dynamic and comprehensive understanding of spatial phenomena over temporal scale, making it particularly useful in fields such as asset and network management, policy decision-making, urban planning and development, land-use management, natural resource management, transportation and logistics, site selection and feasibility study, supply chain optimisation, public safety and security, environmental conservation and monitoring, and risk analysis and mitigation and finally in disaster and emergency situations' management.

By leveraging multidimensional data models, GIS can analyse patterns and trends across different temporal and spatial scales. For instance, researchers can track changes in land use over decades, monitor ocean temperatures across varying depths, or simulate atmospheric conditions at different altitudes. Advances in computing processing and data visualisation technologies have further enhanced the ability of GIS platforms to process and display these complex datasets, offering powerful insights that support decision-making in both scientific and practical applications. Table 1 demonstrates a comparison between traditional and modern mapping approaches.

Table 1 -Traditional vs Modern GIS Mapping Approaches

Traditional Methods in GIS	Modern Methods in GIS
• Paper-based cartography • Single-layer thematic maps • Fixed scale representations • Manual updates	• Dynamic real-time data integration • Interactive 3D visualisations • Machine learning-driven pattern recognition • Automated cross-dimensional analysis • Cloud-based collaborative mapping • Augmented reality integration • Collaborative (crowdsourced) mapping/data collection • Geospatial blockchain data traceability

Considering the growing interrelation and complexity of the real-world challenges using GIS, more advanced methods are needed to enable deeper insights and understanding through advanced data processing and visualisation techniques. Figure 1 illustrates the schematic structure of the MultiGIS process. In general, any MultiGIS application follows a series of essential steps, which are outlined and discussed in detail throughout this document.

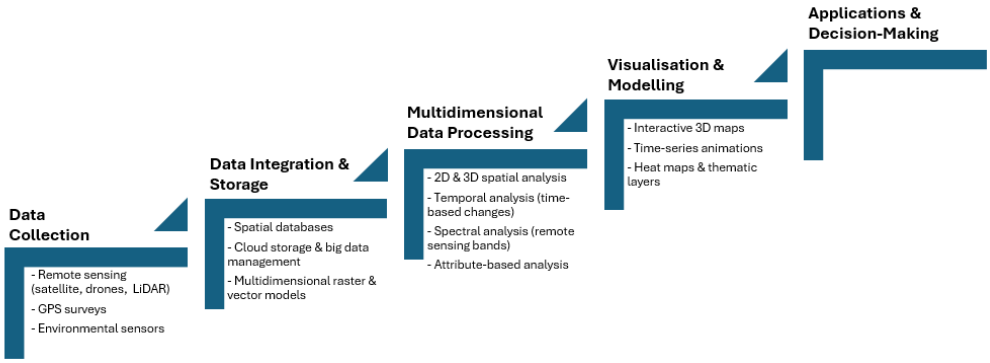

Figure 1 - MultiGIS process

2.2 Data Collection

Data collection is a cornerstone of the AI4MultiGIS project, providing the raw inputs necessary for integrating advanced AI techniques with GIS to generate actionable spatial insights. In this section, we present a comprehensive review of both primary and secondary data collection methods relevant to our project, discuss their applicability in depth, and elaborate on the challenges and opportunities associated with each method. We also examine recent technological advancements, quality control measures, ethical considerations, and integration strategies that underpin robust geospatial analytics.

Classification of Data Types

Primary Data

Primary data are collected directly from the source through active, real-time acquisition methods. These data are critical for capturing high-resolution, current information that is tailored to specific applications within our project. The primary data sources include:

- **Remote Sensing and Satellite Imagery**

  Modern satellite systems offer high-resolution multispectral and hyperspectral imagery that is essential for diverse applications such as land-use classification, environmental monitoring, and disaster response (Ava et al., 2020). The inherent strengths of satellite imagery—its broad spatial coverage and frequent revisit times—make it indispensable for tracking dynamic environmental changes and urban development patterns (Stuart et al., 2019). Advanced techniques, such as SAR and LiDAR-equipped satellites, are now being used to capture structural information and topography, which are crucial for detailed risk assessments and infrastructure planning (Lou et al., 2023). Furthermore, improvements in sensor technology and data processing algorithms (e.g., machine learning-based cloud detection and atmospheric correction) have increased the accuracy and usability of satellite-derived data (Ava et al., 2020). However, challenges such as interference from cloud cover, variations in sensor calibration, and the computational demands of preprocessing large datasets continue to require innovative solutions (Stuart et al., 2019).

- **Aerial Imagery and Drone Data**

  UAVs and manned aircraft provide ultra-high-resolution imagery, which is particularly valuable for localized analyses (Carlos et al., 2014). These platforms are extensively used for infrastructure inspection, urban green space mapping, precision agriculture, and rapid disaster assessments (Syed et al., 2023). The flexibility of UAVs allows them to operate under conditions where satellite imagery might be compromised (e.g., during cloud cover or in urban canyons). Moreover, recent advancements in onboard processing and real-time video transmission have further enhanced their utility in time-sensitive applications such as emergency response and post-disaster damage assessment. Despite their benefits, challenges persist with UAV deployment, including regulatory restrictions, limited flight duration due to battery constraints, and the logistical complexities associated with handling vast volumes of high-resolution imagery (Boubacar et al., 2024). Additionally, ensuring proper geometric corrections and data calibration when fusing UAV data with satellite imagery is a non-trivial task.

- **Internet of Things Sensors**

  IoT sensor networks have revolutionised real-time data acquisition by enabling the continuous monitoring of various environmental parameters such as temperature, humidity, air quality, and traffic flow (Vali et al., 2023). These sensors are strategically deployed across urban and rural landscapes, providing localised data that complement broader remote sensing datasets (Lilin et al., 2020). The real-time nature of IoT data is particularly beneficial for applications requiring instantaneous feedback, such as predictive maintenance, real-time traffic management, and dynamic risk assessment. With the emergence of LPWAN technologies, IoT devices can now transmit data over longer distances while consuming minimal energy (Bharat et al., 2020). However, IoT-based data collection faces challenges including sensor calibration drift, data transmission reliability, power supply limitations, and increased vulnerability to cyber threats. New approaches, such as sensor fusion and error-correction algorithms, are under active development to address these limitations (Naga et al., 2024)

Secondary Data

Secondary data are obtained from pre-existing sources and repositories, such as legacy databases, published reports, and open data portals. These data provide historical context, support trend analysis, and are critical for calibrating and validating primary data sources. The secondary data relevant to the AI4MultiGIS project include:

- **Crowdsourced Data and Social Media Inputs**

  Crowdsourced data, which are collected directly from citizens via mobile applications and social media platforms, provide an immediate source of on-the-ground information. These data are particularly useful in rapidly evolving situations such as natural disasters, where local residents can report incidents, road blockages, or emergency service needs in near real time. In addition to enhancing situational awareness, crowdsourced data can offer unique insights into community perceptions and behavioural responses during crises (Ogie et al., 2018). Recent advancements in natural language processing and sentiment analysis have enabled the extraction of meaningful

patterns from social media streams, further increasing their relevance for disaster management and urban planning (Zihui et al., 2024). However, crowdsourced data are often characterised by variability in quality, spatial bias, and potential misinformation. Robust filtering, cross-validation with other data sources, and the application of statistical bias-correction methods are essential to ensure their reliability (Chen et al., 2021).

- **Institutional and Legacy Databases**

  Many governmental and non-governmental organisations have maintained extensive archives of geospatial information, including cadastral maps, infrastructure inventories, and detailed demographic datasets. These secondary datasets are vital for long-term planning, urban development, and policy formulation, as they provide historical baselines against which current changes can be compared. Integrating these legacy datasets with modern real-time data requires significant effort in data standardisation, format conversion, and quality control. Despite these challenges, legacy data are invaluable for multi-criteria decision-making processes and for ensuring that the platform has a comprehensive temporal context (Sohaib et al., 2024).

  Furthermore, there are several open multispectral and optical satellite datasets for remote sensing and satellite imagery that provide visible and infrared imagery for land cover classification, vegetation analysis, urban planning, and environmental research. These datasets can be classified into MOS Data (Gutman et al., 2013), SAR Data (Tsokas et al., 2022), DEM and 3D Terrain Data (Habib, 2021), and climate and environmental monitoring datasets.

  MOS datasets provide visible and infrared imagery for land cover classification, vegetation analysis, and urban monitoring. For example, The Landsat dataset (NASA/USGA-1)[1] (de Almeida Pereira et al., 2021; Habib, 2021) is a collection of satellite images of Earth, available since 1972, used for environmental monitoring, resource management, and long-term change analysis. Landsat imagery is freely available through USGS Earth Explorer (USGS 2019, USGS 2020), GloVis[2], and Google Earth Engine (Malek et al., 2024). The Sentinel satellites, part of the ESA Copernicus program, provide free global Earth observation data for environmental monitoring. The Sentinel-2 constellation offer 10m–60m resolution optical and near-infrared imagery, ideal for land cover analysis, vegetation monitoring, and agriculture. Similarly, the satellite constellation Sentinel-3 focuses on ocean and land monitoring, measuring sea surface temperature, land surface temperature, and water quality. All Sentinel data is freely accessible via the Copernicus Open Hub (Muszka et al., 2024). Besides, the MODIS (Moderate Resolution Imaging Spectroradiometer (Ghaderi & Rahimzadegan, 2022). Modis[3] is a key instrument on NASA's Terra and Aqua satellites, providing Earth observation data with a resolution ranging from 250m to 1 km. It offers daily global coverage and is widely used for monitoring climate change, calculating vegetation indices (such as NDVI), and detecting wildfires. MODIS data supports a wide range of environmental applications, helping scientists track changes in ecosystems, land cover, and natural disasters. Likewise, PlanetScope[4] (Frazier & Hemingway, 2021)

[1] https://landsat.gsfc.nasa.gov/data/
[2] https://glovis.usgs.gov/

[3] https://modis.gsfc.nasa.gov/data/

[4] https://www.planet.com/

provides high-resolution (3m) optical images of Earth, offering detailed views for a variety of applications. While access to the full dataset is typically paid, Planet's Education & Research Program offers open access to its data for research purposes. This allows academic and non-commercial users to access PlanetScope imagery for environmental monitoring, urban studies, agriculture, and more, under the program's terms.

SAR is useful for all-weather and nighttime observations, terrain deformation analysis, and disaster monitoring. For example, Sentinel-1[5] (Torres et al., 2012) is equipped with a C-band SAR, providing 10m resolution imagery. It is particularly effective for monitoring the Earth's surface in all weather conditions, day, or night. Sentinel-1 data is widely used for flood mapping, infrastructure monitoring, and agriculture, offering valuable insights into land deformation, crop health, and disaster management. The radar capabilities make it a key tool for applications where optical imagery is not sufficient due to weather or lighting constraints. ALOS PALSAR[6] (Advanced Land Observing Satellite, Japan Aerospace Exploration Agency - JAXA) (Costa et al., 2021) is equipped with an L-band Synthetic Aperture Radar (SAR), offering valuable data for forestry and terrain analysis. It provides high-resolution radar images for assessing forest structure, land cover changes, and mapping terrain. Additionally, ALOS PALSAR produces a global 30m DEM, useful for topographic analysis, disaster management, and environmental studies. This dataset supports a wide range of applications in geospatial research and natural resource monitoring. Similarly, NASA NISAR (NASA-ISRO Synthetic Aperture Radar) (Ferdowsi et al., 2024)[7] is an upcoming satellite mission, set to launch in 2024, featuring high-resolution L-band and S-band SAR. NISAR is specifically designed for monitoring natural hazards, such as earthquakes, landslides, and floods, as well as biomass estimation in forests. Its dual-frequency radar system will provide detailed and complementary data, enhancing the ability to track environmental changes, natural disasters, and assess global ecosystems, making it a crucial tool for understanding Earth's dynamic processes.

