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RESEARCH ARTICLE

Leveraging Remote Sensing and GIS for Evidence-Based Policy Implementation of SDGs

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ABSTRACT

The 2030 Agenda for Sustainable Development faces a critical data gap, with recent assessments indicating that only 15% to 18% of the 169 Sustainable Development Goal (SDG) targets are currently on track for completion as of mid-2025. This paper investigated how Remote Sensing (RS) and Geographic Information Systems (GIS) provide the essential "where" dimension required for evidence-based policy implementation and localized decision-making. By integrating Earth observation data with advanced analytics such as Machine Learning (ML) and Convolutional Neural Networks (CNNs), these technologies enable monitoring systems to achieve an average accuracy of 90% in tracking complex indicators. Methodologically, the paper adopts the three-phase SDGs Geospatial Roadmap, encompassing preparation, design, and production, to bridge the divide between traditional statistical records and spatial data. The analysis demonstrated the transformative impact of geospatial intelligence across multiple sectors, including high-accuracy poverty mapping (SDG 1), real-time crop yield prediction (SDG 2), and resilient urban modeling (SDG 11). Case studies, such as Costa Rica's forest management system (SDG 15), further illustrated the role of these tools in securing international climate funding and ensuring accountability. Despite these technical successes, the study identified significant institutional and technical barriers, including fragmented governance, data silos, and a persistent geospatial digital divide. The paper concluded that the successful implementation of the SDGs requires a systemic shift toward anticipatory governance, necessitating robust inter-agency collaboration between National Statistical Offices (NSOs) and National Geospatial Information Agencies (NGIAs), alongside significant investment in local technical capacity.

Keywords: *Remote Sensing; GIS; SDGs; Evidence-Based Policy; Geospatial Analytics; Earth Observation*

1. INTRODUCTION

The 2030 Agenda for Sustainable Development represents a milestone in the evolution of global governance, serving as the first truly data-driven international framework for development policy. It comprises 17 goals, 169 targets, and over 230 indicators designed to balance the three dimensions of sustainable development: economic growth, social inclusion, and environmental sustainability (UN-GGIM, 2018). However, the efficacy of this framework is constrained by the "geospatial digital divide," a gap between the potential of modern spatial intelligence and the current data capacities of national governments, particularly in the Global South and Small Island Developing States (SIDS) (UN Statistical Commission, 2025). The United Nations has explicitly recognized this challenge in Article 76 of the 2030 Agenda, calling for the exploitation of wide-ranging data sources, including Earth observations and geospatial information, to support and track progress while ensuring national ownership (Group on Earth Observations, 2025).

Geospatial information provides an integrative platform for all digital data that has a location dimension, acting as the "connective tissue" that links environmental, social, and economic indicators (Liu & Adam, 2026). Remote sensing, which involves the acquisition of data from a distance via satellites, aircraft, or unmanned aerial vehicles (UAVs), offers a cost-effective and objective means of monitoring terrestrial, atmospheric, and oceanic phenomena across scales (Liu & Adam, 2025b). When integrated with GIS, a system designed to store, manipulate, and visualize spatial data, these technologies enable a transition from descriptive statistics to predictive and prescriptive analytics (Pooja et al., 2025). This transition is critical for evidence-based policy, as it allows decision-makers to simulate future scenarios, identify the root causes of development disparities, and allocate resources with geographic precision (Chukwuebuka & Diping, 2024; Kaleagasi et al., 2022).

The current research explored how the integration of Remote Sensing (RS) and Geographic Information System (GIS) enhances the entire policy cycle, from the identification of gaps to the evaluation of intervention outcomes. It examined the role of Earth observation in tracking key indicators related to poverty reduction (SDG 1), food security (SDG 2), sustainable urbanization (SDG 11), and environmental resilience (SDGs 13, 14, and 15). Furthermore, the study addresses the methodological innovations driving this field, such as machine learning (ML), big data analytics, and participatory mapping, while acknowledging the institutional and technical barriers that must be overcome to realize the full potential of geospatial intelligence.

2. LITERATURE REVIEW

The use of remote sensing for development monitoring is not new; however, its integration into global policy frameworks has accelerated markedly over the past decade (Holloway & Mengersen, 2018). Early efforts, such as those by the Laboratory for Applications of Remote Sensing (LARS) in the 1960s and 1970s, demonstrated the potential of satellite spectral data for applications like crop identification (Klingwort et al., 2026). What distinguishes the current era is the scale and accessibility of geospatial data. Advances in spatial, spectral, and temporal resolution, combined with cloud-based platforms such as Google Earth Engine (GEE) and the Sentinel/Copernicus programmes, have significantly lowered the barriers to data access and analysis (UN-GGIM, 2018). As a result, geospatial technologies are no longer confined to specialized institutions but are increasingly embedded in mainstream development practice.

