Response to Reviewer 1

Reviewer1_Comment1

In Figure 1, it appears that both the input and output variables point to model training, which could be somewhat confusing. Could the authors provide further explanation and clarification??

Reply to Reviewer1_Comment1: Thanks for this valuable comment! We have revised “Output variables” as “Road surface types”; and revised “Input variables” as “Proxy indicators” (see **Figure 2**). We have explained both the “Road surface types” and “Proxy indicators” in the revised manuscript. That is,

“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.” (see **Section 3.1.2**)

“Road surface types from OSM data 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.” (see **Section 3.1.2**)

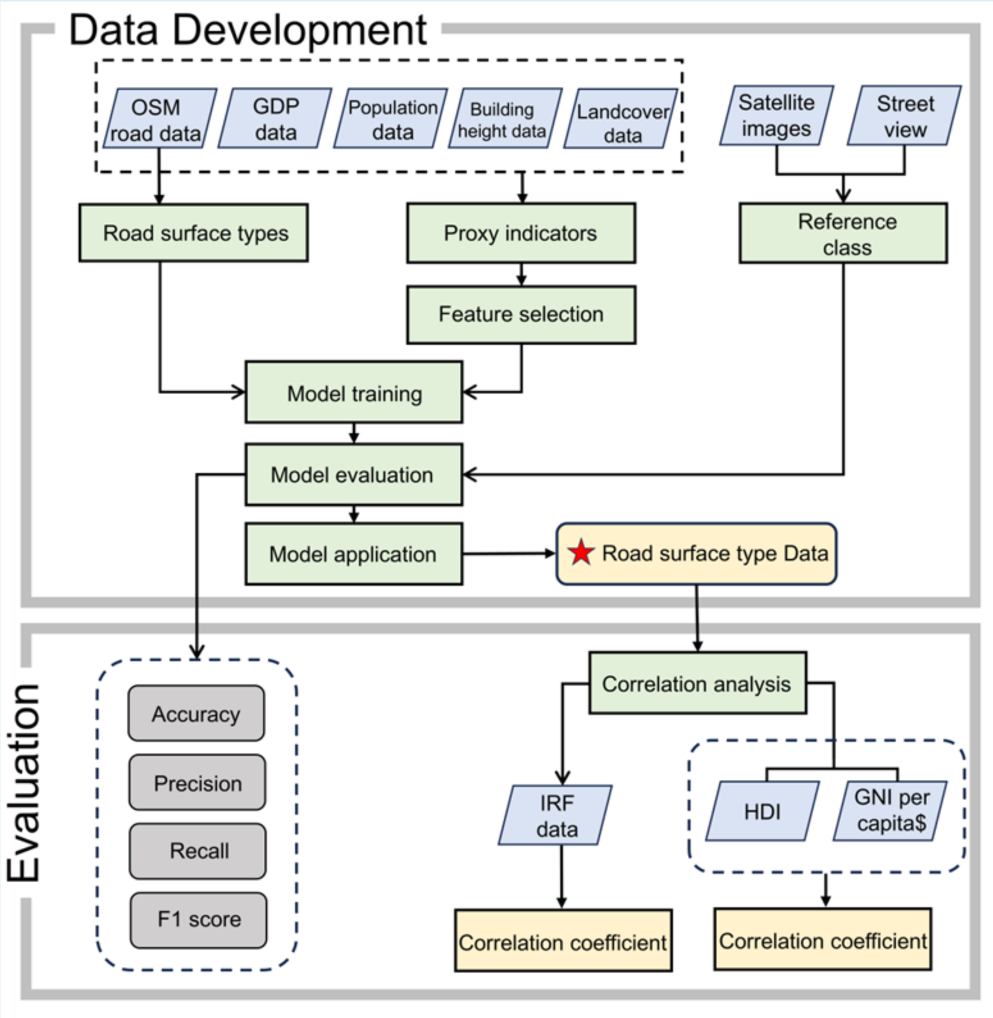

Figure 2. Technical roadmap

Reviewer1_Comment2

In Lines 94-97, there are two "in Shenzhen".

<u>Reply to Reviewer1_Comment2</u>: Thanks for this valuable comment!

We have removed one of the "in Shenzhen". The sentence was revised as: "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.” (see **Section Introduction**)

Reviewer1_Comment3

In Line 285, would it be more appropriate to replace the comma in "For a single road sampling point," with a colon, i.e., "For a single road sampling point:"?

Reply to Reviewer1_Comment3: Thanks for this valuable comment!

In the manuscript, we have revised "For a single road sampling point," as "For a single road sampling point:".

Reviewer1_Comment4

In Line 289, to improve clarity and readability, please explain the "every best fit" rule and how it is implemented.

Reply to Reviewer1_Comment4: Thanks for this valuable comment!

The “every best fit" method, which means to concatenate road segments into individual roads (called strokes). The method has been widely used for street network analysis (Biljecki et al., 2021; Noori et al., 2020) and map generalization (Zhou et al., 2012).

The principle of this method is to connect road segments with the smallest deflection angle. For example, there are three road segments (i.e., Segment 1, Segment 2, and Segment 3 in Figure A). Among these road segments, the angle α is smaller than the angle β, and thus the Segment 1 should be connected to Segment 2. After that, the three segments were divided into two “strokes” (e.g., Stroke 1 and Stroke 2).

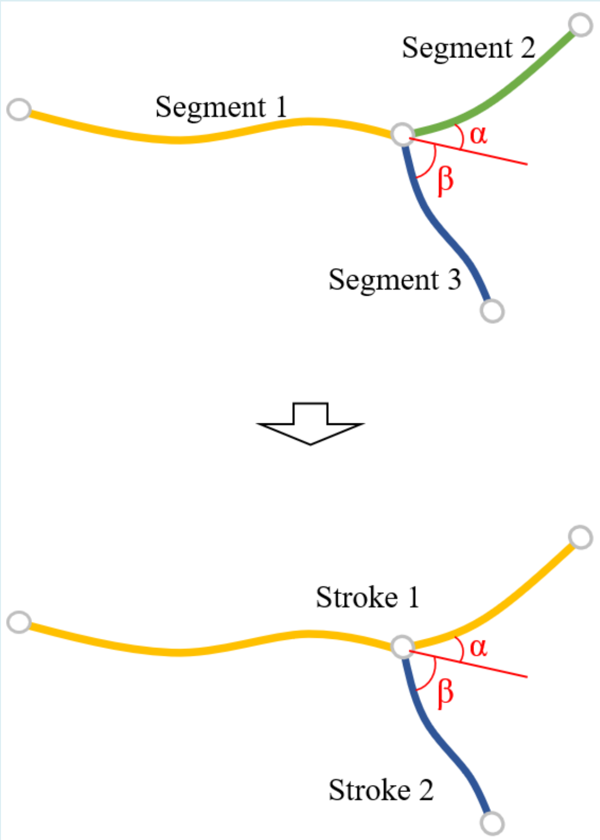

Figure A The principle of “Stroke” building.