DEM data is essential for topographic analysis, hydrology, and urban planning. For example, SRTM (Shuttle Radar Topography Mission) (Nwacholundu et al., 2021)[8] is a NASA mission that provides a 30m global DEM. The data is widely used for terrain modelling, watershed analysis, and topographic mapping. It offers detailed elevation information that supports applications in environmental studies, hydrology, urban planning, and disaster management, enabling accurate simulations of surface features and water flow patterns. The SRTM dataset is freely available and serves as a valuable resource for researchers and decision-makers. ASTER GDEM (Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model) (Yarahmadi et al., 2024)[9] is a 30m resolution global elevation model created by NASA and JAXA. It provides detailed topographic data that is widely used for scientific research, including terrain analysis, climate studies, and disaster management. The ASTER GDEM is freely available for non-commercial use, making it a valuable resource for a range of applications such as hydrological modelling, geospatial analysis, and environmental monitoring. On the other hand, the Copernicus DEM by ESA provides 30m and 90m

[5] https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-1

[6] https://www.eorc.jaxa.jp/ALOS/en/index_e.htm
[7] https://nisar.jpl.nasa.gov/
[8] https://www.earthdata.nasa.gov/data/instruments/srtm
[9] https://search.earthdata.nasa.gov/search

resolution elevation data for global coverage (European Space Agency, 2021)[10]. It is designed to support non-commercial applications in areas like terrain analysis, flood modelling, and urban planning. This dataset offers detailed topographic information, enabling accurate modelling of Earth's surface for scientific research, environmental monitoring, and disaster management. The data is freely accessible for non-commercial uses through the Copernicus Open Access Hub.

The three key climate and environmental monitoring datasets are NOAA AVHRR, ECMWF ERA5, and Global Forest Watch. The NOAA AVHRR[11] (HO & and ASEM, 1986) dataset provides 1 km resolution data for long-term global temperature and vegetation monitoring, enabling the tracking of land surface temperature changes and vegetation indices, which is crucial for understanding climate change and agricultural trends. The ECMWF ERA5 dataset (Hersbach et al., 2020) offers global climate reanalysis data, covering atmospheric, ocean, and land surface variables with hourly data from 1950 to the present. This dataset is widely used for climate research, weather prediction, and studying climate variability. Global Forest Watch[12] (Laso Bayas et al., 2022) monitors deforestation and land use change by integrating satellite data and analytical tools to detect forest cover loss, illegal logging, and the impact of human activities on ecosystems, providing valuable insights for environmental protection and conservation efforts.

To access and use climate and environmental monitoring datasets, several platforms offer valuable tools. GEE provides free cloud-based access to datasets like Landsat, Sentinel, and MODIS, enabling geospatial analysis and visualization. Both QGIS and ArcGIS allow integration of satellite imagery via WMS, making it easy to analyse data in a GIS environment. Additionally, the Copernicus Open Access Hub offers free downloads of Sentinel data, providing access to Sentinel-1, Sentinel-2, and Sentinel-3 imagery for non-commercial and scientific use, supporting applications such as land monitoring and climate research. These platforms offer robust resources for leveraging satellite data in environmental and climate studies.

- **Published Scientific and Technical Reports**

  Scientific literature and technical reports serve as rich repositories of secondary data, providing historical environmental records, detailed case studies, and extensive analyses of regional planning initiatives. These reports often include datasets that have been rigorously vetted and are used as benchmarks for current model validations (Kamil et al., 2021). Although the methodologies used in these studies may differ from current practices, their data remain valuable for cross-validation and for providing a historical perspective on long-term environmental trends (Sibel et al., 2018).

- **Open Data Portals**

  Open data initiatives by government agencies, international organizations, and research institutions offer freely available geospatial datasets, including climate records, land cover maps, and socio-demographic statistics. These datasets are crucial for supplementing primary data, allowing for the

[10] https://dataspace.copernicus.eu/explore-data/data-collections/copernicus-contributing-missions/collections-description/COP-DEM

[11] https://www.class.noaa.gov/data_available/avhrr/index.htm

[12] https://www.globalforestwatch.org

creation of a multi-layered, comprehensive spatial analysis framework (Alfonso et al., 2021). Open data sources not only reduce the cost and complexity of data acquisition but also promote transparency and reproducibility in research. However, the open nature of these datasets can also lead to inconsistencies in update frequencies, data quality, and spatial resolution, which require careful integration and validation (Waldemar et al., 2021)

Advanced Data Fusion and Integration Techniques

One of the most significant challenges in the AI4MultiGIS project is the integration of heterogeneous datasets, each characterized by distinct spatial resolutions, temporal frequencies, and data formats. Advanced data fusion techniques are employed to reconcile these differences and create coherent, high-quality datasets that are suitable for real-time analytics and predictive modelling. Methods such as multi-resolution fusion, Bayesian data integration, and machine learning-based interpolation are being explored to improve data harmonization (Cukjati et al., 2022). For instance, the fusion of high-resolution UAV imagery with coarser satellite data can significantly enhance the spatial detail available for analysis, leading to more precise environmental and infrastructural models. Additionally, combining data from IoT sensors with remote sensing data can help bridge spatial gaps and provide continuous monitoring capabilities (Sarjero et al., 2024).

Quality Control, Validation, and Uncertainty Management

Ensuring the accuracy and reliability of collected data is paramount for any AI-driven MultiGIS system. Quality control measures are implemented at multiple stages, from initial data acquisition through to integration and analysis. These measures include cross-referencing data from multiple independent sources, applying statistical anomaly detection techniques, and using ground-truth measurements to validate remote observations. Uncertainty management is also a critical aspect of the data collection process. Quantifying the uncertainty associated with each data source—whether due to sensor noise, calibration errors, or temporal gaps—allows for more robust decision-making and risk assessment. Recent advances in probabilistic modelling and uncertainty quantification have been applied to estimate error margins, thereby enhancing the credibility and utility of the integrated datasets. For example, probabilistic approaches can effectively manage and query uncertain spatial and spatio-temporal data, enriching query results with reliability information (Züfle et al., 2024).

Ethical, Privacy, and Security Considerations

The collection of geospatial data, especially those that involve personal or sensitive information, raises significant ethical and privacy concerns (Choudhoury et al., 2020). To ensure compliance with regulations such as GDPR and the EU AI Act, robust privacy-preserving techniques are incorporated into the data collection and processing pipelines. These include data anonymization, differential privacy, and the use of federated learning architectures that allow for data analysis without centralized data storage (Hullen, 2024). Ethical guidelines are established to ensure that data collection practices are transparent, consensual, and respectful of individual privacy. Furthermore, advanced encryption protocols and secure data transmission methods are implemented to safeguard against unauthorised access and cyber threats (Deng et al., 2019)

Emerging Trends and Future Directions in Data Collection

The field of geospatial data collection is rapidly evolving, with several emerging trends that are highly relevant to the AI4MultiGIS project. One such trend is the increasing use of multi-modal data sources that integrate not only spatial but also non-spatial data, such as socioeconomic indicators and environmental sensor data. This integration supports a more holistic view of spatial phenomena and enhances the predictive capabilities of AI models (VoPham et al., 2018). Additionally, the advent of real-time data streaming platforms and edge computing technologies is paving the way for more dynamic and responsive data collection systems, capable of processing high-volume data streams with minimal latency. Advances in blockchain technology are also being explored to ensure data provenance, integrity, and secure sharing among multiple stakeholders in a distributed MultiGIS framework (Caleb et al., 2025).

Detailed Challenges in Data Collection

Collecting and integrating the diverse array of geospatial data necessary for AI4MultiGIS is not without its challenges. Key challenges include:

- **Quality Control and Standardisation**

  Variability in data quality, especially in crowdsourced and IoT data, necessitates robust quality assurance frameworks. Automated systems for data validation, such as AI-based outlier detection and cross-referencing against trusted secondary data sources, are critical for ensuring consistency and reliability (Bedard et al., 2015).

- **Scalability and Real-Time Processing**

  High-resolution, continuous data streams impose significant demands on computational resources. Scalable cloud architectures, parallel processing frameworks, and edge computing solutions are required to ensure that data can be processed and analysed in real time, particularly during emergencies or dynamic environmental changes (Wu et al., 2024).

- **Privacy, Security, and Ethical Use**

  The collection of sensitive geospatial information necessitates strict adherence to privacy laws and ethical standards. Implementing robust encryption, secure data storage, and privacy-enhancing technologies such as federated learning and differential privacy is imperative to mitigate risks (Adams et al., 2020).

- **Resource Limitations and Data Gaps**

  In some regions, particularly in developing or remote areas, data availability may be constrained by limited technological infrastructure. Addressing these gaps may involve the use of spatial interpolation techniques, the integration of crowdsourced data to augment sparse sensor networks, and strategic investments in local data collection capabilities (Koldasbayeva et al., 2024).

Relevance to the AI4MultiGIS Project

The AI4MultiGIS platform is designed to harness the strengths of diverse data sources to build a robust, scalable, and responsive spatial analysis framework. By integrating primary data—providing real-time, high-resolution inputs—with secondary data that offers historical context and calibration, the platform achieves comprehensive situational awareness and enhanced predictive accuracy. Advanced data fusion techniques, quality control measures, and privacy-preserving practices ensure that the heterogeneous data can be effectively integrated and analysed. This, in turn, supports critical applications in disaster management, urban planning, environmental monitoring, and infrastructure assessment. Ultimately, overcoming the inherent challenges in data collection through sophisticated methodologies and ethical governance frameworks is key to the successful deployment and long-term sustainability of AI-enabled MultiGIS systems in dynamic, real-world environments. 2 presents a conceptual diagram illustrating the data flow from collection to use.

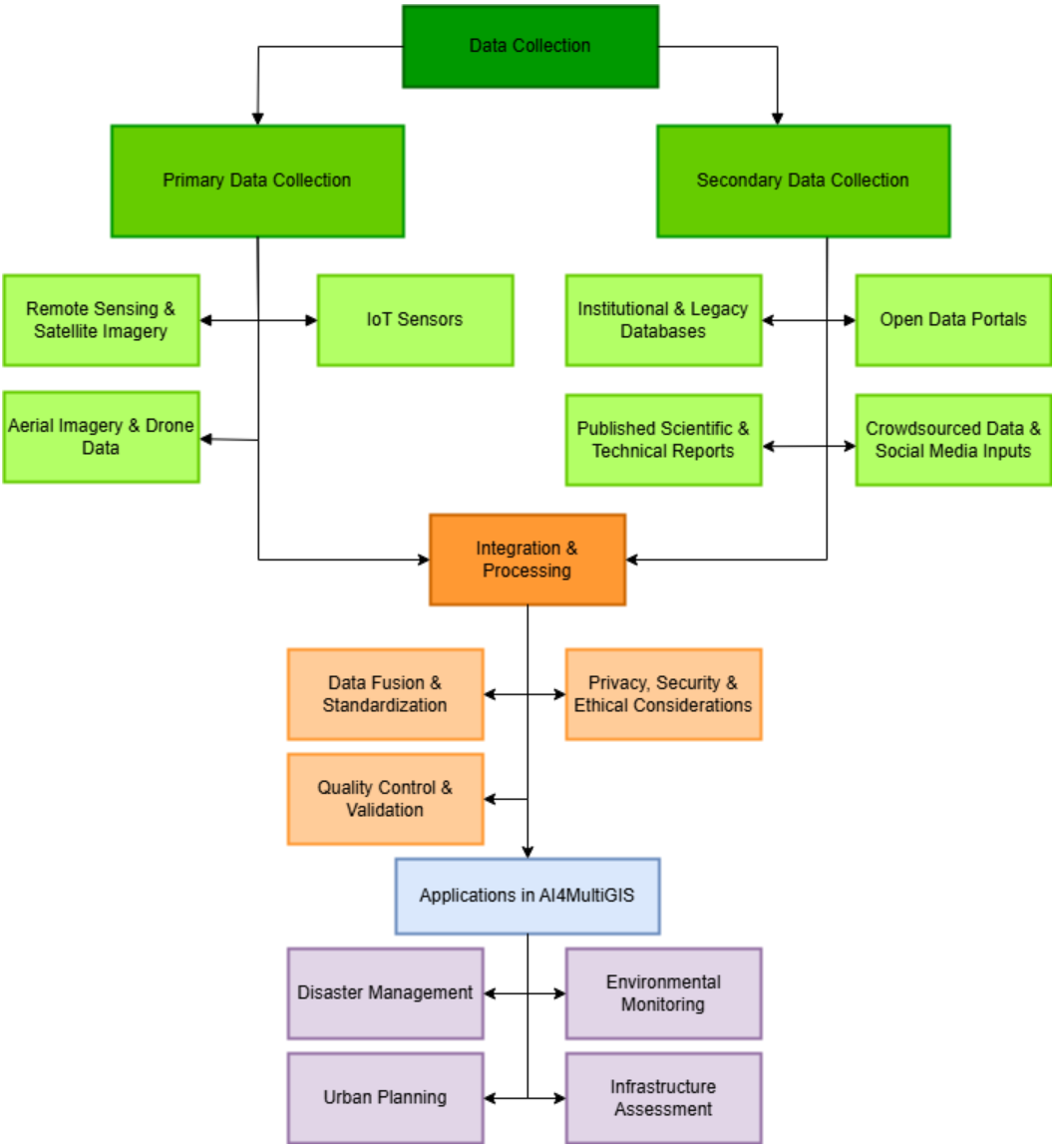

Figure 2 - Diagram explaining the data flow from collection to practical use cases

2.3 MultiGIS Applications

From an application perspective, MultiGIS plays a crucial role in multi-criteria decision-making across different domains (a conceptual illustration can be seen in Figure 3), particularly in complex scenarios that require balancing objective and subjective factors. These scenarios often involve trade-offs across different spatial and temporal dimensions. This section explores a range of key applications, demonstrating that while usage varies across disciplines, the core principles remain both expansive and highly impactful.

