Space-based Mapping And Assessment of a Three-decade Urban Landcover Dynamics Towards a Smart Federal Capital City, Abuja, Nigeria

ABSTRACT

It has been argued that the global urban population is expected to grow by 63% between 2014 and 2050 – compared to an overall global population growth of 32% during the same period. A general notion from majority of researchers noted that connecting rural-urban services with Information Technology (IT), Internet of Things (IOT), Information Communication Technology (ICT) and Artificial Intelligence (AI) is making cities smarter. The Federal Capital City (FCC), Abuja, Nigeria is no exception. This study is aimed at mapping and assessing a three-decade urban dynamics of the FCC, Abuja, towards having a Smart Capital City (SCC) that should ordinarily be digitally developed. Currently, there is paucity of Knowledge on the geospatial extent and changes in urban development in years past. Analyzing 3 epochs of Landsat ETM+ using the maximum likelihood algorithm Remote Sensing image processing technique, the study shows that over the last thirty (30) years (2000, 2010 to 2020), builtup urban land cover has increased significantly from 72.88 km^2 (22.04%) in year 2000 to 145.77km^2 (44.09%) in 2020. As the alteration of natural vegetation paved the way for urban infrastructure, the study confirms a ripple effect on the decrease in light vegetation cover from 119.85km^2 (36.25%) in 2000, to 29.24km^2 (8.84%) in 2010, and down to as low as 13.49km2 (4.08%) in 2020. Same applies to other land covers. The total (overall) accuracy of supervised classifications carried out for the three periods examined are 97.3%, 99.2% and 99% respectively with corresponding strong positive Kappa statistics of 0.95, 0.99 and 0.97. It is recommended that Smart City initiatives anchored on digital hubs be deployed in ongoing and future city-wide development activities in order to fast track smart, smooth, effective and efficient service delivery in the study area.

Keywords: *Smart City, Urban Dynamics, Remote Sensing, Image Processing*

1. INTRODUCTION

The idea of a smart city is a concept with multiple definitions. The majority opinion however views it in the sense of leveraging technology to plan and manage cities using Information Communication Technology (ICT) and the Internet of Things (IoT) (31; 37; 30). Consequently, the concept has been variously explained as intelligent cities, smart communities, digital, wired or networked cities or even ubiquitous cities (10; 17). This is perhaps why Simpson (34) opined that the smart city concept will have different meanings in different cultures and can sound elusive until it is broken down into practical terms. Smart city is not just a term for metropolitan areas that have implemented effective and ergonomic ways of distributing resources rather, it is a movement that is creating citizen-centred ecosystems that improve quality of life and stimulate economic activity by facilitating cashless transactions through contactless technologies (29; 4).

Smart City can be regarded as a digital platform with numerous frontiers coupled with positive ripple effects on urban landscape development (37). In 2020, Smart city developments were greatly influenced by the Covid-19 pandemic as social distancing demanded more contactless interactions when accessing public services or making transactions (9; 29). Therefore, Smart cities are defined as smart both in the ways in which governments harness technology as well as in how they monitor, analyze, plan, and govern the city to meet the challenges of urban growth (26; 11). For instance, as noted by Battista, Evangelisti, Guattari, Basilicata and Lieto Vollaro (7), most of the world's population lives in urban areas and in inefficient buildings under the energy point of view.

Estevez, Lopes and Janowski (14) opined that the global urban population is expected to grow by sixty-three (63) percent between 2014 and 2050 – compared to an overall global population growth of thirty-two (32) percent during the same period. Consequently, mega cities with over twenty million inhabitants will see the fastest increase in population – and at least thirteen (13) new mega cities are expected by 2030, in addition to the twenty-eight (28) existing today. Interestingly, the fastest growing urban centres contain around a million inhabitants, and are located in the lower-middle-income countries in Asia and Africa. According to Dameri (13), the significant increase in urbanization has led to cities of unprecedented sizes and densities which requires high level of technological input. Therefore, the drive for innovative technology is aimed as building support from citizens which the Smart City concept is aimed at (17; 39).

Technology has becomes an integral part of our environment and the volumes and heterogeneity of the geographic data that need to be processed are also on the increase (14). The trend towards mega-cities is likely to continue in the next decades and will lead to even higher concentrations of populations in urban areas like the Federal Capital City, Abuja, Nigeria, the current study area. Consequently, the anticipated growth of cities create unprecedented sustainability challenges. Thus, increasing demands for energy, water, sanitation, education, healthcare, housing, transport and public service are testing the limits of city infrastructures hence, the need to have smart geospatial technologies to manage these challenge (2). Literature reveals that a general notion from majority of the researchers identifies that connecting rural-urban services with Information Technology (IT), Internet of Things (IOT), Information Communication Technology (ICT) and Artificial Intelligence (AI) is making cities smarter (35; 37). The concept, challenges and solutions to smart city initiative in the Federal Capital City (FCC) could be explained using Figure 1, which shows different components of a smart city managed with the aid of ICT. The determined criteria of smart city, according to Sharifi (33) are (i.) Smart economy, (ii.) Smart people, (iii.) Smart data, (iv.) Smart mobility, (v.) Smart living, (vi.) Smart governance, and (vii.) Smart environment.

In fact, experts estimate that up to 80% of future economic growth in developing regions will occur in cities alone (29). Consequently, as cities become an even more important driver of the global economy and wealth, it's becoming crucial to ensure that they are optimized to maximize efficiency and sustainability, while enhancing the quality of life in each urban conglomeration (29). The Federal Capital City, Abuja, the study area, is the seat of the Federal Government of Nigeria with all the structures and infrastructure of government services that needs to be smart in nature in order to be able to meet the challenges facing its large populace that has continued to grow in space and time. Thus, the delivery of good governance in a fast growing multi-faceted urban space like the Federal Capital City, Abuja, requires a more improved digital approach that will meet the need for fast and reliable smart urban system (3). This can only be possible if one knows the changes in landuse landcover (LULC) due to land development and governance policies.

