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Automated Earth Observation Pipelines: Bridging the Data-to-Decision Gap in Emerging Economies

TUBOLAYEFA WAREKUROMOR[1], ASHIBUOGWU KEVIN[2]
[1,2]*Mission Planning Division, National Space Research and Development Agency (NASRDA), Abuja, Nigeria*

Abstract- The proliferation of satellite constellations has shifted earth observation (EO) from a data-scarce to a data-surplus ecosystem. However, many emerging economies are struggling to convert vast volumes of captured satellite data into operational decisions, leaving a significant data-to-decision gap. Through a synthesis of peer-reviewed literature and documented operational EO programmes, we examine the transition from legacy download-and-process workflows to cloud-native pipelines integrated with Geospatial Artificial Intelligence (GeoAI) - analysing case studies from Brazil, Australia, and Nigeria, alongside continental and regional initiatives. We find that legal openness of satellite data is necessary but insufficient for operational impact: technical usability and institutional accessibility are equally binding constraints, and institutional integration between EO pipelines and enforcement or planning workflows, as in Brazil's PRODES/DETER system, produces measurable but incomplete gains, reducing illegal clearing without equally slowing broader forest degradation. Cloud-native, data-proximate architectures and automated GeoAI feature extraction reduce the technical burden of the pipeline, while capacity-aware design and clearer institutional governance address the institutional layer. For Nigeria specifically, we discuss how a previously proposed, centralised Sovereign Satellite Data Hub model could serve as one institutional vehicle for operationalising satellite intelligence, pending implementation and independent evaluation.

Keywords: Earth observation; data-to-decision gap; cloud-native architectures; geospatial artificial intelligence (GeoAI); emerging economies; satellite data sovereignty

I. INTRODUCTION

1.1. Background: The Shift from Data Scarcity to the Data-to-Decision Gap

For decades, national space agencies and environmental institutions in emerging economies operated under conditions of data scarcity. Acquiring high-resolution satellite imagery required lengthy procurement cycles, substantial financial capital, and reliance on foreign providers. Today, the deployment of commercial and government small-satellite constellations generates petabytes of Earth Observation (EO) data daily (Burke et al., 2021). According to the Satellite Industry Association's 2025 industry report, approximately 800 remote sensing satellites were in orbit by 2024, powering a measurable expansion in commercial Earth observation revenue (Satellite Industry Association, 2025). Planet Labs alone reports operating a fleet of approximately 200 satellites, capturing more than 25 terabytes of imagery daily (Planet Labs, 2026). Machine-learning models trained on publicly available satellite imagery have already been shown to generate economically meaningful estimates of household and regional well-being across Africa (Yeh et al., 2020). This underscores the latent development value awaiting emerging economies once high-resolution commercial feeds are similarly processed into usable forms.

However, data abundance and open data alone do not necessarily translate into operational impact. A critical review of EO adoption in developing countries demonstrates that legal openness is insufficient without parallel advances in technical usability and institutional accessibility (Bhattarai, 2026). The literature identifies a systematic last-mile problem between data availability and its integration into operational governance. Structural barriers, including limited internet infrastructure, skills gaps compounded by brain drain, fragmented institutional mandates, and the absence of national coordination mechanisms, prevent technically sound EO outputs from informing routine planning and policy decisions.

This disparity constitutes the data-to-decision gap, which we define in this paper as a situation in which raw satellite observations remain unexploited in static archives. The expectation of a linear progression from open-access satellite data to policy decisions contrasts sharply with observed realities in developing nations, where inadequate infrastructure and weak institutional support hinder the translation of data into operational directives (Sudmanns et al., 2020).

1.2. The Limitations of Legacy Download-and-Process Workflows

Traditional EO data management across emerging institutional frameworks relies predominantly on "download-and-process" architectures. In these conventional models, analysts manually download gigabyte-scale raster files from data providers onto local workstations to execute pre-processing, atmospheric correction, and supervised classification using desktop geographic information systems (GIS). This workflow introduces significant operational inefficiencies (Sudmanns et al., 2020). Local computing hardware is frequently inadequate for processing high-dimensional raster arrays, particularly multitemporal datasets. These infrastructure challenges are further compounded by connectivity constraints. Where internet connections exist, they are often costly or unreliable, exacerbating the data access bottleneck (Bhattarai, 2026). Consequently, freely available medium-resolution datasets often fail to meet local monitoring needs, restricting analytical capacity.

1.3. Problem Statement: Bridging the Gap via Cloud-Native GeoAI Pipelines

Overcoming the data-to-decision gap requires an architectural transition: a paradigm shift from localised desktop computing toward cloud-native EO pipelines integrated with Geospatial Artificial Intelligence (GeoAI). Cloud-native processing environments co-locate massive EO data archives with scalable computing clusters, eliminating the necessity for local data downloads (Gorelick et al., 2017).

Combined with automated feature extraction models, these pipelines can ingest raw satellite streams and output decision-ready vector intelligence (Zhu et al., 2017). Nevertheless, a recent bibliometric analysis of GeoAI research in the Global South finds that persistent barriers include restricted access to high-quality data, infrastructure deficits, and fragmented institutional mandates (Islam et al., 2026).

