USE OF DIGITAL TECHNOLOGIES IN FOREST ASSESSMENT IN ERA OF INSECURITY.

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ABSTRACT
Forest are providers of ecosystem services, thus are vital to the national economy and the wellbeing of the people. Monitoring of the forest ecosystem is essential for management, planning, and policy purposes, however, in the face of insecurity in Nigeria and the West African region the need to adopt a safe, secured, and efficiently reliable means of forest monitoring is proposed herein this paper. Moreover, there is also the need to adopt the concept of smart forestry with digital technologies which is the current trend among forestry practitioners worldwide. Accurate and reliable forestry data can be obtained by continuous monitoring of forestry resources using digital technologies. This is a position paper on the application of digital technology in forestry practices which is a paradigm shift from the known practices of inventorying forest resources by the in situ methods. The paper is a call to smart forestry practices and has been sub-divided into three main applications areas: I) Data collection tools; II) Satellite Remote Sensing applications; II) Data science or big data applications which encompass Satellite Remote Sensing and Geographical Information data embedded in server/ web-based interface with machine learning algorithms. The paper further concludes on the need for collaboration between organizations and scientists in Nigeria to meet the need for digital applications in forestry and close the wide gaps in both research, teaching, and management of the Nigerian forests' ecosystem.

Keywords: *Forest, monitoring, Remote sensing, Data Science, Cloud Computing, Artificial Intelligence.*

INTRODUCTION

Forests cover over one-third of the Earth's surface area and are home to more than half of the world's land-based species (FAO and UNEP. 2020). Forest are providers of ecosystem services such as the supply of timber, fiber, and fuel, carbon sequestration, clean water, and air, biodiversity conservation, and aesthetic values, i.e., provision of cultural and spiritual values to communities thus are vital to the national economy and the wellbeing of her people (Millennium & Assessment, 2005). Forests are multifunctional, with an environmental, economic, and social role, providing multiple benefits: ecosystem services related to soil, erosion control, water cycle, clean air, carbon storage, climate regulation, biodiversity protection; provision of recreational and cultural values; and provision of resources, in particular timber, and non-wood products. Forests are thus a source of employment, particularly in rural areas. The entire amount of degraded forest in the tropics which is estimated to be over 500 million hectares store seven times more carbon than humanity emits annually (Putz FE et al 2014). The International Tropical Timber Organization (ITTO 2002) suggests that up to 850 million ha of tropical forest could already be degraded. Forest loss and degradation have slowed or stopped the flow of a wide range of ecosystem products and services, putting billions of people at risk of a variety of negative consequences.

Forest assessment is an age-long practice of inventorying forest resources. Assessing Forest resources with the traditional grand truthing method is time-consuming and costly and results from grand truthing methods are biased and likely to overestimate or underestimate the targeted population. The current widespread insecurity within the West African region has made forest resource assessment through grand truthing almost impossible. There is the need for ''the alternative'' or scaling up of ''the alternatives'' which is a paradigm shift to digital technology applications or smart forest applications to tropical forest resource assessments.

Digital technology and smart forestry?

Digitalization is the use of digital technologies to enhance the day-to-day living of humans(Bespalova, Polyanskaya, Lipinskaya, Gryazkin, & Kazi, 2021). The 21st century is the age of digital-based technologies and digitalization holds great potential for forest resource monitoring, management, and certification. Thus, digitization would help to support decision-making and improve competitiveness (Nitoslawski et al., 2021). Forestry resource assessments are often based on spatial attributes such as inventory or mapping forest areas, therefore the index in forestry data is mainly based on spatial attributes (Zou, Jing, Chen, Lu, & Song, 2019).

There is a paradigm shift in the use of digital technology by ecologists, earth, and conservation scientist toward the novel approach to data collection, storage, and analysis of data. This paper reviews the application of digital smart technologies in forestry practices from data collection, storage, retrieval, and analysis. These tools have metamorphosized into the practice of smart forestry or smart forest resource assessment. The review has been divided into three sections: I) Data collection tools; II) Remote Sensing; II) Data science or big data applications.