Figure 3 - Conceptual MultiGIS Map

Infrastructure (Grey, Blue, Green) development

The integration of MultiGIS and AI in infrastructure planning enhances decision-making by providing advanced spatial analysis, predictive modelling, and automated optimisation. MultiGIS enables the layering of diverse geospatial data, offering a comprehensive view of terrain, land use, and environmental constraints. AI-driven algorithms further refine this process by identifying patterns, forecasting future developments, and optimising resource allocation. This combination improves efficiency, reduces costs, and supports sustainable urban and rural infrastructure development, ensuring projects are resilient and well-informed.

- **(Green) Energy Infrastructure Planning**

  In the transition towards more sustainable energy sources such as solar farms, offshore wind farms and nuclear power plants, selecting suitable sites for building the infrastructure is a challenging task due to inconsistent scales of site selection and the lack of standard methodological approaches. Therefore, using MultiGIS offers powerful methods to tackle these challenges, sometimes involving contradictory factors, by combining a multiscale framework with GIS.

Shao et al. (2025) developed a framework integrating GIS, GIFAHP, and Method-based Removal Effects of Criteria (MEREC) to optimise wind farm site selection. Fotsing Metegam et al. (2024) conducted a spatial feasibility study for wind farms in Cameroon using MCDM- AHP and GIS. Yousefi et al. (2024) coupled GIS and MCDM to identify suitable wind farm locations considering electrical, techno-economic, environmental, and geo-infrastructure factors. Dimitriou et al. (2025) reviewed GIS and MCDM methods for offshore wind farm site selection using metaheuristic algorithms or GIS Suitability Modeller.

Sánchez-Lozano et al. (2013) combined GIS, AHP, and TOPSIS to evaluate photovoltaic solar power plant placement in Cartagena, Spain. Damoon et al. (2019) linked GIS with MCDM to find safe locations for nuclear power plants in Saudi Arabia. Villacreses et al. (2022) identified sites for photovoltaic solar farms in Ecuador using GIS and MCDM. Jangid et al. (2016) used MCE in GIS to assess wind farm sites in India.

Shao et al. (2020) reviewed MCDM methods coupled with GIS for renewable energy site selection. Defne et al. (2011) combined GIS and MCDA for tidal stream power site selection. Ali et al. (2024) reviewed MCDM methods for offshore wind and floating solar farms using GIS. Godoy et al. (2025) used AHP, PROMETHEE, and QGIS to evaluate renewable energy projects in Ecuador. Guillén-Lambea et al. (2023) developed ESSUM using GIS-LCA-based multi-criteria methodology for urban solar energy potential. Zhou et al. (2023) used GIS and multi-criteria planning for PV systems on building roofs.

- **Transport, Logistic, and Utility Infrastructure Planning**

Transport networks (road, rail etc) are the lifeline of mobility within and between cities and play an important role in the sustainable development of human society. In a study by Lei et al., (2024) combined Remote Sensing imagery and GIS by proposing a full image-vector conflation framework that combines state-of-the-art deep learning methods for image segmentation and optimisation-based models for object matching for a case study in the US. From the lens of industrial development Wang et al., (2025) utilised the Geodetector tool to analyse the impact of various water-related environmental factors on the spatial distribution and development of a port in shipping industry in Guangdong Province enabling them to identify suitable locations for port development and industrial growth while preserving environmental conditions.

MultiGIS is also used in planning for logistics in supply chain, selecting appropriate locations in urban areas for logistics facilities, such as automated parcel lockers and smart loading bays, stands out. However, this is a complex process due to having conflicting objectives of the relevant stakeholders involved. The MCDM-GIS method used the least-cost wide path analysis is suggested for road alignment generation and planning in a study by Jiang et al., (2023).
Coupled GIS and MCDM methods are the most commonly used for water resources and infrastructure development and demand management projects globally. Wanguba et al., (2024) used GIS techniques and MCDA to develop a decision support model that can be applied to improve the utility water demand management for the Lodwar Municipality in Turkana Kenya. Optimal EVCS site selection was conducted by combining MCDM/FAHP and GIS (see Figure 4) in a study by Elomiya et al., (2024).

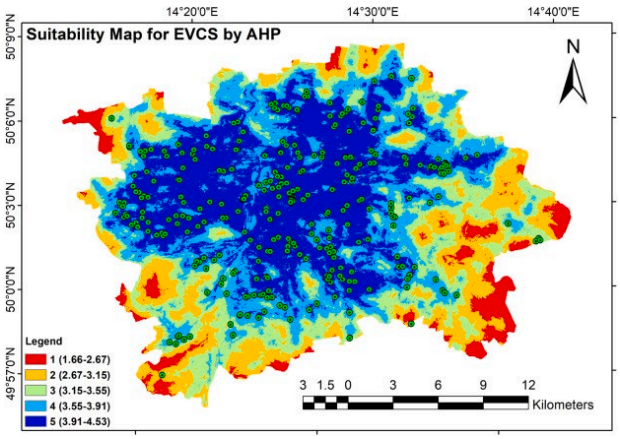

Figure 4 - EVCS suitability map by AHP (Elomiya et al., 2024)

Giuffrida et al., (2024) proposed an innovative approach to address this issue by adopting a spatial participatory process that combines GIS models and Real-Time Spatial Delphi to identify suitable locations for two logistic facilities in a case study in Dublin. In another study for logistics planning by (Önden et al., (2023), GIS/Spatial Analysis and survey studies with over 12K stakeholders combined with quantitative capabilities of GIS to develop maps for suitable locations. Green and Grey infrastructure planning was optimised in a study by Farina et al., (2024) for urban climate adaptation using multi-objective optimisation, MCDM and GIS in a study area in France. Remote sensing, GIS and AHP techniques were integrated for groundwater management (Figure 5), specifically in the delineation of the groundwater potential zones (GWPZs) in India by Achu et al., (2020).

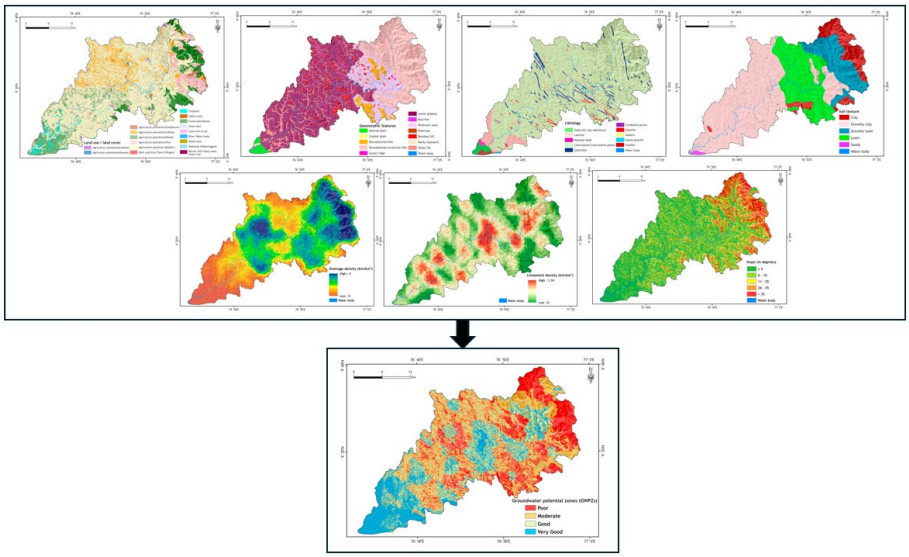

Figure 5 - Groundwater potential zones using MultiGIS (Achu et al., 2020)

Urban and Peri-Urban Planning

Borgogno-Mondino et al. (2015) integrated GIS-MCDA for land use planning in peri-urban areas, focusing on soil quality. Mrawczyńska et al. (2022) used FAHP, GIS, and Bayesian networks for urban decarbonisation

planning. Ustaoglu et al. (2021a) developed an integrated approach using FAHP and TOPSIS for agricultural planning in Istanbul. Bilal et al. (2025) used AHP and GIS-based MCA for fodder crop suitability in Qatar.

Jiang et al. (2024) created a Digital Twin-MCDM-GIS framework for sustainable urban road planning. Hassanshahi et al. (2023) used hybrid MCDM and GIS for tourist walking routes in Shiraz, Iran. Du (2025) developed landscape accessibility maps for urban green spaces using GIS and remote sensing. Vatanparast et al. (2024) used AHP and GIS for urban Greenway planning. Elghazouly et al. (2024) developed a decision support tool using MCDA and GIS for urban slum site relocation. Lu et al. (2024a) integrated MCDA, GIS, and neural networks for urban spatial resilience.

Alves et al. (2024) and Wojcik-Madej et al. (2025) used multi-criteria analysis and GIS for NBS implementation. Pacetti et al. (2022) developed a pluvial Flood Index for Florence using spatial MCA and GIS. Ustaoglu et al. (2021b) used GIS and MCDA for peri-urban agricultural development in Istanbul. Yang et al. developed an urban green resilience index using MCDM-GIS. Foroozesh et al. (2022) used fuzzy BWM, AHP, and TOPSIS-GIS for urban sustainable growth in Karaj, Iran. Coupled MCDA and GIS was used to improve water resilience in city planning to tackle distressed thermal environment in a case study in Bengal, India (Gupta & De, 2025).

Disaster Planning and Management

As we write this report in early 2025, the world has experienced numerous natural disasters in 2024 alone. These include flooding in Afghanistan, Spain, Germany, and Brazil; wildfires devastating large areas in California, USA; and landslides impacting Papua New Guinea and India, among others. Given the significant spatial implications of these disasters, GIS are employed for spatiotemporal analysis and mapping for pre- and post-disasters. GIS helps identify susceptible areas, critical locations, and conduct impact analysis. It also plays a crucial role in intervention planning and decision-making.

- **Flood and Hurricane**

  Floods are among the most widespread natural hazards globally. Ali et al. (2019) used GIS, AHP, and the frequency ratio model for flood vulnerability mapping in India. Gudiyangada Nachappa et al. (2020) created flood susceptibility maps for Salzburg, Austria, using AHP, analytic network process ANP, frequency ratio, and SVM models. Nhamo et al. (2025) combined AHP, MCDM, GIS, and geostatistical techniques to assess drought and flood risks in South Africa's Olifants River Basin. Aloui et al. (2024) used GIS-based AHP to delineate flood and groundwater recharge zones in Qatar (See Figure 6).

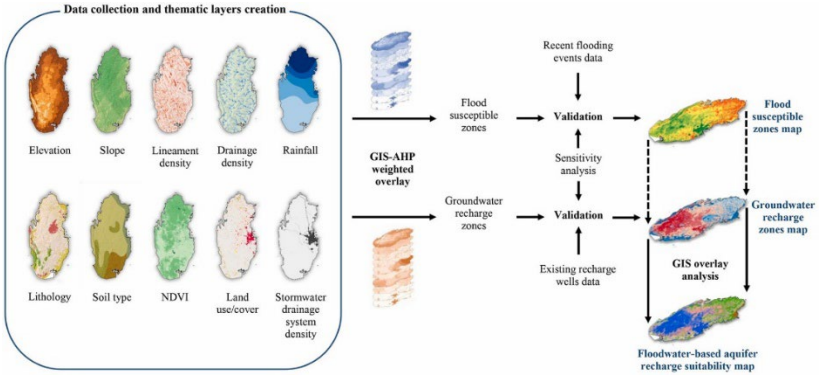

Figure 6 - Flood suitability map of Qatar based on GIS-AHP mapping (Aloui et al., 2024)

Hussain et al. (2023) developed the CapFlooR-M model, integrating ML, GIS, RS, and AHP for flood resilience planning. Gulshad (2024) reviewed methods for low-impact development site selection, including index-based methods, GIS-based MCDA, and multi-criteria models. Chen (2022) used GIS, AHP, TOPSIS, and OWA to analyse flood-prone areas in China's Dadu River basin. Doorga et al. (2022) developed a GIS-based multi-criteria model for flood risk management in Port Louis.