1.4. Objectives of the Study

This study explores the systemic integration of cloud-native EO pipelines to bridge the data-to-decision gap in emerging economies. The specific objectives are to:

- Examine the computational limitations of legacy EO workflows.
- Conceptualise a cloud-native Open Data Cube architecture that co-locates data storage and processing.
- Analyse verified, operational satellite pipelines in the Global South (Brazil and the African continent) and developed economies (Australia) as replicable paradigms.
- Provide institutional and policy recommendations applicable to emerging economies generally, illustrated for the Nigerian context through a previously proposed, centralised Sovereign Satellite Data Hub model.

II. METHODS

This paper adopts a narrative synthesis approach appropriate to a conceptual and policy-oriented review. We searched peer-reviewed remote sensing, geospatial science, and development-economics literature, alongside space agency, industry, and government programme documentation, to identify: (i) conceptual frameworks describing barriers to EO uptake in developing economies; (ii) documented operational satellite data pipelines in the Global South and in comparable developed-economy settings; and (iii) recent technical literature on cloud-native geospatial architectures and GeoAI feature extraction. Case studies were included where a programme's implementation, institutional partners, and outcomes could be verified against at least one independently accessible source. Peer-reviewed evaluation was prioritised where available, with government, agency, or industry reporting used

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where independent evaluation had not yet been published. This mixed evidentiary base is disclosed throughout rather than presented as uniformly peer-reviewed, and is treated as a limitation of the current evidence base. Unlike the verified operational case studies in Section 6, the Nigerian Sovereign Satellite Data Hub discussion in Section 7.6 has not been implemented; it situates a centralised satellite data hub framework already proposed in prior peer-reviewed work (see Section 7.6 for attribution) within the cloud-native GeoAI pipeline literature synthesised in this review, as an illustrative application of this review's own findings rather than as an additional case study or a new empirical finding of this paper.

III. THE ANATOMY OF THE DATA-TO-DECISION GAP IN EMERGING ECONOMIES

3.1. The Pre-Processing Bottleneck and Interoperability Friction

In typical institutional environments, the vast majority of an analytical team's time is consumed by low-level data pre-processing tasks, including radiometric calibration, geometric correction, and cloud masking. Research on remote sensing emergency services (RSES) in China identifies a persistent gap between remote sensing science and emergency practice, driven largely by non-technical factors: the organizational framework, response procedures, and the way emergency tasks are structured at the local level (Zheng et al., 2021). Drawing on case studies and social surveys of Chinese emergency agencies, the study found that these structural and organizational factors, more than the availability of the underlying technology, limit how effectively frontline units convert remote sensing capability into an actual response.

In emerging economies, dedicating specialised personnel to manual data pre-processing severely constrains overall organisational productivity. Analysts who should be deriving insights and supporting policy decisions instead dedicate substantial time to automatable tasks, representing a significant misallocation of specialised human capital. Research on landslide mapping indicates that manual interpretation of high-resolution imagery can be highly time-intensive, while automated and supervised classification approaches can provide substantial efficiency gains for large-area analysis (Galli et al., 2008). This trade-off between accuracy and efficiency is a persistent challenge in institutional settings where both speed and precision are required.
This challenge is further compounded when scaling across multiple missions. When analysts handle data from Sentinel-2, Landsat, and commercial providers simultaneously, they confront inconsistent file formats, varying spatial resolutions, and incompatible projection systems. These interoperability challenges prevent seamless multi-sensor time-series analysis and delay the generation of unified operational dashboards.

3.2. Institutional Fragmentation and Analytical Silos

Beyond technical hurdles, the data-to-decision gap is exacerbated by institutional fragmentation. Ministries of environment, agriculture, water resources and national space agencies frequently maintain independent spatial databases. When agencies build non-interoperable data repositories, national geospatial assets are duplicated, and cross-sectoral insights are lost.

Bhattarai (2026) identifies fragmented institutional mandates and the absence of a national EO coordination mechanism as primary barriers preventing EO outputs from informing routine planning. Agricultural drought monitoring, for instance, requires real-time fusion of meteorological observations, soil moisture sensors, and satellite vegetation indices. Yet in many developing countries, these datasets remain trapped in departmental silos, preventing holistic policymaking.

3.3. The Latency of Manual Interpretation

When spatial data is successfully acquired and pre-processed, traditional workflows still depend heavily on manual visual interpretation and expert-driven vector digitisation. Assessing post-disaster structural damage or tracking illegal mining expansion through manual onscreen digitising is prohibitively slow. Manual digitisation is often sufficiently slow that mapping a major urban area can require extensive analyst time.

Research on remote sensing emergency services suggests that an agency's capacity to convert raw imagery into thematic, decision-ready information, rather than data availability alone, determines whether remote sensing intelligence is actually used during a response (Zheng et al., 2021). By the time spatial reports are compiled, reviewed, and presented to decision-makers, the underlying environmental conditions have evolved. This latency diminishes the tactical utility of spatial intelligence. The effective societal value of remote sensing depends not only on data availability but also on alignment with local needs and decision-making workflows (Bhattarai, 2026). When intelligence arrives too late to influence decisions, it becomes archival rather than operational.