In the revised manuscript, we have highlighted the above point. That is,

“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” method (Zhou et al., 2012). **The core principle of this method is to connect continuous road segments into individual roads (called “strokes”), according to the deflection angle between adjacent road segments**.” (see **Section 3.1.2**)

Reference:

1) Biljecki, F., Ito, K. 2021. An open-source tool to extract natural continuity and hierarchy of urban street networks. Environment and Planning B: Urban Analytics and City Science, 48(2): 218 – 237.

2) Noori, N., Tamim, I., Godin, C., Poulin, P. 2020. A deep learning approach to urban street functionality prediction based on centrality measures and urban indicators. Computers, Environment and Urban Systems, 84: 101523.

3) Zhou, Q., Li, Z. 2012. A comparative study of various strategies to concatenate road segments into strokes for map generalization. International Journal of Geographical Information Science, 26(4): 691 – 715.

Reviewer1_Comment5

In Line 315, the authors used the "surface=" tags in OSM data for road types. Are the existing road types in OSM incomplete? Does this study help to address or fill this gap?

Reply to Reviewer1_Comment5: Thanks for this valuable comment!

(1) Are the existing road types in OSM incomplete?

Yes. To our knowledge, the length of OSM roads with surface type information in a single country usually accounts for **less than 30%**. We have highlighted this point in the revised manuscript. That is, "Although OSM data for different countries or regions in Africa include information on road surface types, 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, highlighting an urgent need for supplementation and improvement." (see **Section 2.2.1**)

(2) Does this study help to address or fill this gap?

Indeed, the purpose of this study is to acquire OSM roads with surface types as training samples. Then, the OSM roads without surface type can be inferred using multi-source geospatial data and deep learning model. Based on the proposed approach, we produced the first road surface type dataset for 50 countries and regions in Africa.

Reviewer1_Comment6

In Line 329, the authors selected 5,000 paved and 5,000 unpaved sampling points for each country as training data. However, considering the substantial differences across African countries in terms of geography, infrastructure, and data availability, it would be helpful if the authors could clarify the rationale for using a uniform sampling strategy.

Reply to Reviewer1_Comment6: Thanks for this valuable comment! We selected 5,000 paved and 5,000 unpaved sampling points for two reasons:

- Firstly, the positive and negative samples are controlled at a 1:1 ratio to achieve equal weights, ensuring sufficient learning for both types.

➢ Secondly, **we found that the model's accuracy improves as the number of sampling points increases**, although it tends to stabilize when the number of sampling points reaches approximately 3,000.

Figure B shows an example of five countries (Cameroon, Djibouti, Egypt, Kenya and Nigeria) that accuracy increases as the number of sampling points increases.

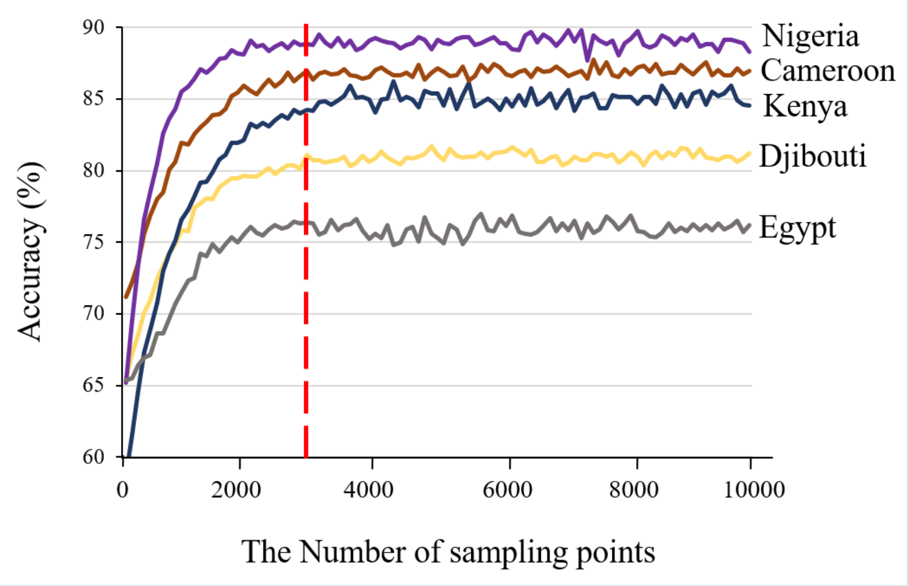

Figure B. An example of five countries (Cameroon, Djibouti, Egypt, Kenya and Nigeria) that accuracy increases as the number of sampling points increases

The above points have been highlighted in the revised manuscript. (see **Section 3.1.3**)

Reviewer1_Comment7

In Line 337, the authors provide a brief introduction to the TabNet model. Although the parameter tuning process using the Optuna framework is automated, the optimization objective and models should be described in more detail.

<u>Reply to Reviewer1_Comment7</u>: Thanks for this valuable comment! In the revised manuscript, we have added more details about the TabNet model and the Optuna framework. That is,

- “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.**” (see **Section 3.1.3**)

- ″The TabNet model is trained, with parameters (e.g., learning rate, number of steps, training epoch) automatically determined using the Optuna framework, which searches for optimal parameters during training. **The core principle of the Optuna framework is to explore various parameter combinations until it identifies the one that yields the highest accuracy. In this study, the search ranges for the parameters—learning rate, number of steps and training epochs—were set to 0.001-0.2, 3-10, and 10-100, respectively**.″ (see **Section 3.1.3**)

Response to Reviewer 2

Reviewer2_Comment1

The calculation methods for the road network features "Degree," "Closeness," and "Betweenness" are not described. Please provide their definitions, formulas, or references to ensure reproducibility.

Reply to Reviewer2_Comment1: Thanks for this valuable comment!

