ADDRESSING THE CHALLENGES OF USING EARTH OBSERVATION DATA FOR SDG ATTAINMENT:

Evidence from the Global South and West Africa Region

TRENDS
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Information from these interviews has been synthesized with information from other sources throughout the paper.

Initiated in 2016 on behalf of the German Federal Ministry for Economic Cooperation and Development and the Federal Ministry for the Environment, Nature Conservation and Nuclear Safety and implemented by GIZ, the Partners for Review (P4R) network's objective is to help foster robust follow-up and review mechanisms at all levels and to ultimately contribute to achieving the Sustainable Development Goals (SDGs).

Acronyms

AU	African Union
CEOS	Committee on Earth Observation Systems
CERSGIS	Centre for Remote Sensing and Geographic Information Systems
CSE	Centre de Suivi Écologique
DANIDA	Danish International Development Agency
DEA	Digital Earth Africa initiative
ECOWAS	Economic Community of West African States
EO	Earth Observations
ESA	European Space Agency
EUMETSAT	European Organization for the Exploitation of Meteorological Satellites
FAO	Food and Agriculture Organization
GEE	Google Earth Engine
GEO	Group on Earth Observations
GIS	Geographic Information Systems
GMES	Global Monitoring for Environment and Security
ICT	Information Communication Technology
IOT	Internet of Things
ISESTEL	Institut privé supérieur d’Etudes spatiales et Télécommunications
LiDAR	Light Detection and Ranging Imagery
NASA	National Aeronautics and Space Administration
NASRDA	National Space Research and Development Agency
NSO	National Statistical Office
NSS	National Statistical Systems
OECD	Organization for Economic Cooperation and Development
P4R	Partners for Review
RCMRD	Regional Centre for Mapping of Resources for Development
SANSA	Africa National Space Agency
SAR	Synthetic Aperture Radar
SDGs	Sustainable Development Goals
SDI	Spatial Data Infrastructure
SDSN TReNDS	Sustainable Development Solutions Network’s Thematic Research Network on Data and Statistics
UNDP	United Nations Development Programme
UNECA	United Nations Economic Commission for Africa
UNGIWG	United Nations Task Team on Satellite Imagery and Geospatial Data
UNSO	United Nations Program for the South Sahara Region
WACREN	West and Central African Research and Education Network

Executive Summary

Earth Observation (EO) data are increasingly being used by governments use to make key development decisions. The COVID-19 pandemic is a case in point. As the pandemic impacted society's most vulnerable disproportionately, effective delivery of social protection required more timely and localized data - two critical benefits EO offers users.

EO broadly applies to any tools or technologies that measure the characteristics of air, water, and land. This may be as simple as a thermometer or as complex as a constellation of satellites. Although ground-based observations and the technologies through which they are derived form a key component in the whole of EO, for this paper, we will focus primarily on the use of space-borne EO technologies.

The power of space-borne EO data lies in its ability to add detail to the geospatial and temporal location of data, its ability to fill in data gaps because of limits in access to certain regions of a country, its capacity to complement major surveys and censuses for finer temporal granularity, and its ability to validate other in-situ data, such as household surveys. EO data also has the potential for integration with other data sources through modeling and simulation, allows for greater data use within non-technical policy communities via maps and other visualizations, and provides citizens with a means to participate in decision-making and hold their political leaders to account.

Harnessing EO data for sustainable development requires governments to work with new partners in the data ecosystem. This paper aims to address weaknesses in information-sharing across stakeholders, a key challenge precluding Global South-based countries' use of EO data, and provides initial guidance to countries on leveraging partnerships for better use of EO. Our guidance draws from interviews with select institutions in West Africa that have begun to use EO data for evidence-based policymaking and SDG attainment, as well as similar experiences documented in the literature.

To frame our findings, we focus on identifying the most pressing challenges for institutions in the Global South to harness EO data, centered around a set of high-level characteristics: Capacity, Processes, Policies, and Infrastructure.

We define capacity as human abilities and knowledge, as well as the requisite institutional arrangements, enabling environment, leadership, and accountability. Regarding leadership, our findings highlight that the stakeholders engaged in using EO for sustainable development decisions are perceived to have relatively high levels of interest and power in the decision-making process. Yet, there is a general lack of awareness and trust amongst policymakers in West Africa on using EO and its value for evidence-based decision-making. Our interviews also revealed that developing and retaining human capacity is another clear obstacle, primarily due to the inability of West African institutions to compete with international salary levels.

Process challenges are becoming less acute with the rise of cloud computing and key technologies to provide analysis-ready data along with the emergence of uniform data standards. However, the expense of foundational IT systems, combined with unreliable power grids, remain impediments to the growth in EO data use. Additionally, the complexity of the regulatory framework that allows for private-public partnerships is a major policy challenge, and, increasingly, individual privacy considerations are coming into play as imagery reaches very high-resolutions.

TReNDS' earlier work on the effective use of big data for national SDG monitoring provides a partnership typology to assist national governments in selecting the right type of partner to overcome critical challenges. We find the EO partnership landscape to be equally as diverse and complex, with similar obstacles, and as such, we have applied our big data partnership typology to demonstrate how countries can optimize EO data partnerships.

To leverage EO data for decision-making, we've aligned the types of partnerships necessary to overcome the greatest challenges along the Data Value Chain – the process of taking raw data and converting into actionable information for decision-makers. To successfully access satellite imagery (a type of EO) and generate data from these images, the first step in the data value chain, requires funding, as access to commercial data, particularly at very high-resolutions is expensive. However, policies regarding access are often missing or out-of-date, and out-of-date. Legal partners can help establish effective legislative frameworks that enable data sharing while safeguarding privacy.

The second step in the data value chain – processing and retrieval - requires costly high-speed computing facilities, and these facilities supplement the growing use of cloud computing. Local processing requires laptops, workstations, and specialized software that are also expensive. Funding partners to support these costs must be complemented by experts in human resource retention and training strategies.

Moving up the value chain, to data analysis and services to foster decisions and actions, requires a stronger pipeline of technical expertise and capabilities to communicate both the findings and their accuracy. Partners with relevant experiences in translating findings can help devise strategies that align communication with client segments.

With this in mind, we acknowledge that a more extensive assessment framework is necessary to leverage the full value of EO data for sustainable development. This framework would recognize human resource capacities, have well-defined policies and processes, reliable and scalable infrastructure, and effective governance arrangements that ensure the process adheres to local social norms and conventions. The framework would also be sustained by capable and ethical people, supporting laws and regulations, policy frameworks, and key stakeholders that are empowered to act and are driven by their interest in harnessing this vital data source for sustainable development.

Such a framework should also reflect the role of local, national, and international support. A second key extension to the framework accounts for the maturity of an organization's current state and the steps needed to progress to higher states of maturity. Through this comprehensive framework, we can arrive at a series of conclusions to demonstrate effective approaches, identify areas of improvement, and suggest policies to increase the effectiveness of big data and the sub-systems of which they are composed.

1. Introduction

Achieving the Sustainable Development Goals (SDGs) is a complex challenge for all countries, but particularly for countries in the Global South. And the COVID-19 pandemic has only further exacerbated these issues for lower-income countries – reversing years, potentially decades of progress (UN Statistics Division, 2021).

Fortunately, over the past several years, via the growth of innovative non-traditional data sources, including big data, more timely, relevant, and granular data and information have revealed their potential for evidence-based decisions, a necessary component for achieving the SDGs. Consequently, the potential for big data to support SDG attainment has incited considerable enthusiasm across stakeholders within the data ecosystem.

In an earlier research phase, SDSN TReNDS undertook a systematic review of the recent scientific literature on innovative data collection methods and the use of big data to support national monitoring of the SDGs (Sustainability Science, 2021). A repository of the innovations is available online at www.bigdatasdgs.com, mapped to each of the SDGs. The results from the systematic review demonstrate a range of potential use cases for different types and sources of big data, with Earth Observation (EO) data highlighted as the dominant type (Allen et al., 2021).