The integration of geospatial data into development policy must be understood within the broader evolution of global sustainability frameworks. Key milestones, from the 1972 United Nations Conference on the Human Environment in

Stockholm to the 1992 Earth Summit in Rio de Janeiro (UN-GGIM, 2018), laid the foundation for measuring development beyond purely economic indicators such as Gross Domestic Product (GDP). These efforts culminated in the Millennium Development Goals (MDGs) and, subsequently, the Sustainable Development Goals (SDGs) (UN-GGIM, 2018).

A key distinction between the MDGs and SDGs lies in the latter's emphasis on spatial disaggregation. The SDGs explicitly recognize that development outcomes vary significantly across geographic contexts, making subnational data essential for addressing inequalities such as rural–urban disparities. To operationalize this, institutional frameworks have been developed to guide countries in integrating geospatial and statistical systems (UN-GGIM, 2019). Notably, the Integrated Geospatial Information Framework (UN-IGIF), developed by the United Nations Committee of Experts on Global Geospatial Information Management (UN-GGIM) in collaboration with the World Bank, outlines strategic pathways for strengthening national geospatial capacity. Complementing this, the Global Statistical Geospatial Framework (GSGF) provides the technical foundation for linking spatial data with official statistics, enabling more coherent and location-based reporting of SDG indicators (Liu & Adam, 2025a; UN Statistical Commission, 2025).

A significant body of recent literature focuses on the role of Artificial Intelligence (AI) and Machine Learning (ML) in processing the petabytes of data generated by Earth observation satellites (Pooja et al., 2025). ML algorithms, including Random Forests (RF), Support Vector Machines (SVM), and Gradient Boosting, are now standard tools for land cover classification, crop yield estimation, and disaster risk assessment (Ferreira et al., 2020). A meta-analysis of studies employing ML for SDG monitoring indicates an average model accuracy of 0.90, demonstrating the reliability of these techniques for official reporting (Klingwort et al., 2026).

Furthermore, deep learning architectures, particularly Convolutional Neural Networks (CNNs), have revolutionized the analysis of "non-traditional" indicators like poverty (Ferreira et al., 2020). By training models to recognize landscape features in high-resolution imagery, such as building density, road materials, and nighttime light intensity, researchers can estimate wealth and asset distribution with accuracy comparable to that of traditional household surveys (Mmbando, 2025). These models are particularly valuable because they can "backfill" data gaps, using historical satellite archives to reconstruct development trajectories from 2015 or earlier (UN Statistical Commission, 2025).

While technological advancements are central to the evolution of geospatial analysis, the literature also underscores the importance of its social dimension. Spatial data is not purely objective; it is shaped by the perspectives and priorities of those who produce and interpret it. In response, participatory mapping and Public Participation GIS (PPGIS) have emerged as approaches that incorporate local and indigenous knowledge into spatial analysis (Hodbod et al., 2019). These methods are particularly valuable for ensuring that marginalized populations, such as residents of informal settlements or indigenous communities, are not excluded from development narratives. Through integrating traditional ecological knowledge with remotely sensed data, participatory approaches provide a more nuanced understanding of environmental processes and resource use (Sever et al., 2025). This not only enhances the accuracy of spatial analysis but also promotes greater equity and legitimacy in policy design.

3. MATERIALS AND METHODS

The application of Remote Sensing (RS) and Geographic Information Systems (GIS) for SDG monitoring in this study is grounded in a conceptual and methodological research design. Rather than focusing on a specific geographic case study, the research developed a generalizable framework that can guide the integration of geospatial technologies into evidence-based policy implementation across different national contexts (Sileyew, 2019). This approach is particularly appropriate given the global scope of the Sustainable Development Goals (SDGs), which require adaptable and scalable methods that can be applied across diverse institutional and geographic settings (Scavuzzo et al., 2026).

The study adopts a structured methodology informed by the SDGs Geospatial Roadmap, which provides internationally recognized guidance for integrating geospatial information into SDG monitoring and reporting and outlines three critical phases for national implementation (UN-GGIM, 2021). This framework is selected because it aligns closely with the operational realities of national governments, particularly in contexts where data fragmentation and institutional silos limit effective policy implementation.

