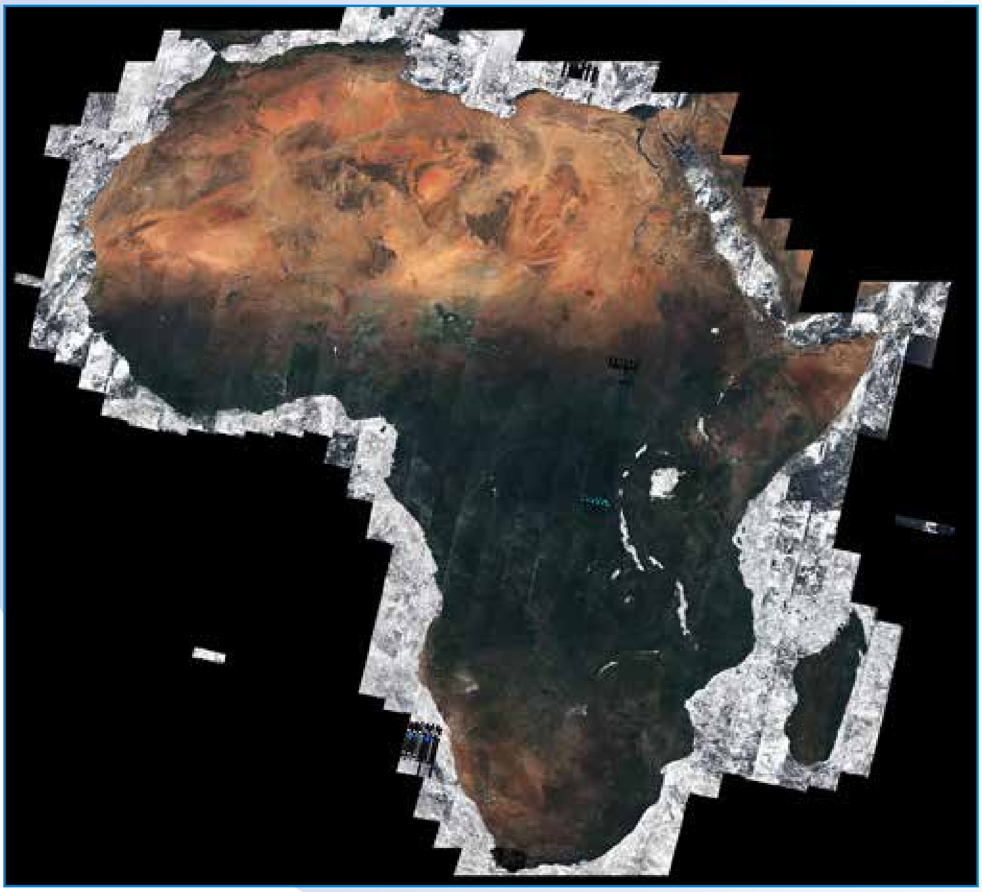
Continental-Scale Assessment of Urban Sprawl in Africa (2016–2024)

Quantifying Built-Up Expansion Using Sentinel-2-Derived Dynamic World V1 Data and Google Earth Engine

by Johnny Muhindo Bahavira*, Michael Paluku Lukumbi, Junior Lukoo Mitsindo, Mpanga Numbi Loïc, Hélène Akilimali Kabisuba, Acacia Muley Nyande



Between 2016 and 2024, Africa's built-up area expanded by 33.3 % (+ 60 687 km²). Large economies—Ethiopia, Nigeria and Kenya—drove most absolute growth, while smaller states—Central African Republic and Mauritius—registered the highest relative increases. Using Dynamic World V1 in Google Earth Engine, this study maps heterogeneous urbanization pathways across 55 countries.

Current findings from the United Nations Global Assessment Report on Disaster Risk Reduction (DRR) points out that the economic loss from disasters such as earthquakes, hurricanes and flooding range from US$250 billion to US$300 billion each year. In this context Space assets, such as satellites and remotely piloted aircraft (drones), can play a crucial role in emergency response and disaster management.