Additional research has also highlighted EO's potential for SDG attainment. For example, the Committee on Earth Observation Systems (CEOS) suggests that EO data has a role to play in most of the 17 SDGs (Anderson et al., 2017). Additionally, a recent assessment highlights that existing EO systems could generate data for 33 SDG indicators across 14 goals (Kavvada et al., 2020), and a 2021 United Nations Economic and Social Commission for Asia and the Pacific (UNESCAP) review of countries using non-traditional data sources specifically for SDG monitoring highlighted more than 20 countries using EO and geospatial data for various initiatives (UNESCAP, 2021).

However, harnessing the breadth and complexity of EO data for decision-making remains a challenge for many governments - particularly in the Global South where physical and digital constraints are critical barriers and reliable digital infrastructure and connectivity is a continuing issue. Irrespective of a country's experience in harnessing EO data for development, governments must work with new partners and entities to support their development agenda.

Within this context, this paper provides reflections for countries aspiring to leverage EO data for SDG attainment by highlighting key obstacles and bottlenecks to use, with a particular focus on the Global South (namely West Africa), and the types of partnerships that may prove beneficial to overcoming these challenges.

The paper synthesizes experiences from countries in the Global South and the West African region that have successfully undertaken EO partnerships, as well as insights from the latest research collaborations that are incorporating these data to support SDG monitoring and SDG-friendly policies. Lastly, it aims to provide a conceptual framework for understanding the actions needed to improve the use of EO data for sustainable development and guidance on building partnerships to support these efforts.

The paper is structured as follows:

- ***Section 2*** summarizes key EO data concepts and definitions and discusses its value proposition for sustainable development.
- ***Section 3*** provides an overview of the EO data landscape.
- ***Section 4*** describes the country case studies which form the primary basis for our analysis.
- ***Section 5*** provides a summary of the findings from our country use cases.
- ***Section 6*** highlights some initial reflections on partnerships to address the most pressing bottlenecks along the data value chain that are necessary for EO data to support SDG attainment in the Global South.
- ***Section 7*** identifies potential next steps for future research.

2. The Value of Earth Observation Data for Sustainable Development

Big Data Attributes and the Growth of EO Data

EO data are a component of big data - a term that describes large volumes of high velocity, complex, and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information (Gandomi & Haider, 2015). The occurrence of big data is largely a post-millennium phenomenon and has become widespread only as recently as 2011 (Sivarajah et al., 2017). Its rapid emergence has been enabled by advances in computational power, ubiquitous and mobile computing, networked storage, new forms of database design, new modes of software-mediated communication and transactions, and data analytics that utilize machine learning (Kitchin, 2015).

Big data have several distinct attributes that distinguish them from other data sources. These attributes (**Table 1**) are important for understanding the contribution of big data to many development applications (MacFeely, 2019).

Table 1. The 10Vs of Big Data

[17-21, 23]

CHARACTERISTIC	DEFINITION
VOLUME	The number of data records, their attributes, and linkages
VELOCITY	The speed at which they are produced, received, processed, and understood
VARIETY	The diversity of data sources, formats, media, and content
VOLATILITY	The changing technology and data storage
VERACITY	The trustworthiness of the origin and availability
VALIDITY	The accuracy, reliability and quality of the data
VALUE	The business value of data collected
VARIABILITY	The meaning of data continues to change
VULNERABILITY	The personal nature of data and the need for privacy and security
VISUALIZATION	The poor scalability and functionality

The nature of big data makes it a disruptive force in the way analysis and research are conducted. Big data, combined with artificial intelligence, have revolutionized the landscape of research, analysis, and modeling.

In the context of the SDGs, big data may offer solutions to data deficits where traditional approaches have so far fallen short (MacFeely, 2019). In national statistical systems (NSS), big data sources have a strong value proposition as they can serve a range of purposes, with key opportunities including (Tam et al., 2015; Florescu et al., 2014; Klein, 2017):

- Increasing the scope, breadth, and quality of statistical insights from existing and new metrics, including the SDGs.
- Enabling more timely data products to fill gaps in time series or meet new demands for real-time data products.
- Increasing the granularity of existing datasets by enabling small area estimates.
- Reducing costs and reporting burden associated with traditional surveys.
- Driving innovation in new methodologies and attracting new talent.

Earth Observation has been accepted as a key source of "big" information for decision-making, particularly since LandSat imagery became widely available in the 1970s (Hua-Dong Guo et al., 2015). Initially used to monitor natural processes, particularly those dealing with vegetation and land cover, its use has expanded to address all phases of disaster response, disease monitoring, and levels of economic development. Now, if one accepts the advent of the "Fourth Industrial Revolution" these data sources are increasingly linked to other technologies in the "Internet of Things" (IOT) (Schwab, Klaus, The Fourth Industrial Revolution, 2016, World Economic Forum).

Earth Observation Data's Utility

The power of EO data lies in its ability to add detail to the geospatial and temporal location of data, its ability to fill in gaps in data records because of limits in access to certain regions of a country, its capacity to complement major surveys and censuses for finer temporal granularity, and its ability to validate other in-situ data such as household surveys (United Nations, 2017).

Along with filling data gaps, EO data has the potential to be integrated with other data sources through modeling and simulations (Hargreaves & Watmough, 2021). This fusion of data represents the overall power of big data usage. Big data-based models allow analysts to capture the complexity of current human-natural systems, which in themselves vastly increase the amount of data available. EO data also allows experts to analyze and model conditions with geographic precision, to create maps and other visualizations that allow for greater capacity to target support, and to provide citizens with a means to participate in decision-making and hold their political leaders to account. As a result, earth observations, geospatial data, and derived information can play important roles in monitoring SDG targets.

Tools That Harness EO Data for the SDGs

Since the adoption of the 2030 Agenda and its SDGs, sources of EO data have become more prevalent, and the tools to translate these data into actionable information are more readily available. For example, a handbook published by the United Nations Task Team on Satellite Imagery and Geospatial Data (UNGIWG) in 2015, highlighted the contributions that were possible from EO for National Statistics Offices (NSOs). Importantly, the effective use of the information in satellite imagery can have a transformational impact on many of humanity's most significant challenges, such as helping global scientists, resource and planning managers, and politicians better monitor and protect fragile ecosystems, ensure resilient infrastructure, manage climate risks, enhance food security, build more resilient cities, reduce poverty, and improve governance, among others (United Nations, 2017).

3. A Primer on Earth Observation Data

Earth Observation (EO) broadly applies to any tools or technologies that measure the characteristics of air, water, and land. This may be as simple as a thermometer or as complex as a constellation of satellites (Schmidt, 2005). Although ground-based observations and the technologies through which they are derived form a key component in the whole of EO, for this paper, we will focus primarily on the use of space-borne EO technologies. Nevertheless, as the Internet of Things (IOT) grows, an increasing level of fusion among systems and platforms is taking place. With the focus on space-born EO, this section provides a brief primer on EO data and its application to the SDGs and sustainable development. It also provides a short discussion of how EO data links to the concept of big data.

Space-Born EO Types

Space-borne platforms, for the most part on satellites, have several key advantages that make them particularly apt for EO. For example, polar-orbiting satellites can observe wide swaths of the earth, while geo-synchronous (stationary) satellites can provide regular images over specific areas, both on a regular and repeatable basis. The data from these satellites also provide a long-term record of images across the years of the particular platform or mission life, with some dating back to the 1970s. Altogether, they provide an efficient and often open access to the data, such as in the case of NASA and EU Copernicus missions (USGEO, 2016 and CEOS, 2018).