As there is no known recent studies on the spatial growth of urban development in the FCC, this study is, therefore, specifically aimed at mapping and assessing the growth dynamics of the city towards having a sustainable Smart Urban territory as the seat of the Federal Government of Nigeria, a primate city, that caters for others. This study is based on trend analysis of synoptic Satellite Images of a three-decade snapshots of landcover (2000, 2010 and 2020) as knowledge of the spatial growth will help the city planners and administrators to effectively and efficiently manege the city in a more acceptable smart way devoid of manual guess work that is usually bedeviled with all sorts of errors and corruption.

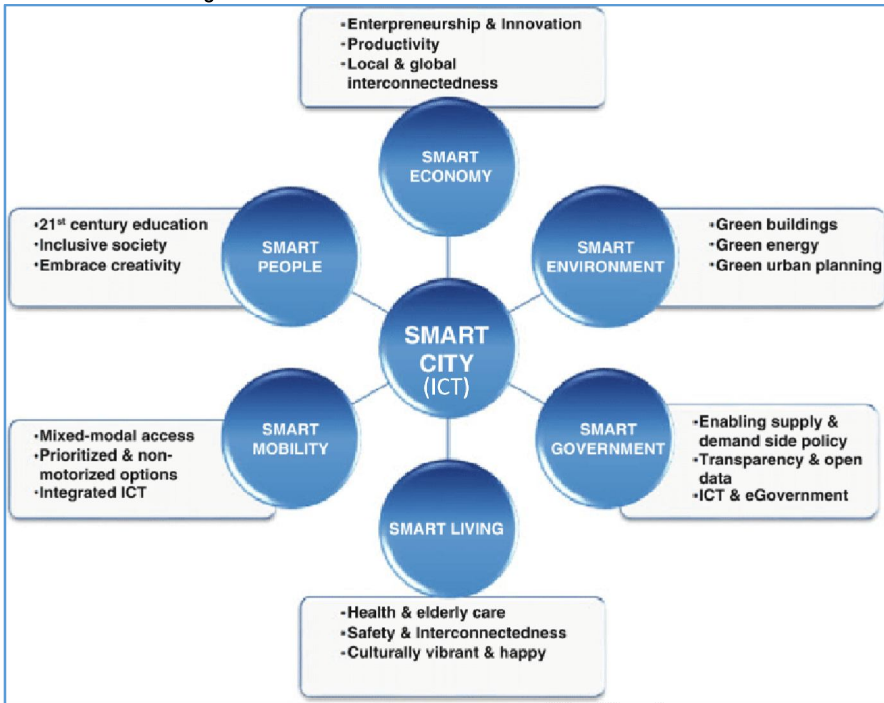

Figure 1: Model of the components of a Smart City

Source*: Modified after Wlodarczak (38) and Dameri (13)*

2. Materials and Methods

2.1 The Study Area

The Federal Capital City (FCC), Abuja is located on the north-eastern part of the Federal Capital Territory (FCT), Nigeria as illustrated in Figure 2. Abuja lies within latitude 9° 15' to 8°56' north of the equator and longitude 7° 09' to 7° 34' East of the Greenwich meridian.

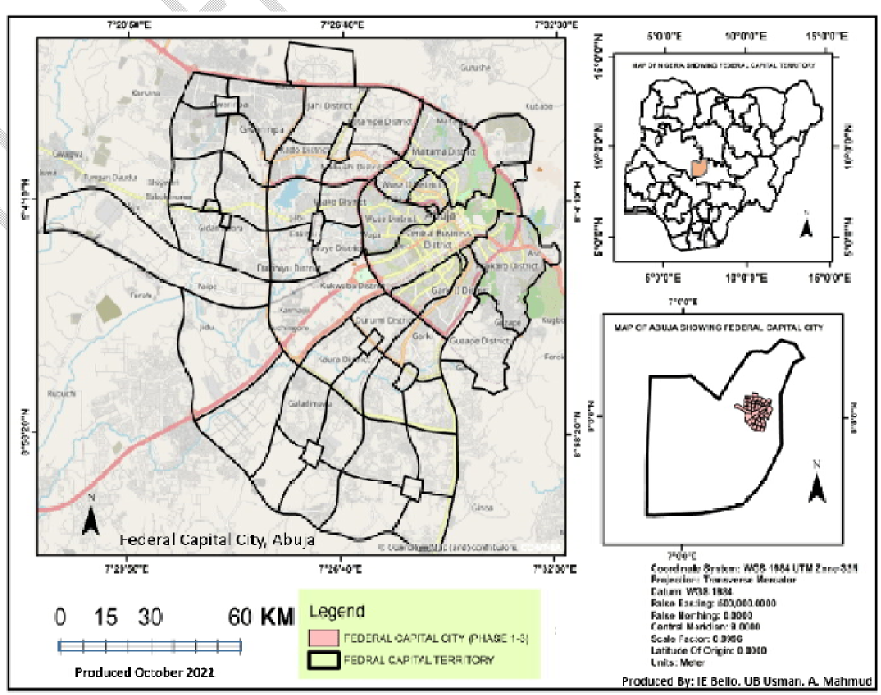

Figure 2: Location of the Federal Capital City, Nigeria.

Source: Modified after (36)

Abuja's Central District in the FCC is located between the foot of Aso Rock and into the Three Arms Zone to the southern base of the ring road. It is like the city's spinal cord, dividing it into the northern sector with Maitama and Wuse, and the southern sector with Garki and Asokoro (5). While each district has its own clearly demarcated commercial and residential sectors, the Central District is the city's principal Business Zone, where practically all parastatals and multinational corporations have their offices situated. An attractive area in the Central District is the region known as the Three Arms Zone, so called because it houses the administrative offices of the executive, legislative and judicial arms of the Federal Government. A few of the other sites worth seeing in the area are the Federal Secretariats alongside Shehu Shagari way, Aso Hill, the Abuja Plant Nursery, Parade Square and the Tomb of the Unknown Soldier across the road facing it. In the Abuja Master Plan, the FCC was conceived to accommodate estimated population of 157,750 persons in residence on inauguration in 1986, then 485,660 persons in 1990, 1,005,800 persons in 1995 and 1,642,100 persons in 2000 as noted by FCDA in 1979 (15; 1; 27). It would then grow to a maximum population of approximately 3.1 million, after which the population growth would be accommodated outside the city in the Satellite towns. No doubt, with increase in population due to migration from different parts of the country, the FCC has experienced rapid urban growth and congestion which this study examined in detailed using space-based technology.

