https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

Open Access Earth System Science Data Discussions

The First Road Surface Type Dataset for 50 African Countries and Regions

Zixian Liu[1], Qi Zhou[1]*, Fayong Zhang[1]*, Prosper Basommi Laari[2]

1. School of Geography and Information Engineering, China University of Geosciences, Wuhan, People's Republic of China

2. Department of Environment and Resource Studies, Simon Diedong Dombo University of Business and Integrated Development Studies, Wa, Ghana

*Corresponding author: Qi Zhou (zhouqi@cug.edu.cn); Fayong Zhang (zhangfayong@cug.edu.cn)

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

Earth System Science Data Discussions
Open Access

Abstract

Road surface types not only influence the accessibility of road networks and socio-economic development but also serve as a critical data source for evaluating United Nations Sustainable Development Goal (SDG) 9.1. Existing research indicates that Africa generally have a low road paved rate, limiting local socio-economic development. Although the International Road Federation (IRF) provides statistical data on paved road length and road paved rates for certain African countries, this data neither covers all African country nor specifies the surface type of individual roads, making it challenging to offer decision-making support for improving Africa's road infrastructure. To fill this gap, this study developed the first dataset for 50 African countries and regions, incorporating the surface type of every road. This was achieved using multi-source geospatial data and a tabular deep learning model. The core methodology involved designing 16 proxy indicators across three dimensions—derived from five open geospatial datasets (OSM road data, GDP data, population distribution data, building height data, and land cover data)—to infer road surface types across Africa. Key findings include: The accuracy of the African road surface type dataset ranges from 77% to 96%, with F1 scores between 0.76 and 0.96. Total road length, paved road length, and road paved rates calculated from this dataset show high correlation (correlation coefficients: 0.69–0.94) with corresponding IRF statistics. Notably, the road paved rate also exhibits strong correlation with GNI per capita and HDI (correlation coefficients: 0.80–0.83), validating the reliability of the dataset. Spatial analysis of African road paved rates at national, provincial, and county scales

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

Earth System Science Data
Open Access Discussions

revealed an average paved rate of only 17.4% across the 50 countries and regions. A distinct "higher in the north and south, lower in the central region" pattern emerged, the average paved rate north of the Sahara is approximately three times that of Sub-Saharan (excluding South Africa). The African road surface type dataset developed in this study not only provides data support for enhancing road infrastructure and evaluating SDG 9.1 progress in Africa but may also facilitate research on how road surface types impact road safety, energy consumption, ecological environments, and socio-economic development.

Keywords: Road surface type; multi-source geospatial data; SDG 9; Africa

1. Introduction

Road surface types (such as paved and unpaved roads) not only affect vehicle driving safety and energy consumption but also impact road accessibility and socio-economic development (Anyanwu et al., 2009; Shtayat et al., 2020; Sha, 2021; Styer J et al., 2024; Chen et al., 2025). Generally, paved roads have a sturdy structure and are resistant to erosion, allowing them to be passable all-season, while unpaved roads may be affected by natural factors such as rain and snow, making them typically difficult to pass all-season. The proportion of the rural population living within 2 kilometers of all-season road has also been adopted by the World Bank as an important indicator for evaluating road infrastructure, and this indicator was incorporated by the United Nations into the Sustainable Development Goal (SDG) 9.1 in 2017. Road surface type data are considered one of the key data sources for assessing SDG 9.1.

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

Existing studies indicate that the road paved rate in African countries is highly positively correlated with national poverty rates, and in some regions, the lack of all-season passable roads has led to significantly increased transportation costs (Anyanwu et al., 2009; Abdulkadr et al., 2022). Particularly in Sub-Saharan, more than 70% of roads remain unpaved (Greening et al., 2010); In Nigeria, for example, over 30 million rural residents have long been unable to access road transportation services. In these countries and regions, the lag in transportation infrastructure has become one of the main bottlenecks restricting socio-economic development (Li et al., 2022). To address these challenges, the World Bank, the International Automobile Federation (FIA), and the International Transport Forum (ITF) signed a Memorandum of Understanding (MoU) in 2018, aiming to strengthen infrastructure construction in Africa over the next fifty years (World Bank, 2018). The Agenda 2063: The Africa We Want, participated in by multiple African countries, also sets goals to improve residents' quality of life and enhance infrastructure in African nations (African Union Commission, 2018). Therefore, high-quality road surface type data for Africa are of great significance for improving local transportation infrastructure and promoting socio-economic development.

However, the currently available, globally open road surface type data are primarily statistical data, and most analyses of road surface types are also based on such statistics. For example, the International Road Federation (IRF) provides statistical data related to road surface types, such as paved road length and road paved rate (Turner, 2015; CIA, 2025). Greening et al. (2010) found, based on IRF and other road statistics, that in Sub-

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

Saharan, the proportion of "all-season road" (e.g., paved roads) does not exceed 30%. Kresnanto (2019) used statistical paved road length data from Badan Pusat Statistik Indonesia (BPS Indonesia) to analyze the relationship between road paved rates and vehicle ownership in Indonesia from 1957 to 2016. Patrick et al. (2022) conducted a survey to estimate the road paved rate in rural areas of Sub-Saharan. However, analyses of road surface types based on statistical data have many limitations. On the one hand, existing statistical data on road surface types do not cover all countries; for example, in 2020, IRF only provided statistics on paved road lengths for 19 African countries, and some countries still face issues with untimely data updates (Barrington-Leigh et al., 2017). On the other hand, these statistical data are collected indirectly by relevant statistical departments or road authorities through surveys and data coordination from various sources (Turner, 2015; CIA, 2025), making it still impossible to accurately identify whether each road within a country or region is paved or unpaved.

In recent years, with the development of sensing devices, remote sensing, and big data technologies, many scholars have proposed methods to identify road surface types based on multiple data sources (Louhghalam et al., 2015; Sattar et al., 2018; Pérez-Fortes et al., 2022). For example, some scholars have suggested methods using vehicle-mounted sensing devices to identify road surface types. Chen et al. (2016) designed a road surface type identification system that can be connected to distributed vehicles and was tested on 100 taxis in Shenzhen to assess the roughness of road surfaces in Shenzhen. Harikrishnan et al. (2017) collected vehicle speed data using the XYZ three-axis accelerometer of smartphones and established road surface type identification

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

models for four different vehicle speeds. Li and Goldberg (2018) developed a similar system using smartphones, collecting data from five different drivers over 15 days to classify road roughness into three categories: "good," "moderate," and "poor". Other scholars have proposed methods using street view data to identify road surface types. Randhawa et al. (2025) used a deep learning model combining SWIN-Transformer and CLIP-based segmentation on Mapillary street-view images to classify road surfaces of global range into paved and unpaved. Menegazzo et al. (2020) collected street view data for some roads in Anita Garibaldi, Brazil, using vehicle-mounted cameras and identified paved and unpaved roads based on a CNN neural network model. Zhou et al. (2025a) recently utilized crowdsourced street view data from Mapillary to develop a dataset of road surface type annotations (paved and unpaved) for the African region. Additionally, some scholars have proposed methods using high-resolution remote sensing imagery to identify road surface types. Workman et al. (2023) developed a framework using high-resolution optical satellite imagery and machine learning to predict the condition of unpaved roads in Tanzania. Zhou et al. (2024) proposed a method that integrates OpenStreetMap (OSM) and high-resolution Google satellite imagery to identify road surface types and used this method to develop the road surface type dataset for Kenya. However, methods based on vehicle-mounted sensing devices require on-site data collection for each road, inevitably requiring significant manpower, material, and financial resources, making them difficult to apply to large-scale study areas such as continents or countries. Data like Google street view are only available in a few countries or specific regions of countries, making it challenging to identify the

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

surface types of all roads in a country. Therefore, although the data developed based on street views covers a global range, it only has 36% of the complete global roads, this proportion is even lower in Africa and Asia (Randhawa et al., 2025). Remote sensing methods may suffer from low accuracy in identifying road surface types due to dense vegetation or building shadows obscuring roads (Zhou et al., 2024). Therefore, Zhou et al. (2025b) recently proposed a new method based on multisource big data and deep learning models to infer road surface types, which has been validated in two African countries. Compared to remote sensing methods, this approach can address the low accuracy of road surface type identification in areas with poor remote sensing image quality; for example, the accuracy of remote sensing methods in Cameroon is only 67%, while the accuracy of the multisource data method in the same region exceeds 85%.

Nevertheless, existing research still has limitations. (1) The method proposed by Zhou et al. (2025b) has only been validated in a few (1-2) African countries, and it remains to be verified whether these methods can be applied to develop road surface type dataset for different African countries. (2) Existing road surface type data are still mainly statistical data at the national scale, with Zhou et al. (2025b) only providing a road surface type dataset for Nigeria, leaving a gap in data products covering different countries and regions in Africa.