3.4. The "Pixels to Policy" Framework: Three Layers of EO Accessibility

To systematically understand the data-to-decision gap, Bhattarai (2026) proposes a three-layer "Pixels to Policy" framework that structures how EO data transitions from satellite to decision.

- Legal Layer: Governs data accessibility and licensing frameworks, determining whether satellite-derived EO data is legally permissible for national adoption and public use.
- Technical Layer: Assesses institutional capacity, including digital infrastructure, network connectivity, and technical expertise required to process raw EO data into actionable intelligence.
- Institutional Layer: Examines governance mechanisms and organizational workflows to ensure decision-making systems are structured to effectively integrate and respond to EO intelligence.

Failure in any single layer can prevent operational impact. A country may have legal access to satellite data and technical capacity to process it, yet if institutional workflows are not designed to receive and act upon EO intelligence, the data remains unused.

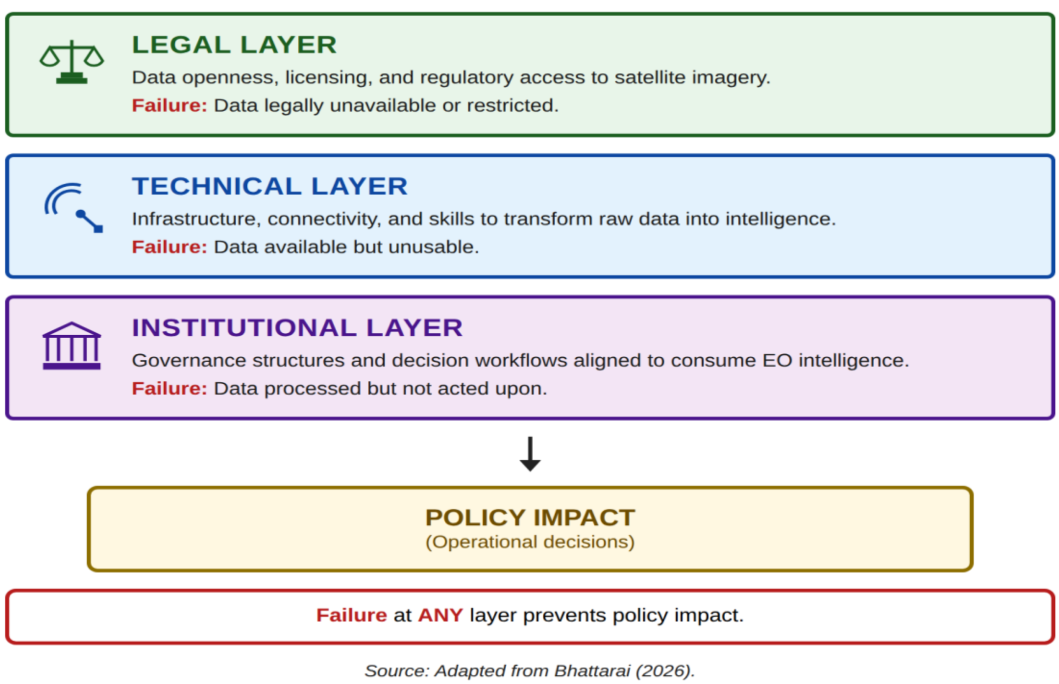

Figure 1: The Pixels to Policy framework.

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This framework is emerging rather than established, having been proposed in a single 2026 study. Current and future research should examine how it relates to the broader science-policy interface literature on usa ble science and knowledge co-production, which has developed similar layered accounts of why technically sound information fails to reach decision-makers.

IV. CLOUD-NATIVE ARCHITECTURES AND DATA-PROXIMATE COMPUTING

4.1. Principles of Cloud-Native earth observation and the Data Cube

The transition from desktop GIS to cloud-native earth observation rests on the principle of data-proximate computing: processing is executed where the data already resides, rather than requiring users to download it first (Verrelst et al., 2026). Instead of pulling massive raster archives to local machines, cloud-native architectures store petabytes of satellite data in optimised formats within distributed cloud storage buckets, paired with SpatioTemporal Asset Catalogs (STAC).

This information-preserving approach is exemplified by the Open Data Cube (ODC) initiative, which organises the metadata of EO products in relational database systems to serve users with Analysis Ready Data (ARD) (Killough, 2018). The ODC stores processed EO datasets as cubes, allowing users to quickly retrieve and analyse data without starting from scratch. This reduces the need for institutions to maintain extensive local computational infrastructure. Computation is executed directly within the cloud environment, reducing data transfer overhead associated with conventional data downloads and enabling efficient API-based access.

4.2. Interoperability and Analysis-Ready Data Standards

To maximise the efficacy of cloud-native pipelines, institutional data strategies must mandate the adoption of Analysis-Ready Data (ARD) standards. ARD products undergo rigorous processing to correct for atmospheric conditions, align sensors, and standardise outputs before they can be analysed. This pre-processing stage is time-consuming and often needs to be repeated by each user of the dataset (Infrastructure News, 2025).