Commercial satellites offer access to high-resolution data, some at a resolution of less than a meter, as well as the capability to target specific areas for monitoring (Demirel & Bayir, n.d.). The satellite industry is led by several companies, such as Maxar and Airbus, who have maintained large platforms for over a decade. However, the recent emergence of small satellites launched in large constellations has the potential to provide greater coverage and at very high levels of resolution (Werner, 2019). Yet, all of this potential comes at a cost to the user that is oftentimes beyond the reach of countries in the Global South, particularly in West Africa.[1]

There are a myriad of types of satellites, as they each operate using different means to observe the Earth. The types of satellites include the following (NASA, 2017):

- **Passive Satellites** receive solar or thermal radiation as input for images. These may operate primarily in the optical-visual spectrum or collect data at hyperspectral levels. Optical satellite images are relatively ubiquitous in the sense that they largely portray the Earth as humans would see it. Hyperspectral images offer the means of a deeper understanding of biological processes.
- **Active Satellites** generate the radiation and then collect its reflectance from the Earth. Radar imagery is one such type. In particular, synthetic aperture radar (SAR) is increasingly used to understand weather, biological, and hydrological processes. These images, depending upon their polarization, are not affected by cloud cover, and thus, are particularly useful in the humid tropics. Additionally, because they generate their own radiation, the geometry of reflected beams allows accurate three-dimensional images to be generated.

[1] Recently, the Norway Ministry of Climate and Environment has partnered with Planet Labs, Kongsberg Satellite Services, and Airbus Industries to provide high-resolution monitoring of the tropics and these data may be available to research institutions (NICFI, 2022).

Light Detection and Ranging (LiDAR) imagery is becoming increasingly available. LiDAR uses laser radiation to reflect off the Earth, providing a point cloud that can then provide three-dimensional images. This is particularly useful in looking at the canopy structure of forests, monitoring ice, and determining the structure of built-up places. LiDAR can be obtained by aircraft as well as ground units. Currently, there are two NASA missions; ICESat and GEDI. The ICESat mission is primarily focused on glaciers and polar mapping, though some data are available for forested areas. The GEDI platform is attached to the International Space Station and provides similar data. Unfortunately, both are inactive over arid zones in an effort to prolong the life of their lasers, which limits their utility in the more arid zones of West Africa.

Both SAR and LiDAR imagery offer tremendous advantages, particularly when combined with spectral imagery. Spectral imagery is simpler to process, using common algorithms, while SAR data requires considerable treatment in order to make sense of the images. Similarly, the analysis of LiDAR imagery is complicated. Increasingly, however, the EO community is seeking to provide “analysis-ready data” (ARD) that removes the burden of processing from the end-user.

NASA and ESA Copernicus Constellations

The NASA and the ESA Copernicus missions have opened the floodgates for EO data. Both space agencies have programs targeted on applications in the Global South and are actively used by researchers and analysts throughout Africa.

COPERNICUS: The European Union leads the Copernicus program in partnership with the European Space Agency (ESA) and the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT), which was initiated in 1998. The constellation consists of seven satellites providing high resolution spectral and radar imagery. Data are organized across five services: Land, Marine Environment, Atmosphere Monitoring Services, Climate Change Service, and Emergency Management Services. Data are available from 1998 and are guaranteed to continue until 2035 (Jutz & Milagro-Perez, 2020).

NASA CONSTELLATIONS: NASA maintains 30 active earth observation missions, several of which are jointly carried out with other national space agencies. Another ten missions are planned in 2022 and 2023, with an additional seven by 2031 (NASA, 2017). The Earth Observing System (EOS) is an international program, comprising a series of coordinated polar-orbiting satellites designed to monitor and understand key components of the climate system and their interactions through long-term global observations. The EOS missions focus on the following climate science areas: radiation, clouds, water vapor, and precipitation; the oceans; greenhouse gasses; land-surface hydrology and ecosystem processes; glaciers, sea ice, and ice sheets; ozone and stratospheric chemistry; and natural and anthropogenic aerosols.

4. Country Use Cases

For this report, we interviewed five local institutions in the Global South and West African region to develop a better understanding of their use of EO data to support policy implementation and development initiatives for SDG attainment. The institutions included:

Centre de Suivi Écologique (CSE), Senegal

The Centre de Suivi Écologique (CSE) was established in 1986 by the Senegalese government with the support of the United Nations Program for the South Sahara Region (UNSO) and the Danish International Development Agency (DANIDA). The center aims to provide data and information for natural resource management in West Africa. CSE works under the technical supervision of the Senegalese Ministry of the Environment and currently receives funding from UNSO and the United Nations Development Programme (UNDP).

Core to its mission, CSE utilizes remote sensing technology to collect, analyze, and disseminate data related to environmental monitoring and natural resource management for evidence-based decision making in Senegal and throughout West Africa. To achieve its mandate, CSE maintains a professional team of 40 engineers and technicians with diverse specializations in geomatics, natural resource management, and environmental assessment, information, and training. The center provides useful information for decision-making, particularly in the management of natural disasters, such as floods, and establishes early warning systems based on spatial analysis of vegetation and brush fires. To achieve its mandate, CSE works in collaboration with a diverse set of actors, including the Senegalese Government, international development organizations, and local cooperatives, to utilize spatial data for environmental and resource management.

Institut privé supérieur d'Etudes spatiales et Télécommunications (ISESTEL), Burkina Faso

The Institut privé supérieur d'Etudes spatiales et Télécommunications (ISESTEL) is a private higher education institution in Burkina Faso. Founded in 2011 in the capital city of Ouagadougou, ISESTEL provides graduate-level training in GIS and related technologies.

National Space Research and Development Agency (NASRDA), Nigeria

The National Space Research and Development Agency (NASRDA) is the national space agency of Nigeria, which works to promote space science and technology in the country. The agency is based in the capital city of Abuja and is regarded as one of the most advanced space agencies in Africa (Giles, 2018). Since its founding in 1999, NASRDA has launched four satellites into space, with ambitions of furthering research in the areas of rocketry and satellite development, as well as in satellite data acquisition, processing, analysis, and management of related software. NASRDA works under the authority of the Federal Ministry of Science and Technology.

Regional Centre for Mapping of Resources for Development (RCMRD), East Africa and Southern Africa

The Regional Centre for Mapping of Resources for Development (RCMRD) was established in Nairobi, Kenya in 1975 under the auspices of the United Nations Economic Commission for Africa (UNECA) and the Organization of African Unity (OAU), known today as the African Union (AU). RCMRD is an inter-governmental organization and currently has 20 Member States in the Eastern and Southern Africa regions which include: Botswana, Burundi, Comoros, Eswatini, Ethiopia, Kenya, Lesotho, Malawi, Mauritius, Namibia, Rwanda, Seychelles, Somali, South Africa, South Sudan, Sudan, Tanzania, Uganda, Zambia, and Zimbabwe.

RCMRD provides GIS and Information Communication Technology (ICT) services with the global mission of promoting sustainable development through geospatial information technologies. Since its founding, the center has been instrumental in regional capacity building in the field of remote sensing, GIS, and natural resource assessment and management in Africa. It has also played an important role in helping countries establish their National Mapping Agencies. To date, RCMRD trains more than 3,000 technical officers each year from its member states and other African countries in the fields of surveying and mapping, remote sensing, GIS, and natural resource assessment and management, and implements numerous projects on behalf of its member states and development partners.

The Centre for Remote Sensing and Geographic Information Systems (CERSGIS), Ghana

The Centre for Remote Sensing and Geographic Information Services (CERSGIS) began in 1990 as the Remote Sensing Application Laboratory, established by the University of Ghana and the Environmental Protection Agency of Ghana. CERSGIS provides remote sensing and geographic information systems (GIS) services for sustainable development planning. In particular, they specialize in remote sensing and GIS services for land and water resource appraisal, as well as support local capacity development for geospatial information management, and offer trainings in geographic data visualization and data collection. Throughout its tenure, the center has worked with a number of govern-ment, NGOs, and private sector partners, including producing a national digital map of current land use and land cover using satellite image data on behalf of the Environmental Protection Agency of Ghana. CERSGIS was also recently involved in the development of spatial databases for mapping land use and land cover changes, desertification, and flood hazards.