Africa is experiencing one of the fastest rates of urban growth worldwide, with its urban population projected to double by 2050 (United Nations Department of Economic and Social Affairs [UN DESA], 2018). This rapid urbanization often manifests as urban sprawl—an outward expansion of built-up areas into peri-urban and rural landscapes—which poses significant challenges for sustainable land management, infrastructure provision, and environmental resilience (Seto, Güneralp, & Hutyra, 2012). Remote sensing has become a pivotal tool for monitoring the

spatiotemporal patterns of urban expansion at multiple scales. Continental-scale land cover mapping in Africa has been demonstrated using Google Earth Engine, achieving high accuracy with multi-source data (Li, Qiu, Ma, Schmitt, & Zhu, 2020). However, most studies on urban sprawl in Africa remain confined to specific cities or regions (e.g., Iandolo, Rossi, & Bonomi, 2023; Mhangara, Gidey, & Manjoo, 2024), and comprehensive assessments across the entire continent are still scarce.
This study addresses this gap by quantifying the evolution of built-up areas in Africa for the years 2016, 2020, and 2024 using the Dynamic World V1 dataset within Google Earth Engine. By aggregating results at both national and provincial levels, it aims to reveal spatial disparities in urban expansion and lay the groundwork for subsequent causal and comparative analyses.

Methodology

The Dynamic World V1 dataset is a 10 m near real-time land use/land cover (LULC) product derived from Sentinel-2 imagery (Brown et al., 2022). National administrative boundaries from the FAO GAUL 2015 dataset were used to delineate each African country (FAO, 2015). For three distinct time periods (2015–2016, 2019–2020, and 2023–2024), the majority land cover class (mode) per pixel was computed, and pixel counts per class were extracted via frequency histograms. These statistics were then aggregated into result tables exported in CSV format, providing a quantitative overview of intra-annual land cover dynamics per country.

Context and Dataset

Dynamic World V1
Dynamic World V1 is a 10 m resolution dataset derived from Sentinel-2 imagery. It provides predictions of nine LULC classes along with associated probabilities. This near real-time product is generated by a deep learning model deployed on the Google Cloud AI Platform and is updated continuously as new Sentinel-2 data becomes available (Brown et al., 2022).

GAUL 2015
National administrative boundaries were obtained from GAUL (Global Administrative Unit Layers), version 2015, developed by the FAO to standardize spatial representations of administrative units (FAO, 2015). On Google Earth Engine, this dataset is available under the identifier "FAO/GAUL/2015/level0".

Study Area and Time Periods

The study covers all countries in Africa, each retrieved as a Feature in a list. Three time windows were defined:

- July 1, 2015 – June 30, 2016 (2016 season)
- July 1, 2019 – June 30, 2020 (2020 season)
- July 1, 2023 – June 30, 2024 (2024 season)

These periods correspond to the historical availability of the Dynamic World dataset (starting June 2015).

Land Cover Extraction and Processing

Spatial Selection and Aggregation

- For each country, the GOOGLE/DYNAMICWORLD/V1 collection was filtered by geometry and time window.
- The mode() function was applied to determine the most frequent label per pixel.
- The resulting image was clipped (clip()) to the country boundary.

Band Renaming

- The band resulting from mode() was renamed to "classification" to standardize naming.
- A time suffix (_2016, _2020, _2024) was dynamically added to each property via a renaming function (Brown et al., 2022).

Statistical Aggregation

To quantify the area of each LULC class:

- The unweighted frequencyHistogram() reducer was applied to the classification band.
- The spatial resolution was set to 10 m, with maxPixels set to 1e13.
- The reduceRegion() method returned a dictionary of pixel counts per class.

Each histogram was converted into a Feature with null geometry and merged to form a single record summarizing statistics for all three periods.

Exporting Results

The outputs were exported to Google Drive as CSV files (one table per country) using Export.table.toDrive(), with the filename specified by fileNamePrefix = countryName and column headers including time suffixes.