Therefore, this study not only aims to evaluate whether the method of developing road surface type dataset based on multisource big data and deep learning models has universal applicability but also uses this method to develop the first dataset of road surface types (paved and unpaved) for 50 countries and regions in Africa. The dataset

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

developed in this study not only provides information on the surface type of each road in various countries or regions of Africa but also verifies the accuracy of the dataset: accuracy ranges from 77% to 96%, and the F1 score ranges from 0.76 to 0.96. Compared to IRF and other road statistical data, the dataset developed in this study can support detailed mapping of road surface types in various African countries or regions and provide data support for road infrastructure construction.

The remainder of this paper is organized as follows: Section 2 introduces the study area and the source data for developing and evaluating the road surface type data. Section 3 introduces the methods for data development and evaluation. Section 4 reports the evaluation results of the road surface type data. Section 5 discusses the implications and limitations of this study. The last two sections provide the data acquisition methods and the research conclusions.

2. Study Area and Data

2.1 Study area

This study takes 50 countries and regions in Africa, the second-largest continent on Earth, as the study area (Figure 1), with a total road length of approximately 6,822,516 kilometers. The main reason for selecting Africa as the study area is that existing research shows that the proportion of unpaved roads in Africa is high (Biber-Freudenberger et al., 2025), while the IRF only provides statistics on the length of paved roads and the road paved rate for some African countries. Due to the lack of spatialized road surface type dataset, it is difficult to provide decision support for improving road

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

infrastructure in Africa.

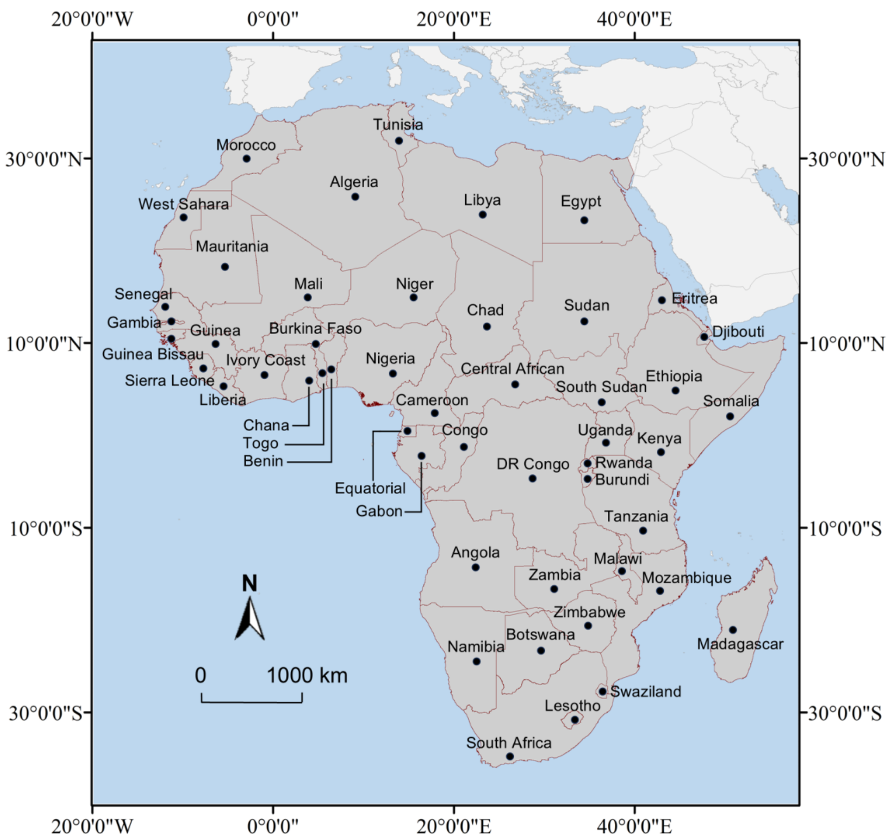


Figure 1. Study area

2.2 Data

2.2.1 Geospatial data

(1) OpenStreetMap road data: OpenStreetMap (OSM) is an open geospatial dataset provided online by global volunteers (Harikrishnan et al., 2017). This dataset includes various geographic elements such as roads, buildings, and water bodies. Each geographic element not only contains geometric information but also describes its

characteristics or attribute information through a series of tags. Specifically, the "surface" tag in OSM road data is designed to describe the road surface type of each road segment. The value of this tag typically refers to the surface material of the road, such as asphalt, concrete, or gravel. Although OSM data for different countries or regions in Africa all include road surface type information, incomplete statistics show that the length of OSM roads with surface type information in a single country usually accounts for less than 30%, meaning that most OSM road data lack surface type information, thus urgently requiring supplementation and improvement. This study obtained road data for 50 countries and regions in Africa (in ESRI Shapefile format) from the Geofabrik platform (http://download.geofabrik.de/index.html), which allows obtaining OSM road data by country.

(2) GDP grid data: This dataset is a 1km spatial resolution GDP grid dataset developed by Southwestern University of Finance and Economics (Chen et al., 2022). The dataset was developed by integrating nighttime light remote sensing data (NPP-VIIRS), land use data, and regional economic statistics using spatial interpolation and machine learning algorithms. This dataset overcomes the limitations of traditional administrative unit statistics and can precisely depict the spatial heterogeneity of economic activities. The dataset spans from 1992 to 2019, and this study used the data from the most recent year (2019).

(3) Population grid data: This dataset is the LandScan global population dataset developed by Oak Ridge National Laboratory (ORNL) in the United States, with a spatial resolution of 30 arc seconds in latitude and longitude (approximately 1km at the

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

equator) (Dobson et al., 2000). The dataset integrates census data, satellite imagery, and mobile communication data, using dynamic modeling methods to simulate 24-hour population distribution. Existing research has found that compared to other population grid datasets (such as WorldPop and Global Human Settlement Population Grid), LandScan has higher accuracy (Jiang et al., 2021; Mohit et al., 2021; Yin et al., 2021). Therefore, this study obtained the 2020 LandScan population raster data for the African region (https://landscan.ornl.gov/).

(4) Building height data: This dataset is a 100-meter resolution building height dataset released by the Global Human Settlement Layer (GHSL). The dataset is based on Sentinel-1/2 and Landsat imagery, using machine learning algorithms to extract the three-dimensional morphology of buildings (Pesaresi et al., 2021). The dataset includes building height raster data. GHSL-BUILT is the world's first building height dataset, and this study obtained the 2018 building height data recommended by GHSL for analysis (https://human-settlement.emergency.copernicus.eu/ghs_buH2023.php).

(5) Land cover data: This dataset is a global land cover dataset with a 10-meter spatial resolution released by ESRI. The dataset was developed based on Sentinel-2 imagery and deep learning methods, including nine different land cover categories (water, trees, flooded vegetation, crops, buildings, bare land, snow, clouds, and pasture) (Karra et al., 2021). Existing research indicates that ESRI land cover data has better accuracy compared to other similar datasets (such as ESA World Cover and Dynamic World) (Yan et al., 2023). This study obtained the 2020 Land Cover data for the African region (https://livingatlas.arcgis.com/landcover/).

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

2.2.2 Statistical data

To verify the effectiveness of the data, this study also obtained two types of statistical data, IRF road statistics and socio-economic statistics.

(1) IRF Road Statistics: The International Road Federation (IRF) is a non-profit international organization dedicated to promoting development and cooperation in the global road transport sector (Turner, 2015). IRF provides free and rich statistical data resources to global users (https://www.irf.global/). These data primarily come from authoritative reports and statistical agencies of various governments, covering multiple fields such as road networks and the transportation industry. This study obtained three statistical data provided by IRF for the African region in 2020, namely the length of paved roads, total road length, and road paved rate.

(2) Socioeconomic Statistics: Existing research has found that the road paved rate is highly positively correlated with the level of socioeconomic development (Anyanwu et al., 2009). Therefore, this study also introduced two indicators related to the level of socioeconomic development, namely the Human Development Index (HDI) and Gross National Income per capita (GNI per capita, based on PPP current international $). HDI is compiled and published by the United Nations Development Programme since 1990, obtained by comprehensively evaluating a country's life expectancy, average years of schooling, and gross national income, and is used to measure the socioeconomic development level of various countries. GNI per capita is published by the World Bank, where GNI is the sum of the incomes of all residents in a country or region; GNI per capita is the average GNI of a country or region, which can measure the average

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

Open Access Earth System Science Data Discussions

economic income level of the nationals in a country or region. This study obtained the 2020 HDI and GNI per capita data, covering 44 and 36 African countries and regions, respectively.