Africa’s Satellites and Space Policy

There are 14 national space agencies in Africa, and a total of 44 satellites have been launched, of which a handful offer earth observation capabilities, though many are targeted for military purposes (Firsing, 2015). The African Union (AU) has been instrumental in expanding the use of EO on the continent. For instance, in 2016, it established an Africa-wide space policy with the goals of greater regional integration in addressing user needs, accessing space services, developing a regional market, adopting good governance and management, coordinating the African space arena, and promoting intra-Africa and other international cooperation (AU. HRST/STC-EST/Exp./15 (II) 2017). This policy has supported the Africa Resource Management Constellation, which has been in development since 2009, and is coordinated by the South Africa National Space Agency (SANSA) in collaboration with the Algeria, Kenya, and Nigeria space agencies. Nigeria currently operates one earth observation satellite, while South Africa has an upcoming EO satellite planned (Space in Africa, 2019). Additionally, the AU collaborates with the European Union on the Global Monitoring for Environment & Security and Africa program, which includes funding regional consortia in the development of services (largely based upon Copernicus data that address key environmental and security issues in the region) (European Commission, 2022).

5. Findings

Leveraging EO data for SDG attainment requires collaboration across many actors and entities. As identified by the World Bank World Development Report (2021), a well-functioning national data system requires "people to produce, process, and manage high-quality data; people to populate the institutions that safeguard and protect the data against misuse; and people to draft, oversee, and implement data strategies, policies, and regulations."

Other frameworks describe the characteristics of effective data use similarly. Demchenk (2014) characterizes a data ecosystem by its components: models, management, analytics, infrastructure, and security. Drawing closer to sustainable development, Menon (2017) describes the associated big data ecosystem in terms of capacities, processes, policies, infrastructure, and stakeholders (Menon, R. 2017). And the recent TReNDS' report (2021) characterizes the SDG big data ecosystem in terms of the seven roles that stakeholders play (Allen, C.; Cameron, G.; and Dahmm, H. 2021). These definitions, and others, describe different aspects of the same whole.

Assessing the full range of actors and entities necessary to leverage the value of EO data for sustainable development is beyond the scope of this research. To frame our findings from our case studies, we have chosen to focus on two critical aspects.

First, is the set of high-level characteristics that institutions and individuals require to harness EO data: ***Capacity, Processes, Policies, and Infrastructure***. These characteristics were chosen as they align with the frameworks referenced above and because they provide a natural organizing principle for describing the key challenges described in the case studies. The second aspect touches upon the political economy aspects of leveraging EO data by assessing key stakeholder interests and agency to bring EO data into decision-making.

Turning to the first aspect, a review of literature and field consultations in West Africa have identified several common challenges facing countries as they seek to use EO to inform sustainable development decisions.

Capacity

Capacity extends beyond human abilities and knowledge. It encompasses the requisite institutional arrangements, enabling environment, leadership, and accountability. One of the primary capacity challenges that has been identified focuses on perceptions and understanding amongst stakeholders, particularly decision-makers.

Based on our interviews, there is a general lack of awareness and trust amongst policymakers in West Africa on using EO and its value for evidence-based decision-making. This lack of trust is partly due to EO and big data's departure from tradition, including the use of imagery rather than land surveys and the use of EO-derived proxies instead of population surveys.

Trust gained by stakeholders in EO findings may be lost if the resulting decisions have not effectively accounted for uncertainty, precision, and standard errors. And it is incumbent upon analytical partners to effectively describe uncertainty, accuracy, and other sources of error to all -users, particularly decision-makers, so that they are aware of the context in which the information is used and to develop trust in EO data.

At a fundamental level, particularly in West Africa, our interviews revealed that developing and retaining human capacity is also a challenge. Turnover and the drain of human resources is high, particularly as a result of the inability of national institutions to compete with international salary levels (UNESCO, 2018). Potential staff with the requisite skills are also lacking, thus allowing for vacancies in key analytical positions.

Further, the Global South, particularly Africa, tends to be isolated from emerging science in the field of EO. Fortunately, in recent years, this is gradually improving, as space agencies, particularly Copernicus and NASA ARSET, international programs such as the FAO and GEO, and others through online courses, offer training in the use of satellite imagery.

Processes

Transforming EO data to inform effective decisions for sustainable development requires overcoming process challenges. Addressing these challenges requires collaborations to complement and extend data and analysis, particularly to address information requirements at highly localized levels where increased resolution, timeliness, discoverability, and interoperability are required

Data management and data storage have become less challenging with the advent of cloud computing and a reduced need for downloading data with the ability to apply analyses in the cloud to imagery. Key technologies that have been applied in Africa include the increased use of Google Earth Engine (GEE) and TensorFlow, and the use of data cubes through the Australian-financed Digital Earth Africa initiative (DEA). For instance, both GEE and DEA have been applied to the monitoring of illicit mining.[2] These technologies provide analysis-ready data in an open format, and GEE has an additional advantage of providing a visualization platform. Some institutions have developed high-speed computing capacity, which offers a supplement to cloud-based solutions, but these centers are often oversubscribed and not available to users outside of the institution that owns the center.

Uniform data standards have increasingly been applied, primarily based upon the ISO system in Africa. In spite of this, the data products from imagery analysis are not well-documented in terms of their metadata (Alford, 2009). Recently, an initiative has begun to certify data archives according to international standards. This process, which includes peer review of data products, will enhance the reliability and trustworthiness of analytical products. However, the certification process is expensive and time-consuming, and this acts as a deterrent to wide application.

Policy

There are a number of policy-related conditions that create challenges to EO data use. While these conditions may be categorized under the rubric of policy, they require consideration from not only government, but also from the private sector. There is a level of complexity of the regulatory framework applicable to EO that may negatively impact access, use, and interoperability. Among these, the application of fees for data access acts as a barrier. It may be widely understood why commercial imagery and statistical data may carry fees, but the application of fees for access to government data, particularly weather data, has stifled its use. In both the cases of commercial licensing fees and government fees for statistical data access, an agreed means of either providing funding or reducing access costs to the levels appropriate for use by regional institutions should be sought.

In addition, national security policies prevent the exchange of geospatial data, particularly high-resolution imagery and the use of unmanned aerial vehicles, such as drones. This is highly important in West and East Africa where large swaths of territory are insecure and inaccessible. While high-resolution imagery may provide important insights in areas that are unsafe for travel, imagery access should be controlled in order to avoid it falling into the wrong hands.

Increasingly, as imagery reaches very high resolutions, individual privacy considerations are coming into play. Google's Street View capability has already moved forward by masking out certain identifiable features that were collected by their roving camera equipment. And at the country-level, Ghana, for example, has an agency responsible for data privacy, which may eventually enact measures to ensure privacy protection with satellite imagery (Schneidman et al., 2021).

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[2] See further details here: https://www.digitalearthafrica.org/media-center/blog/digital-earth-africa-detecting-landscape-change-and-unregulated-mining

Regional economic communities and continental bodies offer important venues for policy dialogue on the application of EO. As previously mentioned, the AU maintains EO programs and has developed a space policy as part of their overall science and technology policy to engage national actors on a common set of objectives. The Economic Community of West African States (ECOWAS) has similarly been engaged in a dialogue on harmonization of land cover/land use change approaches and their use to address national policy.

Infrastructure

Currently, spatial data infrastructure (SDI) remains in the realm of governments, international organizations, and research institutions. However, there has been considerable discussion on the need for increased SDI in Africa. Fortunately, some advances have been achieved in West Africa, particularly in Ghana, Côte d'Ivoire, Senegal, and Burkina Faso (Lance, 2003). For example, Ghana has a governmental agency directly responsible for data protection, and other countries have a federated system. Similarly, the international community has moved forward with common geospatial data and metadata standards as well as standards to certify data archives. However, for these architectures and standards to be broadly applied, national resources are required along with international expertise.

Many of the large internet content providers, particularly Google, Amazon Web Services, IBM, and Microsoft, maintain cloud infrastructures that enable bringing models and algorithms to the data and allow the fusion of various data sources. These are being increasingly applied in the exploitation of EO data, and cost and the reliability of access continue to be a constraint, particularly throughout most of Africa (SERVIR Global, 2017). Further, while some research institutions, such as the Kofi Annan Center in Ghana, and NSOs have high-performance computing clusters capable of undertaking large-scale analyses at a very high-resolution, they are often in high demand and unavailable for the long-time frame needed for these analyses.