Post-Processing of Results

The 55 CSV files (one per African country) included pixel counts for each land use class—Water, Trees, Grass, Flooded Vegetation, Crops, Shrubs, Built-up, Bare Soil, and Snow—for the years 2016, 2020, and 2024. Pixel counts were converted to square kilometers

	2016		2020		2024		relative change in percent		
	area in sq. km	percentage (%)	area in sq. km	percentage (%)	area in sq. km	percentage (%)	2016-2020	2020-2024	2016-2024
water	362448.65	1.20	326728.93	1.08	341467.47	1.13	-9.86	4.51	-5.79
Trees	7803943.06	25.74	8156978.02	26.90	8367859.94	27.60	4.52	2.59	7.23
Grass	511620.74	1.69	484988.85	1.60	443645.19	1.46	-5.21	-8.52	-13.29
Flooded vegetation	41392.20	0.14	53025.22	0.17	63837.67	0.21	28.10	20.39	54.23
Crops	1447514.19	4.77	1684740.50	5.56	1613359.38	5.32	16.39	-4.24	11.46
shrub and scrub	6710345.96	22.13	6806064.03	22.45	6763149.07	22.31	1.43	-0.63	0.79
Built	182059.92	0.60	211862.70	0.70	242747.26	0.80	16.37	14.58	33.33
Bare	12945957.57	42.70	12543866.50	41.37	12447398.70	41.06	-3.11	-0.77	-3.85
snow and ice	4033.29	0.01	1154.63	0.00	854.24	0.00	-71.37	-26.02	-78.82
null_values	308989.43	1.02	48895.62	0.16	33986.08	0.11	-84.18	-30.49	-89.00
total	30318305	100	30318305	100	30318305	100			

Tab. 1 - Africa Land use land Cover distribution.

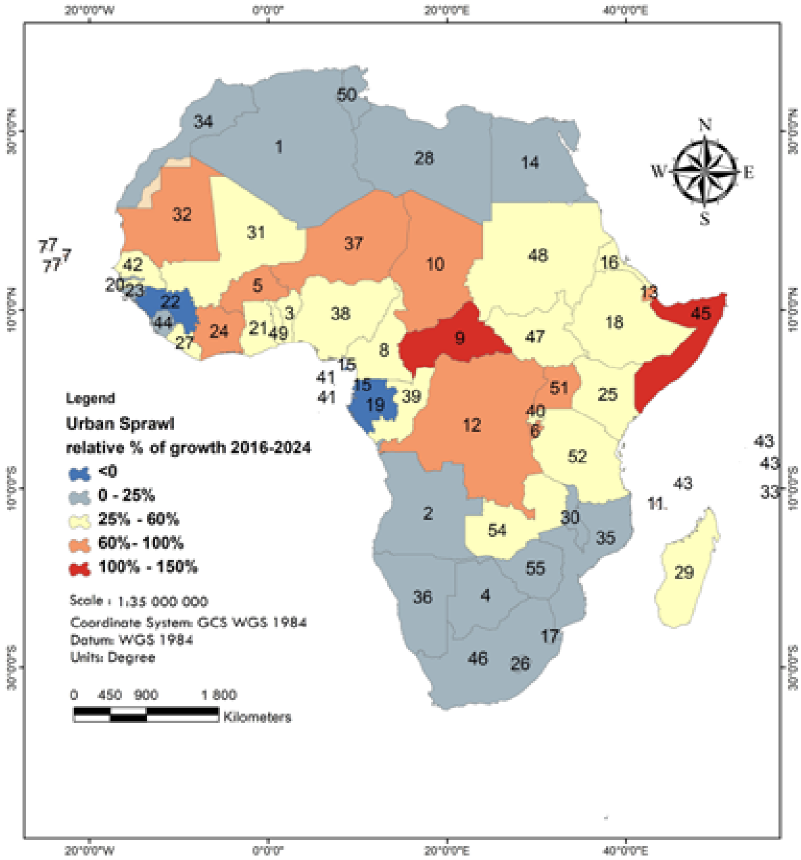


Fig. 1 – Land use land cover (%) 2016-2020-2024.