The calculation methods for the road network features "Degree," "Closeness," and "Betweenness" are listed as follows:

$$Degree(i) = \sum_{j=1, j\neq i}^{n} k_{ij}$$

$$Betweenness(i) = \sum_{j\neq k\neq i}^{n} n_{jk}(i)/\, n_{jk}$$

$$Closeness(i) = (n-1)/\sum_{j=1, j\neq i}^{n} d_{ij}$$

Where, n denotes the number of strokes in a road network; k_{ij} denotes the connectivity between stroke *i* and stroke *j*; n_{jk} denotes the number of shortest paths between stroke *j* and stroke *k*; $n_{jk}(i)$ denotes the number of shortest paths between the stroke *j* and the stroke *k* that contain the stroke *i*; d_{ij} denotes the number of strokes in the shortest path from stroke *i* to stroke *j*.

Because these "road network features" have been widely introduced in the previous studies (Zhou and Li 2015; Zhou et al., 2025b) for the purpose of street network analysis, thus in the revised manuscript, we added a sentence to highlight this point rather than introduce them again. That is,

“These metrics (road length, Degree, Closeness, Betweenness) are calculated for each stroke, by referring to Zhou and Li (2015); Zhou et al. (2025b)” (see **Section 3.1.2**)

References

1. Zhou, Q., Liu, Y., Liu, Z. Mapping National‐Scale Road Surface Types Using Multisource Open Data and Deep Learning Model. Transaction in GIS, 29(1): 123‐141. 2025.

2. Zhou, Q., Li, Z. How many samples are needed? An investigation of binary logistic regression for selective omission in a road network, Cartography and Geographic Information Science. 1545-0465, 20 Nov, 2015.

Reviewer2_Comment2

While Phi_k and SHAP are mentioned for feature selection, no results (e.g., correlation matrices, SHAP summary plots) are presented. Please include key results, either in the main text or supplementary materials, to justify the final selected proxies for different countries.

<u>Reply to Reviewer2_Comment2</u>: Thanks for this valuable comment!

We had added a figure (see **Appendix A**) to present the selected proxy indicators for 50 African countries. That is,

Appendix A

“This figure shows the selected proxy indicators for 50 African countries. For each country, each value in the grid represents the mean SHAP of the corresponding proxy indicator (e.g., road class). Darker colors indicate higher contributions to the classification results. Empty values mean that the corresponding proxy indicator was not used for model training, because it has a high correlation (> 0.7) with at least one other proxy indicator but its mean SHAP is lower.”

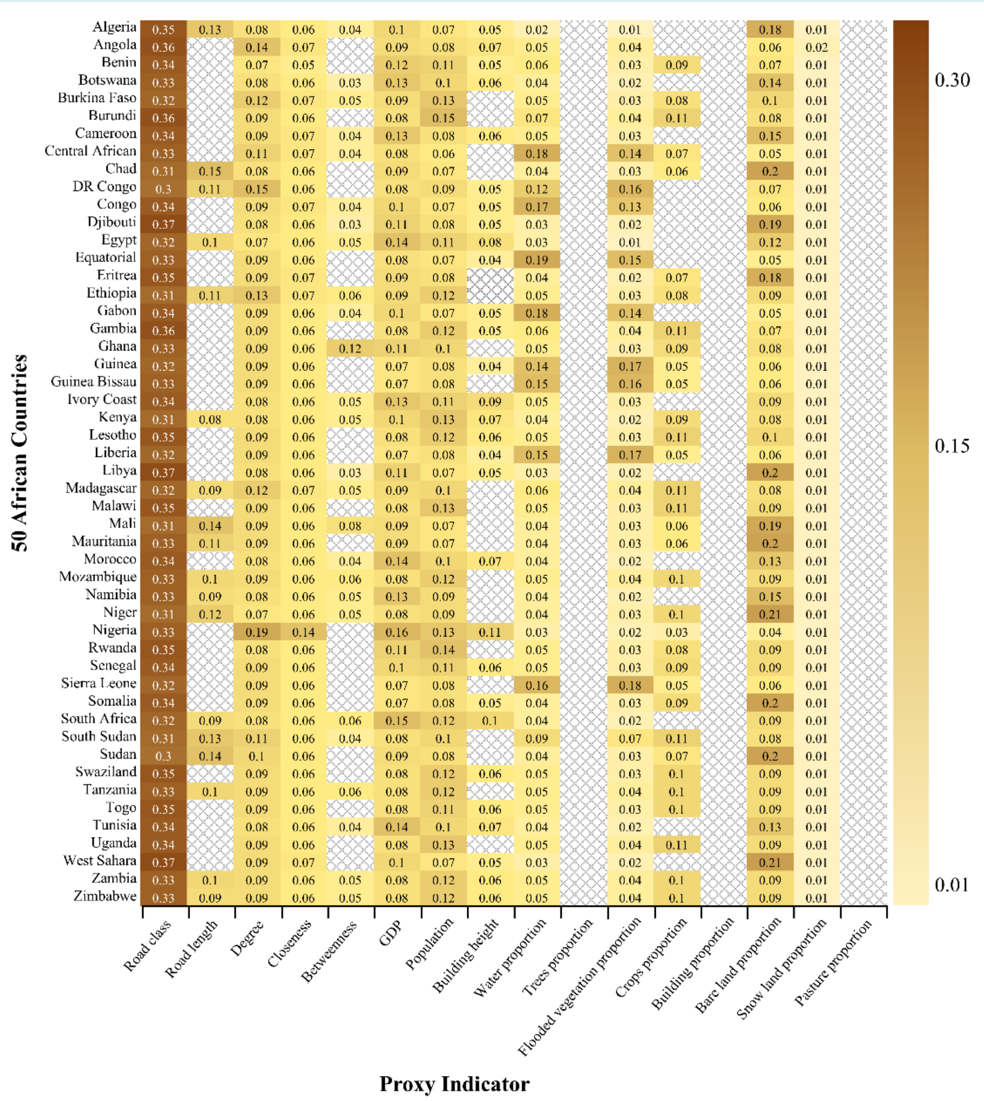

Figure A1. The selected proxy indicators for 50 African countries.

Reviewer2_Comment3

The description of the TabNet model training is insufficient. Please specify the hyperparameter search space used with Optuna (e.g., ranges for learning rate, batch size) and the final model.