Ali et al. (2020) created flood susceptibility maps for Topľa basin, Slovakia, using GIS, MCDM, bivariate statistics, and ML. Msabi and Makonyo (2021) mapped flood susceptibility in Tanzania's Dodoma region using AHP, GIS, and RS. Alamouctar et al. (2024) evaluated flood risk in a data-limited region in China using AHP, RS, and GIS. Liu et al. (2025) and Zhou et al. (2024) used GIS and MCDM for urban emergency shelter site selection during floods in China. Ahmad et al. (2025) developed a novel Urban Flood Risk Index (FRI) for flood risk assessment, integrating GIS with AHP and the PSR framework.

Jodhani et al. (2024) assessed flood risk in Gujarat using earth observations, AHP-MCDM, and GIS. Aichi et al. (2024) integrated AHP, GIS, and remote sensing to plan flood interventions. Lu et al. (2024b) proposed a framework integrating BNs and GIS for flood disaster risk assessment, enabling the study of complex risk factors and spatial risk assessment. Feng (2023) developed a novel risk assessment framework incorporating social-ecological systems for Hurricane Harvey (2017) in Houston, Texas, using AHP and GIS for risk map production.

Alemdar and Yilmaz (2025) used FAHP and GIS with the VIKOR approach to evaluate inundation risk in Istanbul's urban rail system. Wu et al. (2024a) developed an MCDM-GIS framework using DEMATEL and ANP for assessing urban metro system flood resilience. Ahmad et al. (2024) combined Remote Sensing, GIS, and FAHP to determine rainwater harvesting potential zones. Rosa et al. (2024) created a GIS-based multi-criteria approach to identify subsidence-vulnerable areas in Maceio, Brazil, due to salt-gem urban mining. Wu et al. (2024b) also used an MCDM-GIS framework to assess flood resilience in urban metro systems.

- **Earthquake**

Xu et al. (2016) used integrated MCDM and GIS to plan earthquake evacuation shelters. Liu et al. (2012) created earthquake damage zones for Sichuan, China, using satellite remote sensing, GIS, and multi-criteria analysis. Kermanshah et al. (2016) applied a coupled MCDM-GIS for multi-criteria vulnerability assessment of road networks in Los Angeles and San Francisco. Liu (2022) developed a comprehensive suitability framework for selecting post-earthquake emergency medical service facility sites (see Figure 7). Utilised AHP and TOPSIS to systematically evaluate and prioritise alternative locations for EMSF placement in China.

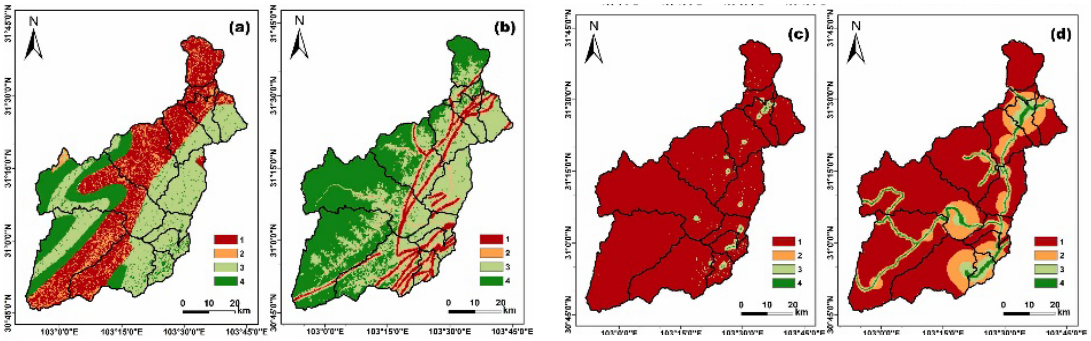

Figure 7 - Suitability maps for EMSF site selection upon four main criteria of (terrain, Safety, Resources, Transportation) (Liu, 2022)

Yariyan et al. (2020) produced an earthquake risk assessment map using FAHP-ANN with GIS. Othman et al. (2012) mapped landslide hazard zones with GIS-based MCDM (AHP). Feizizadeh et al. (2014) created landslide susceptibility maps in Southwest Iran using GIS, MCDM (AHP), and FAHP. Jena et al. (2020) assessed earthquake vulnerability in Northern Sumatra with AHP-GIS-VIKOR. Ghasemi et al. (2025) studied multi-hazard preparedness for earthquakes in Tabriz, Iran, using hybrid MCDM (AHP)-GIS. A hybrid AHP and MCDM was used in Bangladesh (2023) for earthquake vulnerability estimation. Dehnavi Eelagh & Ali Abbaspour (2024) developed an optimisation model for post-earthquake emergency shelters in Iran using network-based MCDM and GIS.

2.4 Research Gaps

Despite advancements in remote sensing and satellite imagery along with data collection and integration, there are still significant research gaps that need addressing. These include challenges in scalability and computational capabilities of MultiGIS and scalable machine learning models to handle large datasets, data integration and standardisation across various platforms, better availability of high-resolution data. Additionally, improving real-time data processing for environmental monitoring, and addressing data quality and uncertainty. Key research gaps include:

- **Technical Challenges**
    - *Scalability and computational demands*

      MultiGIS applications should handle diverse application coming from heterogenous sources and datasets. As these datasets grow, the computational energy consumption required for processing MultiGIS data increases. Hence, MultiGIS applications require energy-efficient GIS data processing to deal with this increasing demands. Moreover, current data parallelisation techniques in GIS analytics struggle with irregular spatial data structures, requiring new models for load balancing and efficient data partitioning. On the other hand, processing MultiGIS data requires advanced AI models for data modelling and analytics. There is a need for scalable, distributed computing frameworks that can handle large-scale geospatial datasets across heterogeneous infrastructures (cloud, edge, and HPC).

    - *Legacy system integration*

Integrating MultiGIS data into existing GIS infrastructure often relies on a diverse set of 63 legacy formats (Löwe et al., 2022), such as GeoJSON, GML, GPX, KML, and KMZ, with this number continuing to grow. Many of these formats have distinct property systems, creating significant challenges for seamless integration with modern MultiGIS platforms. Therefore, advanced research is needed to develop universal interoperability frameworks that can standardise data exchange, ensure compatibility, and facilitate efficient data integration across heterogeneous GIS environments.

Besides, several middleware solutions have been introduced for MultiGIS data to address interoperability challenges and facilitate seamless integration across different GIS platforms. For example, GeoServer[13] (Kshetri et al., 2021) is an open-source server that enables sharing, processing, and editing geospatial data using open standards such as WMS, WFS, and WCS.

Similarly, FME has been introducing Safe[14], which is a powerful data integration platform that supports numerous GIS formats and enables format conversion, data transformation, and automation. GDAL/OGR[15] (Bezabih et al., 2024) is an open-source library that has been widely used for reading and converting between different geospatial formats. OGC's OWS[16] (Open Geospatial Consortium, 2023) has been introduced as a suite of standards developed by the OGC, including WMS, WFS, and WCS, to enable interoperability between GIS systems.

Likewise, PostGIS[17] (Regina O. Obe & Leo S. Hsu, 2021) is a spatial extension for PostgreSQL that allows advanced spatial queries and seamless data integration across GIS applications. Sensor Observation Service (SOS)[18] (Bröring et al., 2013) is a web service specification developed by OGC[19] to enable sensor data retrieval and management over the web. It serves as a middleware component designed for integrating real-time sensor data into GIS platforms. SOS aligns with ISO 19156 (2023) standard[20] (Geographic information — Observations, measurements, and samples) as it provides an implementation of the conceptual model defined in ISO 19156 for handling observations and measurements. Despite these middleware solutions, challenges remain in achieving full interoperability due to the increasing number of legacy formats and proprietary data structures. Further research is needed to develop universal frameworks that enhance compatibility, automate data transformation, and improve real-time data exchange between MultiGIS systems.

Legacy GIS systems often rely on rigid, outdated data structures originally designed for relatively static, isolated datasets. These systems face several common challenges, including data incompatibility, as they struggle to integrate with modern technologies like real-time sensors, satellite imagery, and IoT data. Additionally, traditional GIS models may lack scalability, making it difficult to efficiently manage large volumes of data from diverse sources, such as real-time data streams. Furthermore, legacy systems typically have limited analytical capabilities,

[13] https://geoserver.org/
[14] https://www.safe.com/
[15] https://gdal.org/en/stable/
[16] https://developer.ogc.org/ows.html
[17] https://postgis.net/
[18] https://www.ogc.org/fr/publications/standard/sos/
[19] https://www.ogc.org/
[20] https://www.iso.org/standard/82463.html

preventing them from providing the advanced insights needed for decision-making in today's complex, fast-paced environments.

- **Data Challenges**

  - *Data heterogeneity, quality, and resolution issues*

    MultiGIS systems typically integrate data from a variety of sources such as satellites, UAVs, IoT sensors, and crowdsourcing platforms, require robust and standardized data fusion techniques to ensure seamless integration and interoperability across these diverse data types. The heterogeneous nature of the data generated by these sources — differing in format, scale, accuracy, and frequency — presents a significant challenge for integrating them into a unified, actionable GIS model. Without standardised techniques, data fusion can become fragmented and inefficient, leading to inconsistent or incomplete spatial information that hampers decision-making processes (Mandreoli & Montangero, 2019). Additionally, metadata standardisation is crucial for ensuring that the context of each dataset — including its resolution, accuracy, and collection method — is clearly defined and understood.

    AI and machine learning can further aid the standardisation process by automating data pre-processing tasks, such as data cleaning, transformation, and alignment. Machine learning models can also assist in the harmonisation of spatial data by learning patterns across various data sources and aligning them to a common reference framework. This not only improves the quality of the data fusion process but also ensures that the integrated datasets can be effectively used for spatial analysis, real-time monitoring, and decision-making.

    Furthermore, leveraging semantic data models and ontologies (Kuo & Chou, 2023) can enable better interpretation and integration of diverse data sources. For instance, the use of ontologies allows different types of data (such as environmental, social, or infrastructural data) to be semantically linked, creating a shared understanding of the relationships between different datasets. This semantic layer facilitates more advanced querying, analysis, and decision-making by enabling a deeper understanding of how the data interrelates. On the other hand, the adoption of standardized data fusion techniques in MultiGIS systems not only enhances the accuracy and reliability of geospatial information but also increases the system's ability to handle large-scale, real-time data streams from varied sources (Malinverni et al., 2022). As the demand for dynamic and real-time GIS applications continues to grow, the role of standardized data fusion techniques will become increasingly critical in supporting the seamless integration of diverse data sources into cohesive and actionable geospatial systems.

    Besides, dynamic resolution adaptation in geospatial data is a significant challenge, particularly when combining high- and low-resolution datasets. Effective fusion techniques, such as interpolation, are essential for balancing computational efficiency and data accuracy. Machine learning methods, including deep learning models like CNNs or GANs, show promise in dynamically adjusting resolution based on the data's context. MRA can also be leveraged to decompose data into different frequency bands, although maintaining accuracy when combining high- and low-resolution information remains difficult. Context-sensitive resolution adjustment, where regions of high variability receive higher resolution, could further optimise performance.

Real-time adaptation algorithms are needed in dynamic environments to adjust resolution on-the-fly, while new quality metrics are crucial to evaluate the effectiveness of data fusion.

- *Real-time data processing constraints*

  Traditional GIS systems rely heavily on centralised cloud infrastructures for geospatial data processing, which can lead to high latency. This is especially problematic for real-time geospatial applications such as navigation, disaster management, and environmental monitoring. By leveraging edge computing, geospatial data processing can occur closer to the source of data collection, reducing latency significantly.

  GIS data often comes from various real-time sources, such as satellite imagery, sensor networks, and GPS data. Managing and processing these high-volume streams with minimal delay requires machine learning models that can adapt dynamically to incoming data (Gligorov & Reković, 2023). One significant challenge is ensuring that ML models can handle missing or noisy data from real-time geospatial streams. Machine learning techniques such as imputation algorithms, anomaly detection, and smoothing techniques must be optimised for geospatial data, where spatial correlation and temporal patterns play a crucial role. ML models need to be trained on these specific data types to make accurate predictions despite incomplete or corrupted input.

  Deploying AI models on edge devices introduces constraints such as limited processing power and memory (Li & and Ning, 2023). Edge-specific optimisations such as model quantization, pruning, and edge-friendly architectures like TinyML can make it feasible to run AI-enhanced data processing on these devices. Additionally, model inference should be lightweight to ensure real-time performance while maintaining accuracy.