The most frequently mentioned challenge to the use of EO in West Africa and elsewhere in Africa deals with physical and digital constraints. Internet speeds are low and capacity-limited, and access is expensive. Combined with an unreliable power grid, it is also prone to outages. Some programs, such as the Global Monitoring for Environment and Security (GMES), have addressed this by establishing ground stations for the download of data, which is helpful, but also requires additional preprocessing of imagery before it can be effectively analyzed, requiring increased storage and computing capacity that otherwise would be available on the cloud.

Connectivity is a continuing issue in terms of speed, cost, and reliability. It remains very costly to access high-bandwidth internet, and the dependency on low-speed connections, often over mobile phone hotspots, mean that data download times are extensive, even when computing is cloud-based. Continual issues with electrical power outages are closely linked to this. Furthermore, both Internet and electrical infrastructure may not be keeping pace with technological advances. Niger, for example, has only recently introduced a 4G network, while Europe, many parts of Asia and the Americas are moving to 5G (McKetta, 2021). Additionally, extremely low speeds mean that data downloads—even downloads of analytical products—may take several hours to days. Internet subscription prices in West Africa are substantially more expensive than the Americas, Asia, and Europe (Monks, 2019), which limit the quantity of data to be transferred within the budgetary constraints of an individual or institution. This is partly due to the lack of competition and level of state control over fiber optic lines, as well as business models that fail to prioritize the importance of an ICT infrastructure as an essential service versus a luxury.

Mapping Stakeholders

Stakeholder mapping offers the means to identify the actors, their roles, and their capacity to bring data into decision-making. This process has several benefits; it increases the level and breadth of participation in the decision-making process, it ensures a holistic definition of the necessary information required to make an effective decision, and it identifies potential points of entry to strengthen partnerships and capacities that, in our case, leads to greater value from the use of EO for sustainable development.

Stakeholder mapping also helps to narrow the gap between researchers and decision-makers. As de Sherbinin, et al. (2022) highlight; researchers seek to understand cause and effect relationships, while policymakers are looking for credible information from trustworthy sources within timeliness and relevance constraints. By looking at the relative power and interest levels of stakeholders, we can be more precise in terms of identifying communities of practice that may be organized to address key decision points, the information required, and levels of capacity necessary for this effort to be effective.

The matrix in **Figure 1** below, based upon a set of structured interviews of experts in the West Africa region, shows an aggregate mapping of power and interest among key national organizations found in six African countries, four of which are from West Africa. Although the power and interest of specific organizations vary, particularly from country to country, several key points stand out from this aggregate representation. Firstly, for the most part, the stakeholders engaged in using EO for sustainable development decisions are perceived to have relatively high levels of interest and power in the decision-making process. Secondly, the higher-level government institutions and international actors stand out above the more local organizations (with the sole exception of the military, who control a considerable amount of EO data, but play a relatively small role in sustainable development decision-making). This latter aspect compares markedly with satellite image providers, who have a high level of interest, but are perceived as having low levels of power in sustainable development decisions within the African context.

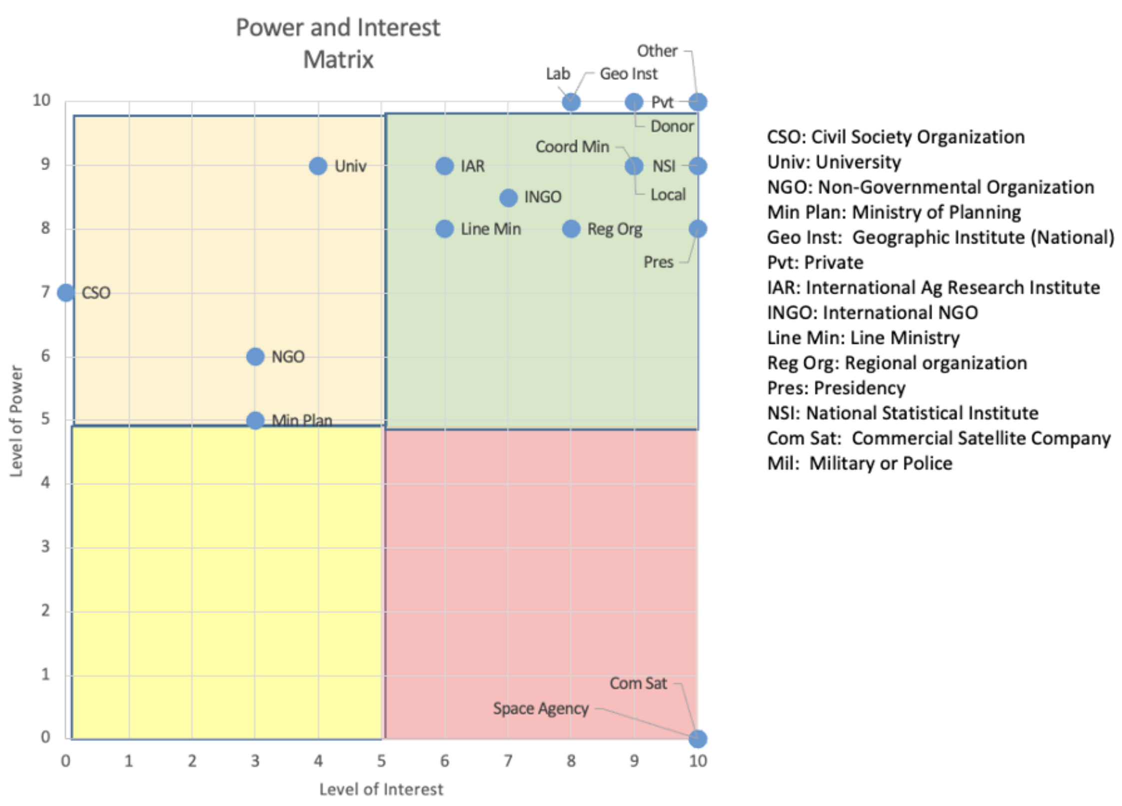

Figure 1: Power and Interest Matrix

6. Actions to Improve Use of Earth Observations for SDG Attainment

EO Data Within the Data Value Chain

Data, including big data, have no intrinsic value on their own. Value accrues as the data are transformed into decisions. This follows a well-discussed sequence, first proposed by Ackoff (1989) and modified by others[3]. The sequence follows the transition of data to information, then to knowledge, and ultimately, wisdom. As we consider the value chain for EO data, as shown in **Figure 2**, we see that the data generation leads to data retrieval, and information is garnered through analysis and the provision of information services. Knowledge occurs in the transition of the information to decisions, which then becomes wisdom as the previous decisions inform those of the future.

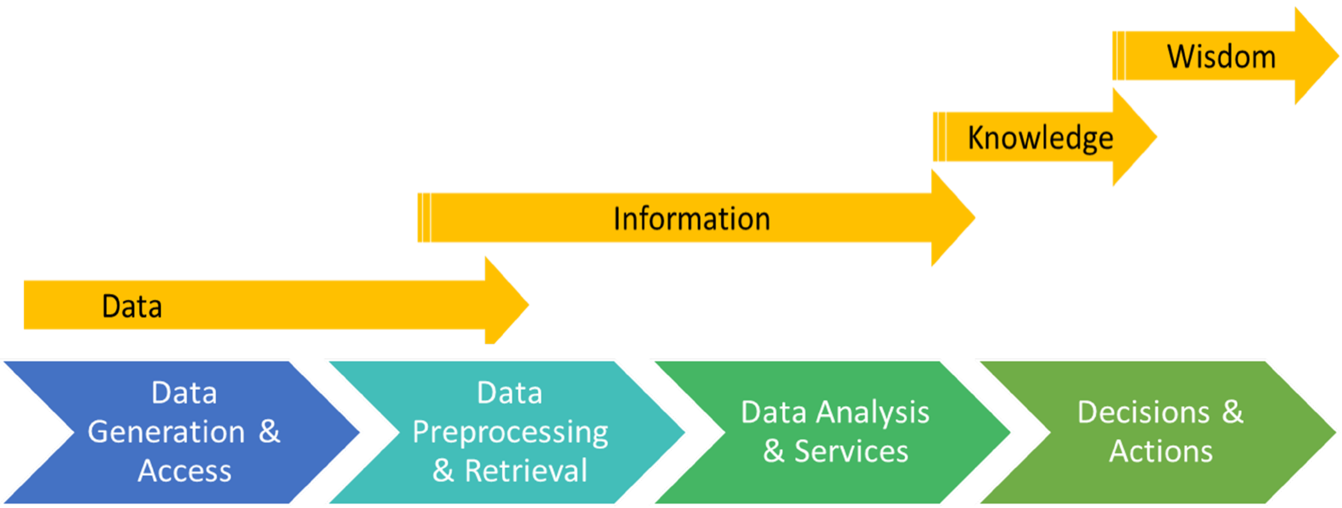

Figure 2: EO Data Value Chain

Suffice it to say at present, that data are only as valuable as the effectiveness of resulting decisions, and that an understanding of how EO data are transformed into decisions is important. Further, actions that lead to SDG achievement in specific cases may provide important lessons to others as EO is applied; i.e., learning from the application of EO results in the wisdom for its application elsewhere—replicability. Finally, the optimal use of EO data also increases the value of other data used for SDGs by increasing their validity, location precision, and overall completeness.