<u>Reply to Reviewer2_Comment3</u>: Thanks for this valuable comment! In the revised manuscript, we have added more details about the TabNet model and the Optuna framework. That is,

- "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.**" (see **Section 3.1.3**)

- "The TabNet model is trained, with parameters (e.g., learning rate, number of steps, training epoch) automatically determined using the Optuna framework, which searches for optimal parameters during training. **The core principle of the Optuna framework is to explore various parameter combinations until it identifies the one that yields the highest accuracy. In this study, the search ranges for the parameters—learning rate, number of steps and training epochs—were set to 0.001-0.2, 3-10, and 10-100, respectively**." (see **Section 3.1.3**)

Reviewer2_Comment4

The validation samples are randomly selected from model predictions. Please clarify if this sampling strategy considers spatial distribution and road class representation to ensure the 1000 points are representative of the entire road network.

Reply to Reviewer2_Comment4: Thanks for this valuable comment! In the revised manuscript, the classification accuracy for each of main road classes has also been given out (see **Figure 8** and **Section 5.1)**. This is,

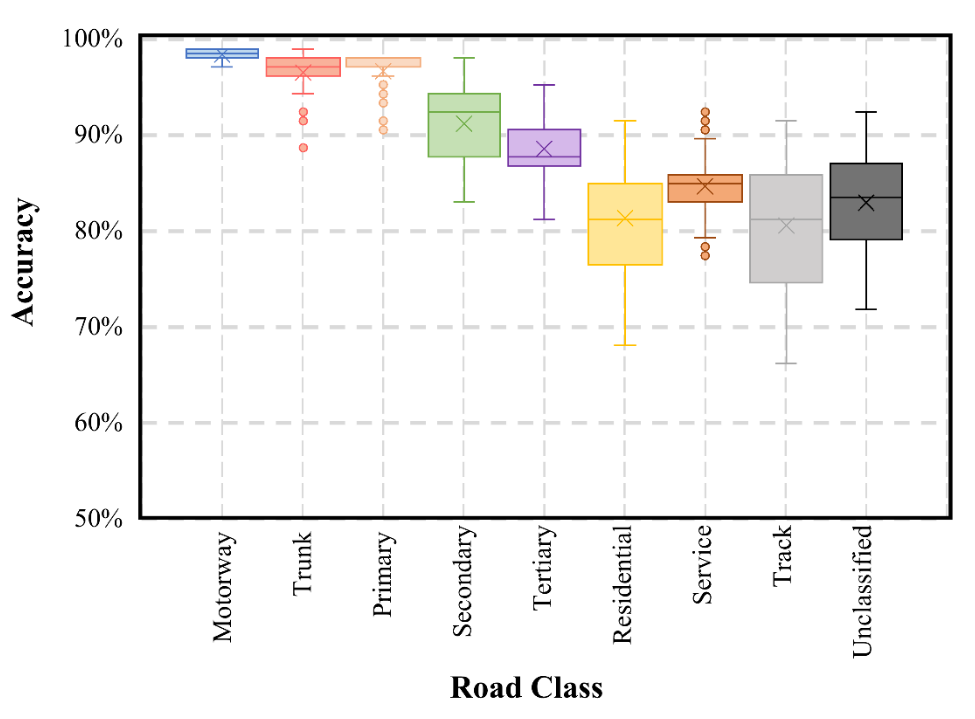

Figure 8. The box plot to show the classification accuracy for each of main road classes for 50 African countries.

"For each country and each road class, 100 sampling points were randomly selected for analysis. As shown, most classification accuracies for these road classes are close to or exceed 80%, with some classes—specifically "Motorway", "Trunk" and "Primary"—achieving accuracies above 95%. These results demonstrate the effectiveness of the road surface type dataset, which is consistent with the finding in Figure 4."

Reviewer2_Comment5

The accuracy varies significantly between countries (e.g., 77% in Egypt vs. 96% in Burundi). A systematic analysis of the potential causes for this variation (e.g., OSM data completeness, image quality, socio-economic context) is missing and should be added.

<u>Reply to Reviewer2_Comment5</u>: Thanks for this valuable comment! In the revised manuscript, A systematic analysis of the potential causes for this variation has been given out. This is (see **Section 5.1**),

"This is likely because the proposed approach relies heavily on the proxy indicator "Road class" (Appendix A), and thus the proportions of various road classes may influence the quality of the developed dataset.

In order to verify this, Figure 8 shows the classification accuracies for nine main road classes in the 50 African countries. For each country and each road class, 100 sampling points were randomly selected for analysis. As shown, most classification accuracies for these road classes are close to or exceed 80%, with some classes—specifically "Motorway", "Trunk" and "Primary"—achieving accuracies above 95%. These results demonstrate the effectiveness of the road surface type dataset, which is consistent with the finding in Figure 4. However, the classification accuracies for the four road classes— "Residential", "Service", "Track" and "Unclassified"—are generally lower than those of other road classes. This is probably because high-class roads are predominantly paved and can be easily identified; in contrast, low-class roads may consist of a mix of paved and unpaved surfaces, making road surface classification more difficult. Moreover, Figure 9 plots the relationship between the proportions of “Residential”, “Service”, “Track” and “Unclassified” roads in 50 African countries and the surface type classification accuracies for these countries. This figure shows that the proportions of both “Residential” and “Service” roads have a moderate negative correlation (i.e., -0.405 and -0.527, respectively) with the corresponding classification accuracy of each country. This finding confirms that the proportions of certain road classes (e.g., “Residential” and “Service”) may affect the quality of the road surface type dataset. For instance, the higher the proportion of “Residential” roads (e.g., 78% for Egypt), the lower the corresponding classification accuracy (e.g., 77% for Egypt).”