3. Methods

The technical roadmap of this study is shown in Figure 2.

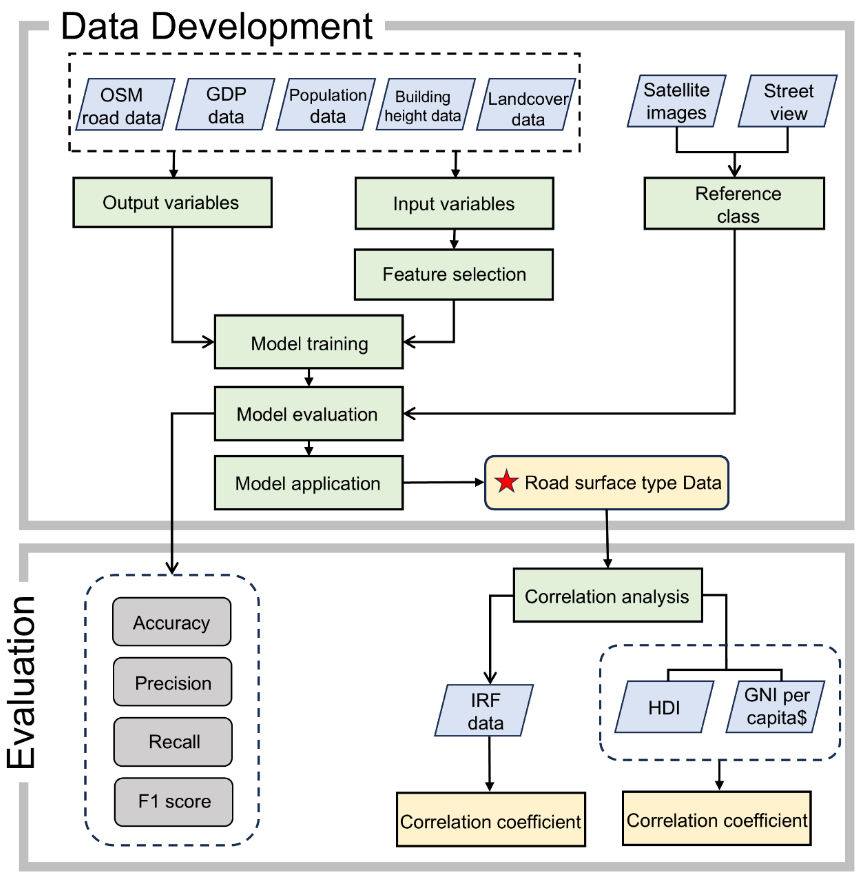


Figure 2. Technical roadmap

3.1 Developing of Road Surface Type Dataset of Africa

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

Open Access Earth System Science Data Discussions

This study utilizes a method recently proposed by Zhou et al. (2025b) that is based on multi-source geospatial big data and deep learning models to develop the road surface type dataset of 50 African countries and regions. The main idea of this method includes the following steps: First, sampling points and corresponding OpenStreetMap (OSM) road surface type labels are acquired based on OSM road data. Then, proxy indicators that characterize road surface types are calculated based on multi-source open geospatial big data. Third, a deep learning model is trained using the proxy indicators and road surface type labels of the sampling points. Finally, the trained model is applied to the road networks of various African countries and regions to identify the surface type of each road.

3.1.1 Road Sampling

According to the definition of OSM road level tags (highway=) as outlined in the OSM wiki (https://wiki.openstreetmap.org/wiki/Key:highway), roads passable by four-wheeled motor vehicles are selected. These specifically include: "highway= motorway, motorway_link, trunk, trunk_link, primary, primary_link, secondary, secondary_link, tertiary, tertiary_link, residential, living_street, service, track, road, unclassified". Other roads primarily intended for bicycles or pedestrians (e.g., cycleway, footway) are excluded from the analysis.

After that, the selected OSM road data are then sampled at 100-meter intervals to generate sampling points. The 100-meter interval is chosen because most roads are greater than or equal to 100 meters in length, ensuring that most roads have at least one sampling point. For roads shorter than 100 meters, the center point of the road is used

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

as the sampling point.

3.1.2 Calculation and Selection of Proxy Indicators

(1) Calculation of Proxy Indicators

It has been found by Zhou et al. (2025b) that road surface types are not only related to road classes but also to the socio-economic and geographical environment of the area where the road is located. Therefore, Zhou et al. (2025b) designed 16 proxy indicators across three feature dimensions—Road network features, Socio-economic features, and Geographical environment features—as shown in Table 1. These indicators serve as "proxies" to identify or infer road surface types.

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

Table 1. Proxy Indicators

Dimension	Data Source	No.	Input	Type
Road network features	OSM road data	1	Road class	Category
		2	Road length	Value
		3	Degree	
		4	Closeness	
		5	Betweenness	
Socio-economic features	GDP	6	GDP	Value
	Population	7	Population	
	Building height	8	Building height	
Geographical environment features	Land cover	9	Water proportion	Value
		10	Trees proportion	
		11	Flooded vegetation proportion	
		12	Crops proportion	
		13	Building proportion	
		14	Bare land proportion	
		15	Snow land proportion	
		16	Pasture proportion	

For a single road sampling point,

Road network features: The road class is directly obtained from the OSM “highway=” tag. To calculate road length, degree centrality (Degree), closeness centrality (Closeness), and betweenness centrality (Betweenness). The road networks of each country or region are constructed into strokes based on the "every best fit" rule. These metrics (road length, Degree, Closeness, Betweenness) are calculated for each

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

stroke. The values are assigned to the corresponding sampling points on the road (Zhou et al., 2012).

Socio-economic features: The sampling point is assigned the value of the grid cell it falls into for corresponding data (GDP, population, or building height).

Geographical environment features: A 100m x 100m grid unit is established. The sampling point's grid unit is identified. The proportion of each land cover type within that grid unit is calculated.

(2) Feature Selection

Since proxy indicators may be highly correlated, this study employs correlation analysis and contribution analysis to select appropriate proxy indicators for model training, aiming to reduce data dimensionality, simplify model complexity, and eliminate multicollinearity.

For a single country or region: First, the correlation between pairs of proxy indicators is calculated using Phi_k (Baak et al., 2020), chosen because it can measure the correlation coefficient between different types of variables. Second, Shapley Additive exPlanations (SHAP) are used to analyze the interpretability of each proxy indicator, quantifying its contribution to the model's predictions. Third, proxy indicators without multicollinearity are directly used as input features. If two proxy indicators exhibit multicollinearity, the one with the highest contribution (based on SHAP values) is retained as the input feature for that country or region.

(3) Road surface type classification

Road surface types are treated as output variables and defined into two categories based on whether the road is paved. Paved roads: roads with a structured surface. Unpaved roads: roads without a structured surface.

Since the labels for training samples are automatically extracted from the OSM "surface=" tag, all OSM tags are reclassified into "paved" or "unpaved" roads, as shown in Table 2. The reclassification criteria follow the guidelines provided by OSM's wiki (https://wiki.openstreetmap.org/wiki/Surface).

Table 2. Reclassifying OSM "surface=" tags into paved and unpaved roads.

OSM "surface=" Tag	**Reclassification**
Asphalt, Concrete, Concrete: Plates, Paved, Paving Stones, Sett	Paved
Compacted, Dirt, Earth, Fine_Gravel, Gravel, Ground, Mud, Pebblestone, Sand, Unpaved	Unpaved

3.1.3 Model Training and Application

Zhou et al. (2025b) compared six machine learning and deep learning models for identifying road surface types and found that the TabNet model achieved the highest accuracy (approximately 86%). Consequently, this study adopts TabNet to develop the road surface type dataset for 50 African countries and regions. TabNet, proposed by Arik et al. (2021), combines the end-to-end learning and representation learning characteristics of deep neural networks (DNNs) with the interpretability and sparse feature selection advantages of decision tree models.

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

For a single African country: From sampling points with "surface=" tags, 5000 paved and 5000 unpaved sampling points are randomly selected as training samples. In some countries or regions where the number of paved sampling points is less than 5000 (e.g., a minimum of approximately 3000), all paved sampling points (e.g., 3000) and an equal number of unpaved sampling points (e.g., 3000) are used.

For each training sample, the 16 proxy indicators from Table 1 are calculated. After feature selection, the selected proxy indicators serve as input features for model training. The OSM road surface type of the training sample is used as the model output. The TabNet model is trained, with parameters (e.g., learning rate, batch size, training epoch) automatically determined using the Optuna framework, which searches for optimal parameters during training.