The use of RS and GIS within this framework is justified by their ability to provide spatially explicit, consistent, and repeatable data for monitoring development indicators. Unlike traditional data collection methods, which are often periodic and resource-intensive, geospatial technologies enable continuous observation and analysis across multiple scales (Mkhitaryan et al., 2025). Furthermore, the integration of machine learning techniques enhances the capacity to process large volumes of Earth observation data, making it possible to generate timely and policy-relevant insights. Collectively, this approach supports a shift from reactive to proactive policymaking by enabling scenario analysis, early warning systems, and targeted intervention planning (Masó et al., 2020).

Phase 1: Prepare and Plan

This foundational phase involves the alignment of national SDG priorities with geospatial data requirements (Liu & Adam, 2025b). Policymakers must define the purpose and scope of their interventions, identifying thematic areas, such as climate resilience or urban expansion, where spatial intelligence can provide the greatest value. A key activity in this phase is the establishment of institutional arrangements between National Statistical Offices (NSOs) and National Geospatial Information Agencies (NGIAs) to ensure that data sharing is governed by clear legal and policy frameworks (UN Statistical Commission, 2025).

Phase 2: Design, Development, and Testing

The second phase focuses on the selection of appropriate data sources and the development of technical workflows (UN Statistical Commission, 2025). This involves a data fusion approach, where multispectral imagery from missions like Sentinel-2 or Landsat 8/9 is integrated with administrative registers, census data, and in-situ observations (Tarashtwal et al., 2026).

Table 1. Context of Phase 2 (Key Actions)

Technical Step	Description	SDG Context
Preprocessing	Radiometric and geometric correction of satellite images.	Ensuring data consistency across temporal sequences.
Feature Extraction	Identifying spectral signatures or spatial patterns (e.g., NDVI for vegetation).	Monitoring crop health (SDG 2) or forest cover (SDG 15).
Classification	Using ML models to categorize land use/cover (e.g., urban vs. rural).	Tracking land consumption (SDG 11) or habitat loss (SDG 15).
Spatial Analysis	Modeling relationships between locations (e.g., distance to schools).	Assessing service accessibility (SDG 4) and inequalities (SDG 10).
Validation	Comparing RS-derived indicators with ground-truth data.	Ensuring accuracy for official reporting.

Source: (Singh & Bhadauria, 2024)

Methodological innovations in this phase include the use of strategic foresight and technology assessment (Liu & Adam, 2026). For instance, policymakers in SIDS use geospatial analysis to simulate the impact of sea-level rise over a 20-year horizon, allowing them to test the feasibility of different adaptation technologies before large-scale implementation (Liu & Adam, 2025b).

Phase 3: Production, Measurement, and Reporting

The final phase involves the routine generation of geospatially enabled SDG indicators. This requires the establishment of automated workflows and data cubes that can process high-resolution imagery into standardized metrics (Çelik et al., 2025; Giuliani et al., 2020). The results are then visualized through interactive dashboards and story maps that translate complex spatial patterns into intuitive narratives for decision-makers and the general public (UN Statistical Commission, 2025). This phase also includes co-design workshops where policymakers and data scientists work together to ensure that the outputs are directly relevant to policy levers and budget allocation processes (Miguel-Lago, 2020).