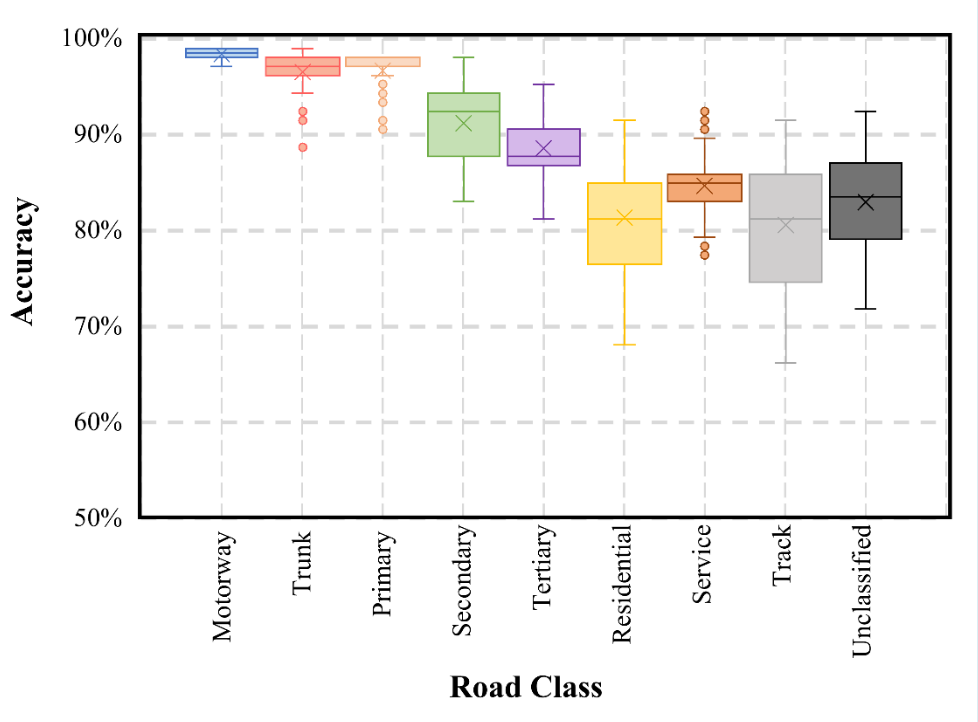

Figure 8. The box plot to show the classification accuracy for each of main road classes for 50 African countries.

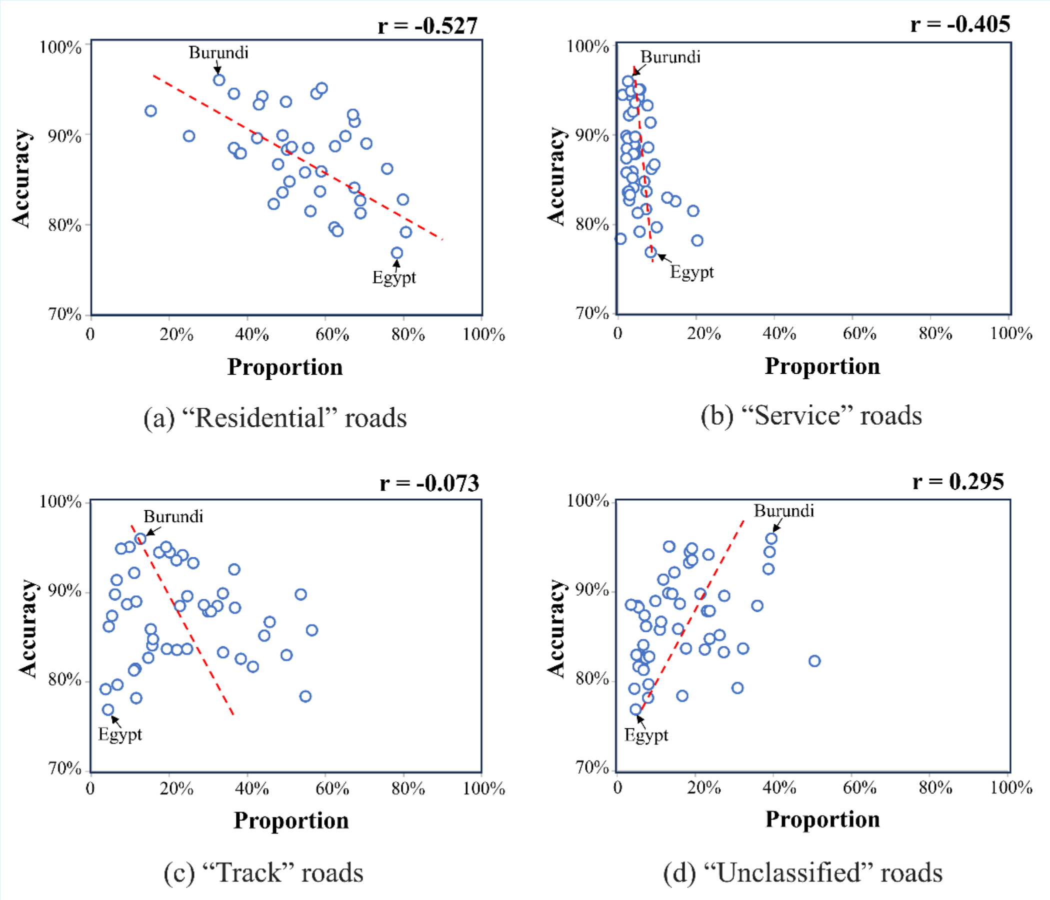

Figure 9. The correlation between the proportions of four road classes (a. "Residential", b. "Service", c. "Track" and d. "Unclassified") and corresponding classification accuracies for 50 African Countries.

Reviewer2_Comment6

The discussion of discrepancies with IRF data, while noted, could be deeper. Please elaborate on the potential implications of these systematic differences (e.g., consistent overestimation of road length) for downstream applications and the relative advantages of your dataset.

Reply to Reviewer2_Comment6: Thanks for this valuable comment!

- First of all, the IRF data only provided statistical values for road length and paved road length for each country. That means **the IRF data did not indicate the road surface type for each individual road**. So, the IRF data cannot be used for determining which roads should be improved or paved.

- In contrast, **our road surface type dataset can provide the road surface type for each individual road.** Therefore, our dataset can not only provide decision-making support for improving local transportation infrastructure (e.g., upgrading unpaved roads to paved roads) but also be an important data source for assessing SDG 9.1. Furthermore, the dataset can be combined with other data (e.g., population and income) to explore the relationship between road surface types and socioeconomic development.

We have highlighted the above points in the revised manuscript. That is (see **Section 5.2**),

"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 enables the calculation of statistical indicators such as paved road length and road paved rate for each country and region but also facilitates detailed analyses of which roads are paved or unpaved. This provides valuable decision-making support for improving local transportation infrastructure (e.g., upgrading unpaved roads to paved ones). Additionally, road surface types serve as an important data source for assessing SDG 9.1. Therefore, this dataset can also be combined with population and urban builtup 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 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)."

Reviewer2_Comment7

Several figures (e.g., Fig. 3, 4, 5, 7, 8, 9) are referenced but not provided in the preview. Please ensure all figures are included and are clearly explained in the text. High-resolution versions are essential for review.

<u>Reply to Reviewer2_Comment7</u>: Thanks for this valuable comment!

All the figures (e.g., Fig. 3, 4, 5, 7, 8, 9) were added in the revised manuscript. **The DPI of each figure is 600, but the DPI may become lower after uploading them into the submission system for review**.