Each country trains a separate model. The trained model infers the road surface type of each sampling point in that country. A correction strategy proposed by Zhou et al. (2025b) is applied to determine the final surface type of each road segment, where the surface type is determined by the majority surface type of its sampling points.

3.2 Result evaluation

This study evaluates the effectiveness of the developed road surface type dataset from three aspects.

3.2.1 Accuracy assessment

For each African country or region: From all sampling points (excluding training samples), 500 points predicted as "paved" and 500 predicted as "unpaved" are randomly

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

selected, totaling 1000 validation points. Three different operators visually interpret the classification results of each validation point using high-resolution Google satellite imagery and Google street view, with the final reference surface type determined by voting.

At last, the model's predictions are compared with the reference road surface types, and effectiveness is assessed by calculating accuracy, precision, recall, and F1 score.

3.2.2 Comparative evaluation with existing statistical data

Based on the developed road surface type dataset, the paved road length, total road length, and road paved rate for each country and region are calculated and compared with International Road Federation (IRF) statistical data. Specifically, correlation coefficients between the results calculated from this data product and IRF statistical values are explored.

Since IRF provided statistical values for only 19 African countries in 2020, only these 19 countries are included in the correlation analysis.

3.2.3 Correlation evaluation with socio-economic indicators

Existing research indicates that the road paved rate is highly positively correlated with socio-economic development levels (Anyanwu et al., 2009). Therefore, this study explores the correlation between the road paved rate calculated from this data product and two indicators: Human Development Index (HDI), Gross National Income per capita (GNI per capita, based on PPP current international $).

More precisely, the analysis includes 44 African countries with HDI data and 36 with GNI per capita statistical data to verify the effectiveness of the data product.

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

Open Access Earth System Science Data Discussions

4. Results and Analyses

4.1 Description of the Africa Road Surface Type Dataset

This study has developed the road surface type dataset that records the roads and its surface type attribute information for 50 African countries and regions, as shown in Figure 3.

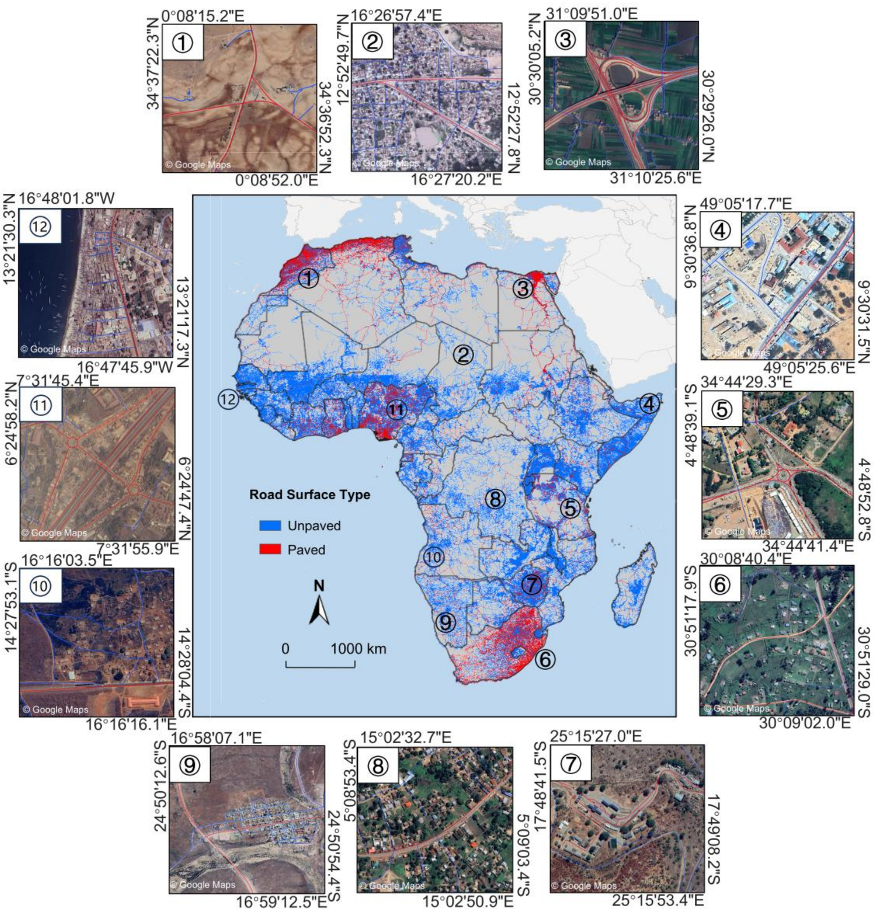


Figure 3. Visualization of road surface type dataset for 50 African countries and regions (source: Google Maps. 2025, https://www.google.com/maps/ (last access: 2

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

Jul 2025))

This dataset was developed based on OpenStreetMap (OSM) road data for Africa, with each country and region stored as a separate vector file in ESRI Shapefile format, using the WGS 1984 Web Mercator projection. The road data for each country and region includes five attribute fields: road ID, coordinates of the start and end points (Table 3), road length, and road surface type. The entire dataset comprises approximately 13,309,000 road segments, with a total length of about 6,822,516 km.

Table 3. Descriptions of dataset

Attribute	**Description**	**Type**
ID	Road segment ID	Int
Start point	Coordinates of the road segment's start point (x, y)	String
End point	Coordinates of the road segment's end point (x, y)	String
Road length	Length of the road segment (calculated based on WGS 1984 Web Mercator)	Float
Surface type	Road surface type, i.e., paved or unpaved	String

4.2 Accuracy Assessment of the Road Surface Type Identification Model

The accuracy assessment results of the road surface type dataset for 50 African countries and regions are presented in Figure 4. As indicated in the figure, the average accuracy across the 50 countries and regions is 86.8%. Out of these, 44 countries and regions have an accuracy above 80%, and 12 out of 50 have an accuracy exceeding 90%. The country with the highest accuracy is Burundi, surpassing 96%, while the

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

lowest is Egypt, at approximately 77%.

For paved roads, the average precision, recall, and F1 score across the 50 countries and regions are 88.0%, 85.0%, and 0.86, respectively. Specifically, 45 countries and regions have a precision above 80%, 32 have a recall above 80%, and 43 have an F1 score above 0.80 for paved roads.

For unpaved roads, the average precision, recall, and F1 score are 86.3%, 88.2%, and 0.87, respectively. Among the 50 countries and regions, 36 have a precision above 80%, 46 have a recall above 80%, and 46 have an F1 score above 0.80 for unpaved roads.

These results demonstrate that the road surface type dataset developed in this study has relatively high accuracy, consistent with the accuracy reported in existing research (approximately 86%) (Zhou et al., 2025b), indicating that the method using multi-source geospatial big data and deep learning models for identifying road surface types has certain universality.