Standardisation across radiometric and geometric surface reflectance levels, calibrated across sensors (Giuliani et al., 2017), ensures that downstream GeoAI models consume uniform inputs, promoting more consistent model inputs. By reducing the complexity of dealing with raw satellite data, ARD ensures that institutional analysts can focus directly on interpretation and insight generation rather than redundant data preparation.

4.3. Addressing Low-Bandwidth and Infrastructure Constraints

The challenge of connectivity in emerging economies demands specific design responses. Recent developments in EO platform design demonstrate that technological innovation can directly address bandwidth constraints through compression, edge computing, and satellite-based data distribution.

4.3.1. Technical Innovation s in Low-Bandwidth EO Delivery

The DUNIA platform, developed by GeoVille under the European Space Agency's flagship programme, enables high-efficiency streaming and compression of large volumes of satellite data. Performance gains are substantial: downloading one month of Sentinel-2 data for three 10 m bands takes less than 30 min on a 10 Mbit/s connection, compared to over two hours using traditional methods (Space in Africa, 2025b). DUNIA also introduced a WebAssembly (WASM) module suite that brings earth observation analytics directly into users' browsers, eliminating server-side cloud computing dependencies for lightweight tasks, while remaining interoperable with cloud-native archives (GeoVille, 2025). A year-end review of the platform's continental rollout reported expanding use of these tools across national mapping agencies and research institutions during its first year of operation (Space in Africa, 2025a).

4.3.2. Satellite-Based Data Distribution Networks

The ESA-GeoVille-Eutelsat OneWeb collaboration integrates satellite internet constellations with the Copernicus ecosystem to deliver high-bandwidth internet access and reliable dissemination of

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environmental data to underserved areas (ESA, 2025). This approach leverages satellite communications to substantially reduce dependence on terrestrial connectivity, helping remote institutional stakeholders access critical EO data during emergencies.

4.3.3. Mobile Edge Computing

The "Mobile EO Twins" concept, built around the company Hydramo, employs device-level edge AI processing coupled with optimised transmission protocols to deliver actionable EO insights directly to smartphones (EARSC, 2026). This architecture eliminates dependency on continuous high-bandwidth connectivity by enabling local interpretation of EO intelligence on the user's device.

4.3.4. The IrrEO Project: A Nigerian Case Study in Capacity-Aware Implementation

The Irrigation earth observation (IrrEO) project provides a concrete example of addressing capacity constraints through institutional partnerships. Funded by a £3 million grant from the Bill & Melinda Gates Foundation, the project aims to develop national-scale irrigation mapping tools in Nigeria, Kenya, and Ethiopia (News Agency of Nigeria, 2026; University of Manchester, 2025). Rather than requiring continuous internet connectivity, IrrEO integrates high-resolution satellite imagery with advanced machine learning techniques to produce reliable maps accessible through offline-capable tools (Space in Africa, 2026a). The project is implemented in Nigeria by the University of Manchester's Manchester Environmental Research Institute (MERI), the National Space Research and Development Agency (NASRDA), and Airbus (Space in Africa, 2026b).

4.3.5. Addressing Capacity Constraints Through Training and Institutional Engagement

Technical solutions alone cannot overcome connectivity and capacity challenges. Research indicates that many agricultural professionals lack formal training in geospatial technologies, and awareness of EO-ARD products remains low even when datasets are freely available (Bhattarai, 2026). Platforms like DUNIA and projects like IrrEO address this by prioritising capacity-aware tool design, multilingual accessibility, and participatory training programmes.

Table 1: Comparative matrix of EO processing paradigms.

Operational Dimension	Legacy Download-and-Process	Cloud-Native Automated GeoAI Pipeline
Data storage & access	Local hard drives; manual provider downloads; fragmented archives	Centralised cloud buckets with STAC indexing; API-based discovery
Preprocessing overhead	Manual radiometric/geometric correction (a substantial share of analyst time, per case-study evidence)	Automated Analysis-Ready Data (ARD) pipelines; one-time processing
Computing infrastructure	Local desktop workstations; hardware-limited scalability	Elastic, distributed cloud compute clusters; on-demand scaling
Feature extraction	Manual on-screen digitising; heuristic spectral thresholds	Automated deep-learning segmentation (Convolutional Neural Networks [CNNs] / Vision Transformers [ViTs]); transfer learning
Decision latency	Weeks to months (retrospective reporting; intelligence arrives too late)	Minutes to hours (potential for near-real-time operational intelligence)
Human resource use	Analysts spend majority of time on data preparation	Analysts focus on interpretation, validation, and strategic insight
Scalability	Poor; cannot handle multitemporal large-area analysis	Excellent; parallel processing across thousands of scenes
Cost model	Capital-intensive (hardware, storage); physical infrastructure	Operational expenditure (pay-as-you-go cloud); reduced upfront infrastructure burden

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V. AUTOMATED FEATURE EXTRACTION AND GEOAI INTEGRATION

5.1. Transitioning from Heuristic Classification to Deep-Learning Pipelines

Bridging the data-to-decision gap increasingly involves complementing conventional rule-based and heuristic classification methods with deep-learning-based feature extraction and classification models (Reichstein et al., 2019). Convolutional Neural Networks (CNNs) and more recent transformer-based architectures, including Vision Transformers (ViTs), can automatically learn spatial and contextual features for remote-sensing image classification and segmentation (LeCun et al., 2015; Zhu et al., 2017).