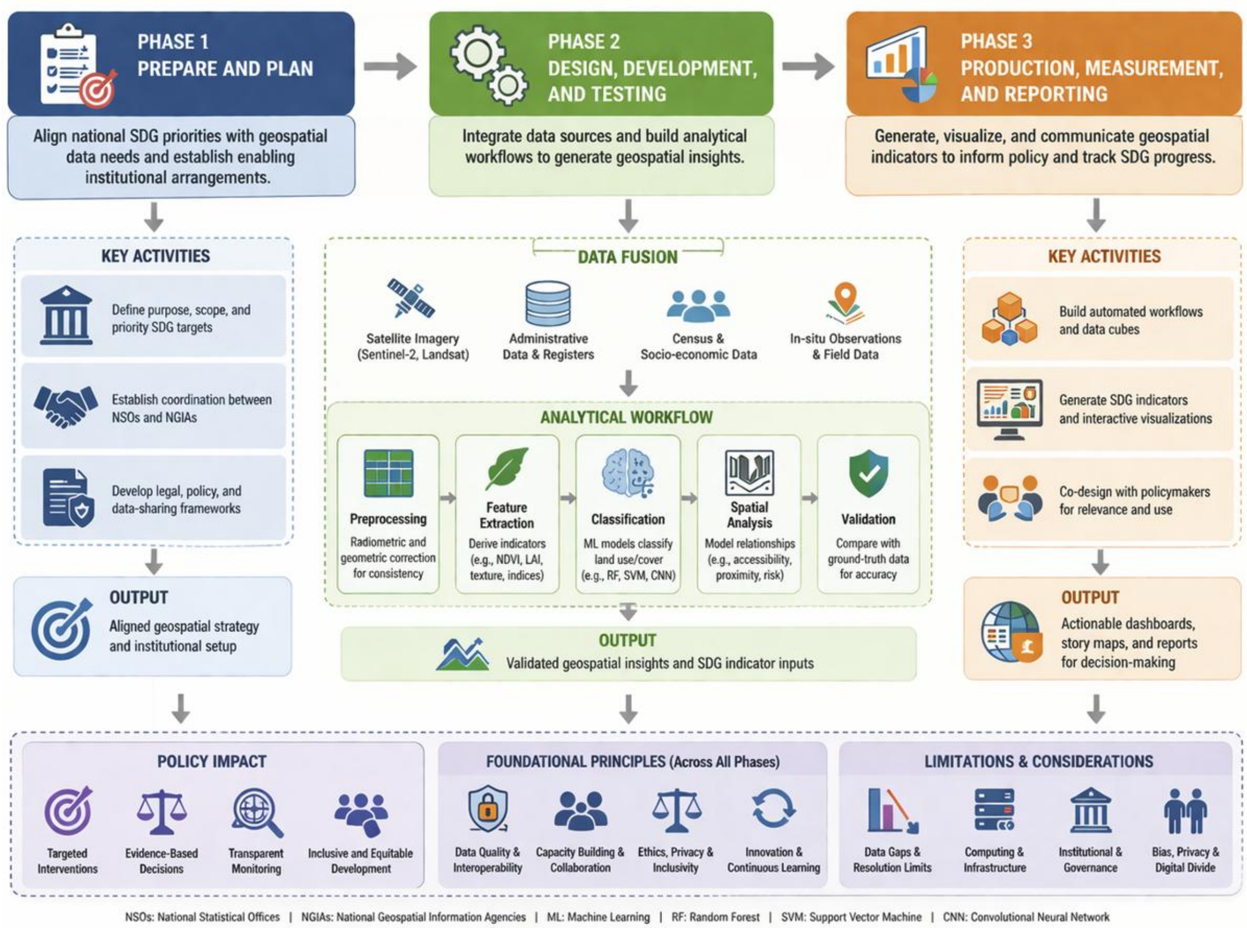

Figure 1. Methodology Workflow for using RS/GIS in SDGs (Derived from (UN-GGIM, 2021))

Despite its strengths, this methodological approach is subject to several limitations. First, the reliance on remotely sensed data introduces constraints related to spatial and temporal resolution, which may affect the accuracy of certain indicators, particularly in heterogeneous or densely populated environments (Pooja et al., 2025). Second, while machine learning techniques improve analytical efficiency, their outputs depend heavily on the quality and representativeness of training data, which may be limited in data-scarce regions.

In addition, the framework assumes a level of institutional coordination and technical capacity that may not yet exist in all national contexts. Challenges such as limited access to high-performance computing infrastructure, data governance issues, and skill gaps within public institutions can hinder effective implementation (O'Connor et al., 2020). Finally, although the methodology emphasizes integration with socio-economic data, the absence of standardized and up-to-date ground-truth datasets remains a significant constraint for validation and reporting. These limitations show the need for continued investment in geospatial capacity development, institutional strengthening, and data infrastructure to fully realize the potential of RS and GIS in supporting evidence-based SDG implementation.

4. RESULTS AND DISCUSSION

The integration of RS and GIS demonstrates substantial potential across multiple Sustainable Development Goals (SDGs), particularly in enhancing the precision, timeliness, and inclusivity of policy interventions. The findings from existing studies reveal that geospatial intelligence not only improves data availability but also reshapes how development challenges are understood and addressed.

Socio-Economic Welfare and Poverty Mapping (SDGs 1, 4, 10)

One of the most significant contributions of geospatial technologies lies in addressing data scarcity in socio-economic monitoring. Traditionally, poverty assessment has relied heavily on household surveys, which are often expensive, infrequent, and spatially limited. However, the integration of nighttime lights (NTL) data and high-resolution daytime imagery has enabled new approaches to poverty estimation (Zheng et al., 2024).