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

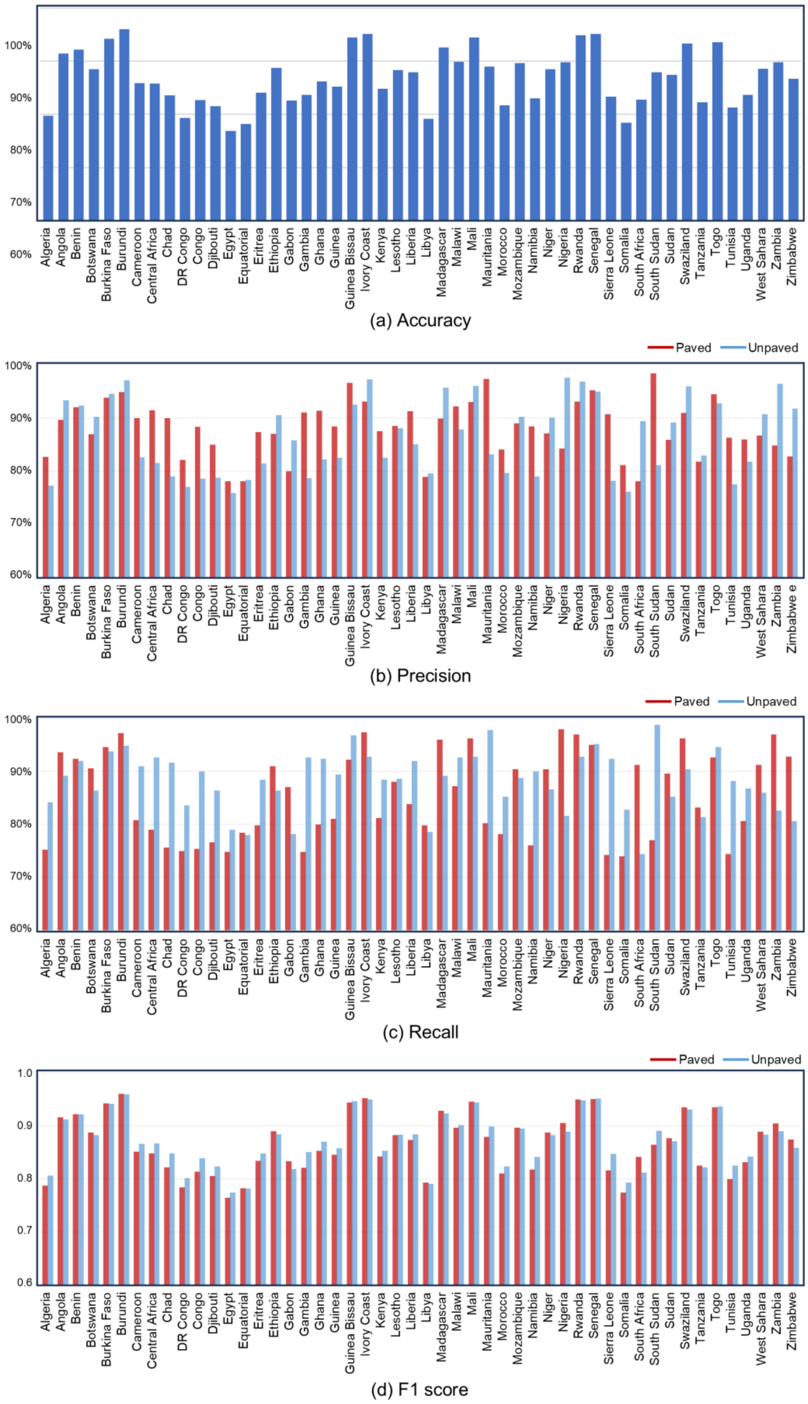


Figure 4. Accuracy Assessment Results of the Road Surface Type Dataset

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

4.3 Comparative Assessment with IRF Statistical Data

Figure 5 presents the correlation analysis results between the total road length, paved road length, and road paved rate calculated based on the road surface type dataset developed in this study and the corresponding statistical data from the International Road Federation (IRF).

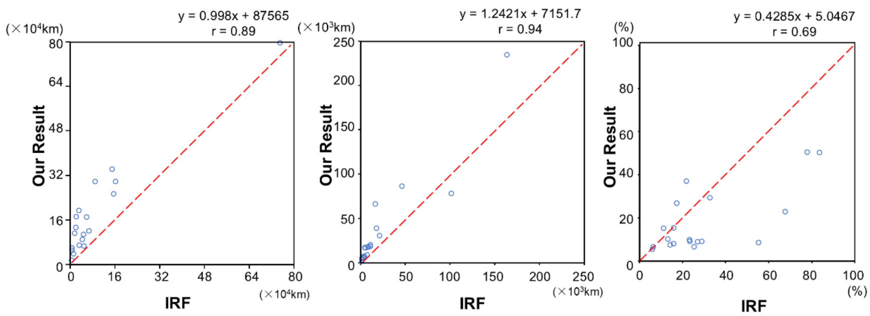
The correlation coefficients for total road length, paved road length, and road paved rate are 0.89, 0.94, and 0.69, respectively, all indicating a high correlation. This suggests that the calculations based on our data product are generally consistent with the IRF statistical data in terms of trends. For example, South Africa has the longest total road length and paved road length, while Gambia has the shortest; Tunisia and Morocco have the highest road paved rates. These results indicate the rationality of the road surface type dataset.

However, as shown in the scatter plots (Figure 5), there are still discrepancies between the calculations based on our data product and the IRF statistical data. Specifically, the total road length calculated from our data product is consistently higher than that reported by IRF (as seen in Figure 5a, where points are located to the left of the diagonal). Similarly, for 18 out of 19 countries, the paved road length is higher than the IRF statistics. Existing research has pointed out that IRF statistical data may underestimate the total road length globally, with an average underestimation of 36%, and for 94 countries, the underestimation exceeds 50% (Barrington-Leigh et al., 2017). Therefore, IRF statistical data may underestimate the total road length and paved road

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

length in African countries.

Additionally, for 15 out of 19 countries, the road paved rate is lower than that reported by IRF. This may be because IRF data underestimates the total road length in African countries, and the unaccounted roads are likely mostly unpaved, leading to an overestimation of the road paved rate in IRF statistics.



(a) Total Length of All Roads (b) Total Length of Paved Roads (c) Road Paved Rate

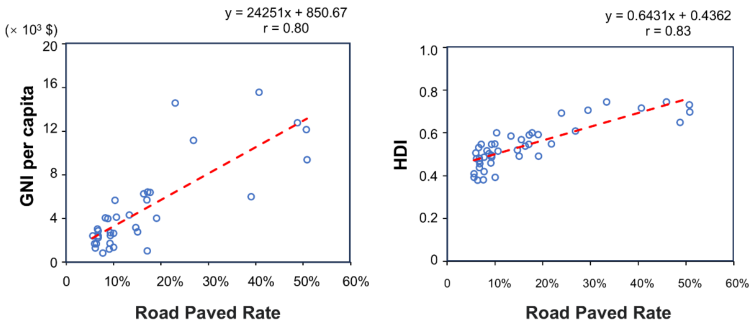
Figure 5. The Correlation Analysis Results with IRF Statistical Data

4.4 Correlation Assessment with Socioeconomic Indicators

The correlation analysis results between the road paved rate calculated based on our data product for 50 African countries and regions and the Gross National Income per capita (GNI per capita) and the Human Development Index (HDI) are shown in Figure 6. As indicated, the correlation coefficients between the road paved rate and GNI per capita and HDI are 0.80 and 0.83, respectively, both showing a strong positive correlation. This indicates that the road paved rate in African countries is highly positively correlated with their level of socioeconomic development, consistent with findings from existing research (Anyanwu et al., 2009), indirectly validating the

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

effectiveness of our road surface type dataset.



(a) GNI per capita

(b) HDI

Figure 6. The Correlation Analysis Results of The Road Paved Rate Calculated Based on The African Road surface type dataset with Per Capita GNI (a) and HDI (b)

4.5 Spatial Pattern Analysis of Road Paved Rates in Africa

Based on the road surface type dataset, the spatial patterns of road paved rates in 50 African countries and regions were analyzed at the national, provincial, and county levels, as shown in Figure 7. Compared to IRF, which only provides statistical data for 19 African countries (Ken et al., 2008), our dataset not only allows for the analysis of road paved rates in all 50 African countries and regions but also enables detailed analysis at different administrative levels.

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

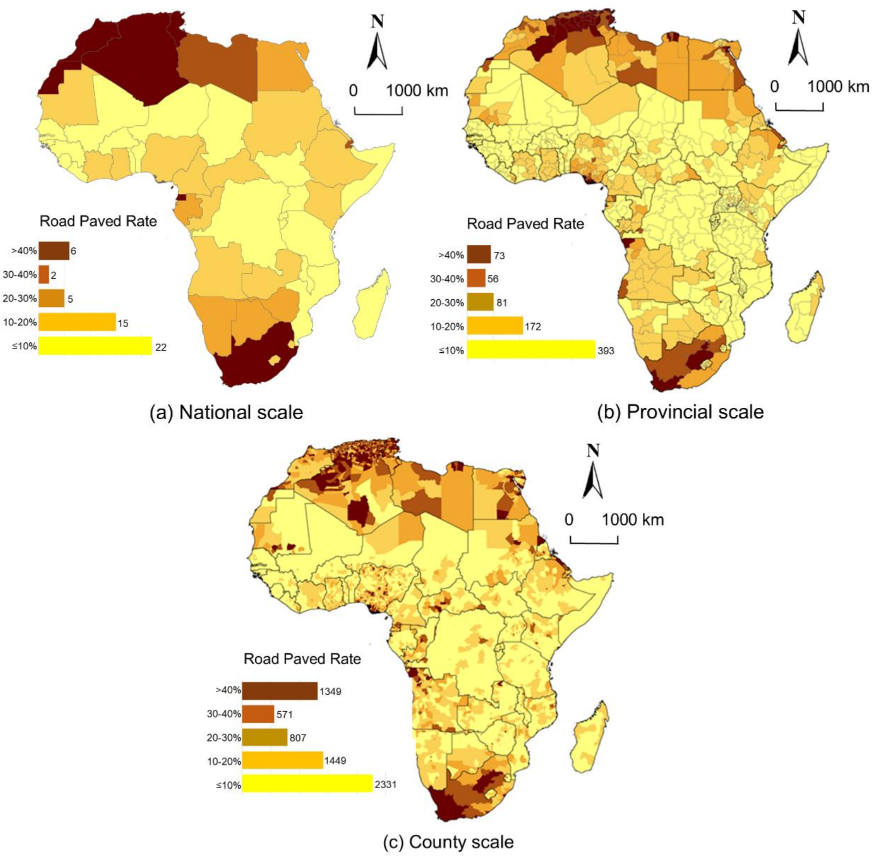


Figure 7. Spatial Pattern Analysis at National, Provincial, and County Levels

At the national level, the average road paved rate across the 50 African countries and regions is only 17.4%, ranging from a low of 5.54% in Chad to a high of 50.77% in Morocco. Only six African countries have a road paved rate above 40%, while 37 countries and regions have a rate below 20%. The average road paved rate for 43 countries and regions in Sub-Saharan (excluding South Africa) is merely 13.6%. These results indicate that road paved rates in African countries and regions are generally low, with significant north-south disparities. At the provincial and county levels, only 9% of