	AFRICA
Built Up area 2016 (KM2)	182059.92
Built Up area 2020 (KM2)	211862.70
Built Up area 2024 (KM2)	242747.26
Urban sprawl 2016-2020 (KM2)	29802.78
Growth 2016-2020 (%)	16.37
Urban sprawl 2020-2024 (KM2)	30884.56
Growth 2020-2024 (%)	14.58
Urban sprawl 2016-2024 (KM2)	60687.33
Growth 2016-2024 (%)	33.33

Tab. 2 – Built-up areas in Africa and Urban sprawl between 2016, 2020 and 2024.

in Excel, and only the Built-up class was retained. A summary table was then created with built-up surface area per country for the three years.
From these values, we calculated the relative percentage increase for each period (2016–2020, 2020–2024, and 2016–2024), and the percentage contribution of each country to the overall continental urban expansion from 2016 to 2024.

Visualization
The final table was joined to the shapefile of African countries in ArcGIS to visualize two indicators: the relative increase in built-up area between 2016 and 2024, and each country's percentage contribution to overall urban growth in Africa.

Results
The land-cover classes provided by the Dynamic World Version 1 dataset, accessed through Google Earth Engine, include: Water; Tree; Grass; Flooded Vegetation; Crops; Shrub & Scrub; Built; Bare Soil; and Snow & Ice. Together, these nine classes span a total area of 30 318 305 km² across the African continent as shown in Table 1.
Pixels lacking reliable satellite observations—i.e., null or

ID	COUNTRY	Urban sprawl 2016-2020 (KM2)	Growth 2016-2020 (%)	Urban sprawl 2020-2024 (KM2)	Growth 2020-2024 (%)	Urban sprawl 2016-2024 (KM2)	Growth 2016-2024 (%)
1	Algerie	1091.20	14.21	-396.52	-4.52	694.68	9.05
2	Angola	-203.91	-7.35	287.64	11.20	83.73	3.02
3	Benin	265.51	10.58	471.20	16.98	736.71	29.35
4	Botswana	-19.19	-1.32	245.03	17.06	225.84	15.52
5	Burkina Faso	606.13	40.96	679.09	32.56	1285.22	86.86
6	Burundi	355.60	44.63	406.09	35.24	761.69	95.59
7	Cabo Verde	51.79	58.61	26.29	18.76	78.08	88.36
8	Cameroon	933.73	29.81	517.69	12.73	1451.42	46.34
9	Central African Republic	121.50	57.49	189.31	56.88	310.81	147.07
10	Chad	214.80	35.87	297.97	36.62	512.76	85.63
11	Comores	58.18	59.81	5.73	3.68	63.91	65.70
12	Democratic republic of the congo	1431.91	33.59	1291.08	22.67	2722.99	63.88