Section I: Open-source digital tools for data collections

This section presents a description of the various open-source digital tools for gathering specific knowledge and forestry ecosystem services data and their potential as an effective database support system. There are several open-source tools available for forestry data collections ranging from forest inventory to socioeconomic survey support systems (Table:1). The Open-source digital tools enable the authoring and use of digital survey forms without users needing software development expertise with form design enabling a high degree of customization to be achieved by means of specifying a wide range of data flow control mechanisms (Campus et al., 2020). Collect Earth or Open Foris is an example of Open Source digital tools. It was introduced to Nigeria at the onset of the National Forest Monitoring program by the Food Agriculture Organisation of the United Nation in 2018.

Collect Earth is a free and open source software developed by the Food and Agriculture Organization of the United Nations (FAO) to facilitate the collection, management and analysis of land data (Saah et al., 2019). The open source software enables expert and non-expert users to draw on Google technology to freely access and visually interpret satellite imagery for data collection and it geo-synchronizes the visualization and use of imagery of varying spatial and temporal resolutions, including DigitalGlobe, SPOT, Sentinel 2, Landsat and MODIS imagery within Google Earth, Bing Maps and Google Earth Engine (Saah et al., 2019). Collect Earth differs from previously existing land monitoring tools by offering access to: (a) multiple archives of VHR satellite imagery that can support the assessment of land use and land cover dynamics; (b) graphical representations of inter-annual and intra-annual vegetation indices generated with Landsat and MODIS imagery in Google Earth Engine (GEE), new technology for cloud-based, automated processing of satellite imagery; and (c) built-in data analysis tools through an integration with Saiku Analytics. Collect Earth also differs from previous land monitoring software in that (d) it offers a robust data collection framework that is fully customizable by non-experts; and (e) it streamlines the use of probability sampling statistics. Collect Earth accesses three archives of satellite imagery that have an expansive coverage and collectively enable users to assess any area in the world. However, where supplementary VHR imagery has been acquired, such imagery can be imported into Google Earth (Pro) in numerous formats and immediately used for a land assessment with Collect Earth.

Table 5: Open-source Digital Tools For Data Collections

S/N	Tool	Website
1.	Collect Earth (Open Foris)	https://openforis.org/tools/collect-earth/
2.	Open Data Kit (Android)	https://projectredcap.org/software/mobile-app/
3.	KoboToolbox (Android & Web)	https://www.kobotoolbox.org/
4.	REDcap (Android, iOS & Web)	
5.	Magpi (Android & iOS)	https://www.magpi.com/
6.	Survey CTO (Android & Web)	https://www.surveycto.com/
7.	CommCare (Android & Web)	https://devimpactinstitute.com/courses/mobile-technologies/training-on-mobile-data-collection-and-data-management-using-commcare
8.	Jotforms mobile (Android, iOS &n Web)	https://www.jotform.com/products/mobile-forms/
9.	Team scope (Android, iOS & Web)	https://www.teamscopeapp.com/
10.	Open source Open Data Kit	https://getodk.org/

SECTION II: FOREST ASSESSMENT WITH SATELLITE REMOTE SENSING (SRS).

Tropical forests represent a rare and fragile ecosystem that is under threat in many parts of the world and urgent action is needed to conserve these rich forests, not only because they harbor concentrations of endemic and threatened species but to maintain their vital role in the provision of ecosystem services such as the supply of timber, fiber and fuel, carbon sequestration clean water and air, biodiversity conservation and aesthetic values, i.e., provision of cultural and spiritual values to communities (Bubb, May, Miles. L, & Sayer.J, 2004).

The effects of such loss have both local and global implications on the climate. Efforts at combating such loss of forests and their implications led to the formation of the Essential Biodiversity Variables (EBV) by the United Nations Convention for Biological Diversity (CBD). EBV was established to monitor the progress made by signatories to the CBD on forest ecosystem diversity.

Monitoring EBV such as forest biomass, tree species diversity, forest phenology, and temporal and multi-temporal change detection (forest cover, loss, and gain) are important in determining the progress toward the Convention on Biological Diversity's 2020 Aichi targets (Pereira et al., 2013).

The EBV indicators also provide the foundation for developing scenarios for future biodiversity observations under different policy and management options. For instance, local and regional biomass information is essential for assessing the status and monitoring the dynamics of ecosystem structure. Phenology is also an important EBV that indicates trends, shifts, and structural changes of species traits within an ecosystem. Forest cover, loss and gain mapping, and biomass information are relevant for the CBD target 5, 11, 14, and 15. Information on plant phenology is relevant to the CBD targets 10 and 15 (Pereira et al., 2013).