Transfer learning can be particularly valuable in EO applications where labelled training data are limited, as pretrained representations can reduce the volume of task-specific data and computational resources required for model development (Jean et al., 2016). Embedding these models within automated cloud-processing pipelines can substantially reduce the time required to transform incoming satellite data into classified or decision-ready geospatial products. Recent developments have demonstrated the feasibility of onboard AI for earth-observation satellites, including autonomous cloud detection that can be used to prioritise which imagery is worth downlinking, with the potential to reduce data-downlink requirements and accelerate the delivery of actionable information (Giuffrida et al., 2020).

5.2. Multi-Sensor Data Fusion for Comprehensive Spatial Insight

Advanced GeoAI pipelines increasingly utilise multi-sensor data fusion to extract more reliable and temporally consistent information under challenging environmental conditions. By combining optical imagery, which provides rich spectral information, with Synthetic Aperture Radar (SAR), which can acquire observations through cloud cover and during low-light conditions, multi-sensor deep-learning models can mitigate some of the limitations associated with relying on a single sensor (Choukri et al., 2024).

This fusion capability has transformative implications. In regions where persistent cloud cover limits the availability of usable optical observations, such as monsoon-affected or tropical rainforest environments, integrating SAR can improve the temporal continuity of EO monitoring. A review of optical and radar crop classification approaches in Africa documents this directly in West Africa, where high-resolution optical and dual-polarised SAR data have been combined to sustain crop-type classification through cloud-affected growing seasons (Choukri et al., 2024). During tropical wet seasons in West Africa, automated pipelines can similarly integrate optical vegetation indices with SAR-derived information to support monitoring of agricultural conditions and flood dynamics despite periods of substantial cloud cover. By fusing these sensors, automated pipelines can help maintain monitoring continuity, a critical capability for early warning systems and food security assessments.

5.3. Operationalising Insight Through Automated Web Interfaces

The delivery stage of a cloud-native EO pipeline can incorporate RESTful APIs and dynamic web dashboards that transform extracted geospatial outputs into near-real-time key performance indicators. The operational use of GeoAI also requires attention to model interpretability and explainability, particularly where analytical outputs are used to support decisions by non-technical stakeholders. Recent research on explainable AI in Earth observation highlights the importance of making model outputs understandable to intended users and decision-makers (Gevaert, 2022). This shift from static reporting to dynamic dashboarding enables immediate consumption and interactive exploration of EO products.

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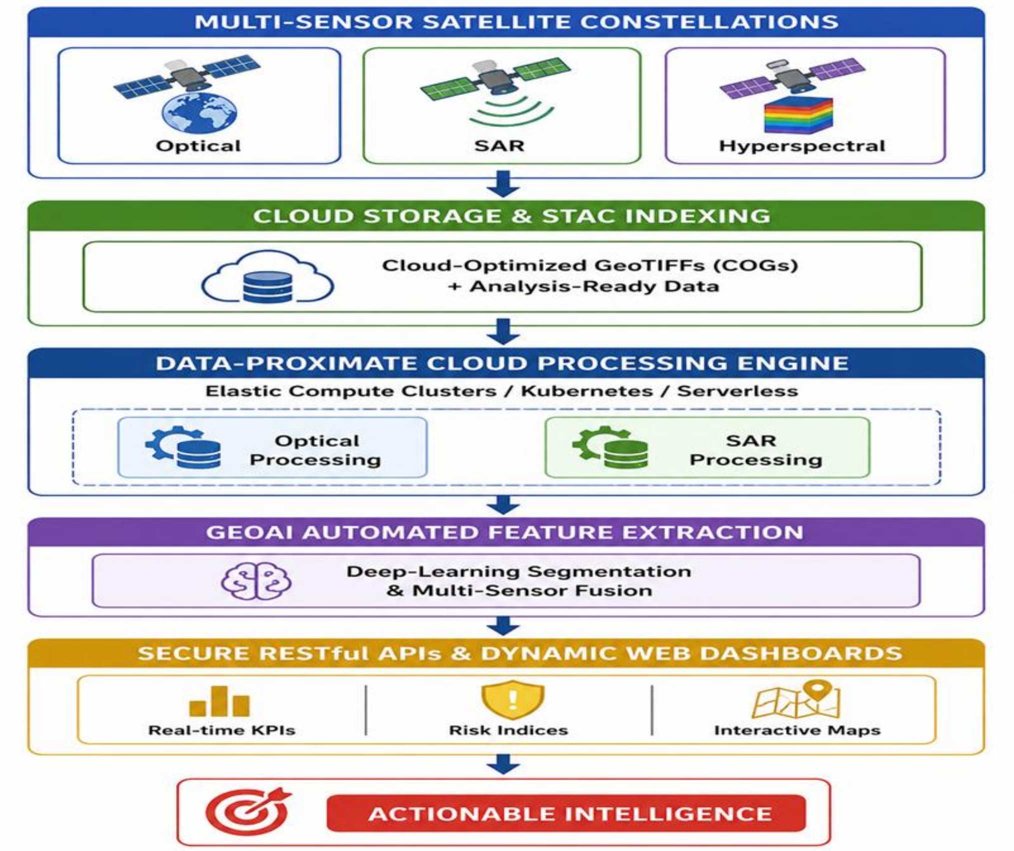

Figure 2: Cloud-native automated earth observation pipeline architecture.