2.2 Methodology

This study is based on time series research design (Figure 3) with respect to the urban development change initiatives in making the FCC, Abuja a Smart City. To validate the above, three epochs synoptic Landsat ETM+ satellite images covering three decades (2000, 2010, and 2020) were digitally processed using supervised classification approach with Erdas Imagine Digital Image Processing (DIP) software. The changes in the spatial classes were analyzed using the Geographic Information System (GIS) Technique.

In theory, the digital image classification uses the quantitative spectral information contained in an image which is related to the composition or condition of the target surface (8).

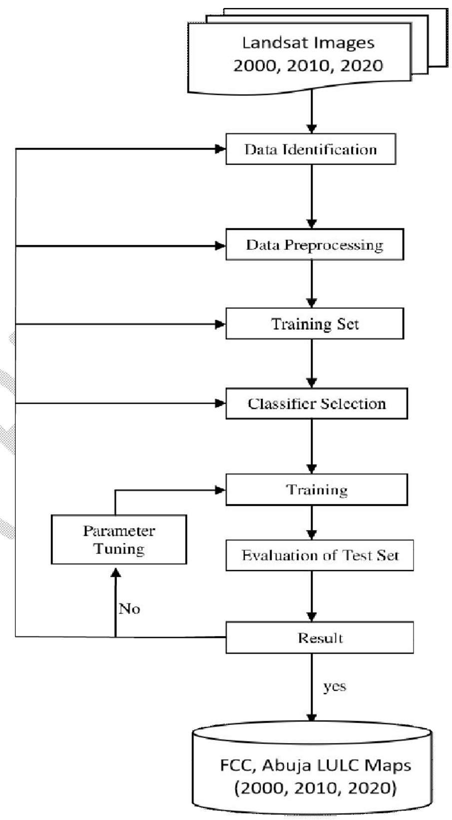

Figure 3: Adopted Digital Image Processing Workflow Methodology

Source: Authors (2022)

Image analysis requires an understanding of the way materials and objects of interest on the earth's surface absorb, reflect, and emit radiation in the visible, near-infrared, and thermal portions of the electromagnetic spectrum. In this study, combined Bands 4,3,2, (Near Infrared, Red and Green) were used to display the multi-spectral reflectance signal content of the area before analysis. Note that, the extraction of information from remotely sensed data is frequently accomplished using statistical pattern recognition hence, land-use/land-cover classification is one of the most frequently used methods (18).

Procedural, the Supervised digital image classification requires the image analyst to choose an appropriate classification scheme, and then identifies training sites in the imagery that best represent each class. In this study, the Anderson *et al.,* (19) Classification scheme (Table 1) was adopted because it is the most well documented and detailed scheme in LULC analysis. In this method, a sufficient number of training sites in each class to represent the variation present within each class in the image composite were selected. The Maximum Likelihood Classification algorithm then uses spectral characteristics of the training sites to classify the remainder of the entire image coverage. Accuracy/Kappa coefficients of classifications are evaluated as part of the Spatial Data Quality (SDQ) requirement in relying on the results obtained (16).

Table 1. Land cover classification scheme adopted in the study

SN	Land Cover Classes	Component
i.	Built-up/Urban area	Urban and rural built-up including homestead area such as residential, commercial, industrial areas, villages, settlements, road network, pavements, and man-made structures
ii.	Thick Vegetation	Old plantation, unaltered forest, undisturbed vegetation
iii.	Light Vegetation	Cropland and pasture, Orchards, groves, vineyards, nurseries, and ornamental horticultural areas, Confined feeding operations, Other agricultural lands
iv.	River/Water bodies	Open water features including lakes, rivers, streams, ponds and reservoirs
v.	Bare surface	Fallow land, earth and exposed river sand land in-fillings, construction sites, excavation sites, open space and bare soils
vi.	Rock Outcrop	Rock Faces on Mountains, Rock Slides, and Cliffs.

Source: Modified after Anderson et al., (19)

(i) Maximum Likelihood Classifier (MLC)

The Maximum Likelihood Classifier (MLC) algorithm was used to execute the classifications into six (6) spatial classes of Builtup area (urban), Rock outcrop, Bare Surface, Thick Vegetation, Light Vegetation and Water respectively. The justification for using the MLC algorithm is because as shown from previous studies by Roostaei, Alavi, Nikjoo and Valizadeh-Kamran (32), it has a major advantage over other classifiers as mathematically explained below.

Mathematically, using the MLC based on the Bayesian probability theory:

> 'an unknown pixel **x** with multi-spectral values (n bands) will be classified into the class (k) that has the maximum likelihood [max Lk (**x**)]'. The likelihood function is given on the assumption that the ground truth data of class k will form the gausian (normal) distribution as denoted in equation 1 (32).

$$L_k(x) = \frac{1}{(2\pi)^{\frac{n}{2}}|\Sigma_k|^{\frac{1}{2}}} \exp\left[-\frac{1}{2}(x-\mu_k)\sum_k^{-1}(x-\mu_k)\right] \quad - \quad \textit{(eqn. 1)}$$

Where μ_k: mean vector of the ground truth data class, $k\sum_k$: variance-covariance matrix of k class produced from the ground data, and $|\sum_k|$ is the determinant of $\sum k$.