Recent studies in Sub-Saharan Africa, including Nigeria, show that deep learning models can predict village-level asset-based wealth with considerable accuracy of 70%. These models rely on observable spatial features such as roofing materials, settlement density, road connectivity, and agricultural patterns (Hall et al., 2023). Notably, asset-based indicators tend to yield stronger predictive performance than income-based measures, largely because physical assets leave clearer spatial signatures that can be captured through satellite imagery.

In the context of education (SDG 4), GIS-based accessibility analysis has proven effective in identifying spatial inequalities in service provision. For example, applications of Kernel Density Estimation (KDE) and network analysis have been used to map access to schools in fragile contexts (Tarashtwal et al., 2026). These analyses reveal that proximity to educational infrastructure is closely linked to broader development outcomes, including poverty reduction and social stability. By identifying underserved areas, such approaches enable more targeted infrastructure planning and resource allocation (United Nations Geospatial Network, 2021).

Food Security and Sustainable Agriculture (SDG 2)

Geospatial technology is the backbone of "Climate-Smart Agriculture" (CSA) (Mmbando, 2025). By integrating AI with remote sensing, governments can monitor crop conditions in real-time, predict yields, and identify regions at risk of food insecurity. For example, the use of Sentinel-2 data to calculate the Leaf Area Index (LAI) has enabled highly accurate yield predictions for staple crops like cotton and maize (Ferreira et al., 2020). In Kenya, the application of solar-powered, AI-driven sensors has reduced crop losses for smallholder farmers by 30% through early detection of pests and diseases (Malick et al., 2025; Ruuhulhaq, 2025).

Table 2. Metric Measures for SDG 2 and Policy Implications

Metric	Role of RS/GIS	Policy Implication
Crop Yield Prediction	ML models (Random Forest, RT) on multispectral imagery.	Early warning systems for famine and market stabilization.
Precision Irrigation	UAV-based thermal sensors and soil moisture mapping.	Optimizing water use and enhancing climate resilience.
Land Degradation	Tracking "Annual Net Primary Productivity" (ANPP).	Identifying areas for soil restoration and sustainable management.

Market Access	GIS-based analysis of transport networks and cold chains.	Reducing post-harvest losses and improving farmer livelihoods.

Source: (Ferreira et al., 2020)

Environmental Resilience and Life on Land (SDGs 13, 15)

SDG 15.3.1 (land degradation neutrality) is one of the indicators most directly supported by remote sensing (Acharya & Lee, 2019; Ruuhulhaq, 2025). Using the "one out, all out" approach, land is classified as degraded if any of the three sub-indicators, such as land cover, land productivity, or soil organic carbon, shows a negative trend (Wang et al., 2020). In China's Honghe Prefecture, long-term satellite time-series data revealed that human-induced urbanization was the primary driver of degradation between 2005 and 2015. Costa Rica provides a global benchmark for forest management (SDG 15) (EO4SDG, 2024). The country's SIMOCUTE system uses Landsat wall-to-wall mapping and LiDAR-derived 3D forest structures to track deforestation and degradation. This transparent, EO-based monitoring framework has allowed Costa Rica to secure international carbon funding by providing auditable evidence of its conservation efforts.

Sustainable Cities and Disaster Risk Management (SDGs 11, 13)

Urbanization (SDG 11) is monitored using indicator 11.3.1, which measures the ratio of the land consumption rate to the population growth rate (UN-GGIM, 2019). GIS-based "Digital Twins" are increasingly used in smart cities to model urban growth and flood risk (Kaleagasi et al., 2022). In India, the Bhuvan platform and NRSC software facilitate the deployment of drones for village mapping and urban planning (Teja et al., 2026). In the UAE, geospatial visualization of historical population and land-use trends has informed the design of resilient infrastructure (Malick et al., 2025).

Disaster risk management (SDG 13 and the Sendai Framework) relies on the integration of RS into early warning systems (Van Westen, 2013). Geospatial analytics was used to map elements-at-risk, such as populations and critical infrastructure, allowing for targeted evacuation and relief efforts. For instance, during floods, remote sensing provides real-time identification of inundated areas, while GIS models the potential path of lahar flows or landslide runouts based on Digital Elevation Models (DEMs).