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

provincial administrative divisions have a road paved rate above 40%, mostly located in north of Africa and South Africa. Similarly, only about 20% of county administrative divisions have a road paved rate above 40%, primarily in north of Africa, South Africa, and some urban areas. Therefore, the overall spatial pattern of road paved rates in Africa shows a " higher in the north and south, lower in the central region " distribution, with higher rates in north of Africa and South Africa, and lower rates in Sub-Saharan excluding South Africa. The average road paved rate in the north of Africa (40.7%) is approximately three times that of Sub-Saharan (excluding South Africa).

5. Discussion

5.1 Data Quality

This study developed road surface type dataset for 50 African countries and regions and verified its validity (accuracy ranging from 77% to 96%; F1 score ranging from 0.76 to 0.96). However, the quality of the dataset varies across different African countries and regions. For example, Burundi has an accuracy of 96%, while Egypt's accuracy is only 77%. Further, taking a local area in Egypt as an example, combined with Google high-resolution remote sensing imagery and Google street view, it can be observed that the backbone of the road network in this region predominantly consists of paved roads (Figure 8b), while non-backbone roads (especially in rural areas) are mostly unpaved (Figure 8c); urban areas in Egypt are predominantly paved (Figure 8d), although some roads remain unpaved (Figure 8e). These results indicate that the road surface type classification in this study is reasonable.

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

Open Access Earth System Science Data Discussions

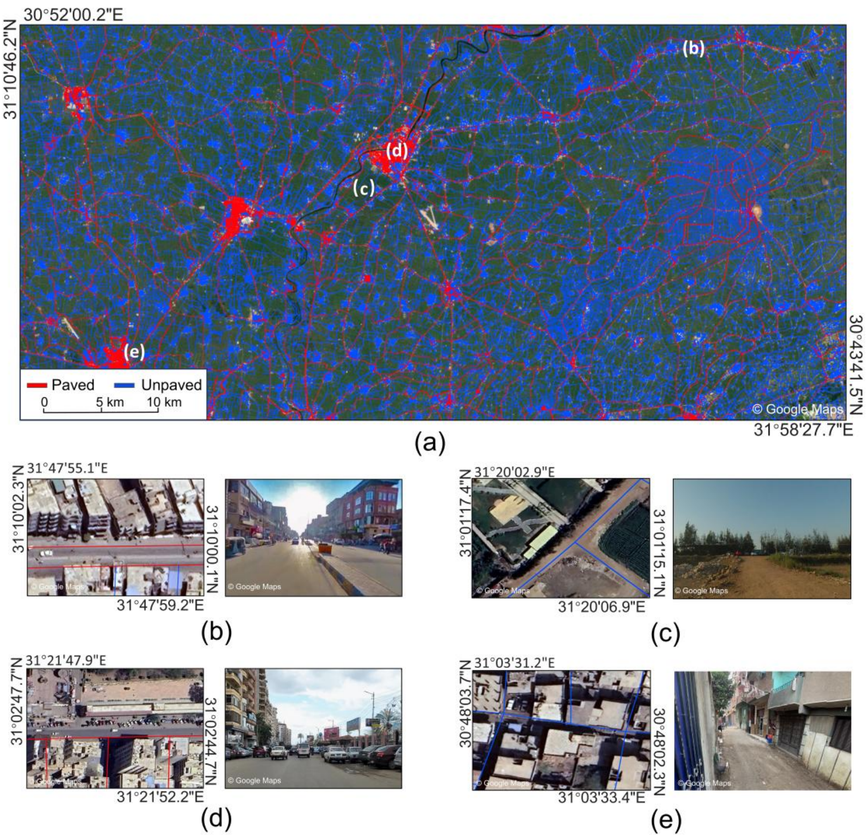


Figure 8. An Example of Road Surface Type Data in Egypt (source: Google Maps. 2025, https://www.google.com/maps/ (last access: 2 Jul 2025))

Despite this, we found that misclassifications of road surface types are inevitable. Taking urban areas in Egypt as an example (Figure 9a), Figure 9b shows a 1 km × 1 km grid area in this region. Figure 9c displays two road classes in this grid area: "trunk" and "residential." From Figures 9b and 9c, it can be seen that most "trunk" roads in this area are classified as paved, while most "residential" roads are classified as unpaved. However, based on street view imagery of this area, it is evident that "residential" roads include both unpaved (Figure 9d) and paved (Figure 9e) types. Therefore, it is difficult

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

Open Access Earth System Science Data Discussions

to distinguish road surface types in this area based solely on road class, and the spatial resolution of the GDP and population data we obtained (both 1 km) also makes it challenging to finely differentiate road surface types within this area.

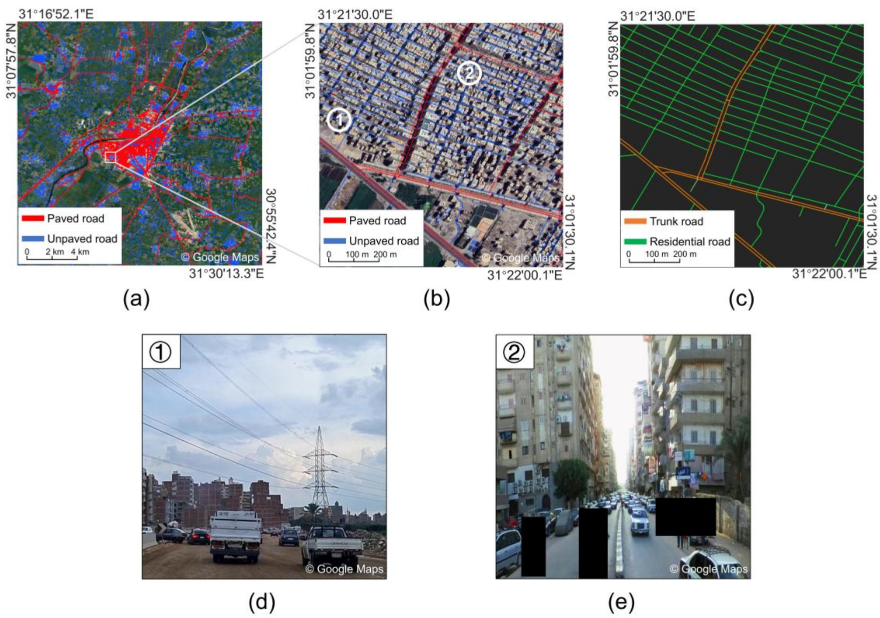


Figure 9. An Example of Explaining the Data Quality of The African Road surface type dataset (source: Google Maps. 2025, https://www.google.com/maps/ (last access: 2 Jul 2025))

Additionally, open geospatial data inevitably have quality issues. For instance, although existing studies have found that the geometric positional accuracy and completeness of OSM road data in Africa are generally high, road data gaps are unavoidable (Zhou et al., 2022); road surface types and road classes labeled by global volunteers in OSM may also contain errors (Zhou et al., 2022). The GHSL-BUILT building height data, derived from medium-resolution remote sensing imagery (Sentinel-2), also inevitably has estimation biases for building heights (Pesaresi et al.,

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

2021)[34]. LandScan data may be underestimated in urban-rural transition zones and overestimated in sparsely populated areas (Beata et al., 2019). Nevertheless, OSM road data remain the only globally available open data source that includes road surface type labels; GHSL and LandScan data are also globally covered, freely accessible geospatial data products with long time series, which is why this study selected these data for experimental analysis. However, in the future, other data sources (e.g., CORINE Land Cover (Pontius Jr et al., 2017), World Settlement Footprint (Marconcini et al., 2020), and Global Human Settlement Population Grid (Yin et al., 2021)) could be considered, and their impact on the quality of road surface type dataset could be analyzed.