Satellite Remote Sensing (SRS) offers the possibility of achieving the above targets more accurately and efficiently than the usual extensive ground field campaign often employed by ecologists. The implementation of the CBD's-Essential Biodiversity Variables using field assessments or in situ data gathering method in the tropical forest terrain is costly and time-demanding. SRS data has the capability of constant, repetitive, and cost-effective monitoring of large areas and its application in forest ecosystem monitoring studies is on the increase. Therefore, SRS data can provide precious information nearly impossible to be acquired solely by field assessment.

In other to enhance and broaden biodiversity monitoring in time and space with the EBV classes. The remote sensing-essential biodiversity variables (SRS-EBVs) were introduced as a subset of EBVs and their application relies largely on the use of satellite-based data (Pettorelli et al., 2016). SRS-EBV includes variables whose monitoring relies on the integration of satellite-based data with in situ data. SRS-EBVs can therefore be used as proxies for indicating defined targets for biodiversity conservations (Table 1).

Table 2: SRS-EBV Variables

Examples of SRS-EBV measurable variables			
EBV Class	**EBV Examples**	**Variables meeting SRS-EBV**	**Relevance for CBD Targets**
Genetic composition	Habitat structure	Specific plant genotype	5, 11, 14,15
Species population	Abundance and distribution	Specie occurrence	4,5,6,7,8,9,10,11,12,14,15
Species traits	Phenology	Specie leaf area	10,15
Community composition	Taxonomic diversity	Taxonomic diversity	Targets 10, 15
	Remote sensing of cover	Vegetation height	
Ecosystem structure	(Biomass inclusive) regionally or globally	Aboveground biomass	8,10,14
	Fractional cover	Aboveground biomass	
	Forest cover		
	Land cover		
	Fraction of absorb		
	Leaf area index		
Ecosystem function	Vegetation Phenology		5,8,14

Remote sensing offers the possibility of measuring forest carbon stocks using instruments mounted on satellites or airborne platforms. Optical remote sensing, radar (microwave), and LiDAR data are the three main types of remotely sensed data that are used to extract information for biomass and stand parameters. The passive optical and hyperspectral provides information on tree canopy attributes, leaf area, and tree species types. Optical remote sensing data are mostly used in tropical forest aboveground biomass studies because of the availability in a wide range of spatial and spectral resolutions, affordability(cost), and easy access (Nichol. J. E & .R., 2011).

Forest structural parameters such as the tree heights, canopy height, aboveground biomass, etc have been modeled using optical remote sensing in conjunction with the ground truth measurement and spectral signals such as vegetation indices using the Red and Near Infrared wavelengths (Sarker & Nichol, 2011). Vegetation indices, principal components analysis, minimum noise fractions, tassel cap transformation, spectral mixture analysis, and texture measures are a few of the techniques that are used to produce variables for estimating AGB from optical data (Lu et al., 2016). There are limitations to the use of optical satellite remote sensing for aboveground biomass modeling in tropical forests. The limiting factors include vegetation heterogeneity, canopy shadows, and undulated landscapes that characterized most tropical forest ecosystems. Similarly, the possibilities of data saturation in forests with high forest structural parameters (e.g., AGB) levels have been observed with optical remote satellite images.

The active sensors such as Light Detection and Ranging (LiDAR) and Radar are independent of the sun and the time of the day. LiDAR is known to provide accurate information on the vertical distribution of canopy/ height structure and is useful for three-dimensional (3D) characterization of forest attributes such as the aboveground biomass. LiDAR data was used in mapping forest biomass in French Guiana with an error of 14% and estimates of 340 Mg/ ha. LiDAR use for tropical forest biomass estimations is limited by coverage and the economic cost of procuring the images. Radar data are also independent of the time of the day, and weather and can provide a multi-faceted source of information such as frequency, incidence angle range, polarization, and interferometric baseline. Its advantages also include sensitivity to surface roughness, and imaging possibility from different types of polarised energy (HH, VV, HV, and VH). Forest structural parameters retrieval using radar satellites in the tropical forest has risen significantly in the last few years. The Advanced Land Phased Array Synthetic Aperture Radar (ALOS-PALSAR) data were used in the estimation of the aboveground biomass of the Guinea-Bissau forest and the result obtained from the study (65.17 mg/ha^{-1}) was concurrent with the regional estimate of AGB.