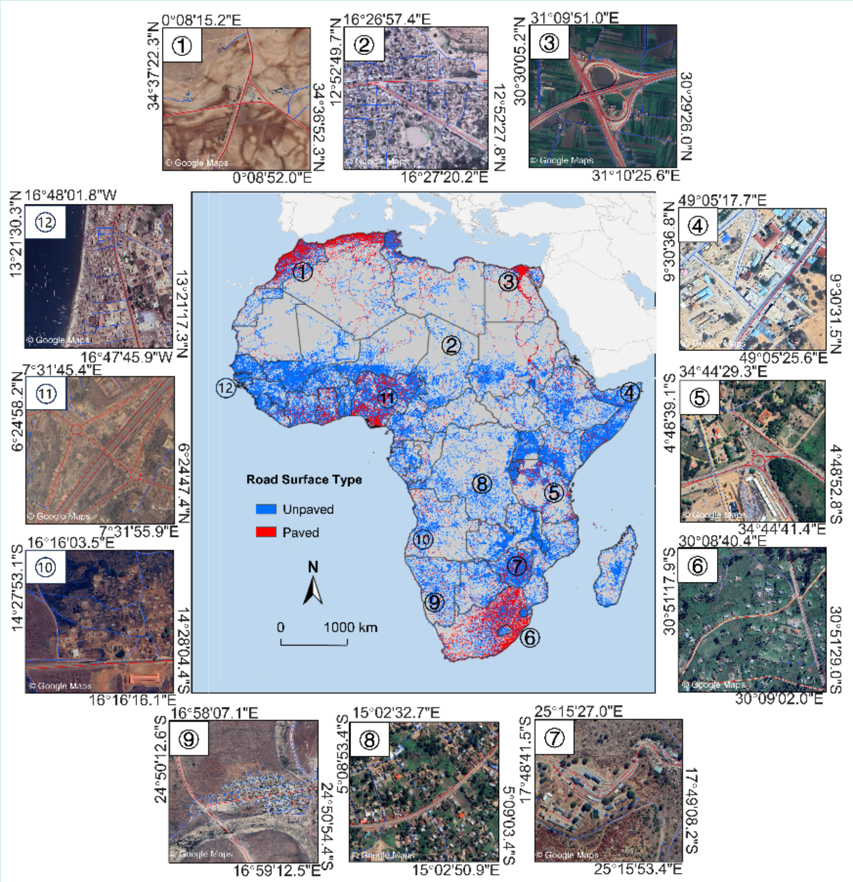

Figure 3. Visualization of road surface type dataset for 50 African countries and regions (source: Google Maps. 2025, https://www.google.com/maps/ (last access: 2 Jul 2025)).

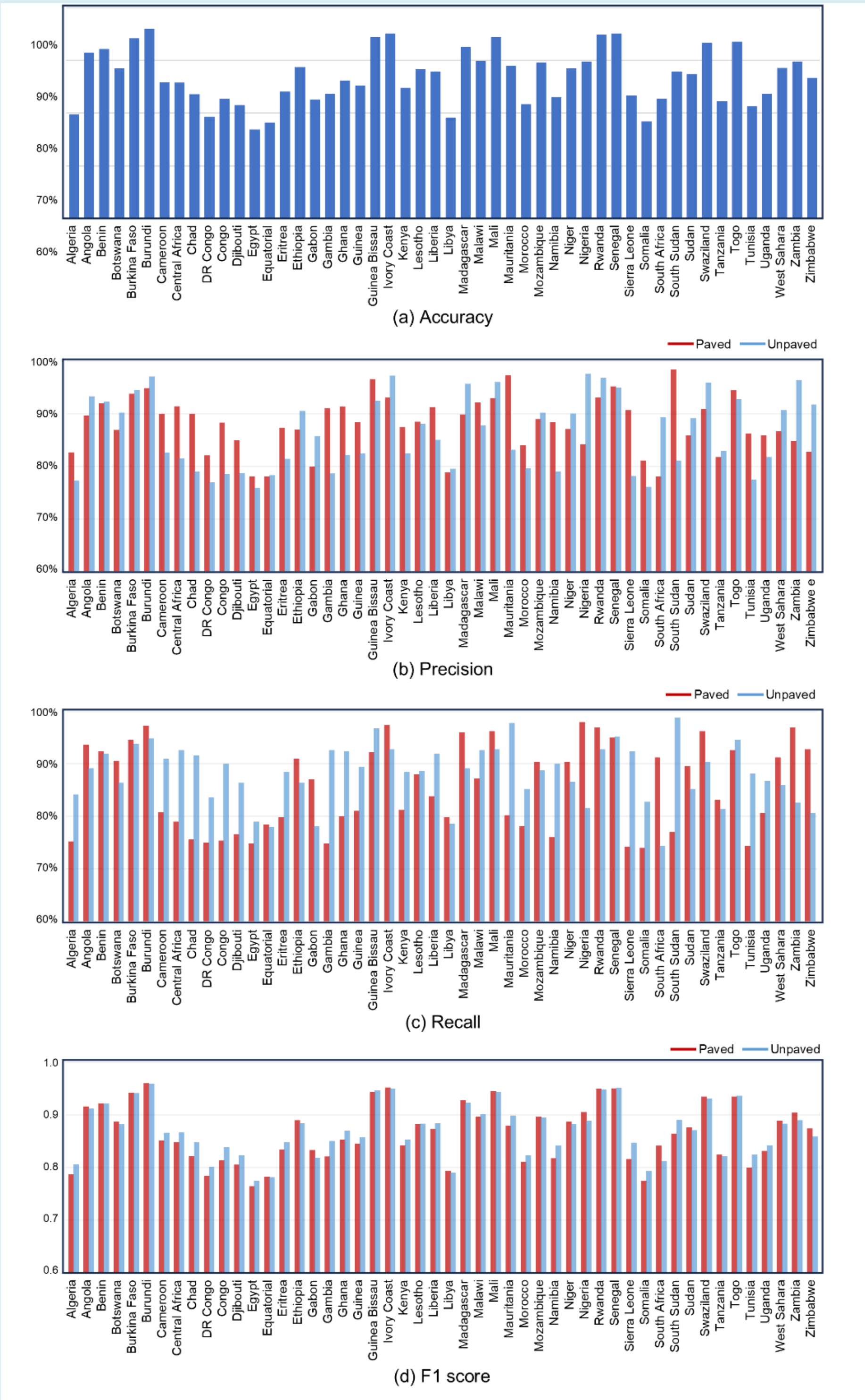

Figure 4. Accuracy Assessment Results of the Road Surface Type Dataset.