(ii) Accuracy and Kappa Statistical Assessment of the Classifications (2000, 2010, 2020)

The statistical accuracy assessment was done with the view of ascertaining the reliability of the spatial classifications done for the three decades LULC images. Thus, accuracy actually reflects the difference between the target dateset and the reference dataset (16). The process usually summarizes all data in a confusion matrix and reports several indicators such as overall/per class accuracy, Kappa index of agreement, user's accuracy and producer's accuracy. In this study, a confusion matrix analysis was applied to achieve these measures. These have been the most straight forward and practical statistical tools for checking the degree of match between two thematic datasets (12). A measure for the overall accuracy is calculated by dividing the number of identical pixels by the total number of pixels and expressed in percentage. However, it does not identify how well individual classes between the two datasets match. Hence, the user's accuracy and producer's accuracy were calculated to measure for each class.

Overall accuracy and Kappa Statistics are mathematically defined thus:

a) The Overall Accuracy (**OA**) equation (Matinfar *et al.,* 2007) is given as:

$$OA = \frac{\sum_{i=1}^{c} \mathrm{Eii}}{\mathrm{N}} \qquad - \qquad \textit{(equ. 2)}$$

Where ***c*** is the number of the classes, **N** is the number of certain classes; **Eii** is the error matrix diagonal cell.

b) The Kappa (**K**) statistical analysis equation (12; 24; 32) is given as:

$$K = \frac{\mathrm{N}\sum_{i=1}^{k} \mathrm{nii} - \sum_{i=1}^{k} \mathrm{ni+n+1}}{\mathrm{N}^2 - \sum_{i=1}^{k} \mathrm{ni+n+1}} \qquad - \textit{(equ. 3)}$$

Where **nii** is the number of observations in $\mathbf{i_{th}}$ row and $\mathbf{i_{th}}$ column on the main matrix diagonal, n+1 is the total number of observations in $\mathbf{i_{th}}$ row and $\mathbf{i_{th}}$ column and **N** is the total observations.

3. Results and Discussions

3.1 Urban Spatial Dynamics of FCC, Abuja Towards a Smart City

As shown in Table 2, the study revealed that there has been remarkable multi-dimensional dynamics in urban land uses in the study area. Thus, it is abundantly clear that over the last thirty (30) years (2000 and 2020), the Federal Capital City (FCC), Phase 1-3 has grown with noticeable LULC dynamics evidently captured from remotely sensed satellite image coverage from which the maps for years 2000, 2010 and 2020 were produced (Figure 4 and 5). Thus, the urbanized land area has increased tremendously from 72.88km^2 (22.04%) in 2000 to 145.77km^2 (44.09%) in 2020. Urban expansion leads to reduction in other land covers as evidence in the light and thick vegetation covers.

Table 2. FCC-Abuja LULC Change Indices for 2000, 2010 and 2020

LULC Classes		**2000**		**2010**		**2020**	
		Area Covered (Km²)	**(%) Covered**	**Area Covered (Km²)**	**(%) Covered**	**Area Covered (Km²)**	**(%) Covered**
i.	Bare Surface	60.01	18.15	175.65	53.13	115.07	34.80
ii.	Built-Up	72.88	22.04	39.84	12.05	145.77	44.09
iii.	Light Vegetation	119.85	36.25	29.24	8.84	13.49	4.08
iv.	Rock Outcrop	52.18	15.78	23.70	7.17	23.59	7.14
v.	Thick Vegetation	24.23	7.33	60.68	18.35	31.48	9.52
vi.	Water Body	1.40	0.42	1.49	0.45	1.22	0.37
Total		***330.6***	***100***	***330.6***	***100***	***330.6***	***100***

Source: Author's Analysis (2022)

One of the major characteristics of a smart city is a growing urban landuse and a functional city population with its attendant noticeable changes in landuse and landcover (LULC) (28). The noticeable urban changes in the study area is a clear physical manifestation of an emerging geographic space requiring high level of e-governance structures to be able to manage the businesses of government. Thus, the observed increase in urbanization of the FCC, Abuja is an indication of a remarkable need to consider the FCC-Abuja for a full-scale smart city in view of the growing urban land occupation and different landuse potentials. In fact, the available buildings in the FCC since the advent of the 1999 civilian democratic rule which saw to the relocation of elected political leaders and government workers to the city led to having several state-of-the-art modern architectural designs. These emerging innovative structural designs have lots of smart city components which include, but