- **Ethical and Social Issues**

  As the use of remote sensing and MultiGIS grows, ethical and social concerns have become increasingly important in geospatial data collection (Chen et al., 2024). These concerns need to be addressed to ensure that these technologies are used responsibly and equitably. This section delves into key ethical and social issues related to privacy and accessibility in geospatial data collection and sharing.

  - ***Privacy concerns in geospatial data collection and sharing***

    Remote sensing and MultiGIS technologies rely on large volumes of geospatial data that can provide detailed insights into individuals, communities, and environments (White et al., 2022). However, the increased availability of high-resolution satellite imagery raises privacy concerns, especially regarding surveillance and data misuse. These technologies can track individuals' movements or monitor private properties without consent, even allowing for the re-identification of individuals through advanced algorithms. The sharing of geospatial data also opens the door to data breaches, unauthorised access, and potential misuse. To address these risks, geospatial data collection and sharing must comply with privacy regulations like the GDPR. There is a need for privacy-preserving technologies, such as anonymization and encryption, along with ethical frameworks that balance surveillance capabilities with privacy rights.

  - ***Accessibility and equity in MultiGIS adoption***

While MultiGIS has the potential to improve decision-making in sectors like urban planning, environmental monitoring, and agriculture, its adoption may not be equally accessible to all (Zhang et al. 2023). Access to geospatial technologies often requires expensive hardware, software, and high-speed internet, creating a digital divide, especially in developing countries. Additionally, high-quality satellite imagery and remote sensing data are sometimes behind paywalls or restricted to certain stakeholders, limiting equity in their use. Furthermore, geospatial data may not reflect the diverse needs of marginalised groups, and biases in data collection, such as more availability in urban areas or wealthier regions, can lead to inequitable decision-making and policies.

By addressing these ethical and social concerns, the adoption of MultiGIS can be guided toward a more equitable and responsible path. Ensuring that these technologies are accessible, inclusive, and respectful of privacy allows them to contribute to sustainable development, informed decision-making, and fair resource management. This approach will help maximise the benefits of MultiGIS while minimising potential harms and ensuring that all communities can participate in and benefit from these advancements.

3 MULTIGIS SPATIOTEMPORAL DATA PROCESSING AND MANAGEMENT

Spatiotemporal data processing in MultiGIS involves handling geographic information that evolves over time, enabling dynamic insights into changes within physical or digital environments. These systems integrate diverse geospatial data from satellites, IoT devices, sensors, and crowdsourced platforms to facilitate tasks like urban planning, disaster management, and environmental monitoring. The integration of spatiotemporal elements introduces complexities in data heterogeneity, resolution, and temporal continuity, requiring robust frameworks for storage, pre-processing, and analytics.

MultiGIS spatiotemporal data processing requires integrating and analysing geospatial data from diverse sources across varying timescales, such as satellite imagery, IoT devices, and social media feeds. This process is fundamental for real-time applications like disaster response and urban planning. The challenges of handling multi-source data include aligning spatial resolutions, managing temporal consistency, and processing large data volumes. To address these, distributed systems such as cloud-based GIS and edge computing enable efficient data fusion and high-speed analytics. These systems also ensure that nodes from different geolocations contribute seamlessly to a unified spatiotemporal framework. For instance, the Kawak model combines retrospective meteorological data with ground-based observations, achieving comprehensive territorial coverage and supporting real-time applications such as climate monitoring and urban planning (Barron-Lugo et al., 2025).

3.1 Various Techniques for Multi GIS Data Processing:

Spatiotemporal data processing in AI4MultiGIS involves handling, analysing, and managing geospatial data over time to extract meaningful insights. Given the diverse sources of data—including satellites, UAVs, IoT sensors, crowdsourced inputs, and legacy databases—efficient processing techniques and data management strategies are crucial for real-time analytics, predictive modelling, and multi-source data fusion.

- **Data Acquisition & Preprocessing**

  Data cleaning and noise reduction are essential steps in spatiotemporal data processing, ensuring that the collected data is accurate, consistent, and reliable. Given the vast array of sources in AI4MultiGIS—including satellite imagery, UAV data, IoT sensor readings, and crowdsourced inputs—errors, inconsistencies, and noise are inevitable. Noise can arise due to sensor malfunctions, environmental interference, human errors, or transmission issues. Cleaning and filtering this data is crucial to prevent inaccurate analyses and incorrect decision-making. The following techniques can be used for data cleaning & noise reduction: (1) Kalman Filtering: A recursive algorithm that estimates the true value of a dynamic system by reducing measurement noise. It is widely used in GPS tracking and environmental monitoring. (2) Anomaly Detection and Outlier Removal: Machine learning techniques, such as Isolation Forests, One-Class SVMs, and DBSCAN clustering, are used to detect and remove data points that deviate significantly from expected values. (3) Statistical Normalisation and Standardisation: Data normalisation ensures consistency when merging datasets collected at different scales or by different sensors. (4) Interpolation and Missing Data Handling: Methods such as linear interpolation, Kriging, or deep learning-based imputations are used to estimate missing values.

- **Spatiotemporal Data Indexing**

Spatiotemporal data indexing in AI4MultiGIS is critical for managing vast, multi-source geospatial datasets efficiently. Advanced indexing techniques like R-trees, Quad-trees, and KD-trees optimise spatial queries, while grid-based and adaptive indexing enhance real-time analytics. AI-powered indexing supports multi-agent simulations and predictive modelling, enabling dynamic GIS applications like disaster response and environmental monitoring. By integrating distributed frameworks like SpatialHadoop and GeoSpark, AI4MultiGIS ensures scalable, high-speed processing of heterogeneous geospatial data, facilitating seamless multi-source data fusion and decision-making (Barron-Lugo et al., 2025).

The advancements in data processing techniques for MultiGIS systems have been driven by the need to manage, process, and analyse massive spatiotemporal datasets effectively. These advancements span multiple frameworks and methodologies, incorporating both legacy GIS functionalities and cutting-edge technologies such as distributed computing, multi-agent systems, and predictive analytics.

Scalable Big Spatiotemporal Data Infrastructures

Recent research emphasises the role of scalable systems like Hadoop and Spark in processing massive spatiotemporal datasets. Systems like SpatialHadoop and GeoSpark extend these platforms to incorporate spatial and temporal data types, enabling efficient partitioning, indexing, and query execution. For instance, Spatial Hadoop provides support for geometric operations, two-level indexing, and integration with the Pigeon language for SQL-like queries, while GeoSpark integrates spatial RDDs with partitioning techniques like R-tree and Quad-tree, allowing high-speed processing of range, join, and KNN queries (Alam et al., 2022). These systems demonstrate how distributed frameworks can handle trajectory and raster data effectively for applications like urban planning and climate simulations (Yang et al., 2020).

Multi-Agent Simulations for Dynamic Data Processing

MAS have emerged as a robust framework for modelling dynamic spatiotemporal phenomena in MultiGIS. A conceptual data model, integrated into the MARS framework, allows the simulation of temporal changes such as object movements and attribute evolution, addressing the limitations of traditional GIS tools. The MARS framework (Brommer et al., 2021) supports vector and raster data processing with temporal layers and provides operators for incremental updates, enhancing decision-making in simulations like urbanisation and disaster management (Glake et al., 2020). By incorporating temporal lifting and federated queries, MAS models bridge the gap between static GIS representations and dynamic spatiotemporal systems.

Spatiotemporal Risk Assessment and Predictive Maintenance

GIS techniques have proven indispensable for risk assessment and predictive maintenance in asset management. Tools such as LiDAR, UAVs, and satellite imagery facilitate data collection, offering high spatial and temporal resolution for applications like infrastructure monitoring and hazard prediction. Emerging hotspot analysis integrates spatial and temporal data, enabling the detection of risk patterns over time. Studies highlight the use of spatiotemporal clustering and 3D GIS models to visualise risks dynamically and predict failures of assets such as pipelines and roads (Syafiq and Azri, 2023). This approach ensures timely interventions and enhances the resilience of asset-intensive industries.

Integration of AI and Cloud Computing

The integration of AI techniques and cloud computing infrastructures has further enhanced data processing for MultiGIS. Machine learning models, such as neural networks and decision trees, are being employed to identify spatiotemporal patterns in data streams. Coupled with cloud-based GIS, these systems provide scalable, real-time analytics for applications ranging from traffic monitoring to environmental conservation (Yang et al., 2020). Additionally, frameworks like GeoAI leverage AI-driven insights to improve geospatial decision-making, addressing challenges like data heterogeneity and real-time processing.

MultiGIS applications rely heavily on efficient data processing techniques to integrate and analyse spatiotemporal data effectively. GIS, coupled with advanced methodologies like ML, spatial statistics, and big data integration have emerged as pivotal technologies in addressing the complex requirements of MultiGIS platforms.

Data Integration and Spatial Modelling

GIS-based data integration techniques are essential for combining diverse datasets, including geospatial, climatic, and demographic data, to enhance decision-making processes. Kawak, a GIS-big data model, exemplifies a cutting-edge approach by fusing retrospective meteorological data with ground-based observations, offering complete territorial coverage through virtual stations (Barron-Lugo et al., 2024). Similarly, machine learning models have been incorporated into GIS workflows to improve spatiotemporal distribution modelling, particularly in marine and urban ecosystems (Benavides Martínez et al., 2024; Kazempour et al., 2025). These methods enable the generation of accurate predictions, supporting sustainable resource management.

Multi-Criteria Decision-Making in Spatial Analysis

MCDM techniques, integrated with GIS, have shown significant advancements in identifying suitable locations for renewable energy systems, groundwater recharge zones, and urban infrastructure. For instance, the AHP has been applied to determine optimal photovoltaic site selection in Algeria, leveraging spatial data to account for topographic and environmental constraints (Halimi et al., 2025). Another study in Oman utilised GIS-based MCDM to identify high-potential sites for solar farms, highlighting the adaptability of these techniques across diverse geographic regions (Al-Awadhi et al., 2025).

3.2 Data Management in Multi GIS Systems

Data management in MultiGIS systems involves integrating, processing, and analysing large, heterogeneous datasets to enable robust spatial decision-making. Effective data management frameworks in MultiGIS address challenges like scalability, heterogeneity, and real-time processing by leveraging advanced GIS techniques, ML, and big data integration. Techniques like the BP integrate multidimensional data, including depth and time, to enhance real-time spatiotemporal analysis (Benavides Martínez et al., 2024). MCDM tools such as the AHP further enhance decision-making by evaluating complex factors like environmental, economic, and social constraints in site suitability analyses (Al-Awadhi et al., 2025). Ownership and security concerns, such as ensuring data privacy and integrity across geolocated nodes, are addressed using

blockchain technologies and federated learning frameworks, enabling collaborative yet secure data management. By integrating these methods, MultiGIS platforms provide scalable, secure, and adaptive solutions, meeting the demands of dynamic, real-world geospatial applications (Figure 8).