The previous section highlighted several key challenges from the literature review and case studies for the effective use of EO data to support development decisions. In **Figure 3**, we have aligned the most pressing challenges to the different components of the data value chain.

[3] Baskarada, S. and Koronios, A.; 2013. Data, Information, Knowledge, Wisdom (DIKW): A Semiotic Theoretical and Empirical Exploration of the Hierarchy and its Quality Dimension. Australasian Journal of Information Systems · November 2013. R. I. Jony, et al. Big Data Characteristics, Value Chain and Challenges 2016; and Faroukhi et al. Big data monetization throughout Big Data Value Chain: a comprehensive review. J Big Data (2020) 7:3. See also, T.S. Eliot: The Rock

EO Partnerships for SDG Attainment

TReNDS' earlier work on the effective use of big data for national SDG monitoring provided a partnership typology to assist national governments in selecting the right type of partner to overcome critical challenges (Allen et al., 2021). For leveraging EO data for decisions, the partnership landscape is equally diverse and complex as for any big data source. This is due to EO data's many attributes, which as described above, require sophisticated techniques and technologies to enable the capture, storage, distribution, and analysis. For example, in addition to data providers, government entities using EO data may need to partner with a technical service and technology providers to gain access to these capabilities if they are not available in-house. To initially explore the possibilities and contributions of EO data sources, knowledge brokers or convening organizations may be also needed to raise awareness and build trust among the various partners. Additional funding is also often needed to get big data projects off the ground, which can benefit from an executive sponsor to champion a business case for internal funding allocations, or an external donor willing to provide funding. Lastly, a legal or data privacy partner to assist in navigating the regulatory landscape is another important partner that is often overlooked.

Completing **Figure 3**, the type of partner has been aligned to each segment of the data value chain to address the most pressing concerns.

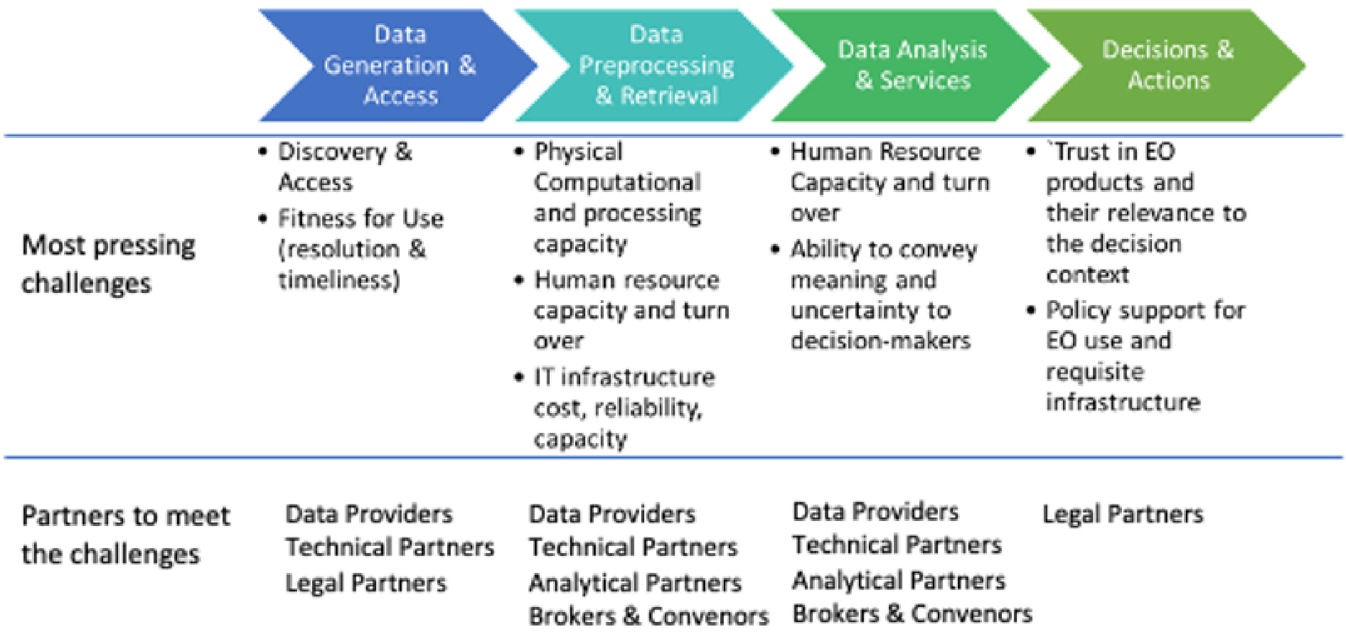

Figure 3: Aligning Partners to Meet the Most Pressing Challenges Along the Data Value Chain

Data Generation and Access

While the location and nature of EO imagery are relatively well-known and the means of access are clear, there remain two essential issues. First, access to commercial data, particularly at very high-resolutions, is expensive and requires some level of donor support. As imagery is increasingly combined with in situ or ground sensor data, analytical partners are often left to fend for themselves in their discovery and access. Second, there is no clear consistency in the cataloging and documentation of in situ data among various existing platforms, and policies regarding access are often prohibitive.

Analytical capabilities are challenged to access data that are fit-for-use [see below sidebar]. As EO is applied to increasingly local requirements, the level of resolution, both temporal and spatial, are increasing. In addition to cost and computing requirements, the suitability of imagery is challenged. This is particularly true in humid zones where cloud cover over long periods of time, or at critical periods (e.g., flooding) make optical imagery difficult to use.

Fortunately, there are emerging solutions, such as cutting-edge Artificial Intelligence algorithms that provide cloud-free EO data intelligence in near time (Aspia Space Clear Sky Web),[4] but these are proprietary and require considerable preprocessing before their use. Additionally, NASA has provided training to several regional institutions in Africa on approaches that mitigate the cloud cover issue, and these have been successfully applied in crop and forest degradation monitoring.

Along with technical and data providers, legal support as legislative frameworks have not kept pace with technological advancements and do not extend to arrangements with platform providers or EO data sources. There may also be shortcomings in the legal framework governing the processing, use, or transmission of data including cybersecurity, data privacy, and data protection. In such cases, the ***legislative framework for EO organizations may first need to be strengthened.***

However, establishing effective legislative frameworks that enable data sharing while safeguarding privacy, in general, have proven challenging. Governments will need to invest considerable efforts in establishing an effective authorizing framework. In lieu of this framework, government and quasi-government data agencies have used ad hoc arrangements to facilitate big data sharing, often in the form of MoUs or more formalized agreements with data providers or other partners.[5] This helps set the ground rules for how big data sets can be combined, protected, shared, exposed, analyzed, and retained, and these rules would apply naturally to EO data. However, negotiating these agreements can create significant delays in EO data projects and will require early advice from legal and privacy partners to navigate the regulatory landscape.