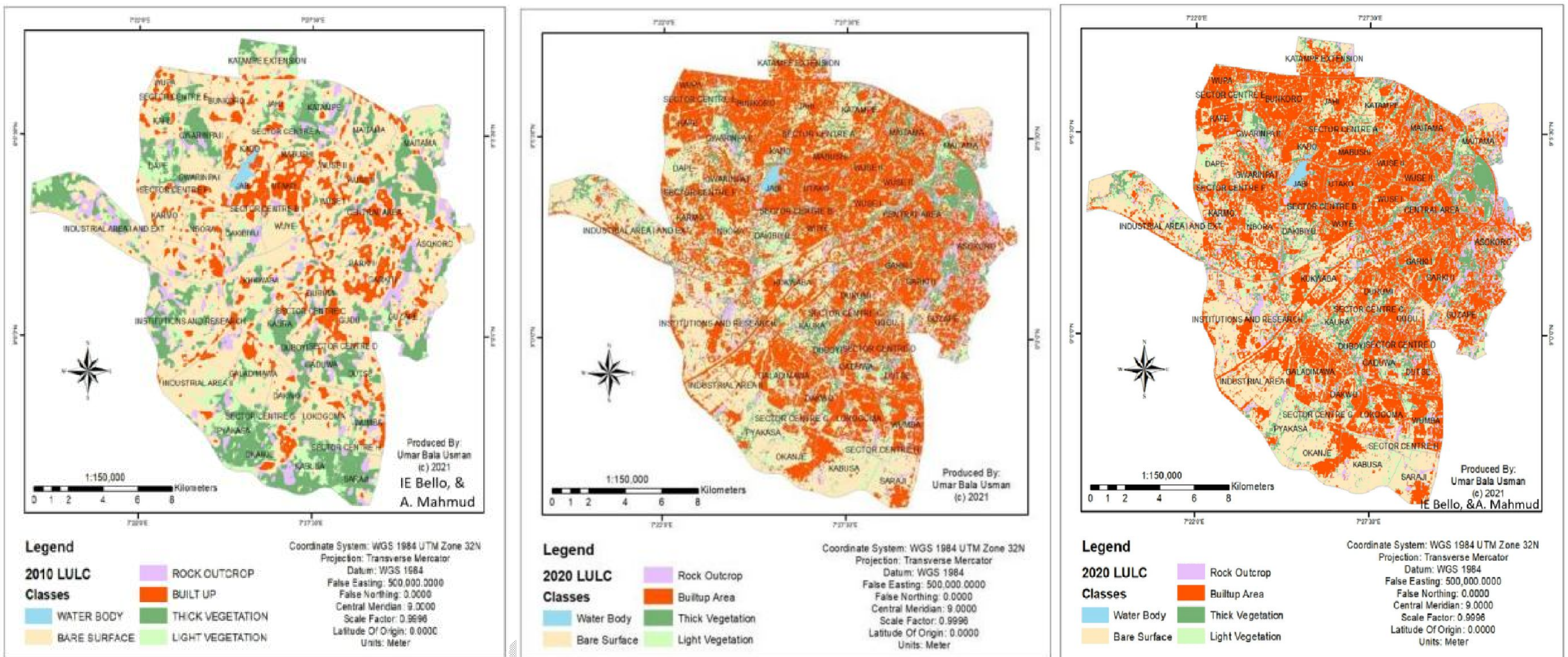

Figure 4. Mapping of Landcover Dynamics of The Federal Capital City, Abuja

Source Data: Extracted from Landsat ETM+ (2000, 2010, and 2020 respectively)

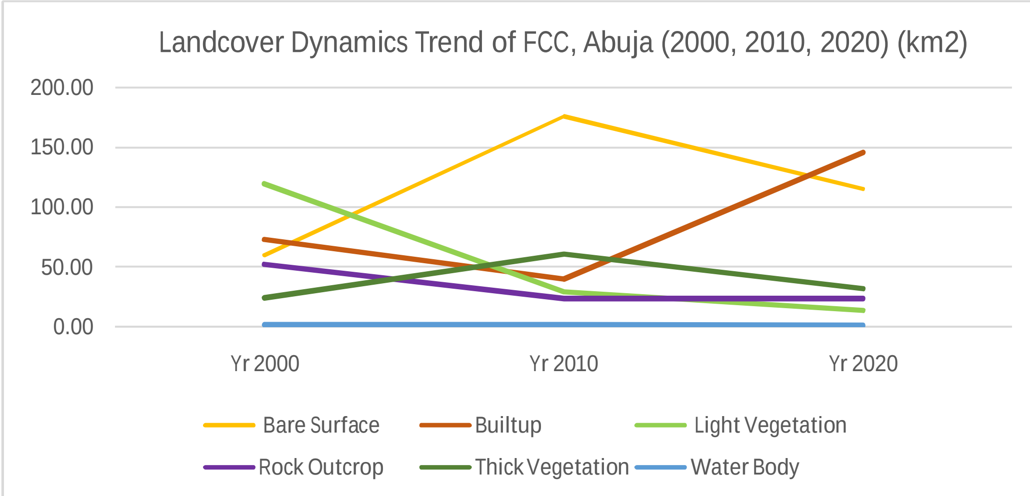

Figure 5: Trend of Landcover (km^2) Changes in FCC, Abuja (2000, 2010, and 2020)

not limited to electric gates, CCTV installations, Voice-enabled security doors, safe and vehicles of all kinds abound. Several quarters housing government functionaries and commercial housing estates have also increased to cater for the teeming population trooping into the city.

Globally, increased urbanization has raised various challenges which affect the economic and environmental sustainability of cities around the world (37). In fact, as captured in the LULC dynamics maps over the past thirty (30) years in the study area, built-up (urban) has grown astronomically (Figure 4). This implies a corresponding increase in human population as well. Various cars, houses and gadgets are becoming smart in nature. In essence, it is, therefore, empirically correct to assert that the LULC dynamics of the Federal Capital City (Phase 1- 3), for the year 2000, 2010 and 2020 respectively demonstrate that the city is digitally ripe to be considered a smart city though with more e-governance structures yet to be fully deployed.

Rapid growth in urban land cover in time and space indicates a corresponding decrease in other LULC. The implication of the decrease in other land covers is that more digital efforts are needed to be able to effectively and efficiently govern and manage the geo-ecosystem in a sustainable manner if the health of the people is to ever be guaranteed to a reasonable degree. This is because, the supply of oxygen by trees, has no doubt, be reduced due to the rapid urbanization activities of the government and residents in the study area. It is important to note that effort have been
made in previous attempt to make the Federal Capital City a smart one. This can be supported in view of the enormity of existing literature to that effect (23; Ishaku and Obasanya, 2012; 6). Unfortunately, over the years, Abuja FCC continued to experience persistent urban problems (20; 21).

At least, for the three decades under review, two principal factors were responsible. Firstly, the implementation of the Abuja Master Plan. Although this exercise had been grossly marred by overzealous and greedy officials who intentionally distorted the plan to achieve selfish interests of powerful officials and Nigerians. Secondly, the adoption of unsuitable/unworkable conceptual and or theoretical city planning paradigm to guide the growth and development of the capital city (22). It is important to also point out that to further create the awareness of smart city among city planners in the country, and the Federal Capital Territory (FCT) in general, the 2017 Abuja Planners' Conference marked on September 28th focused on the theme: 'Making Abuja A Smart City. Between 2017 and 2019, the city of Abuja has undertaken numerous efforts toward making Abuja a master city, prominent being the proposed Abuja ICT and Smart City Policy currently under formulation. But, before now, Abuja has been developing strategic infrastructure and programme expected to drive the takeoff of Abuja as a smart city. This efforts should be sustained toward making the FCC, Abuja, Nigeria a full fledged Smart City in no distant time.