13	Djibouti	36.18	51.58	12.00	11.28	48.18	68.68
14	Egypt	822.50	11.10	666.42	8.09	1488.91	20.09
15	Equatorial Guinea	-65.45	-21.30	8.10	3.35	-57.35	-18.67
16	Eritrea	61.76	24.67	55.56	17.80	117.32	46.86
17	Eswatini	23.33	4.45	5.23	0.96	28.56	5.45
18	Ethiopia	5688.86	33.01	2920.74	12.74	8609.60	49.95
19	Gabon	-942.61	-47.40	-169.75	-16.23	-1112.36	-55.93
20	Gambia	21.90	4.98	39.24	8.50	61.14	13.90
21	Ghana	1363.38	22.38	1871.16	25.10	3234.54	53.09
22	Guinea	-21.57	-1.03	17.72	0.86	-3.86	-0.19
23	Guinea-Bissau	19.14	3.95	6.51	1.29	25.65	5.30
24	Ivory coast	1135.69	36.98	1132.63	26.93	2268.32	73.87
25	Kenya	3611.85	26.78	3082.29	18.03	6694.14	49.63
26	Lesotho	3.25	0.42	119.94	15.60	123.18	16.09
27	Liberia	123.68	17.14	121.05	14.32	244.73	33.92
28	Libya	488.04	14.22	-72.28	-1.84	415.76	12.11
29	Madagascar	252.77	15.54	256.77	13.67	509.55	31.33
30	Malawi	-363.92	-9.58	429.85	12.51	65.93	1.73
31	Mali	516.76	32.64	430.52	20.50	947.29	59.84
32	Mauritania	1.72	2.83	40.23	64.33	41.95	68.98
33	Mauritius	197.72	119.45	30.43	8.38	228.15	137.83
34	Morocco	706.78	9.70	79.00	0.99	785.78	10.79
35	Mozambique	-244.44	-5.68	508.54	12.53	264.10	6.14
36	Namibia	-50.06	-7.53	107.57	17.49	57.52	8.65
37	Niger	171.70	32.53	268.47	38.38	440.18	83.39
38	Nigeria	2597.06	11.87	5312.45	21.71	7909.51	36.16
39	Republic of the congo	267.19	47.99	-23.44	-2.84	243.75	43.78
40	Rwanda	856.01	33.05	660.01	19.15	1516.02	58.52
41	Sao Tome and Principe	4.89	22.12	0.43	1.58	5.32	24.05
42	Senegal	190.03	11.84	509.47	28.38	699.50	43.57
43	Seychelles	19.92	103.53	3.50	8.94	23.42	121.72
44	Sierra Leone	13.06	1.94	41.85	6.09	54.91	8.14
45	Somalia	374.73	54.80	311.36	29.41	686.10	100.34
46	South Africa	1659.76	7.30	1105.80	4.53	2765.57	12.17
47	South Sudan	-2.91	-0.66	200.31	45.93	197.40	44.96
48	Sudan	914.55	38.43	378.93	11.50	1293.47	54.35
49	Togo	279.86	19.46	581.43	33.84	861.29	59.88
50	Tunisia	1214.27	40.57	-729.96	-17.35	484.31	16.18
51	Uganda	2106.10	29.77	2497.80	27.21	4603.90	65.08
52	United Republic of Tanzania	1029.19	11.42	2835.59	28.24	3864.78	42.88
53	Western sahara	-	-	-	-	0.00	0.00
54	Zambia	210.32	9.00	755.63	29.66	965.95	41.32
55	Zimbabwe	-397.43	-18.33	454.85	25.69	57.42	2.65