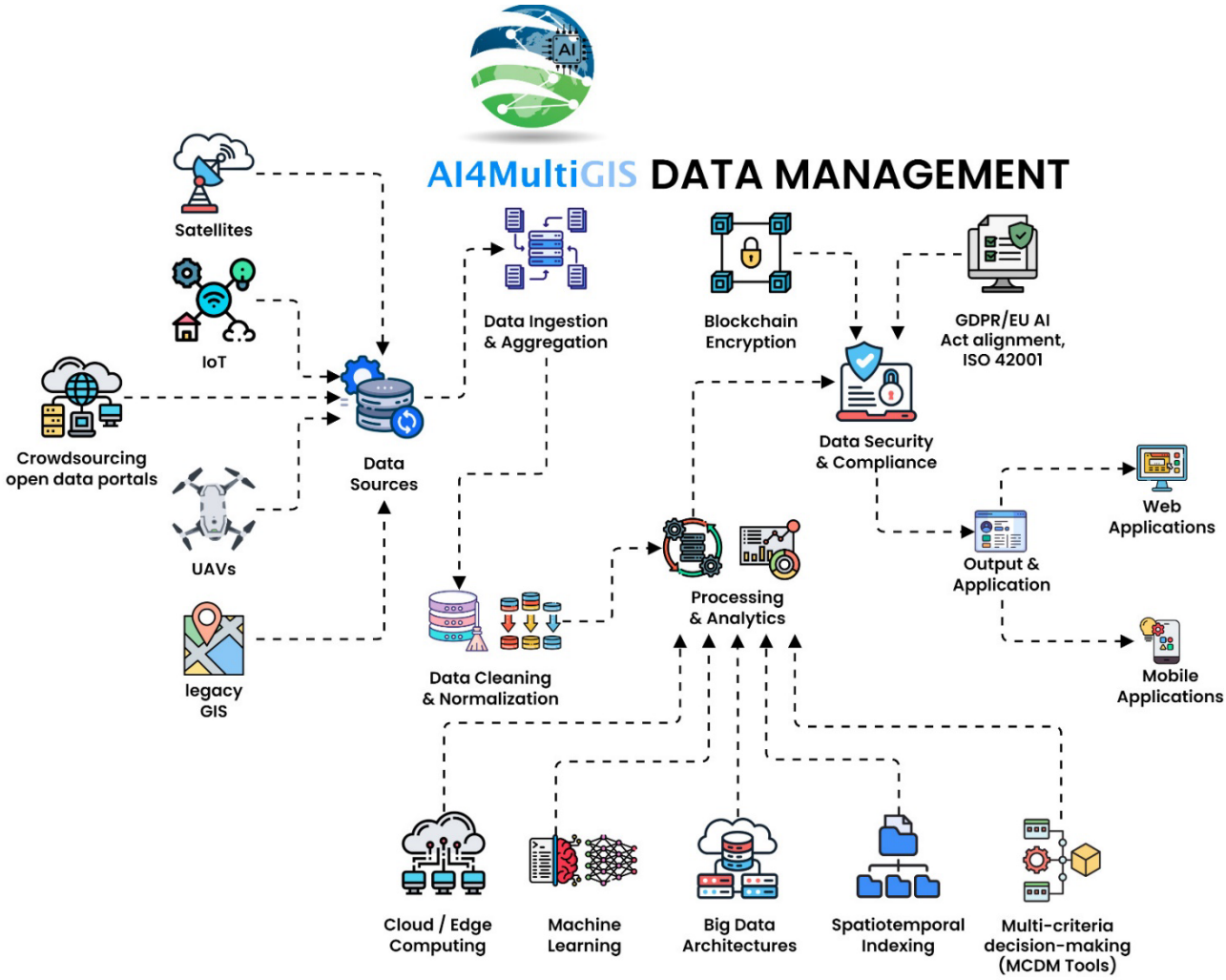

Figure 8 - Data Management architecture in MultiGIS System

Real-Time Data Processing and Scalability Challenges

Real-time data handling is critical for MultiGIS systems to support dynamic applications like urban planning, transportation modelling, and environmental monitoring. Tools like BP have successfully integrated multidimensional data for real-time habitat modelling, demonstrating scalability in large datasets (Benavides Martínez et al., 2024). However, challenges persist in managing the computational and storage demands of massive spatiotemporal datasets, necessitating the adoption of cloud-based and parallel processing solutions.

Ownership, security, and Compliance Considerations

As MultiGIS systems grow in complexity, ownership, and data security emerge as pressing concerns. Ensuring data integrity and access control across geolocated nodes becomes critical in scenarios involving multi-agency collaborations or public-private partnerships.

Furthermore, compliance with regulatory frameworks such as the EU AI Act, ISO 42001, and GDPR is essential in ensuring the ethical, transparent, and secure management of data in MultiGIS systems. The EU AI Act mandates robust measures for transparency, accountability, and risk management in AI-driven systems, aligning with the principles of human oversight and fairness. Similarly, ISO 42001 establishes guidelines for information management systems, ensuring that data processing frameworks are efficient, secure, and compliant with international standards. The GDPR imposes stringent requirements on the processing of personal data, including user consent, data minimisation, and the right to erasure. MultiGIS platforms must implement privacy-by-design practices, secure storage protocols, and robust encryption to protect geospatial and personal data. Ensuring adherence to these frameworks not only enhances trust but also mitigates legal and operational risks in sensitive applications like urban planning, disaster management, and public safety.

- **Research Gaps**

  Key research gaps include scalability challenges in processing large, heterogeneous datasets and integrating legacy GIS formats. Moreover, data quality and fusion techniques remain underdeveloped, limiting interoperability. Real-time processing faces constraints due to limited AI efficiency at the edge. Privacy, security, and ethical concerns demand trustworthy AI frameworks. Furthermore, AI adaptability in dynamic geospatial environments is limited, and its integration into GIS decision-making is minimal. Responsible AI governance is lacking and requires ethical frameworks and bias mitigation strategies in the context of GIS-based applications. Addressing these gaps necessitates scalable AI architectures, improved data fusion methods, privacy-preserving AI, and ethical AI deployment strategies to enhance MultiGIS applications.

4 AI-enabled Geographic Information System

GIS have transformed the collection, analysis, and use of spatial data for efficient resource management and informed decision-making across many industries, such as urban planning, disaster response, and environmental conservation. Traditional GIS systems, though powerful, are usually bound to analysing single or closely related datasets (Oliviera et al., 2024). However, as the real-world challenges become increasingly complicated, there is also an increasing requirement for systems capable of handling diverse datasets simultaneously. MultiGIS systems are significant in geospatial analysis developments. Integration of data from different domains, such as satellite imagery, real-time sensors, demographic data, and environmental metrics, aids in providing cross-domain insights enabled by MultiGIS systems (Baumann, Peter et al., 2018). For instance, analysing the impact of urban growth on biodiversity and evaluating preparedness for disasters by integrating infrastructure data with climate information. Such integration of a variety of diverse data sources provides new opportunities but also raises many challenges related to consistency, quality, and integration of data.

In this context, AI-powered MultiGIS enhances the analytics by adding automation, predictive modelling, and real-time insights. AI algorithms can process vast geospatial datasets at unprecedented speeds, thus enabling applications such as anomaly detection, predictive forecasting, and real-time monitoring. For example, AI-powered multi-GIS systems can predict flooding patterns by analysing historical climate data in combination with real-time rainfall metrics. Similarly, urban planning can make use of the combination of traffic patterns and population density for optimised layouts. These are just some examples of how AI can transform MultiGIS applications. However, the integration of AI into Multi-GIS has its challenges too. Data integration and quality continue to be an important concern, as datasets sourced from diverse sources often differ in format, resolution, and accuracy (Rozony et al., 2024). It is very essential to ensure consistency and reliability; otherwise, to avoid flawed analyses. Besides, bias in spatial data may generate discriminatory outcomes, such as unequal resource distribution in cities. Another critical issue is privacy concerns, since geospatial data typically contains personally identifiable information. In this respect, robust safeguards through encryption and differential privacy are needed in order to make sure that protection of individual rights and public trust are retained. Simultaneously, model interpretability is a critical requirement for high-stakes applications in GIS, including delivering crystal-clear insights transparent to decision-makers. MultiGIS complicates achieving explainability by incorporating more data types and algorithms. Finally, there is regulatory compliance with initiatives such as the EU AI Act, which demands extra complexity due to the resulting legal and financial risk associated with non-compliance (Guadamuz, 2024).

ML and neural networks have been effectively applied to anomaly detection, classification, and spatiotemporal forecasting in applications such as disaster management, urban planning, and environmental monitoring. Techniques like CNNs have shown superior performance in geospatial tasks, including feature extraction and land-use classification, surpassing traditional methods (Aendikova and Azayeva, 2024; Shahrabi-Farahani et al., 2024). Furthermore, the incorporation of Explainable AI (XAI) has enhanced the transparency and accountability of decision-making processes in GIS (Hoshi-Numahata et al., 2023).

4.1 AI Model for MultiGIS

With rapid development, AI techniques have been increasingly applied with GIS domain by researchers in recent years, bringing improvements in spatial analysis and decision-making, and monitoring the environment. Indeed, AI-driven applications of GIS cover disaster management, rural landscape planning,

and distributed retrieval of spatial data, among many others, with creative solutions being provided to a number of geospatial problems. Several works have used the potential of AI in GIS using various machine learning models and frameworks.

One such study finds its application in GIS by applying AI to forest fire susceptibility modelling, whereby the potential of machine learning and hybrid AI models was underlined for predicting high-risk fire zones (Tien Bui, et al., 2017) . This work applies a NFIS optimised with PSO to make the assessment of fire risk more accurate and reliable. The NFIS model effectively captures complex nonlinear relationships through the integration of neural network adaptability and fuzzy logic interpretability, while PSO tunes its parameters in order to optimise predictive performance. Other machine learning methods, such as Random Forest and Support Vector Machines, are also applied here for comparison, enriching this fire susceptibility analysis with more depth. The model was trained on historical fire occurrence data and ten important environmental and anthropogenic factors such as, topographical variables (slope, aspect, elevation), land cover features (NDVI, land use), human-induced factors (distance to roads and residential areas), and climatic conditions (temperature, wind speed, rainfall). In this paper, the PSO algorithm is used to optimise the premise and consequent parameters of the NFIS model to improve the classification process and enhance model performance. The ROC-AUC curve and AUC scores verify the performance of the model, with AUC values of 0.932 for training and 0.916 for validation, confirming that the model has high accuracy in its prediction. From the results, it is inferred that the hybrid PSO-NFIS outperforms typical machine learning methods such as RF and SVM and proved to be quite robust in the wildfire risk assessment. This model, by integrating AI with GIS, enables the precise spatial mapping of fire-prone areas, thus helping in proactive disaster management, forest conservation, and emergency planning. The study underlines the critical role that AI-driven GIS plays in the assessment of environmental risks, which is of great value for decision-makers to undertake effective resource allocation and mitigation strategies.

The integration of GIS and AI, specifically focusing on CNNs, for rural landscape protection and planning is proposed by Hu et al., (2024) . Traditional GIS methods often struggle with complex spatial data processing and real-time monitoring, which AI enhances by improving data analysis and pattern recognition capabilities. The study highlights that CNNs excel in feature extraction, achieving 95% accuracy in identifying rural landscape characteristics, outperforming other models such as MLP (85%), RF (80%), and SVM (82%). Furthermore, CNNs enable precise detection of landscape changes, surpassing traditional remote sensing techniques by identifying small-scale transformations in land use. The fusion of GIS and CNN also demonstrated improvements in species richness (15%), landscape heterogeneity (20%), and landscape connectivity (25%), making it a robust approach for sustainable rural planning. This methodology provides a data-driven solution for landscape management, ensuring efficient land use assessment, environmental conservation, and public satisfaction prediction. The findings suggest that AI-driven GIS applications can significantly enhance decision-making processes in urban and rural planning, offering a scalable and adaptive framework for dynamic monitoring and policy formulation. Future research could expand this integration by incorporating more advanced deep learning models and multi-source data fusion techniques to further optimise spatial analysis.

Another dimension of work focuses on Agent-Based Distributed Artificial Intelligence in GIS. The study further emphasizes MAS and DPS as key methodologies of artificial intelligence in enhancing spatial data processing, decision-making, and automation (Wang et al., 2005). The Intelligent GIS Agents of the system have characteristics such as spatial autonomy, spatial reasoning, and goal-oriented; thus, they are able to respond dynamically to environmental data and perform spatial computations on their own without the need for

human intervention. Geolets, or mobile GIS agents that navigate around heterogeneous distributed networks, retrieve, process, and manage geospatial data autonomously. These AI-driven GIS systems significantly enhance real-time environmental monitoring, spatial analysis, and collaborative decision-making, offering scalable solutions for land-use planning, disaster management, and infrastructure development. The paper further shows how spatial cognitive architectures, including Belief-Desire-Intention models of agents, enhance the intelligence of GIS agents by enabling them to reason, learn, and adapt to changing spatial environments. In all, the research has presented a new AI-GIS integration framework that shows how distributed AI can help in optimising large-scale geospatial data processing and predictive analytics. Further developments may involve enhanced learning mechanisms of agents, improved data fusion techniques, and real-time AI-driven GIS applications for more effective and autonomous spatial decision-making.

Moreover, TAI is pivotal for MultiGIS applications, addressing data reliability, bias mitigation, and ethical concerns in geospatial analysis. Advances like federated learning and XAI ensure privacy and interpretability of spatial models, vital for high-stakes domains such as disaster management and urban planning (Sela et al., 2025; Temenos et al., 2024). Despite progress, integrating robust TAI frameworks with GIS demands adaptive governance to reconcile technical scalability with societal trust (Das, 2025).

The concept of Autonomous GIS, an AI-powered GIS that embeds LLM such as GPT-4 to automatically collect, analyse, and visualise spatial data, is introduced by [ref]. The research introduces LLM-Geo, a prototype system designed to autonomously execute spatial analysis tasks without human intervention. Unlike traditional GIS, which is manually processed, Autonomous GIS achieves five key autonomous goals: self-generating, self-organising, self-verifying, self-executing, and self-growing. The discussion covers how LLMs extend the capabilities of spatial reasoning and decision-making by decomposing tasks in GIS into modular operations, automatic generation of geospatial processing workflows; these workflows are coded, executed, and even checked without requiring direct user interactions to make spatial analysis easier. The paper also underlines the domain of GeoAI, which is at the core of this interdisciplinary research combining AI and GIScience, further utilizing deep learning models like GAN in spatial interpolation and GCNs in spatial regression and flow analytics. Further, the paper supports the view that such a GIS is autonomous and represents a paradigm shift from conventional GIS tools to address a self-sufficient, AI-driven system. In this regard, further research could be directed to the following areas: better adaptability for LLM, integrating real-time geospatial data retrieval, and developing Large Spatial Models, trained over large GIS data, which give good spatial awareness. This has very useful applications in town planning, disaster control, and management, and environmental monitoring-mediating GIS toward access, intelligence, and automation.