3.2 Accuracy/Kappa Assessment of Classifications for 2000, 2010 and 2020 LULC

Clarification of urban dynamics and analysis is incomplete without accuracy assessment (18). This is because, accuracy assessment helps to ascertain the level of confidence to rely on when using the result (map) from classifications for decision making (8).

Based on the above premise, the study reveals that from the statistical analysis derived from the classified images and mapped landcover classes, the total (overall) accuracy for the three periods examined were 97.3%, 99.2% and 99% respectively for the years 2000, 2010 and 2020. These were derived from Error matrices (contingency Tables) shown in Tables 3, 4 and 5.

Table 3. 2000 Error Matrix for Land cover classes (Landsat TM)

LULC Classes	Water Body	Bare Surface	Rock Outcrop	Builtup Area	Thick Vegetation	Light Vegetation	*Row Total*	*User Accuracy*
Water Body	215	0	1	0	0	0	***216***	**99.5%**
Bare Surface	0	134	0	16	0	0	***150***	**89.3%**
Rock Outcrop	12	0	428	9	0	0	***449***	**95.3%**
Builtup Area	1	0	0	969	0	0	***970***	**99.9%**
Thick Vegetation	1	0	8	0	75	0	***84***	**89.3%**
Light Vegetation	0	2	0	0	0	17	***19***	**89.5%**
Column Total	***229***	***136***	***437***	***994***	***75***	***17***	***1888***	
Producer Accuracy	**93.9%**	**98.5%**	**97.9%**	**97.5%**	**100%**	**100%**		

Table 4. 2010 Error Matrix for Land cover classes (Landsat ETM+)

LULC Classes	Water Body	Bare Surface	Rock Outcrop	Builtup Area	Thick Vegetation	Light Vegetation	*Row Total*	*User Accuracy*
Water Body	98	0	0	0	0	0	***98***	**100%**
Bare Surface	1	199	0	3	0	0	***203***	**98.0%**
Rock Outcrop	1	0	163	0	0	0	***164***	**99.4%**
Builtup Area	0	0	0	356	0	0	***356***	**100%**
Thick Vegetation	2	0	0	0	318	0	***320***	**99.4%**
Light Vegetation	0	2	0	0	0	53	***55***	**96.4%**
Column Total	**102**	**201**	**163**	**359**	**318**	**53**	**1196**	
Producer Accuracy	**96.1%**	**99.0%**	**100%**	**99.2%**	**100%**	**100%**		

Table 5. 2020 Error Matrix for Land cover classes (Landsat ETM+)

LULC Classes	Water Body	Bare Surface	Rock Outcrop	Builtup Area	Thick Vegetation	Light Vegetation	*Row Total*	*User Accuracy*
Water Body	191	0	0	0	0	0	191	**100%**
Bare Surface	0	160	0	20	0	0	180	**88.9%**
Rock Outcrop	0	0	96	1	0	0	97	**98.9%**
Builtup Area	6	0	0	2161	0	0	2167	**99.7%**

Thick Vegetation	0	0	0	0	70	0	70	**100%**
Light Vegetation	0	0	0	0	0	89	89	**100%**
Column Total	***197***	***160***	***96***	***2182***	***70***	***89***	***2794***	
Producer Accuracy	**96.9%**	**100%**	**100%**	**99.0%**	**100%**	**100%**		

Source: *Authors' Analysis, 2022*

In addition, the various user and producer accuracy for each of the LULC classes analyzed are also shown in the Tables. Similarly, the results of the three periods of 2000, 2010 and 2020 further showed a strong positive Kappa statistic of 0.95, 0.99 and 0.97 respectively hence, the LULC models can be relied upon to make informed decision on City-wide Smart Development by relevant authorities and the populace. Details of the calculations are shown below.

2000 Total Accuracy Assessment (TO) *(See Equ. 2)*

TO = 215+134+428+969+75+17/1888*100

= 1838/1888 * 100 = 97.3%

2000 Kappa (k) Statistics *(See equ. 3)*

K = (1888*1838) – (216*229 + 150*136 + 449*437 + 970*994 + 84*75 + 19*17)/

3564544 – (216*229 + 150*136 + 449*437 + 970*994 +84*75 + 19*17)

= 3470144 – 1236880 / 3564544 – 1236880

K = 2233264/ 2327664 = 0.95

2010 Total Accuracy (TO) Assessment:

TO = 98+199+163+356+318+53/1196*100

= 1187/1196 = 99.2%

2010 Kappa (k) Statistics:

K = (1196*1187) – (98*102 + 203*201 + 164*163 + 356*359 + 320*318 + 5*53)/

1430416 – (98*102 + 203*201 + 164*163 + 356*359 + 320*318 + 55*53)

= 1419652 – 310010 / 1430416 – 310010

K = 1109642/ 1120406 = 0.99

2020 Total (TO) Accuracy Assessment:

TO = 191+160+96+2161+70+89/2794*100

= 2767/2794 = 99.0%

2020 Kappa (k) Statistics:

K = (2794*2767) – (191*197 + 180*160 + 97*96 + 2167*2182 + 70*70 + 89*89)/

7806436 – (191*197 + 180*160 + 97*96 + 2167*2182 + 70*70 + 89*89)

= 7730998 – 4816954 / 7806436 – 4816954

K = 2914044/ 2989482 = 0.97

4. Conclusions

Development in 21st Century should be digital and smart in nature in order to effectively and efficiently support the delivery of good governance with less physical contacts as obtains in the developed world like Japan Singapore, United Kingdom, United Arab Emirate, United States of America, Germany, Netherlands, China, among others.