Tab. 3 – Urban sprawl for the periods 2016-2020, 2020-2024 and 2016-2024 and the percentage of relative increase for each country.

missing data—decline markedly over time, from 1.02 % of the continental extent in 2016 to 0.16 % in 2020 and 0.11 % in 2024. This reduction reflects a progressive enhancement in both spatial coverage and data quality, yielding an overall data completeness exceeding 99 % for Africa and thereby ensuring high confidence in land-cover analyses.
In 2016, vegetation-related coverages (the sum of Tree, Grass, Shrub & Scrub, Flooded Vegetation, and Crops) accounted for 54.47 % of Africa's surface. This proportion increased to 56.68 % in 2020 and 56.90 % in 2024, indicating a modest upward trend in vegetated areas (figure 1). The Bare Soil class—principally comprising desert and sparsely vegetated lands—remains the second most extensive cover type, representing 42.70 % of the continent's area.

The results show that the area of built-up areas in Africa in 2016 was 18,259.92 km², while in 2020 it was 211,862.70 km², compared to 242,747.26 km² in 2024. Africa thus experienced an urban sprawl of 16.37% between 2016 and 2020 and an increase

Rank N°	Country ID	PAYS	Urban sprawl 2016-2024 (KM2)	Contribution % of Africa
1	18	Ethiopia	8609.60	14.19
2	38	Nigeria	7909.51	13.03
3	25	Kenya	6694.14	11.03
4	51	Uganda	4603.90	7.59
5	52	United Republic of Tanzania	3864.78	6.37
6	21	Ghana	3234.54	5.33
7	46	South Africa	2765.57	4.56
8	12	Democratic republic of the congo	2722.99	4.49
9	24	Ivory coast	2268.32	3.74
10	40	Rwanda	1516.02	2.50
11	14	Egypt	1488.91	2.45
12	8	Cameroon	1451.42	2.39
13	48	Sudan	1293.47	2.13
14	5	Burkina Faso	1285.22	2.12
15	54	Zambia	965.95	1.59
16	31	Mali	947.29	1.56
17	49	Togo	861.29	1.42
18	34	Morocco	785.78	1.29
19	6	Burundi	761.69	1.26
20	3	Benin	736.71	1.21
21	42	Senegal	699.50	1.15
22	1	Algerie	694.68	1.14
23	45	Somalia	686.10	1.13
24	10	Chad	512.76	0.84
25	29	Madagascar	509.55	0.84
26	50	Tunisia	484.31	0.80
27	37	Niger	440.18	0.73
28	28	Libya	415.76	0.69
29	9	Central African Republic	310.81	0.51
30	35	Mozambique	264.10	0.44
31	27	Liberia	244.73	0.40
32	39	Republic of the congo	243.75	0.40
33	33	Mauritius	228.15	0.38
34	4	Botswana	225.84	0.37
35	47	South Sudan	197.40	0.33
36	26	Lesotho	123.18	0.20
37	16	Eritrea	117.32	0.19
38	2	Angola	83.73	0.14
39	7	Cabo Verde	78.08	0.13
40	30	Malawi	65.93	0.11
41	11	Comores	63.91	0.11
42	20	Gambia	61.14	0.10
43	36	Namibia	57.52	0.09
44	55	Zimbabwe	57.42	0.09
45	44	Sierra Leone	54.91	0.09
46	13	Djibouti	48.18	0.08
47	32	Mauritania	41.95	0.07
48	17	Eswatini	28.56	0.05
49	23	Guinea-Bissau	25.65	0.04
50	43	Seychelles	23.42	0.04
51	41	Sao Tome and Principe	5.32	0.01
52	53	Western sahara	0.00	0.00
53	22	Guinea	-3.86	-0.01
54	15	Equatorial Guinea	-57.35	-0.09
55	19	Gabon	-1112.36	-1.83

Tab. 4 – Percentage contribution of each country to urban sprawl in Africa between 2016-2024.

of 14.58% between 2020 and 2024, resulting in an overall increase of 33.33% in built-up areas in Africa between 2016 and 2024, or 60,687.33 km², as shown in Table 2.

Table 3 presents the results of urban sprawl for the periods 2016-2020, 2020-2024 and 2016-2024 and the percentage of relative increase for each country. When considering relative growth (percentage increase relative to the 2016 baseline) for the period 2016-2024 as illustrate in the figure 2 , the Central African Republic had the highest rate at +147%, followed by Mauritius (+137%), Seychelles (+121%), Somalia (+100%), Burundi (+95%), Burkina Faso (+86%), Chad (+85%), Niger (+83%), and Côte d'Ivoire (+73%). The Democratic Republic of the Congo ranked 15th with a +63.8% increase. The number labeled on the maps in Figures 2 and 3 indicates the Country ID that you can find in Tables 3 and Table 4.

These results underscore significant heterogeneity in urban sprawl across Africa. The absolute growth is concentrated in large economies and rapidly expanding cities (e.g., Lagos, Nairobi, Addis Ababa), while the highest relative growth rates are observed in smaller or rapidly urbanizing nations, possibly reflecting emerging urban centers or peri-urban development (Seto et al., 2012).

Discussion

The spatial patterns suggest that economic size, population pressure, and governance frameworks are key drivers of urban sprawl. For example, Ethiopia's large-scale urban development and infrastructure investments have led to rapid expansion around Addis Ababa and other cities (World Bank, 2021). Conversely, countries with limited infrastructure may exhibit lower absolute growth, even when relative growth is high.

Future research should incorporate socioeconomic variables (e.g., GDP per capita, population density, governance indices) to analyze causal relationships and simulate urban growth under alternative development scenarios (Seto et al., 2012; Schneider & Woodcock, 2008).

Conclusion

This study offers a comprehensive, continent-wide assessment of urban sprawl in Africa from 2016 to 2024, using high-resolution remote sensing data (Dynamic World V1) and cloud-based processing (Google Earth Engine). The findings illustrate both absolute and relative growth patterns, revealing stark differences between countries.