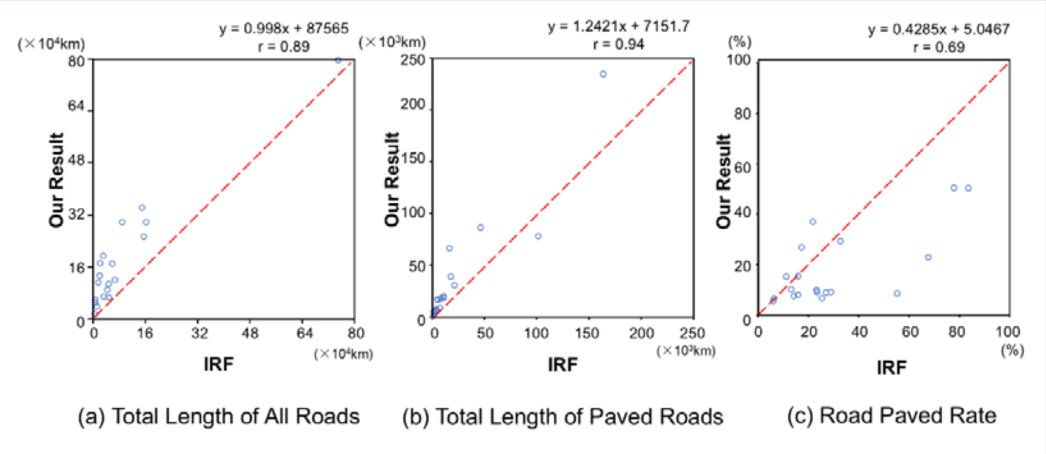

Figure 5. The Correlation Analysis Results with IRF Statistical Data.

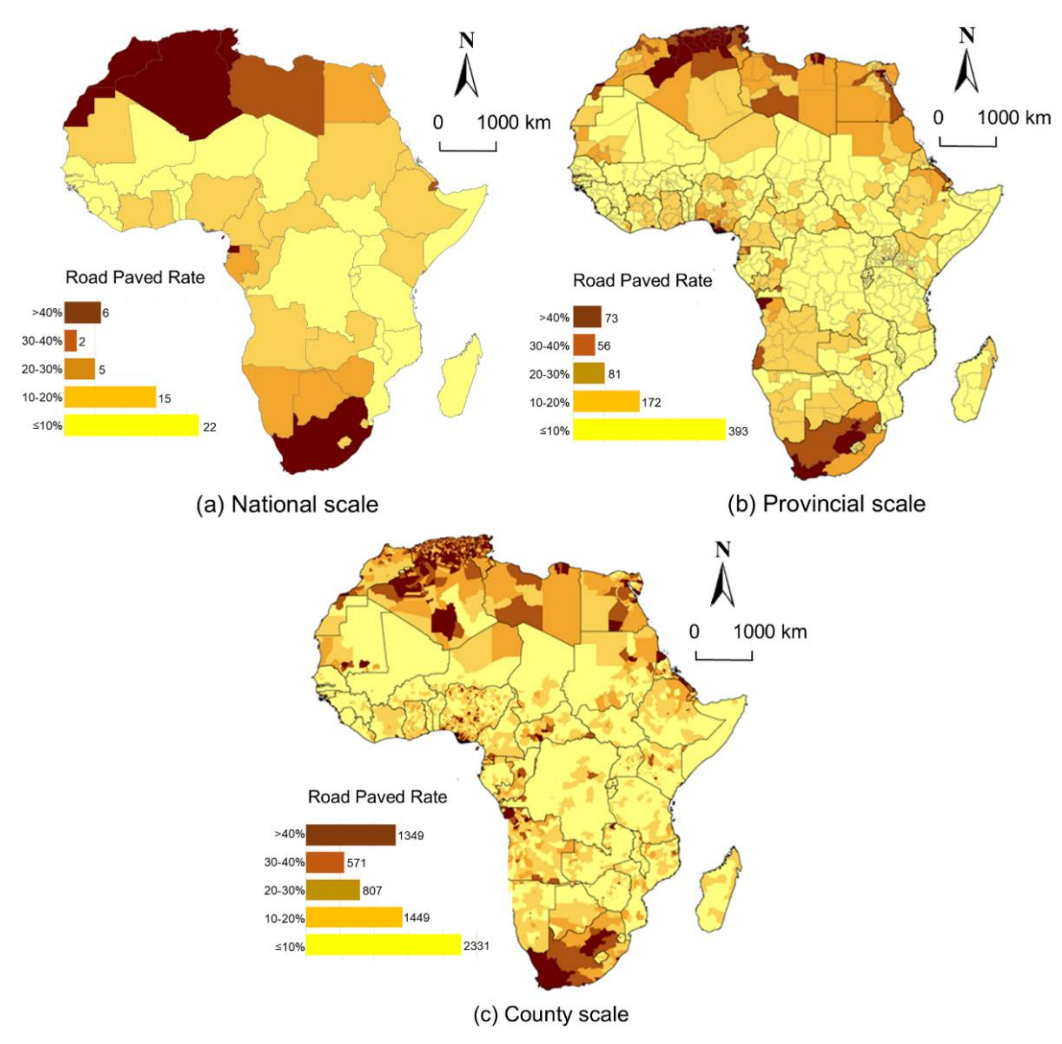

Figure 7. Spatial Pattern Analysis at National, Provincial, and County Levels.