The specific objective of this study was to map and examine a three-decade urban dynamics of the Federal Capital City (FCC), Abuja, as the seat of the Federal government of Nigeria that should ordinarily be digitally developed as a Smart City. It has become evident that a number of initiatives had already been made to kick-start the digitalization of the FCC, Abuja as a Smart City but, knowledge on the geospatial extent and changes in urban development in years past have not been factored into such initiatives due largely to inadequate monitoring of the urban dynamics over the years. This study was, therefore, aimed at mapping the growth in physical urban development using Space-based satellite products (Landsat ETM+

images - 2000, 2010 and 2020) by analyzing the spectral reflectance of the identified classes and calculating the spatial changes in six land covers within the 30-year period under review. Remote Sensing and Geographic Information System technologies were applied to carry out the digital image processing and mapping respectively. Using the Maximum Likelihood Classifier (MLC). The total/overall, producer and user accuracy of classifications were calculated in addition to the kappa coefficient of each classifications. The study revealed that urban landscape increased from 72.88 km^2 (22.04%) in 2000 to 145.77km^2 (44.09%) in 2020 due to rapid migration into the city and corresponding rapid urban infrastructural development. Rapid rural-urban migration into the city has also been attributed to the increase in population and urban infrastructure. Therefore, with increasing population, there is the need to increase and improve on the digital system of governance which the Smart City Concept is all about. Otherwise, there will be difficulty in government service delivery as earlier corroborated by Rilwani and Bello (31) and Jibril (20; 21).

From this study, it is important to reiterate that increased urbanisation has raised various challenges which affect the economic and environmental sustainability of cities around the world. To Tuominen (37), the concept of smart cities has emerged as an urban development model focusing on finding solutions to urban challenges. Smart cities are often characterised by the utilisation of ICT and focus on issues such as creativity, innovation, and democratic participation processes which are expected to contribute to the creation of cities that foster sustainability, innovations, citizen-driven and citizen-centric governance, and business-led urban development (25). Innovations are often viewed as key ingredients of smart cities. However, while cities as built environments can be viewed as advantageous platforms for innovations to flourish, the existing infrastructure, resources, and governance structures of cities can also hinder innovation-based smart city development. Therefore, it is recommended from this study that the Federal Government of Nigeria through her Federal Capital Territory governance structures should start to integrate Smart City Concept in future urban development initiatives. This has become very important in view of increasing population coupled with the need to meet up with effective and efficient service delivery in the City. In addition, all new urban development plans must factor in the inclusion of Information Communication Technology (ICT) and Internet of Things (IoTs) in areas like building infrastructure, transportation, land administration, population management, and business services for both government and non-governmental organizations: whether private or public.

REFERENCES

1. Abuja Master Plan. *The New Federal Capital of Nigeria.* Federal Capital Development Authority (FCDA), State House, Marina, Lagos, Nigeria. 1979.
2. Agbaje GI, Bello IE, Ojo AG. Empirical assessment of the role of geospatial technology in delivering governance and strengthening democracy in Nigeria. *GeoJournal* (Germany), 2017; 82(331), 1–14. (Online): available at https://doi.org/10.1007/s10708-017-9797-4.
3. Akingbade AO. E-Land administration in the context of e-government in Africa: An evaluation of Nigeria's Abuja Geographic Information Systems. *ITC Ph.D. Dessertation Number 216.* Faculty of Geo-information Science and Earth Observation, University of Twente, The Netherlands. 2012.
4. Albino V, Berardi U, Dangelico RM. Smart cities: Definitions, dimensions, performance, and initiatives. *Journal of Urban Technology,* 2015; 22(1): 3-21.

5. Ayuba HK, Aguocha O, Medugu NI. Fire Vulnerability Assessment of the Federal Capital City, Abuja, Nigeria. *International Journal of Innovative Science, Engineering & Technology,* 2016, 3(5): 39 - 46.
6. Balogun O. *The Federal Capital Territory of Nigeria: A Geography of its Development.* University Press Ibadan, Nigeria. 2001.
7. Battista G, Evangelisti L, Guattari C, Basilicata C, Lieto Vollaro R. Buildings Energy Efficiency: Interventions Analysis under a Smart Cities Approach. *Sustainability,* 2014; *6, 4694-4705; doi:10.3390/su6084694.*
8. Bello IE, Rilwani ML. Quantitative Assessment of Remotely Sensed Data for Landcover Change and Environmental Management. *Indonesian Journal of Geography (Indonesia),* 2016; 48(2): 135 – 144. (Online): https://jurnal.ugm.ac.id/ijg/article/view/17629
9. Bello IE, Shaba HA. Geospatial Analysis of Hydrometeorological Dynamics for Managing Socio-economic and COVID-19 Threats in the Ossiomo Watershed, Nigeria. *The Indonesian Journal of Geography,* 2021; 53(3): 318-327. (Online): https://doi.org/10.22146/ijg.59605
10. Chatterton P. Will the real Creative City please stand up?. *City,* 2000; 4(3): 390-397.
11. Chatterton P, Hollands R. Theorising urban playscapes: producing, regulating and consuming youthful nightlife city spaces. *Urban studies,* 2002; 39(1): 95-116.
12. Congalton R, Green K. *Assessing the accuracy of remotely sensed data: principles and practices.* Boca Raton, Florida: CRC/ Lewis Publishers, 1999; 137 p.
13. Dameri RP. *Using ICT in Smart City, Smart City Implementation:* Creating Economic and Public Value in Innovative Urban Systems, Springer, Berlin. 2017; pp. 45–65.
14. Estevez E, Lopes NV, Janowski T. *Smart Sustainable Cities – Reconnaissance Study.* United Nations University, UNU-EGOV: Operating Unit on Policy-Driven Electronic Governance. International Development Research Center (IDRC), Canada. 2016. (Online): Accessed December 3, 2021 from http://collections.unu.edu/eserv/UNU:5825/Smart_Sustainable_Cities_v2final.pdf.
15. FCDA. *Nyanya Urban Renewal: Report on Nyanya Labour Camp Relocation*. URP, Federal Capital Territory, Nigeria. 1989.
16. Hennig T, Kretsch J, Salamonowicz P, Pessagno C, Stein W. The Shuttle Radar Topography Mission, *Proceedings of the First International Symposium on Digital Earth Moving.* London, UK: Springer Verlag. 2001.
17. Ishida T, Isbister K. (Eds.). *Digital cities: technologies, experiences, and future perspectives.* Springer Science & Business Media. 2000.
18. Jensen JR. *Introductory digital image processing: A remote sensing perspective* (2nd edition). Upper Saddle River, New Jersey, USA. Prentice Hall, Inc. 1996.
19. Anderson JR, Hardy EE, Roach JT, Witmer RE. A land use and land cover classification system for use with remote sensor data. USGS Professional Paper 964. A revision of the land use classification system as presented in the USGS Circular 671. 1976.
20. Jibril IU. Resettlement Issues, Squatter Settlements and Problems of Land Administration in Abuja, Nigerian's Federal Capital. Promoting Land Administration and Good Governance, *5th FIG Regional Conference,* Accra, Ghana. 2006; 1- 13.
21. Jibril IU. Planning and Land Administration Challenges in Developing New Cities:– The Abuja Experience in Nigeria. A paper presented at the *FIG Working Week 2015 From the Wisdom of the Ages to the Challenges of the Modern World,* Sofia, Bulgaria, (7723). 17-21 May 2015.
22. Jiriko KG. *Urban Master Planning Paradigm in Nigeria: What Future?* Mba Prints + Graphics and Publishing, Kaduna. 2008.
23. Jiriko GK, Dung Gwom JY, Wapwera SD. The Evolution Of Abuja As a 'Smart City' a Prognosis. 2015. (Online): Accessed February 18 2022, Available from: https://www.researchgate.net/publication/286458553_THE_EVOLUTION_OF_ABUJA_AS_A_'SMART_CITY'_A_PROGNOSISow=full.