5.2 Implications and Significance

Compared to traditional statistical data such as those from IRF, the first-ever road surface type dataset for 50 African countries and regions developed in this study not only allows for the calculation of statistical indicators such as paved road length and road paved rate for each country and region but also enables detailed analysis of which roads are paved or unpaved, providing decision-making support for improving local transportation infrastructure (e.g., upgrading unpaved roads to paved roads). Additionally, road surface types are an important data source for assessing SDG 9.1. Therefore, this dataset can also be combined with population and urban built-up area data to analyze the proportion of rural populations within 2 km of paved or unpaved roads in various African countries (Wanjing et al., 2021), to provide data support for evaluating Africa's sustainable development goals. Last but not least, this dataset can

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

be combined with location data of traffic accidents to analyze the relationship between road surface types and traffic accidents (Patrick et al., 2022); with traffic carbon emission data to analyze the relationship between road surface types and environmental impacts (Ling et al., 2024); or with national income data to analyze the relationship between road surface types and socioeconomic development (Anyanwu et al., 2009).

Moreover, this study utilized multisource geospatial big data and deep learning models to develop the African road surface type dataset. The primary advantage of this method is that its source data (including OSM, LandScan, GDP, GHSL-BUILT, and ESRI Land Cover) are not only openly accessible but also globally covered. Therefore, this method could also be applied to identify road surface types in other countries and regions worldwide, providing methodological support for developing global road surface type dataset.

5.3 Limitations and future work

(1) This study adopted the method proposed by Zhou et al. (2025b) to develop the African road surface type dataset. This method designs 16 proxy indicators across three dimensions (Road network, Socioeconomic, and Geographical Environment) from five types of open geospatial data to infer road surface types. In the future, other data sources such as terrain data could be introduced, and additional proxy indicators such as slope, aspect, and surface roughness could be designed to investigate whether these indicators can improve the classification accuracy of the data product.

(2) Road surface types are not limited to just paved and unpaved roads; they can also be further subdivided into categories such as asphalt, concrete, and dirt roads.

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

However, we found that most paved roads in Africa are asphalt roads, and most unpaved roads are dirt roads; thus, this study only considered "paved" and "unpaved" categories. Nevertheless, in the future, by supplementing field-measured data, it could be explored whether this method can be used to develop dataset that include more detailed road surface type classifications.

(3) The African road surface type dataset developed in this study is limited to a single year, approximately 2020. This is because the source data used were all obtained from 2020 or nearby years to ensure temporal consistency across dataset for different African countries. Although most open geospatial big data (such as OSM, GDP, and population data) include data from different years, which could potentially be used to develop road surface type dataset for multiple years, validation data are difficult to obtain. Specifically, it is challenging to interpret roads and their surface types using open-source medium- to low-resolution satellite imagery (e.g., Landsat or Sentinel-2). Although Google satellite imagery has higher resolution, the update years of Google imagery for different areas within a country may not be consistent, making it difficult to analyze changes in road surface types. Nonetheless, in the future, this method could be attempted to develop road surface type dataset for different years, and accuracy could be validated using long-time-series high-resolution remote sensing imagery; further, spatiotemporal changes in road surface types at a large scale could be analyzed.

6. Data availability

The First Road Surface Dataset for 50 African countries and reigns is distributed

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

under the CC BY 4.0 License. The data can be downloaded from the data repository Figshare at https://doi.org/10.6084/m9.figshare.29424107 (Liu et al., 2025).

7. Conclusion

This study developed the first dataset containing road surface types for every road in 50 African countries and regions, based on multi-source geospatial data and deep learning model. The accuracy of this dataset was evaluated through visual interpretation using high-resolution Google satellite imagery and Google street view, while its effectiveness was indirectly analyzed by comparing it with IRF statistical data and socio-economic indicators such as HDI and GNI per capita. Finally, the spatial patterns of road surface types across these 50 African countries and regions were analyzed using the developed dataset. The main findings are as follows:

(1) The accuracy of the road surface type dataset for the 50 African countries and regions ranges from 77% to 96%, with F1 scores between 0.76 and 0.96, validating the effectiveness of the developed dataset.

(2) In terms of total road length, paved road length, and road paved rate, the correlation coefficients between the calculations based on our dataset and the IRF statistical data show high correlation, ranging from 0.69 to 0.94. Regarding socio-economic indicators (GNI per capita and HDI), the calculations based on our dataset also exhibit high correlation with the relevant statistical data, ranging from 0.80 to 0.83, indirectly verifying the effectiveness of our dataset.

(3) From a spatial perspective, the road paved rate in Africa is generally low. The average road paved rate across the 50 African countries and regions is only 17.4%,

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

displaying a spatial pattern of "higher in the north and south, lower in the central region." Specifically, the average road paved rate in the north of Saharan is approximately 3 times that of Sub-Saharan (excluding South Africa).

The dataset developed in this study includes the surface type of every road in Africa, offering decision-making support for improving the region's road infrastructure. Additionally, this dataset can be combined with data on population and urban built-up areas to assess Africa's Sustainable Development Goals (e.g., SDG 9.1). Furthermore, it can be integrated with other datasets—such as traffic accidents, carbon emissions, and national income—to analyze the impact of road surface types on road safety, energy consumption, ecological environment, and socio-economic development.

Author contributions ZL developed the data and wrote the original manuscript. QZ proposed methods and designed experiments. FZ reviewed and improved the manuscript. LP checked and validated data quality. All authors discussed and improved the manuscript.

Competing interests The contact author has declared that none of the authors has any competing interests.

Acknowledgements The project was supported by National Natural Science Foundation of China (Grant No. 42471492).

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

References

Anyanwu, J.C., Erhijakpor, A.E.O. The Impact of Road Infrastructure on Poverty Reduction in Africa. In: Poverty in Africa (Ed. T.W. Beasley), 1–40, 2009.

Shtayat, A., Moridpour, S., Best, B. A Review of Monitoring Systems of Pavement Condition in Paved and Unpaved Roads. J. Traffic Transp. Eng., 7(5): 629–638, https://doi.org/10.1016/j.jtte.2020.03.004, 2020.

Sha, A. Advances and Development Trends in Eco-friendly Pavements. J. Road Eng., 1: 1–42, https://doi.org/10.1016/j.jreng.2021.12.002, 2021.

Styer, J., Tunstall, L., Landis, A.E., Grenfell, J. Innovations in Pavement Design and Engineering: A 2023 Sustainability Review. Heliyon, 10(13): e33481, https://doi.org/10.1016/j.heliyon.2024.e33602, 2024.

Chen, Y., Li, C., Wang, W., et al. The Landscape, Trends, Challenges, and Opportunities of Sustainable Mobility and Transport. npj Sustain. Mobil. Transp., 2: 8, https://doi.org/10.1038/s44333-025-00026-8, 2025.

Abdulkadr, A.A., Juma, L.O., Gogo, A.F., Neszmélyi, G.I. East African Transport Infrastructure: The Cases of Ethiopia, Kenya and Tanzania. Reg. Econ. South Russ., 10(4): 89–102, 2022.

Greening, T., O'Neill, P. Traffic Generated Dust from Unpaved Roads: An Overview of Impacts and Options for Control. Proc. 1st AFCAP Pract. Conf., 23–25 Nov 2010, 2010.

Li, W., Zhou, Q., Zhang, Y., Chen, Y. Visualising Rural Access Index and Not Served Rural Population in Africa. Environ. Plan. A Econ. Space, 54(2): 215–218, http://doi.org/10.1177/0308518X211035786, 2022.

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

World Bank First African Observatory to Tackle the Continent's Road Safety Crisis. World Bank Press Release, 23 May 2018, 2018a.

African Union Commission Agenda 2063. African Union Policy Doc., 2015.

Kresnanto, N.C. Model of Relationship Between Car Ownership Growth and Economic Growth in Java. IOP Conf. Ser. Mater. Sci. Eng., 650: 012047, https://doi.org/10.1088/1757-899X/650/1/012047, 2019.

Patrick, M., Yves, A. Access to Paved Roads, Gender, and Youth Unemployment in Rural Areas: Evidence from Sub-Saharan Africa. Afr. Dev. Rev., 35(2): 165–180, https://doi.org/10.1111/1467-8268.12701, 2022.

Barrington-Leigh, C., Millard-Ball, A. The World's User-Generated Road Map Is More Than 80% Complete. PLoS ONE, 12(8): e0180698, https://doi.org/10.1371/journal.pone.0180698, 2017.

Central Intelligence Agency (CIA) The World Factbook. CIA Publ., 2023.

Turner, B. International Road Federation (IRF). Statesman's Yearb., 2015: 49–50, 2014.

Louhghalam, A., Akbarian, M., Ulm, F.J. Roughness-Induced Pavement–Vehicle Interactions: Key Parameters and Impact on Vehicle Fuel Consumption. Transp. Res. Rec., 2525(1): 62–70, 2015.