It is also worth mentioning that external partnerships do not necessarily equate with donor funding. A variety of approaches to partnership are available, and these approaches may be tailored to the specific challenge at hand. For example, mobile phone providers are increasingly partnering on projects to enable information to be disseminated to a broader population on food security and crop production issues (Decuyper et al., 2014). As such, publicly-funded data providers and analytical partners provide information, while the private sector enables targeted distribution. This process may also work in reverse where mobile phone and internet providers enable citizen scientists and the general public to provide in situ data that then can be combined in EO analyses.

The commercial satellite imagery market is also engaging in such efforts, and a dialogue with them may allow for targeted programs to free data for critical services. This dynamic may also empower national space agencies, although they may lack satellites, to facilitate this data exchange. From this exchange, two objectives are achieved: an increased open flow of information and increased societal benefits from national space agencies.

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[4] See website for further information: https://aspiaspace.com/

[5] See case study for examples: https://contractsfordatacollaboration.org/static/files/un-environment-and-google-case-study_3.pdf

Fitness-for-Use Considerations When Selecting EO Imagery

The use of EO imagery to inform decisions regarding the achievement of the SDGs is a valuable asset, but not a magic bullet. Several questions should be answered to make an effective choice on the EO source:

- **RETURN RATE AND LATENCY:** What is the timeframe for decision-making? The return rate (frequency of images being provided) and the latency (waiting time) for images are important considerations when selecting imagery. Certain analysis-ready data are comprised of mosaics of the best available individual images. In certain situations, particularly for addressing disasters, these images will not provide an accurate image of the current situation.
- **LENGTH OF DATA RECORD:** Some changes require several years to be detected or can be affected by seasonal variations. In order to remove these interannual variations and determine a reliable trend, longer-term imagery records should be used. Thus, even though certain data sources may be more advanced, higher in resolution or capabilities, longer-term records may be more reliable.
- **RESOLUTION:** What is the scale of the phenomenon to be analyzed? Small areas, such as buildings, agricultural plots, and water bodies require higher-resolution imagery. Broader changes, such as vegetative quality and urbanization, may be detected by lower-resolution imagery. Higher-resolution implies the need for higher computing power. Lower-resolution images are more freely available and require less computing power.
- **ACCURACY**: An image, particularly when presented in a format that resembles human visualizations of the state of nature, assumes a level of certainty that may be misleading. Analysts should be explicit in their description of accuracy, validity, and uncertainty. End-users should look for such descriptions and effectively communicate this to decision-makers.
- **COST AND SUSTAINABILITY:** Consideration of the ability to replicate analyses using the available imagery given the financial resources at hand is also important. Potentially costly high-resolution imagery may provide an excellent analytical product at present, but the costs of replicating this for continual monitoring may exceed available budgets. Further, some satellite missions have limited lifespans and may not be replaced. Analysts should be aware of the end objective of the analysis to be provided and the technology lifespan to be applied.
- **DATA VOLUME:** As discussed previously, long-range and high-resolution data require a large storage and computing capacity. These constraints are mitigated through the use of cloud computing, but attention must also be paid to the cost of access to cloud computing, particularly where internet limitations exist.

Data Processing and Retrieval

Turning to the **Data Processing and Retrieval** segment of the value chain, sustained and predictable physical computational and processing capacity, human resources talent management, and IT reliability are the major obstacles to be overcome. Several West African institutions have established high-speed computing facilities, and these facilities supplement the growing use of cloud computing. Demand continues to exceed capacity, however. The management and operation of these facilities remain challenging, particularly with respect to unstable or unreliable electrical power supplies. Additionally, basic equipment, such as laptops and workstations, remain very expensive relative to the local economy. Software is also prohibitively expensive, and counterfeit or hacked versions are found throughout the region. Many programs have moved to open source software that can be freely obtained, but this requires higher levels of expertise to provide the functionality that proprietary software has. Further, as the software industry moves from stand-alone licenses to cloud-based subscriptions, the recurring fees and inability to make international payments excludes many from access.

In addition, for human resources to be effective, their capabilities must be nurtured and retention schemes must be in place to transform the fit-for-purpose data into evidence for decision-making. A multi-pronged approach to upskilling employees is also essential. After establishing a baseline measurement of staff capabilities, HR strategies must be refreshed to leverage best practices and accelerate capacity building. Refreshed strategies should include developing training and curricula and fostering communities of practices. To assist, external partners with experience in devising these strategies and training programs will be critical. These may include private sector entities or twinning arrangements with other EO-data intensive institutions that can provide direct advice and mentoring. Academics and universities will also continue to prove important by providing a pipeline of future graduates able to perform EO processing. As mentioned earlier, cloud-based approaches may be a fundamental, but necessary shift in the processing of information and provide a cost-effective alternative to data centers, as new platforms provide easy scalability.

Data Analysis and Services

Considerable effort has been made to establish human resource capacity in the use of EO. For instance, space agencies, international organizations, and regional programs regularly train specialists in the science and methodologies to use geospatial imagery. The global demand for these skills exceeds supply, and particularly in West Africa, a promising and talented analyst is likely to be snatched up by a Global North-based organization that can pay a much higher salary. Further, on-site training often qualifies a young analyst for a sponsored scholarship, which in turn, takes that talent away. Opportunity is a fine ideal, and the approach to counter this is to ensure that there is sufficient depth in personnel to adapt to the departure of others.

Furthermore, analytical partners in the region, who are responsible for the provision of information and services are challenged to effectively communicate findings. There remains a tendency among professionals in the region and internationally to focus their communication to their peers with an emphasis on peer-reviewed scientific journals. The peer-review process is critical in the validation of the science applied, but decision-makers have different format demands, and analytical partners should consider the end-users in the format in which information is provided. SERVIR West Africa has addressed this through the inclusion of end-users in the communities of practice that co-develop services, thus ensuring that the service itself is fit-for-purpose.

The format for communicating findings is important, but it is equally important to communicate the uncertainty that surrounds these findings. Analytical partners can be challenged to maintain end-user trust in the face of uncertainties of the product, and analytical partners are often hesitant to admit uncertainty for fear of the findings being dismissed. The Food and Agriculture Organization (FAO) has outlined robust guidance on how to document accuracy, variance, and uncertainty, and these can serve as standards as services are disseminated (FAO, 2016).

Human resource strategies must develop current and future staff for both Data Processing/Retrieval and Data Analytics and Services segments of the value chain. Engaging with credible industry and global experts to stay abreast of the latest tools and technologies is critical. More generally, the refreshed HR strategy should touch upon the recruitment, talent management, training, performance management, and compensation factors essential for a talented and effective staff. To recruit and hire people with the right skills, some governments are moving away from passive approaches and are fast-tracking the staffing process to be competitive in the marketplace. In West Africa, the West and Central African Research and Education Network (WACREN) offers a platform through which government and non-government actors partner with academia to develop, promote, and sustain human resource capacity in the region.[6]

[6] See platform here: https://wacren.net/en/network/infrastructure-maps/.

Decisions and Actions

The impact of EO products is largely based upon developing trust in EO and their relevance to the local decision context. Indeed, trust is earned through accuracy, but also from being able to provide the right information, at the right time, and in the right format. Co-development of services with the direct engagement of end-users helps to ensure this. In addition, transparency in the process and product allows for a greater understanding of the findings. Black box solutions are giving way to solutions based upon open science principles. External partners, international organizations, NGOs, universities, and donor-funded programs are and should continue to provide technical support and training in open-source solutions, and some countries, such as South Africa, have mandated this. Rather than a requirement, open-source solutions should be encouraged through administrative guidelines, and sufficiently trained personnel should be maintained by government actors. Equally, government actors may take advantage of a growing private sector fee-for-service market in the region.

Whole-of-government responses to leverage their data to respond to the COVID-19 pandemic have relied on brokering and convening functions to align data products to support near real-time decision-making. These intermediary functions are critical to converting data into actionable evidence for SDG attainment. These intermediary activities are necessary at various staffing levels throughout the organization. For example, senior management may be engaged in crafting the overall strategy for aligning new data products to the most pressing policy needs. Whereas, at the technical level, multi-disciplinary teams must come together to ensure integrating data from disparate sources is done with minimum information loss. External partners with experience in developing these intermediary processes can support EO organizations that are only beginning to develop these capabilities.