Major economies and urban hubs drove most of the absolute expansion, while smaller or less urbanized nations exhibited remarkable relative growth—highlighting future urbanization hotspots. These insights are crucial for land-use planning and policy design. Integrating remote sensing data with socioeconomic and governance indicators will enable predictive modeling and scenario-based planning to guide sustainable urban development across Africa.

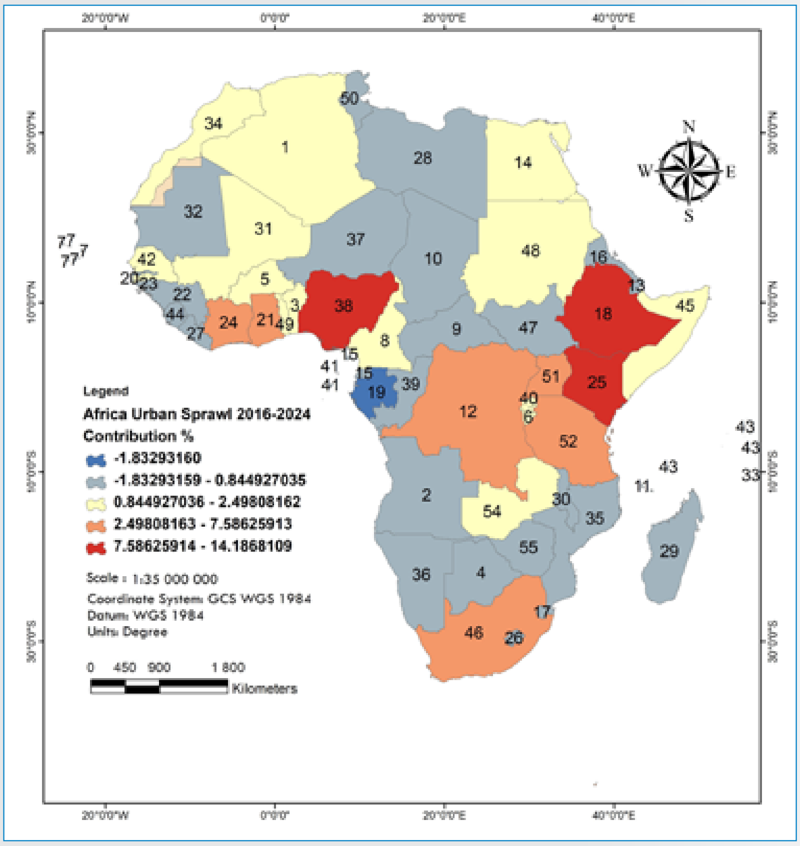


Fig. 3 – Percentage contribution of each country to urban sprawl in Africa between 2016-2024.