VI. OPERATIONAL PARADIGMS: LESSONS FROM GLOBAL SOUTH IMPLEMENTATIONS

6.1. Institutionalisation of Spatial Monitoring: Brazil's PRODES and DETER

Brazil's National Institute for Space Research (INPE) provides a well-documented operational example of a satellite monitoring pipeline (Potapov et al., 2026). INPE operates the PRODES (annual deforestation assessments) and DETER (daily, automated alerts) systems (Diniz et al., 2015). The success of the Brazilian model lies in its deep institutional integration; the satellite data pipeline is integrated to feed directly into federal environmental enforcement workflows, allowing agencies to counter illegal deforestation in near-real-time.

Independent econometric evaluation of this integration supports the general claim that near-real-time DETER alerts have been shown to measurably increase enforcement actions and reduce deforestation relative to pre-DETER baselines (Assunção et al., 2023). More recent evidence complicates the picture. A 2026 analysis of deforestation-focused monitoring and enforcement policy found that it did not correspondingly reduce forest degradation in the Brazilian Amazon, suggesting that the PRODES/DETER model addresses illegal clearing without fully addressing more diffuse forms of forest loss such as selective logging and fire (Cammelli et al., 2026). The Brazilian case therefore illustrates both the promise and the limits of institutional integration as a strategy.

6.2. Cloud-Native Continental Architectures: Digital Earth Africa

Digital Earth Africa processes petabytes of satellite imagery into Analysis Ready Data tailored for continental monitoring (Killough, 2018). Crucially, the platform provides an operational Sentinel-1 normalised radar backscatter dataset that processes SAR data natively in the cloud, allowing researchers to overcome pervasive optical cloud-cover limitations

(Yuan et al., 2022). The open-source design of the ODC also promotes transparency and democratises access to high-level spatial analytics. Independent, peer-reviewed evaluation of institutional-level adoption barriers for continental cloud-native platforms such as Digital Earth Africa nonetheless remains limited outside pilot-scale case studies, a gap this paper does not resolve.

6.3. Developed Economy Paradigm: Australia's Water Compliance Monitoring
The EU-funded WaterSENSE project addressed water usage compliance in Australia's Murray-Darling Basin (CORDIS, 2025). By matching EO and hydrological modelling data with regulatory compliance databases, authorities could track agricultural water consumption. This case demonstrates that successful operationalisation requires close integration with regulatory frameworks. It also highlights viable pathways toward commercial service sustainability.

6.4. European Capacity-Building Models: Copernicus in Africa and Latin America
The WG Africa project supports the utilisation of Copernicus data through a "training of trainers" programme (Tomasini et al., 2025). Co-developed with African partners via a digital learning platform, this model creates a self-reinforcing ecosystem of expertise. Similar capacity-building efforts in Ecuador and Bolivia highlight the importance of flexible event design and alignment with local contexts to enhance stakeholder engagement (Santos et al., 2025).

The centralised Sovereign Satellite Data Hub model discussed in this section was proposed by Warekuromor et al. (2026); this paper's contribution is to situate that model within the cloud-native, GeoAI-integrated pipeline architecture developed in Sections 4 and 5, and to argue for its adoption as the institutional layer of Nigeria's EO ecosystem specifically. Rather than requiring each government ministry, research institution, or commercial user to negotiate separate data access and processing arrangements, the proposed Hub consolidates satellite data storage, indexing, and API-based delivery within a single national platform operated by the space agency, serving these different user groups through a tiered, free-data-fee-for-processing access model (Warekuromor et al., 2026). Standardised STAC metadata cataloguing and open OGC APIs allow this single hub to serve heterogeneous downstream users, from statutory public-good access to bespoke, fee-based analytics, without each sector building or maintaining its own separate satellite data infrastructure.

By embedding automated metadata and provenance tagging within this centralised architecture, the Hub can support transparency and auditability for every user tier without requiring each sector to replicate its own data governance infrastructure (Warekuromor et al., 2026). Warekuromor et al. (2026) identify federated regional network integration, connecting the national hub's STAC endpoints with broader regional and international clearinghouses, as a future direction once the domestic platform is established, rather than a feature of the initial architecture. This centralised approach nonetheless raises data-sovereignty questions of its own, and aligns with emerging peer-reviewed work on geospatial data sovereignty, including tooling designed to give institutions verifiable, jurisdictional control over their own spatial data assets without abandoning interoperability (Sharma et al., 2023).

Table 2: Summary of operational paradigms and key lessons.