Furthermore, hybrid models, such as NFIS and deep learning approaches, improve predictive modelling, spatiotemporal analysis, and decision-making accuracy in applications like disaster management and urban planning (Wang et al., 2025). Scalability and data heterogeneity remain critical challenges.

The synergy between AI and GIS for disaster management, showing how AI enhances the capability of GIS in predictive analysis, early warning, and coordination in disaster responses. AI models in particular, ML and DL, are very crucial in sensor data, satellite imagery, and social media feeds for detecting anomalies and predicting disaster events before they scale (Emami & Marzban, 2023) . AI-powered GIS helps in real-time damage assessment during a disaster, using computer vision algorithms that compare pre-disaster and post-disaster imagery to perform automatic damage assessments of the affected areas, infrastructural damage, and resource distribution. AI also enhances spatial decision-making: It optimises emergency resource

allocation, evacuation planning, and rescue operations with real-time geospatial insights. The paper also points out emerging challenges in integrating AI with GIS, such as assurance of data accuracy, algorithmic bias, and incorporation of ethical considerations. Human oversight, interdisciplinary collaboration, and regulatory frameworks are needed to ensure that AI is responsibly deployed in disaster management.

4.2 Trustworthy AI in the Context of MultiGIS

The TAI in GIS is essential for ensuring that the decision-making by the AI-enabled GIA model is reliable, fair, transparent, and secure. It is of paramount importance to address concerns about bias, interpretability, privacy, and accountability. By embedding techniques of XAI, data fusion strategies, and ethical governance frameworks, GIS will be able to foster public trust and stakeholder confidence in its decision-making processes. Various surveys have discussed different ways AI in GIS is being made explainable, fair, and responsible.

TAI for GIS provides insights into the necessity of ethics, reliability, and accountability in spatial decision-making (Xu et al., 2024). In particular, key characteristic such as fairness, transparency, robustness, and privacy all bind in significant concepts toward banishing any concept of biased and unreliable geospatial predictions within this approach. Biased mitigation techniques mainly include demographic parity and equalized odds in an attempt to develop a non-biased AI-driven GIS model. Moreover, SHAP, LIME, and Grad-CAM are some of the interpretability techniques that enhance explainability in understanding AI-driven spatial decisions on disaster prediction, environmental monitoring, and urban planning. Differential privacy, federated learning, and encrypted data-sharing techniques are some other techniques used to protect sensitive location information with privacy and security. Besides, human oversight mechanisms through HITL and HOTL approaches ensure that AI-driven GIS is kept only as an assistive tool and not a fully autonomous system. Ethical governance frameworks, inspired by the regulations such as the EU AI Act, further reinforce accountability in spatial AI applications. Future developments will also need to turn their focus towards self-assessing AI models for bias, improving real-time interpretability, and improving security protocols as necessary prerequisites for AI to be trusted and transparent in GIS.

A paper systematically analyses current AI applications in the field of natural disasters related to disaster management, risk assessment, and prediction. The aim of this paper is to show how AI-driven models will enable improvement in EWSs, evacuation planning, and resource allocation (Albahri et al., 2024). However, deploying AI in such life-critical situations requires an assurance from AI that it is trusted-robust, transparent, fair, accountable, and secure. This analysis appraises the findings of the paper on the Guidelines for TAI by the European Commission, including fairness, explainability, security, accountability, and data privacy. The research points out seven key challenges that prevent AI from being trustworthy in disaster management applications: bias in AI models, unexplainable predictions, security and privacy vulnerabilities, inefficiency in disaster response models, inability to integrate with real-time monitoring systems, ethical issues in automated decision-making, and lack of human oversight. These challenges outline the dire need for trustworthy AI principles embedded in disaster responses. One of the key issues about disaster prediction is algorithmic bias, whose worst impact falls on the most sensitive populations. The paper discusses some fairness constraints in AI models and demographic parity in AI-driven risk assessments. To have faith in AI-based disaster prediction models, the research emphasizes the use of XAI techniques such as SHAP, LIME, and Grad-CAM.

Similarly, AI-powered Geospatial AI modernizes urban planning and decision-making by integrating machine learning and computer vision into sophisticated spatial analysis (Marasinghe et al., 2024). However,

undertaking appropriate measures for ensuring the trust of AI remains highly imperative for ethical, transparent, and accountable GeoAI applications. The study thus contends that there is a need to develop techniques of XAI in enhancing transparency in models of AI-powered urban planning. It also focuses on bias mitigation, preservation of privacy, and algorithmic fairness to ensure responsible AI adoption in geospatial applications. GeoAI could enhance urban sustainability, spatial justice, and equitable development by incorporating ethical AI frameworks, human-in-the-loop approaches, and participatory decision-making. RAI integration is required for the optimisation of AI benefits while minimizing risks in urban geospatial planning.

Furthermore, AI is now transforming urban planning, improving data-driven decision-making, public engagement, and infrastructure management. But at the same time, trustworthiness in AI should be guaranteed in order to mitigate bias, transparency, accountability, privacy, and misinformation within urban governance systems (Sanchez et al., 2024). This research points out ethical challenges for AI in smart cities, public participation, and environmental planning. Key concerns are bias in decision-making, affecting the already marginalized communities, and lack of transparency in AI-driven urban policies, making them difficult to interpret and hence trusted. The study proposes XAI, inclusive datasets, preservative methods of privacy, and robust ethical frameworks as a recipe for trustworthy AI. Besides, human oversight and public engagement will go a long way in making the AI adoption in urban planning fair, accountable, and responsible.

4.3 Responsible AI in the Context of MultiGIS

The integration of Responsible AI into GIS is an absolute necessity for fairness, transparency, accountability, and ethical governance of applications in urban security. While AI-driven GIS systems analyse large volumes of spatial data related to threat detection, risk assessment, and protection of infrastructure, there is an urgent need to discuss issues related to bias, privacy, and accountability in decision-making to avoid unintended consequences. In the case of multi-GIS, dealing with diverse data, such as geospatial coordinates, satellite images, and real-time sensor data, the role of RAI becomes even more critical [ref]. Fairness, transparency, and privacy are important for GIS applications to avoid harming society and help gain the trust of stakeholders, since many applications of GIS involve critical areas like urban planning, disaster response, and environmental conservation. RAI addresses challenges around bias mitigation, data privacy, and model explainability to align multi-GIS systems with ethical standards, ensuring solutions are secure, equitable, and impactful for informed decision-making and long-term societal benefits.

Many AI-driven MultiGIS applications have emerged across domains, integrating artificial intelligence with geospatial intelligence to enhance EO data analysis (Ghamisi et al., 2024) . These applications span diverse use cases, including disaster management, city planning, environmental monitoring, and law enforcement. AI-powered MultiGIS systems significantly improve data fusion from various sources, enabling real-time insights for better decision-making. However, deploying RAI within such applications remains a challenge due to the absence of standardised regulations, insufficient ethical oversight, and the complexity of embedding privacy-preserving techniques like federated learning and differential privacy into geospatial AI systems.

Recent studies have extensively explored the ethical and governance challenges associated with AI applications in geospatial intelligence and DE systems. One such study highlights how AI-driven DE applications integrate diverse spatial-temporal data sources to model, visualize, and simulate real-world environments (Micheli et al., 2022) . Despite their benefits, these systems raise pressing concerns related to privacy, data governance, and AI ethics. The rapid expansion of AI in geospatial intelligence has introduced risks such as surveillance overreach, power imbalances in data ownership, and biased decision-making. The

study argues that existing AI ethics guidelines often fail to fully address the unique challenges posed by DE, particularly regarding data sovereignty, transparency, and accountability in large-scale geospatial models. Without appropriate ethical governance, DE applications could inadvertently reinforce inequalities and expose vulnerable populations to excessive surveillance and unfair treatment.

Additionally, the Endowment for Climate Intelligence (ECI) [ref] has been at the forefront of promoting Responsible AI in geospatial intelligence, particularly within climate-related GIS applications. ECI focuses on integrating ethical AI principles into climate-focused geospatial analytics to enhance safety, transparency, and inclusivity. Their initiatives aim to mitigate misinformation, foster participatory governance, and ensure equitable decision-making in AI-powered geospatial models. ClimateGPT, one of their AI-driven projects, seeks to provide accurate climate intelligence while adhering to strict ethical AI standards. ECI's work underscores the necessity of applying Responsible AI frameworks to GIS applications, particularly in climate science, where ethical and equitable data governance is crucial.

4.4 Research Gaps and Future Directions

Challenges with the adoption of AI for MultiGIS

The adoption of AI in MultiGIS presents several challenges that must be addressed to ensure its effective and responsible implementation. While AI enhances geospatial data integration, analysis, and decision-making, several technical, ethical, and regulatory issues hinder its widespread adoption in MultiGIS applications, as summarised in Figure 9.

- **Data Heterogeneity and Integration Complexity**

  One of the primary challenges is data heterogeneity and integration complexity. MultiGIS relies on multiple geospatial data sources, including satellite imagery, LiDAR, drone surveillance, IoT sensor data, and crowdsourced information (Bordogna & Fugazza, 2023) . These data sources vary in format, resolution, and accuracy, making it difficult to integrate them into AI-driven decision-making models. AI algorithms need harmonized high-quality datasets and data-based AI models tailored for end-user services, yet numerous geospatial datasets are not aligned temporally and experience inconsistencies or missing values, resulting in decreased performance of AI-generated insights.

- **Computational Complexity and Resource Constraints**

  Another significant challenge is computational complexity and finite resources. Large-scale spatial data processing, real-time analytics, and action insights generation done by AI-based MultiGIS applications demand huge computational power. Many organizations, especially in developing regions, do not have the infrastructure, computational resources, and cloud-based AI capabilities for large-scale AI-managed MultiGIS solutions (Böhlen et al., 2024). Growing these gaps also necessitates scalable AIs, border computing designs, and ambient geospatial AIs that can perform as well in constrained and poorly designed environments and mineral resource-rich locations.

- **Human and Organisational Resistance**

There is a resistance from humans and organizations to adapt AI models for MultiGIS due to the fear of losing control, trust, and skill of decision-makers (Westover, 2024) . Moreover, many urban planners, security agencies, and policymakers stick to traditional GIS methods and are, overall, not comfortable trusting spatial predictions generated by AI. To ensure successful adoption of AI technologies in MultiGIS, capacity building of analysts, AI literacy programs, and HITL decision-making models should be the top priorities, whereby AI augments rather than replaces human decision-makers.

- **Lack of focus on Privacy and Security**

  Another big challenge to the mainstreaming of AI in MultiGIS is related to the concerns on privacy and data security (Nallam et al., 2024). Geospatial intelligence involves substantial amounts of location-based data, aerial surveillance images, and personal movement tracking; hence, ethical concerns arise with respect to mass surveillance, unauthorized data access, and misuse of sensitive information. Most of the existing AI-driven MultiGIS models have inadequate mechanisms for preserving privacy, hence making data breach more possible. Privacy-preserving AI techniques, including differential privacy, federated learning, and secure multi-party computation, need to be implemented in practice to balance geospatial intelligence with data protection and individual privacy rights.