BIBLIOGRAPHY

Anderson JR, Hardy EE, Roach JT & Witmer RE A Land Use and Land Cover Classification System for Use with Remote Sensor Data. *U.S. Geological Survey* , Report 964 (1976).
Brown CF et al. Dynamic World training dataset for global LULC categorization of satellite imagery. *PANGAEA* (2021). https://doi.org/10.1594/PANGAEA.933475
Brown CF, Brumby SP, Guzder -Williams B. et al. Dynamic World, Near real-time global 10 m land use land cover mapping. *Scientific Data* 9, 251 (2022). https://doi.org/10.1038/s41597-022-01307-4
Deng, X., Shang, S., & Li, S. (2022). Dynamic World: A near real-time global land use land cover dataset at 10 m resolution derived from Sentinel-2 imagery. *International Journal of Remote Sensing, 43* (10), 3500–3525.
ESA. Comparative validation of recent 10 m-resolution global land cover maps. *Remote Sensing of Environment* (2024).
Food and Agriculture Organization. (2015). *Global Administrative Unit Layers (GAUL)* . FAO.
Gorelick , N., Hancher , M., Dixon, M., Ilyushchenko , S., Thau , D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment, 202* , 18–27. https://doi.org/10.1016/j.rse.2017.06.031
Iandolo , A., Rossi, F., & Bonomi , M. (2023). Urban sprawl dynamics in West African cities: A remote sensing approach. *Journal of Urban Studies, 58* (2), 213–231.
Li, Q., Qiu, GY, Ma, R., Schmitt, M., & Zhu, AX (2020). Continental-scale urban mapping using Google Earth Engine. *Remote Sensing of Environment, 234* , 111482.
Mhangara , P., Gidey , WT, & Manjoo , V. (2024). Monitoring urban sprawl in Southern Africa using satellite imagery and GIS. *International Journal of Applied Earth Observation and Geoinformation , 102* , 102779.
Phiri D. et al. Sentinel-2 Data for Land Cover/Use Mapping: A Review. *Remote Sensing* 12, 2291 (2020). https://doi.org/10.3390/rs12142291
Schneider, A., & Woodcock, C.E. (2008). Compact, dispersed, fragmented, extensive? A comparison of urban growth in twenty-five global cities using remotely sensed data. *Landscape and Urban Planning, 87* (1), 54–73.
Seto , K.C., Güneralp , B., & Hutyra , LR (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon. *Proceedings of the National Academy of Sciences, 109* (40), 16083–16088.
Shekhar , S., & Xiong , H. (2008). *Encyclopedia of GIS* . Springer.
United Nations Department of Economic and Social Affairs. (2018). *World Urbanization Prospects: The 2018 Revision* . United Nations.
World Bank. (2021). *Ethiopia Urbanization Review* . World Bank Publications.

KEYWORDS

URBAN SPRAWL; AFRICA; IMAGE ANALYSIS; SATELLITE IMAGES

ABSTRACT

This study provides a comprehensive, continent-wide quantification of urban sprawl in Africa between 2016 and 2024 by exploiting the Dynamic World V1 dataset within Google Earth Engine. We computed the dominant land-cover class per pixel for three time windows (2015–2016, 2019–2020, 2023–2024), aggregated built-up area changes nationally, and calculated both absolute and relative growth rates. Results reveal a net increase of 60,687 km² of built-up land in Africa, driven primarily by Ethiopia, Nigeria, and Kenya in absolute terms, while smaller states like the Central African Republic and Mauritius exhibit the highest percentage gains. Our findings highlight pronounced spatial heterogeneity in urban expansion and underscore the need to integrate socioeconomic and governance indicators to inform sustainable land-use planning across Africa.

AUTHOR

Johnny Muhindo Bahavira (1, 2,)
Johnny.muhindo@inbtp.com

Michael Paluku Lukumbi (2, 3, 4)
Junior Lukoo Mitsindo (2, 3,4)
Mpanga Numbi Loïc (5)
Hélène Akilimali Kabisuba (5)
Acacia Muley Nyande (6)

Department of Building and Civil Engineering, Institut National du Bâtiment et des Travaux Publics (INBTP), Kinshasa, Democratic Republic of Congo (1)
Laboratoire INBTP : Geomatics, IT, Civil Engineering, Geotechnics, Hydraulics, Physics and Chemistry, Institut National du Bâtiment et des Travaux Publics (INBTP), Kinshasa, Democratic Republic of Congo (2)
Department of Hydraulic and Environmental Engineering, Institut National du Bâtiment et des Travaux Publics (INBTP), Kinshasa, Democratic Republic of Congo (3)
Engineering of Structures, Foundations and Material's PhD Program, Universidad Politécnica de Madrid (UPM), Madrid, Spain (4)
Geotechnical Engineering Master's Program, Department of Building and Civil Engineering, Institut National du Bâtiment et des Travaux Publics, Kinshasa, RDC (5)
Department of Environmental Science, Université Nouveaux Horizons, Lubumbashi, Democratic Republic of Congo (6)

Solve Mission-Critical Challenges With Geospatial Data and Solutions

At NV5, our geospatial experts use advanced technology to help you mitigate risk, plan for growth, better manage resources, and enhance scientific understanding.

Contact us and let's discuss how NV5 can help you solve challenges faster, more efficiently, and more effectively.

NV5