Data sharing agreements at various levels may be negotiated that ensure the access, quality, and security of the data, while protecting intellectual property rights as well as privacy. Governments can offer guidelines in terms of property and privacy rights. Other organizations can provide the model data sharing agreements and guidelines for their successful implementation.

Nevertheless, brokers and conveners must establish an effective means of making potential beneficiaries of this training aware of its availability. Data providers and analytical partners are also needed, along with the financial support of funding partnerships.

7. Reflections on Future Work

Assessing the full range of actors and entities necessary to leverage the value of EO data for development is beyond the scope of this research. However, drawing from the structures proposed by the World Development Report (World Bank Group, 2021), it is clear that a robust framework for building the EO data needed for SDG attainment starts with producing fit-for-purpose data that is reusable by many of society's institutions (TReNDS, 2020). Institutions that take EO data through the segments of the data value chain must demonstrate human resource capacities, have well-defined policies and processes, reliable and scalable infrastructure, and effective governance arrangements that ensure the process adheres to local social norms and conventions. We've developed an initial framework (see **Figure 4** below) to conceptualize these needs. The framework is sustained by capable and ethical people, supporting laws/regulations, policy frameworks, and key stakeholders that are empowered to act and are driven by their interest in harnessing this vital data source for sustainable development.

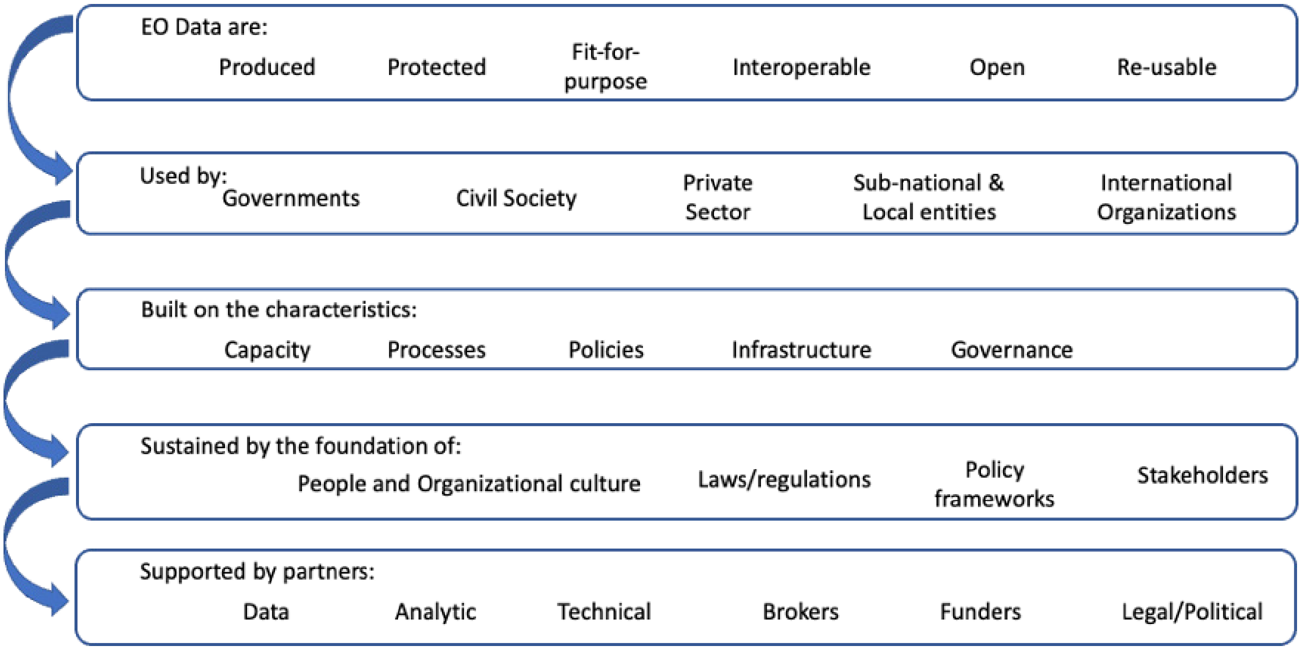

Figure 4: A Framework to Ensure EO Data Support SDG Attainment

Extensions to the Framework

For future potential work, we recommend extending the framework to reflect activities mapped on a scale from local through national and international levels. This is essential, as collaboration and partnership include international exchanges of data, data products, and platforms, as well as the incorporation of locally-derived data, particularly through contributions of "citizen scientists." Global entities must facilitate knowledge exchange and collaboration reflecting the ever-increasing localization of SDG decision-making.

Citizens should be empowered to play an integral role in achieving sustainable development. This is the nature of the consultation process that takes place in establishing and reviewing national action plans. Citizen Science is one avenue for this to occur because it empowers local people to inform decision-makers and engenders a two-way flow of information. Further, as local actors contribute to national reporting, the acceptance and adoption of findings become broader and deeper because everyone has a sense of ownership.

A second key extension to the framework accounts for the maturity of an organization's current state and the steps needed to progress to higher states of maturity. They generally include a sequence of levels or stages that define a path from the lowest (initial) to the highest (ultimate) state of maturity based on a set of attributes, such as the four high-level characteristics used in this paper.

Once the organization's attributes under the three characteristics are determined, EO data maturity is categorized in one of five stages: nascent, pre-adoption, early implementation, proficient, and mature. We have described earlier how different partners are required for different segments of the EO data value chain. For example, for organizations exploring the potential of EO data for the first time (nascent stage), it is critical for data providers and analytical partners not to oversell EO as a "magic bullet". Instead, effectively (and accurately) convey the potential of EO to aid decision-making. However, as organizations move through these maturity stages, they require different services from partners and partnership models to gain greater value from their investments.

Deriving Value From EO Data

SDSN TReNDS' earlier work on big data for national SDG monitoring introduced a formal maturity model that provides an intuitive framework to understand the current state and progress of NSOs to derive value from big data. The same model applies equally to government centers engaged in deriving value from EO data. Big data maturity is categorized in one of five stages: nascent, pre-adoption, early implementation, proficient, and mature. As government EO centers move through these stages, they require different partners and partnership models to gain greater value from their investments.

The **Nascent Stage** represents a pre-EO data environment. In this stage, the EO Centers have a low awareness of big data and the potential value for official statistics and SDG monitoring.

The **Early Implementation Stage** is typically characterized by a few pilots that become more established. There is generally at least one executive sponsor involved, however broader interest is likely growing as pilots deliver successful outcomes.

As organizations move from early adoption to the more mature production stages, they need to overcome a **"chasm."** While pilot applications have been deployed, gaps may remain in terms of capability development and the governance context, including securing ongoing funding.

Reaching the **Proficient and Mature** stages means an organization has well-established, ongoing EO data programs that are executed as budgeted.

It is through this comprehensive framework that we can arrive at a series of conclusions to demonstrate effective approaches, identify areas of potential for improvement, and suggest policies to increase the effectiveness of big data and the sub-systems of which they are comprised.

This is a massive task, and not one assessment tool or analysis can cover such a span of actions and actors. However, work to identify existing tools and approaches to assess elements of these processes and identify remaining gaps in these tools could help formulate effective partnerships to help Global South EO centers unleash the full potential of EO data.

8. Conclusion

This paper has outlined the range of activities underway to harness EO data for the SDG agenda, with a particular focus on the Global South. It also documents the experiences of countries in West Africa in harnessing EO data and highlights key supporting partnerships to advance the use of this data at the national level.

While big data, specifically EO, offers great opportunities, challenges exist for bringing them to scale. In spite of increasingly open access to a variety of imagery, access is constrained by the ITC capacity in the region, and as more sophisticated imagery platforms are developed, human capacity requirements may constrict the region's ability to exploit these new sources and methodologies. Furthermore, more is required to align partners with entities to ensure EO data contributes to relevant and appropriate development decisions. As the trend for local development decision-making that is evidence-based and timely continues, EO data will only become even more important.

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