Sattar, S., Li, S., Chapman, M. Road Surface Monitoring Using Smartphone Sensors: A Review. Sensors, 18(11): 3845, https://doi.org/10.3390/s18113845, 2018.

Pérez-Fortes, A.P., Giudici, H. A Recent Overview of the Effect of Road Surface Properties on Road Safety, Environment, and How to Monitor Them. Environ. Sci. Pollut. Res., 29(44): 65993–66009, https://doi.org/10.1007/s11356-022-21847-x, 2022.

Chen, K., Tan, G., Lu, M., Wu, J. CRSM: A Practical Crowdsourcing-Based Road Surface Monitoring System. Wirel. Netw., 22: 765–779, https://doi.org/10.1007/s11276-015-0996-y, 2016.

Harikrishnan, P.M., Gopi, V.P. Vehicle Vibration Signal Processing for Road Surface Monitoring. IEEE Sens. J., 17(16): 5192–5197, https://doi.org/10.1109/JSEN.2017.2719865, 2017.

Li, X., Goldberg, D.W. Toward a Mobile Crowdsensing System for Road Surface Assessment. Comput. Environ. Urban Syst., 69: 51–62, https://doi.org/10.1016/j.compenvurbsys.2017.12.005, 2018.

Randhawa, S., Eren, A., Guntaj, R., Herfort, B., Lautenbach, Sven., Zipf, A. Paved or unpaved? A deep learning derived road surface global dataset from Mapillary Street-View Imagery. ISPRS J. Photogramm. Remote Sens., 223: 1–14, https://doi.org/10.1016/j.isprsjprs.2025.02.020, 2025.

Menegazzo, J., von Wangenheim, A. Multi-Contextual and Multi-Aspect Analysis for Road Surface Type Classification Through Inertial Sensors and Deep Learning. Proc. IEEE SBESC, 1–8, https://doi.org/10.1109/SBESC51047.2020.9277846, 2020.

Zhou, Q., Duan, J., Qiao, J., Liu, Z., Yang, H. A Large Crowdsourced Street View Dataset for Mapping Road Surface Types in Africa. Sci. Data, 12: 1003, https://doi.org/10.1038/s41597-025-05153-y, 2025a.

Workman, R., Wong, P., Wright, A., Wang, Z. Prediction of Unpaved Road Conditions Using High-Resolution Optical Satellite Imagery and Machine Learning. Remote Sens., 15(16): 3985, https://doi.org/10.3390/rs15163985, 2023.

Zhou, Q., Liu, Z., Huang, Z. Mapping Road Surface Type of Kenya Using OpenStreetMap and High-resolution Google Satellite Imagery. Sci. Data, 11: 331, https://doi.org/10.1038/s41597-024-03158-7, 2024.

Zhou, Q., Liu, Y., Liu, Z. Mapping National-Scale Road Surface Types Using Multisource Open Data and Deep Learning Model. Trans. GIS, 29(1): 123–141, https://doi.org/10.1111/tgis.13305, 2025b.

Biber-Freudenberger, L., Christina, B., Georg, B., et al. Impacts of road development in sub-Saharan Africa: A call for holistic perspectives in research and policy. iScience, 28(2): 111913, https://doi.org/10.1016/j.isci.2025.111913, 2025.

Chen, J., Gao, M., Cheng, S., Hou, W., Song, M., Liu, X., Liu, Y. Global 1 Km× 1 Km Gridded Revised Real Gross Domestic Product and Electricity Consumption During 1992–2019 Based on Calibrated Nighttime Light Data. Sci. Data, 9(1): 202, https://doi.org/10.1038/s41597-022-01322-5, 2022.

Dobson, J.E., Bright, E.A., Coleman, P.R., Durfee, R.C., Worley, B.A. Landscan: A Global Population Database for Estimating Populations at Risk. Photogramm. Eng. Remote Sens., 66(7): 849–857, 2000.

Yin, X., Li, P., Feng, Z., Yang, Y., You, Z., Xiao, C. Which Gridded Population Data Product Is Better? Evidences from Mainland Southeast Asia (MSEA). ISPRS Int. J. Geo-Inf., 10(10): 681, https://doi.org/10.3390/ijgi10100681, 2021.

Mohit, P.M., Slobodan, P.S. Understanding dynamics of population flood exposure in Canada with multiple high-resolution population datasets. Sci. Total Environ., 759: 143559, https://doi.org/10.1016/j.scitotenv.2020.143559, 2021.

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

Jiang, S., Zhang, Z., Ren, H., Wei, G., Xu, M., Liu, B. Spatiotemporal Characteristics of Urban Land Expansion and Population Growth in Africa from 2001 to 2019: Evidence from Population Density Data. ISPRS Int. J. Geo-Inf., 10(9): 584, https://doi.org/10.3390/ijgi10090584, 2021.

Pesaresi, M., Corbane, C., Ren, C., Edward, N. Generalized Vertical Components of Built-Up Areas from Global Digital Elevation Models by Multi-Scale Linear Regression Modelling. PLoS ONE, 16(2): e0244478, https://doi.org/10.1371/journal.pone.0244478, 2021.

Karra, K., Kontgis, C., Statman-Weil, Z., Mazzariello, J., Mathis, M., Brumby, S. Global Land Use/Land Cover with Sentinel-2 and Deep Learning. Proc. IEEE IGARSS, 4704–4707, https://doi.org/10.1109/IGARSS47720.2021.9553499, 2021.

Yan, M., Pang, Y., He, Y., Meng, S. Consistency Analysis and Accuracy Evaluation of Multi-Source Land Cover Products in Pu'er. For. Resour. Manag., (1): 173–182, https://doi.org/10.13466/j.cnki.lyzygl.2023.01.020, 2023.

Zhou, Q., Li, Z. A comparative study of various strategies to concatenate road segments into strokes for map generalization. Int. J. Geogr. Inf. Sci., 26(4): 691–715, https://doi.org/10.1080/13658816.2011.609990, 2012.

Baak, M., Koopman, R., Snoek, H., Klous, S. A new correlation coefficient between categorical, ordinal and interval variables with Pearson characteristics. Comput. Stat. Data Anal., 152: 107043, https://doi.org/10.1016/j.csda.2020.107043, 2020.

Arik, S.Ö., Pfister, T. Tabnet: Attentive Interpretable Tabular Learning. Proc. AAAI Conf. Artif. Intell., 35(8): 6679–6687, https://doi.org/10.48550/arXiv.1908.07442,

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

2021.

Gwilliam, K., Foster, V., Archondo-Callao, R., Briceño-Garmendia, C., Nogales, A., Sethi, K. The Burden of Maintenance: Roads in Sub-Saharan Africa. Africa Infrastruct. Ctry. Diagn., 14(1), 2008.

Zhou, Q., Wang, S., Liu, Y. Exploring the accuracy and completeness patterns of global land-cover/land-use data in OpenStreetMap. Appl. Geogr., 145: 102742, https://doi.org/10.1016/j.apgeog.2022.102742, 2022.

Calka, B., Bielecka, E. Reliability Analysis of LandScan Gridded Population Data. The Case Study of Poland. ISPRS Int. J. Geo-Inf., 8(5): 222, https://doi.org/10.3390/ijgi8050222, 2019.

Pontius Jr, R.G. European Landscape Dynamics: Corine Land Cover Data. Photogramm. Eng. Remote Sens., 83(2): 79, https://doi.org/10.1201/9781315372860, 2017.

Marconcini, M., Metz-Marconcini, A., Üreyen, S., et al. Outlining where humans live, the World Settlement Footprint 2015. Sci. Data, 7: 242, https://doi.org/10.1038/s41597-020-00580-5, 2020.

Li, W., Zhou, Q., Zhang, Y., Chen, Y. Visualizing Rural Access Index and Not Served Rural Population in Africa. Environ. Plan. A Econ. Space, 54(2): 215–218, https://doi.org/10.1177/0308518X211035786, 2022.

Ling, C., Tang, J., Zhao, P., Xu, L., Lu, Q., Yang, L., Huang, F., Lyu, W., Yang, J. Unraveling the Relation Between Carbon Emission and Carbon Footprint: A Literature Review and Framework for Sustainable Transportation. npj Sustain. Mobil. Transp., 1:

https://doi.org/10.5194/essd-2025-386
Preprint. Discussion started: 24 September 2025

13, https://doi.org/10.1038/s44333-024-00013-5, 2024.

Liu, Z., Qi, Z.: The First Road Surface Type Dataset for 50 African Countries and Regions, Figshare [data set], https://doi.org/10.6084/m9.figshare.29424107, 2025.