Machine learning methods for aboveground biomass retrieval

In satellite remote sensing applications, the use of retrieval algorithms or machine learning methods has become an essential component of forest structural parameter modeeling or estimation. Retrieval algorithms are crucial to remote sensing-based forest structural parameter modeling and can be grouped into two broad categories: parametric and nonparametric algorithms. In a parametric algorithm, it is assumed that the relationship between dependent variables(eg, volume, canopy height, basal area, AGB) and the independent variables (features derived from SRS data) can be explicitly specified(Lu et al., 2016). Simple or multiple linear regression models are examples of parametric algorithms. Most often, the AGB relationship with satellite remote sensing variables is nonlinear because the relationship between AGB and remote sensing variables is too complex to be captured by parametric algorithms.

Therefore, nonparametric algorithms are flexible and easy to adapt to complicated no-linear biomass models (Lu et al., 2016). Examples of nonparametric include artificial (ANN), K-Nearest

Neighbor (K-NN), support vector machine (SVM), maximum entropy (MaxEnt), and random forest algorithm. Regression-based models are the most common approach to forest structural parameter modelling using SRS data (Lu et al., 2016). A review of retrieval algorithms and their performance in table 4 by Ali et al,. (2015) showed a wide range of excellent performance with various Satellite Remote Sensing images.

Table 4: Examples of Machine Learning Algorithms

Sensor	Resolution	Parameter(s)	Algorithm	Performance (r)	Reference
LiDAR					
ICESat-1		Tree height			
Quick Bird		Height, Biomass, Volume	Support vector regression	0.72	(Huang, Peng, Lang, Yeo, & McCarty, 2014)
Quick Bird		Aboveground Biomass	Random forest	0.8	Adewoye et al, 2015
World view		Biomass	Random forest	0.75	(Mutanga & Skidmore, 2004)
Landsat 5		Aboveground biomass	Random forest	0.943	(Sarker & Nichol, 2011)
Spot		Aboveground biomass	Random forest	0.84	(Thenkabail, Enclona, Ashton, Legg, & De Dieu, 2004)
Landsat-7		Aboveground biomass	Support vector regression	0.75	(Cutler, Boyd, Foody, & Vetrivel, 2012)
MODIS		Aboveground biomass	Random forest	0.82	(Anaya, Chuvieco, & Palacios-Orueta, 2009)
GlAS		Aboveground biomass	Random forest	0.82	(Fatoyinbo & Simard, 2013)
Landsat 8		Canopy height	Random forest		

SECTION III: FOREST ASSESSMENT WITH BIG DATA OR DATA SCIENCE

Data science is the techniques, and processes of gathering, synthesizing, and understanding information through the automated analysis of data. Data science can also be defined as a set of fundamental principles that support the extraction of information and knowledge from data and a closely related concept to data science is data mining which is the extraction of knowledge from data through technics and principles known as algorithms (Provost & Fawcett, 2013). While hundreds of different data-mining algorithms exist, the ultimate goal of data science is to improve decision-making for policy and management (Provost & Fawcett, 2013).

Big data is an emerging frontier discipline, and the main purpose of big data is to quickly learn and acquire knowledge from the data (Zou et al., 2019). In forestry applications, big data is playing an increasingly important role in forest monitoring and forestry decision-making. Big data has ushered in new development opportunities in forestry practice. The availability of large volumes of data in the forestry sector has made data science applications to the gained ground for modeling, prediction, and forecasting. Data science becomes easier on migration to the web or server-based interphase with the major advantages of analysis based on the server, quick and efficient data analysis, and storage and retrieval from the server. Several high precisions modeled data have been generated covering the entire world. The modeled data are gradually replacing the traditional in-situ data. For instance, the High-Resolution Global Maps of 21st-Century Forest Cover Change was produced by the University of Maryland in conjunction with the National Aeronautic Space Agency (NASA) in 2013 and has since been updated yearly with the current version in 2020 (Hansen et al., 2013). The forest cover change map by Hansen et al., 2013 was produced with 30-meter Landsat images with forest cover, forest gain, and forest loss maps for the entire world, Incidentally, the Forest Reference Emission Level (FREL) data submitted in 2018 by the Federal Ministry of Environment to the United Nations Framework Convention on Climate Change program on Reducing Emissions from Deforestations and Forest Degradation in Developing Countries (UNFCC REDD +) used the High-Resolution Global Maps of the 21st Century by Global data (UNFCC, 2018, 2019).