Case Study	Region	Primary Application	Key Technology	Institutional Integration	Key Lesson
PRODES/DETER	Brazil	Deforestation monitoring	Automated alerts; high-resolution optical	Direct integration with federal environmental enforcement	Institutional integration helps, but evidence on forest degradation shows its limits.
Digital Earth Africa	Africa	Multi-thematic	Open Data Cube;	Regional	Cloud-native platforms

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		monitoring	SAR backscatter; ARD	collaboration; open-source resources	democratise access; SAR overcomes cloud cover.
WaterSENSE	Australia	Water compliance monitoring	EO + hydrological models + regulatory databases	Integration with licensing framework	Regulatory alignment is essential; commercialisation pathways exist.
WG Africa	Africa	Capacity building	Training of trainers; digital learning platform	Partnership between EU and African institutions	Local ownership is more sustainable than direct service provision.
Copernicus Capacity-Building	Ecuador, Bolivia	Capacity building	Interactive workshops	Alignment with local contexts	Flexible design yields higher learning outcomes.

VII. INSTITUTIONAL POLICY RECOMMENDATIONS

7.1. Deploying Federated, Distributed Geospatial Architectures

As opposed to investing in rigid, monolithic centralisation, emerging nations operating across multiple institutions or jurisdictions should consider federated and distributed cloud geospatial architectures for cross-agency and cross-border data sharing (Gonzalez-Compean et al., 2017). By interconnecting decentralised institutional nodes via OGC APIs and STAC metadata catalogues, agencies can share workloads, pool compute resources, and avoid single points of failure while retaining operational autonomy over domain-specific workflows. Research on federated geospatial infrastructure demonstrates that multi-cloud synchronisation and distributed data-sharing networks drastically reduce storage redundancy and network bottlenecks compared to traditional centralised repositories (Gonzalez-Compean et al., 2017), while complementary tooling for geospatial data sovereignty offers a practical path to jurisdictional control without sacrificing interoperability (Sharma et al., 2023). This federated approach operates at a different institutional scale from the centralised, single-agency Sovereign Satellite Data Hub discussed in Section 7.6; the two are not mutually exclusive, and a nation could operate a centralised domestic hub while still participating in a federated cross-border network.

7.2. Alignment with Data Sovereignty, Metadata, and Governance Frameworks

The deployment of automated GeoAI pipelines must be anchored within national data privacy, metadata standards, and governance regulations (Yoo, 2026). Enforcing standardised provenance tracking ensures auditability, ethical AI deployment, and complete traceability across every tier of a national EO platform, whatever its specific institutional form.

7.3. Comprehensive Workforce Upskilling

Institutions must focus training pipelines on cloud-based geospatial computing, Python-based spatial data science, and GeoAI model management to mitigate technical skills gaps (Bhattarai, 2026). The “training of trainers” approach and co-development methodologies ensure relevance and foster local ownership (Santos et al., 2025; Tomasini et al., 2025). Training must also be accompanied by career development pathways to retain skilled personnel (Group on Earth Observations, 2022).

7.4. Leveraging Regional and International Partnerships for EO Infrastructure

Emerging economies should leverage partnerships to subsidise computational costs. Platforms like Digital Earth Africa and the GMES and Africa initiative enable shared algorithm development and capacity building (Killough, 2018). Nigeria's existing participation in African Union-led environmental collaboration frameworks provides an institutional starting point for extending this kind of partnership arrangement to satellite data specifically (News Agency of Nigeria, 2023).

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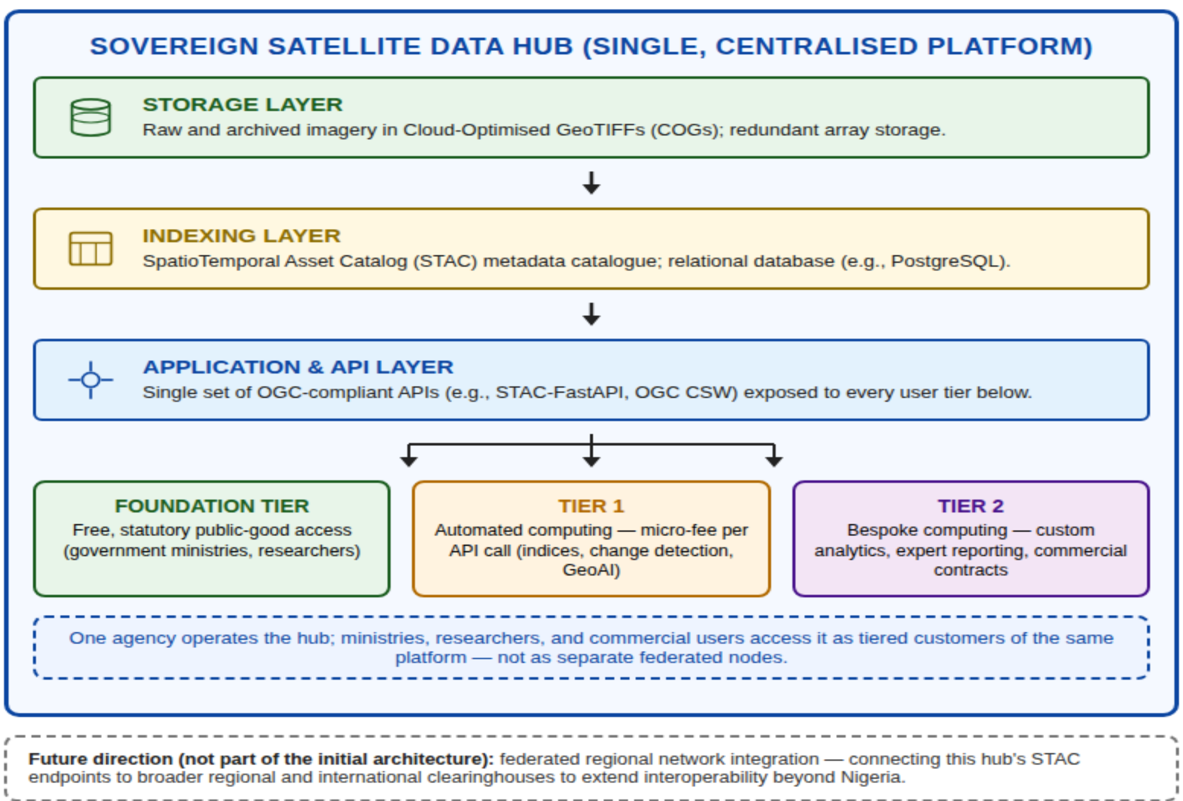
7.5. Measuring Success: An Evaluation Framework
Institutions should adopt a multi-dimensional evaluation framework addressing:

- Latency reduction: Time from satellite overpass to decision-ready intelligence.
- Decision quality: Assessing improved policy outcomes.
- Capacity outcomes: Tracking institutional expertise growth.
- Coverage: Scope and consistency of monitoring.
- Institutional adoption: The extent to which EO products are utilised in routine decision-making.

7.6. Illustrative Application: A Centralised Hub for Nigeria
As one illustration of how the recommendations above could be institutionalised, this section discusses a centralised Sovereign Satellite Data Hub model proposed by Warekuromor et al. (2026) for Nigeria specifically; this discussion situates that proposed model within the cloud-native, GeoAI-integrated pipeline architecture developed in Sections 4 and 5, without presenting it as an implemented system or as evidence comparable to the operational case studies in Section 6. Rather than requiring each government ministry, research institution, or commercial user to negotiate separate data access and processing arrangements, the proposed Hub consolidates satellite data storage, indexing, and API-based delivery within a single national platform operated by the space agency, serving these different user groups through a tiered, free-data-fee-for-processing access model (Warekuromor et al., 2026). Standardised STAC metadata cataloguing and open OGC APIs allow this single hub to serve heterogeneous downstream users, from statutory public-good access to bespoke, fee-based analytics, without each sector building or maintaining its own separate satellite data infrastructure.



Source: Adapted from Warekuromor et al. (2026).

By embedding automated metadata and provenance tagging within this centralised architecture, the Hub can support transparency and auditability for every user tier without requiring each sector to replicate its own data governance infrastructure (Warekuromor et al., 2026). Warekuromor et al. (2026) identify federated regional network integration, connecting the national hub's STAC endpoints with broader regional and international clearinghouses, as a future direction once the domestic platform is established, rather than a feature of the initial architecture. This centralised approach nonetheless raises data-sovereignty questions of its own, and aligns with emerging peer-reviewed work on geospatial data sovereignty, including tooling designed to give institutions verifiable, jurisdictional control over their own spatial data assets without abandoning interoperability (Sharma et al., 2023).

VIII. CONCLUSIONS

The transition from data-scarce archives to data-surplus satellite constellations has exposed a critical data-to-decision gap in emerging economies. Legacy download-and-process workflows are increasingly ill-suited to handling modern data volumes and velocities; their manual, sequential nature introduces latency that renders satellite intelligence obsolete before it informs policy.

Legal openness of satellite data is necessary but insufficient. Real-world EO outcomes rely on technical and institutional accessibility. By integrating cloud-native architectures, rigorous metadata and provenance standards, and automated deep-learning feature extraction, emerging nations can bypass legacy bottlenecks; centralised institutional data platforms, illustrated in this review by a proposed model for Nigeria, offer one promising vehicle for doing so, pending implementation and evaluation. Operational paradigms like Brazil's PRODES/DETER, Digital Earth Africa, and capacity-building projects like IrrEO demonstrate that integrating satellite processing directly into institutional workflows yields tangible governance outcomes, even as independent evidence shows that no single system solves every dimension of the underlying problem.

For Nigeria specifically, one illustrative institutional vehicle for this transition is the centralised Sovereign Satellite Data Hub model proposed by Warekuromor et al. (2026); whether this or an alternative institutional design proves most effective will depend on implementation, which has not yet occurred. More broadly, by adopting API-driven ecosystems underpinned by robust provenance tracking, emerging spacefaring nations can operationalise their orbital assets, ultimately translating petabytes of raw pixels into timely, strategic policy execution.

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