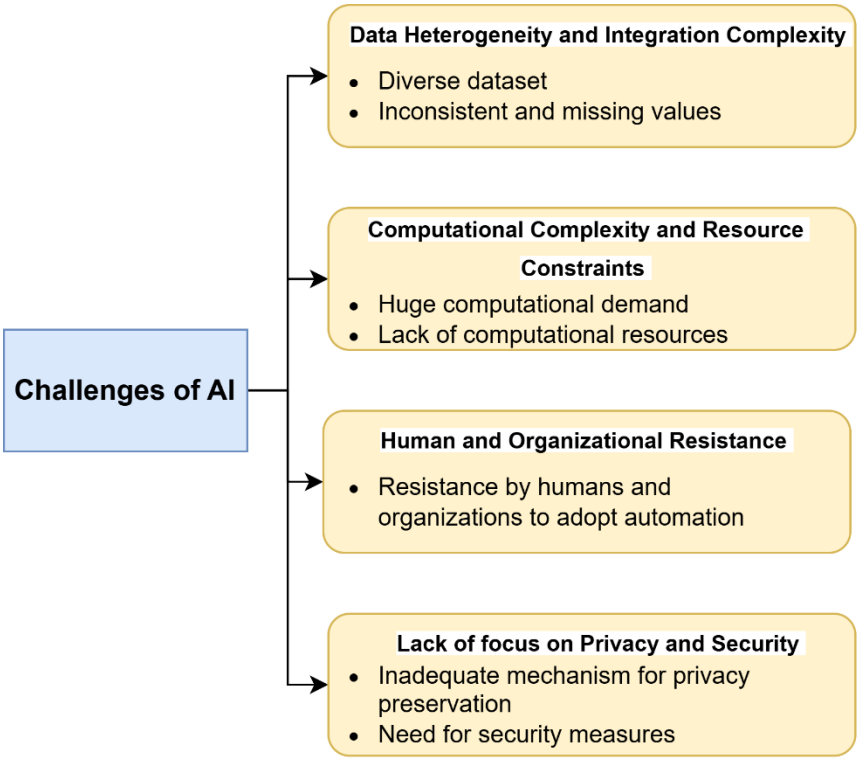

Figure 9 - Challenges of AI Adoption for GIS Applications

To address these challenges, it is recommended to adopt a multi-faceted approach. Standardisation of the geospatial data formats and enhancement in pre-processing techniques will help reduce issues of heterogeneity. While scalable AI architectures and edge computing solutions will provide computational efficiency at lower resource platforms. AI literacy, capacity-building programs, and human-in-the-loop

frameworks enable overcoming resistance to change by assuring that AI will enhance human expertise, not replace it. Besides, the integration of privacy-enhancing techniques like differential privacy, federated learning, and secure multi-party computation can raise the security and ethical use of AI in MultiGIS. These strategies combined will ensure a correct and responsible integration of AI into MultiGIS applications, realising their full potential by addressing technical, ethical, and regulatory concerns.

5 Standardisation document

AI4MIltiGIS focuses on various aspects of MultiGIS including data generation, processing, and management to enhance GIS capabilities. Therefore, it is necessary to review the existing regulation that are relevant with the scope of AI4MultiGIS. This allows ensuring that the outcomes from the project specifically AI-enabled applications support to comply with the relevant regulations towards creating responsible AI-enabled framework.

5.1 EU AI Act

The EU AI Act aims to provide a comprehensive legal framework for AI systems deployed within the EU. The focus is to ensure that AI systems developed and used are safe and respect fundamental rights and values of individuals. The Act was entered into force on August 1, 2024, and imposed restriction to the stakeholders who are involved in development, usage, distribute AI system across EU.

According to the Act, each organisation needs to assess their AI system which are deployed within their context, developed or procured from any third party to understand the current state as a part of inventory. The core of the Act (Art 6) is to classify the AI system based to four risk categories, i.e., unacceptable risk, high risk, limited risk and minimal risk.

The systems fall into the unacceptable risk category such as social scoring system, exploit individual person vulnerabilities to cause harm, are prohibited to deploy into EU as shown in Figure 10.

The high-risk systems such as HR recruitment or employee rating system, credit scoring or insurance claim system, systems that are used in critical infrastructure, biometric identification systems, etc must undergo a conformity assessment process before such system can deploy into the EU. The activities related to such assessment include register central EU database, adequate documentation and logs management, AI risk management, data governance for training, testing, and validation of data, and human oversight. These activities aim to ensure the security, robustness, and fairness of the system.

The limited and minimal risk systems such as chatbots, spam filers, deep fakes, Gen AI models, etc require providing adequate obligation practice for the use of GPAI system. In this context, any GPAI system with systematic risk GPAI with systemic risk requires complying with additional requirements including model evaluation, reporting obligations, and systematic risk mitigation. The transparency obligations (Art 50) is one of the key priorities to ensure that AI systems provide detailed about their working mechanism, data use, and decision-making process to enhance user trust on the system. Therefore, AI systems intend to interact with human need to ensure that humans are aware about their interactions with an AI system.

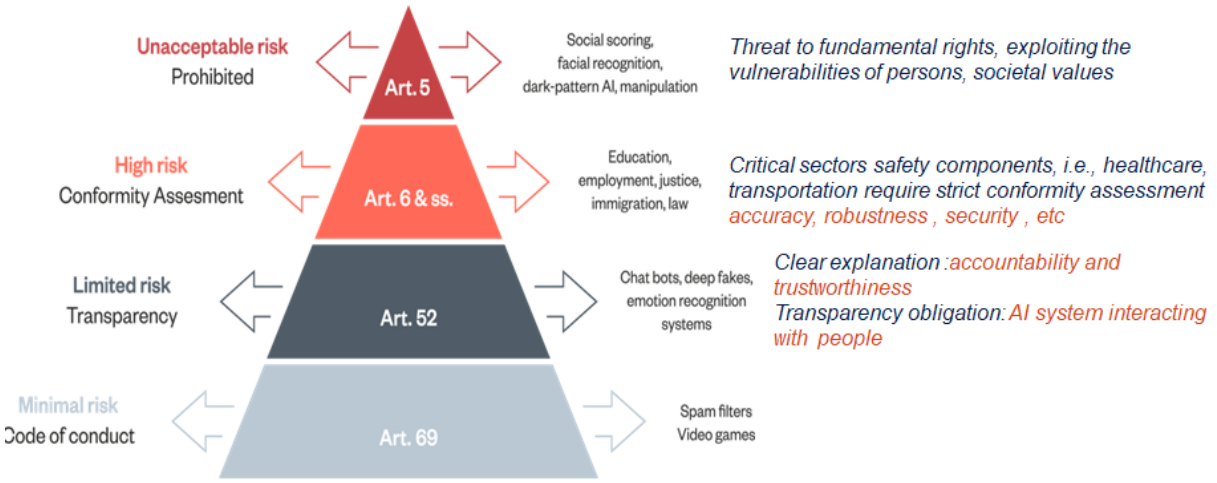

Figure 10 - EU AI Act based AI Systems Risk Types

5.2 OGC (Open Geospatial Consortium)

The OGC[21] (Reed, 2011) is a key global organization that develops and maintains standards for geospatial and location-based services. These standards enable the interoperability of geospatial data, services, and systems. OGC's work is critical for MultiGIS, as it provides specifications that facilitate the integration of multidimensional geospatial data, including spatial, temporal, and other non-spatial information (Baumann, P., 2021). One of OGC's well-known standards is the WFS, which allows for the sharing and querying of geospatial data over the web. OGC also works on standards related to 3D geospatial data (such as CityGML) and time-based data (through the Time Series Web Services). Their contributions are significant in ensuring that geospatial systems can handle complex, multidimensional datasets, which is essential for the effective deployment of MultiGIS in a variety of applications, from urban planning to environmental monitoring. The organization's efforts in standardizing formats like GeoTIFF, KML, and GML have helped drive widespread adoption of geospatial data technologies. OGC's standards ensure that diverse geospatial data from multiple sources can be accessed, analysed, and visualized cohesively, which is crucial for the evolving demands of MultiGIS systems.

OGC is a global network of government, business, research institutions, startups, and geospatial community entities that focus on sectors and technologies that create and share geospatial data. OGC Standards are internationally recognized specifications that let different systems exchange geospatial information seamlessly (Baumann 2010). These include (https://www.ogc.org/publications/):

- **OGC APIs** - resource-centric APIs that take advantage of modern web development practices.
- **Services** - XML Remote Procedure Calls using the Hypertext Transfer Protocol (HTTP).
- **General Data Models and Encodings** - general rules to organize geospatial information, typically sent by a service provider or produced by an application.
- **Domain Specific Data Models and Encodings** - domain specific rules to organize geospatial information.

[21] http://www.ogc.org

- **Publish-subscribe, Syndication & Context** - subscription management and other syndication purposes.
- **Sensors** - accessing sensors that are connected to the Web or the Internet of Things (IoT).
- **Discovery** - searching and finding geospatial resources.
- **Containers** - rules for storing and retrieving geospatial information efficiently.

Within the AI4MultiGIS, primary data and secondary data are merged and processed across various applications and sites. Some of this data will be proprietary or under copyright restrictions. Challenges such as data integration, searching, sharing, and encoding are vital to scalable distributed MultiGIS applications. Relying on standards provided by OGC is therefore essential, as it enables transparent access to the provided APIs for developed case studies and future applications that will use the proposed solution. For instance, the OCG API provide fundamental RESTful building blocks for querying features, accessing processes for data preprocessing on remote servers or environmental data. Our solution will leverage this to provide end users with RESTful APIs for access to the developed MultiGIS platform.

5.3 Inspire Directive

INSPIRE (BARTHA & KOCSIS, 2022) aims to create a European Union SDI for the purposes of EU environmental policies and policies or activities which may have an impact on the environment. It is based on the infrastructures for spatial information established and operated by the Member States of the European Union. The Directive addresses 34 spatial data themes needed for environmental applications. It provides data specification on several topics including addresses, cadastral parcels, geographical names, land use, mineral resources, oceanographic geographical features, population distribution, sea regions, atmospheric conditions and meteorological geographical features, biogeographical regions etc.

INSPIRE is based on several key principles:

- **Data** should be **collected only once** and kept where it can be maintained most effectively.
- It should be possible to **combine seamless spatial information from different sources** across Europe and share it with many users and applications.
- It should be possible for **information collected at one level/scale to be shared with all levels/scales**; detailed for thorough investigations, general for strategic purposes.
- **Geographic information** required for good governance at all levels should be **readily and transparently available**.
- It should be **easy to find what geographic information is available**, how it can be used to meet a particular need, and under which conditions it can be acquired and used.

The AI4MultiGIS project will follow the same principles by providing seamless access to MultiGIS data by adhering to the OGS standards and formatting data using the UML data specification in the spatial data themes. This will effectively integrate the project solutions in the EU SDI, allowing seamless integration with tools developed by third parties in the EU.

5.4 ISO/TC 211 (International Organisation for Standardisation - Technical Committee 211)

ISO/TC 211 (Wang, W., 2022) is an international committee that focuses on developing standards for geographic information and geomatics. The committee plays an essential role in setting international

standards that govern how geographic data is represented, processed, and exchanged across different systems. For MultiGIS, the standards provided by ISO/TC 211 are fundamental, as they ensure that geospatial data from various sources and in various formats can be integrated effectively (Kresse et al., 2022).

Danko (Danko, 2022), for instance, defines metadata for geospatial data, providing important context about data's origin, quality, and use, which is essential for ensuring data integrity and interoperability in MultiGIS systems. Additionally, ISO 19123 (Nativi et al., 2008) standardizes spatial schema, providing guidelines for how spatial data should be structured. ISO/TC 211 also addresses key aspects like spatial data transfer (ISO 19136 – GML) and feature modelling (ISO 19109), both of which are critical for MultiGIS systems that rely on sophisticated datasets involving 3D, temporal, and thematic information. These standards ensure that geospatial information is accurate, reliable, and usable, forming the backbone of geospatial data infrastructures that support MultiGIS.

5.5 W3C Spatial Data on the Web Working Group:

The W3C has a working group focused on spatial data on the web, and its work is highly relevant for the development of MultiGIS systems. W3C is responsible for developing web standards and protocols that ensure the interoperability of geospatial data across different platforms and technologies (Mara et al., 2024)(Mara et al., 2024). In the context of MultiGIS, W3C's work on standards for the integration and visualisation of spatial data on the web helps ensure that multidimensional geospatial datasets (including 3D, temporal, and sensor data) can be accessed and visualized in a user-friendly and efficient way. The group has developed standards such as GeoJSON (Horbiński & and Lorek, 2022), which is a format for encoding geospatial data in JSON and is commonly used for spatial data sharing and web mapping applications. Additionally, W3C's focus on Linked Data and the development of specifications for spatial RDF enhances the ability to integrate spatial data with other types of web data. The W3C's efforts are instrumental in ensuring that MultiGIS platforms can share and present complex datasets effectively in web environments, making geospatial data more accessible and interactive for a wide range of users.

6 Conclusion

The deliverable D2.1 provides a comprehensive understanding of the MultiGIS domain including the techniques and tools used for the data consolidation, processing, and decision-making through the review of the state of the art. The deliverable has also underscored the challenges and opportunities in adoption of AI-enabled MultiGIS application with responsible AI practice.

In conclusion, through D2.1, AI4MutiGIS has established common knowledge based that informs the technical work and development across various work packages of the project. It will ensure that the technical implementations build upon state-of-the-art knowledge, address key gaps, meet the project expectations.

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