Several big data platforms that support data storage and analysis with machine learning capabilities are freely available. While some of the big data platforms are easy to use, others require programming language skills such as python, java, cc+, etc. For instance, big data platforms such as the System for Earth Observation Data Access, Processing, and Analysis for Land Monitoring (SEPAL. IO) and European Space Agency Sentinel Hub have easy navigation and analysis interphase, while platforms such as Google Earth Engine and pip cloud requires knowledge of python and java programming languages. Platforms for big EO Data Management and Analysis" as computational solutions that provide functionalities for big EO data management, storage, and access; that allow the processing on the server-side without having to download big amounts of EO data sets; and that provide a certain level of data and processing abstractions for EO community users and researchers(Gomes, Queiroz, & Ferreira, 2020). Below are examples of internet-based data science platforms for forestry and environmental monitoring artificial intelligence embedded for analysis.

TABLE 3: Examples of Internet-Based Data Science Platforms

S/N	Data Science Platform	Forestry & Environmental Based Applications	Website
1	System for Earth Observation Data Access, Processing, and Analysis for Land Monitoring (SEPAL)	Forest change detection Near real-time change detection	https://sepal.io/
2	Google Earth Engine	Forest change detection and Climate change studies early warning systems.	https://earthengine.google.com/
3	Earth Blox	Forest change detection Climate change studies early warning system.	https://www.earthblox.io/
4	Sentinel Hub	Forest change detection Near real time change detection	https://www.sentinel-hub.com/
5	Open Data Cube (ODC)	Forest change detection Near real time change detection	https://www.opendatacube.org/

S/N	Data Science Platform	Forestry & Environmental Based Applications	Website
6	JEODPP	Forest change detection Near real time change detection	https://jeodpp.jrc.ec.europa.eu/
7	pipsCloud	Forest change detection Near real time change detection	
8	openEO	Forest change detection Near real time change detection	https://openeo.org/
9	**Earth on AWS**	Forest change detection Climate change studies early warning systems.	https://aws.amazon.com/earth/
10	Microsoft Azure Cloud Services	Forest change detection Climate change studies early warning systems.	https://azure.microsoft.com/en-us/

CONCLUSION

The current technology and strategy of forestry big data can effectively deal with massive forestry data and meet the requirements of real-time queries and analysis for forestry and environmental-based applications. This paper has reviewed the current trends of forest digitization and big data applications from three perspectives: data acquisition, Satellite Remote Sensing, and Big data applications or smart forestry. The use of AI technology has reduced the pressure on data storage and processing, thereby improving the performance of forestry big data and the development of artificial intelligence (AI) related technologies has created enormous value for various fields.

The current trend worldwide is the formation of joint research between organizations. For instance, the Brazilian Environmental Monitoring Project (Map Biomass) and the Swiss Data Cube (SDC) are joint research initiatives between scientific organizations. No organization (Research Institute or University) can do it alone. The need for consortiums of Research Institutes and Universities in Nigeria to come up with the common goals of a joint big data center is necessary. The big data center will form the backbone for data archiving, analysis and dissemination.

Integrating big data or data science applications into the undergraduate and postgraduate curriculum is now a necessity to meet up with the current development in the forestry sector. Some Forestry and Environmental-based departments are ahead in the teaching and analysis of data using the R packages. However, forest digitization requires knowledge of other programming languages such as Python, Java, CC++, etc. Therefore, the University curriculum needs to be updated either through the Nigerian University Commission (NUC) or individual course restructuring as observed with some departments in Nigerian Universities.

Technology is always evolving and humans have learned to adapt to technological developments. The age of smart forestry through big data applications is here, curriculum developments through the National University Commission or individual universities are not enough. Training and re-training of scientists must be accommodated in other to be at the same pace with the current developments and funds for training can be sourced from organizations such as the Tertiary Education Trust Fund (TETFUND), Education Trust Fund (ETF), Ecological Funds and host of other Institutions.

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