Discussion of Findings

The meta-analysis of ML applications in remote sensing for the SDGs indicates a high level of performance, but highlights that success is "heavily dependent on the ability to extract and synthesize characteristics from data" (Ferreira et al., 2020). Supervised learning algorithms, particularly Random Forest and ANN, consistently achieve classification accuracies above 97% when regional scores are included as features (Çelik et al., 2025). However, the spatial resolution of imagery, while important, is often less critical than the number of datasets used and the choice of model architecture (Hall et al., 2023). The research also revealed strong interdependencies between the goals. For example, progress in SDG 15 (Life on Land) often has positive ripple effects on SDG 2 (Zero Hunger) through the preservation of ecosystem services (Ruuhulhaq, 2025). Conversely, unplanned urban expansion (SDG 11) can lead to habitat fragmentation and increased vulnerability to climate hazards (SDG 13) (Mkhitaryan et al., 2025). A region-specific, systemic approach is therefore necessary to manage these complex correlations (García-Rodríguez et al., 2025).

Institutional and Technical Barriers

Despite the robust technical performance of RS and GIS, their integration into policy implementation is hampered by significant barriers:

i. The Technical and Data Gap: Persistent challenges include gaps in technical knowledge within academia and government agencies, particularly in developing countries (Ruuhulhaq, 2025). Ensuring data quality, resolution, and interoperability remains a hurdle, as different sensors and platforms often use non-standardized formats. Moreover, the lack of bandwidth and high-performance computing infrastructure in remote areas and SIDS restricts the processing of large-scale, high-resolution datasets (Liu & Adam, 2025b).

ii. Governance and Institutional Barriers: Institutional inertia and fragmented governance often prevent the translation of geospatial insights into local action (UN Statistical Commission, 2025). Stored data systems and limited coordination between ministries hinder the development of coherent national development strategies. Furthermore, many countries struggle with the geospatial digital divide, where the expectation to integrate spatial data is high, but the necessary investment in human capital and infrastructure is missing (UN Statistical Commission, 2025).

iii. Social and Ethical Considerations: Data privacy, bias in AI models, and fairness in algorithmic decision-making are critical ethical concerns (Pooja et al., 2025). Low digital literacy and language barriers also restrict the participation of local communities in the geospatial process, potentially exacerbating existing inequalities (Malick et al., 2025). Bridging these gaps requires inclusive citizen science frameworks and vernacular interfaces that make spatial intelligence accessible to non-experts.

Table 3. Challenges and Impact on SDG Policy

Barrier Category	Primary Challenge	Impact on Policy
Technical	Lack of data standards and interoperability.	Inconsistent monitoring and reporting (Liu & Adam, 2025b).
Institutional	Fragmented governance and "siloed" datasets.	Uncoordinated development interventions (Mkhitaryan et al., 2025).
Capacity	Shortage of skilled GIS and RS professionals.	Dependence on external experts and global datasets (Malick et al., 2025).
Economic	High cost of high-resolution imagery and ICT.	Data-scarce regions remain unmonitored (Acharya & Lee, 2019).
Socio-Ethical	Algorithmic bias and digital illiteracy.	Risk of deepening social inequalities (Pooja et al., 2025).

5. CONCLUSION

Remote sensing and GIS are no longer merely auxiliary tools for environmental research; they are the foundational infrastructure for evidence-based policy implementation of the SDGs. This research demonstrated that the integration of Earth observation data with advanced analytics and participatory methodologies provides a transformative capacity to monitor progress, identify vulnerabilities, and design targeted interventions. The technical evidence is clear that machine learning models and deep learning architectures can provide highly accurate, spatially explicit indicators for poverty, agriculture, urban growth, and ecosystem health, often filling critical gaps where traditional data is absent. The success stories of Costa Rica's forest monitoring, India's smart city initiatives, and Afghanistan's infrastructure planning prove that geospatial intelligence can lead to more accountable and effective governance. However, the geospatial digital divide remains a significant threat to the 2030 Agenda.

To bridge this gap, global and national efforts must focus on investing in education, training, and the establishment of dedicated geospatial units within government agencies. There is also a need to break down institutional barriers to ensure that geospatial information serves as a whole-of-government resource for development planning, as well as expand access to free, high-quality satellite data and support the development of open-source tools for spatial analysis. Through translating complex data into actionable visions, RS and GIS empower policymakers to navigate the uncertainties of the 21st century and ensure that the vision of a resilient, inclusive, and sustainable world becomes a reality for all. The transition from what is to what could be is now fundamentally a spatial endeavor.

5. COMPETING INTEREST

None to declare

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