24. Lu D, Weng Q. A Survey of image classification methods and techniques for improving classification performance. *International Journal of Remote Sensing*, 2007; 28(5): 823-870, DOI: 10.1080/01431160600746456.
25. McLaren D, Agyeman J. (2015). *Sharing Cities: A Case for Truly Smart and Sustainable Cities.* MIT Press. ISBN 9780262029728.
26. Mills D, Pudney S, Pevcin P, Dvorak J. Evidence-Based Public Policy Decision-Making in Smart Cities: Does Extant Theory Support Achievement of City Sustainability Objectives? *Sustainability,* 2022, 14, 3. https://doi.org/10.3390/su14010003
27. Obiadi BN, Onochie AO. Abuja, Nigeria Urban Actors, Master Plan, Development Laws and their Roles in the Design and Shaping of Abuja Federal Territory and their Urban Environments. *IARD International Journal of Geography and Environmental Management*, 2018; 4(4): 23-26.
28. Onokerhoraye AG. Geographic thought, philosophy and methodology. Benin Social Science for Africa. Ibadan: Intec Printers Limited. 1994.
29. Pelikh k. (2021). *Top Smart City trends.* O-City. (Online), Accessed January 4, 2022 from https://www.o-city.com/blog/top-smart-city-trends-2021.
30. Peris-Ortiz M, Bennett DR, Yábar DP. *Sustainable Smart Cities: Creating Spaces for Technological, Social and Business Development.* Springer. 2016. ISBN 9783319408958.
31. Rilwani ML, Bello IE. Holistic Approach to development of Smart Urban Cities and Emerging Challenges: An appraisal of some initiatives in Nigeria. *AAU Journal of Environmental Studies,* 2020; 5(2), 1-22.
32. Roostaei SH, Alavi SA, Nikjoo MR, Valizadeh-Kamran KH. . Evaluation of object-oriented and pixel-based classification methods for extracting changes in urban area. *International Journal of Geomatics and Geosciences,* 2012; 2(3), 738-749.
33. Sharifi A. A critical review of selected smart city assessment tools and indicator sets. *Journal of cleaner production,* 2019; 233, 1269-1283.
34. Simpson P. Smart cities: understanding the challenges and opportunities. *Smart City World.* 2018. *(Online): Accessed January 11, 2023 from https://smartcitiesworld.net/AcuCustom/Sitename/DAM/012/Understanding_the_Challenges_and_Opportunities_of_Smart_Citi.pdf*
35. Singh A, Kalita PC. Smart Cities: Literature Review and Case Studies. Conference: *State of The Art Seminar.* 2019. *(Online),* Accessed December 3, 2021 from https://www.researchgate.net/publication/331641045_Smart_Cities_Literature_Review_and_Case_studies#fullTextFileContent, DOI: 10.5281/zenodo.2589283.
36. Skyscrapercity.com. *Abuja City Master Plan:* Info, Images, News. 2008. Pages 1-6. (Online): Accessed August 3, 2021 from https://www.skyscrapercity.com/threads/abuja-city-master-plan-info-images-news.657904/
37. Tuominen E. Diffusion of innovations in a smart city context: Facilitation of innovation-oriented smart city development in Kalasatama. Turku University Library. 2018. (Online): Accessed November 7, 2021 from https://www.utupub.fi/handle/10024/144902?sh.
38. Wlodarczak P. Smart cities–enabling technologies for future living. In: A. Karakitsiou, et al. (*eds.*), *City Networks.* Springer. 2017; 128,1-16. DOI 10.1007/978-3-319-65338-9_1.
39. Onyekwelu, S. (2021). How prepared is Nigeria to become a smart nation?. (Online): Accessed December 2021 from https://businessday.ng/interview/article/abuja-has-the-potential-and-resources-to-attain-smart-city-status-essiet/#:~:text=Making%20Abuja%20a%20smart%20city%20was%20our%20intension,Platform%29%20to%20create%20a%20digital%20ecosystem%20for%20Abuja.