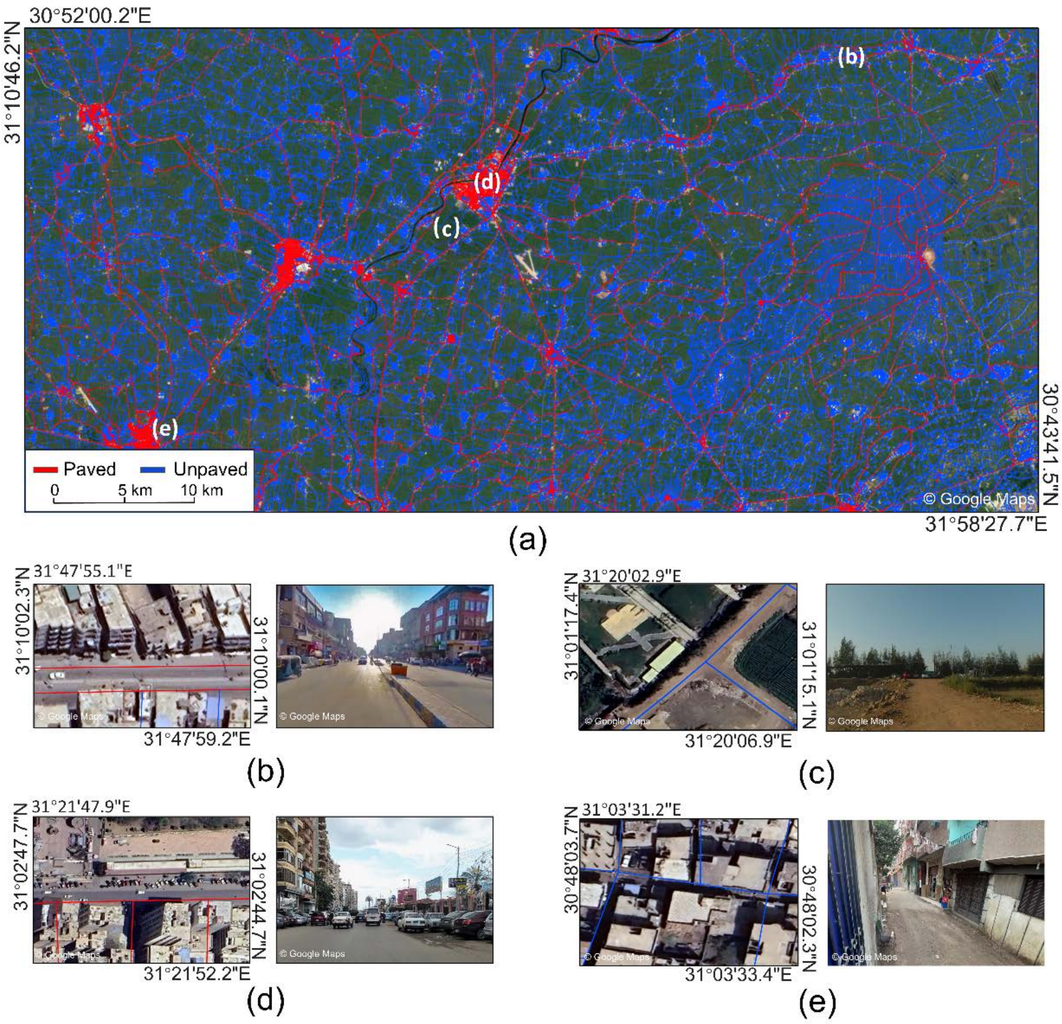

Figure 8. An Example of Road Surface Type Data in Egypt (source: Google Maps. 2025, https://www.google.com/maps/ (last access: 2 Jul 2025)).

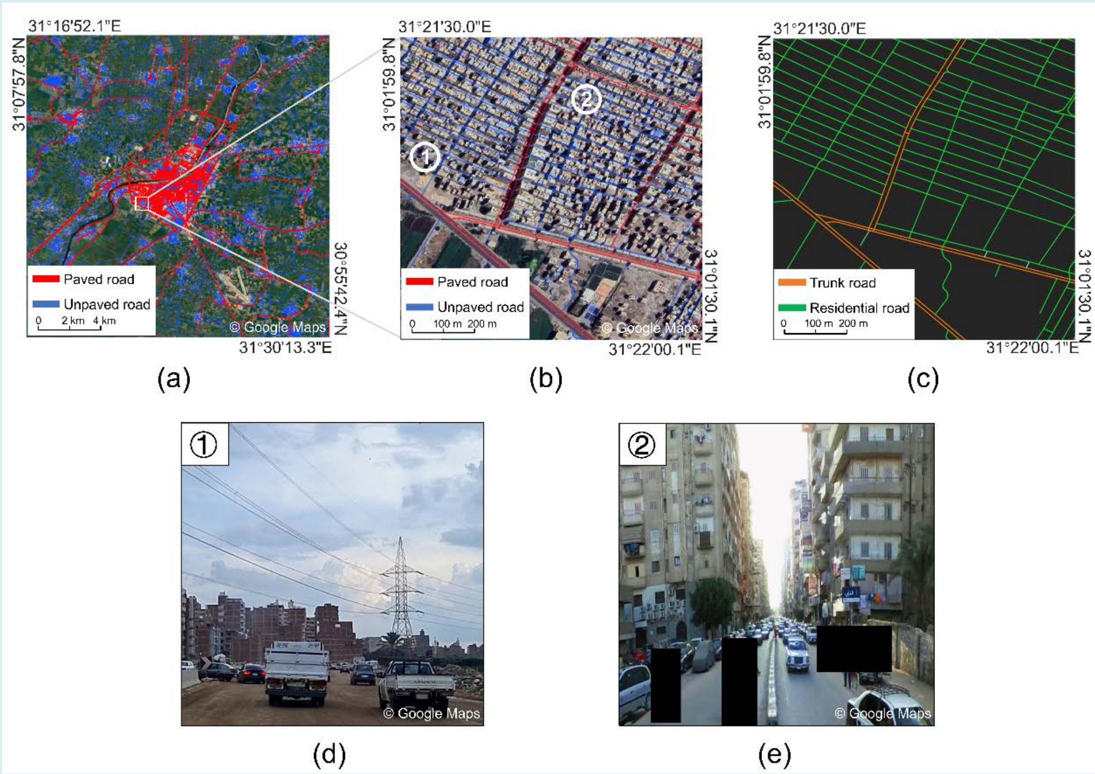

Figure 9. An Example of Explaining the Data Quality of The African Road surface type dataset (source: Google Maps. 2025, https://www.google.com/maps/ (last access: 2 Jul 2025)).

Reviewer2_Comment8

The manuscript requires thorough proofreading by a native English speaker or professional editing service to correct grammatical errors and improve sentence fluency (e.g., the phrasing in the abstract "Africa generally have" should be "Africa generally has").

Reply to Reviewer2_Comment8: Thanks for this valuable comment!

- First of all, "Africa generally have" has been revised as "Africa generally has" (see **Abstract**).
- Then, the whole manuscript has been polished by a professional editing service company named **Charlesworth** (https://charlesworth.com.cn/author-services.html). Please see the revision in the **Supplement Materials**.

Reviewer2_Comment9

The data availability statement is brief. Please enhance it by describing the file format(s), the structure of the attribute table, and providing a direct link or clear instructions for access.

<u>Reply to Reviewer2_Comment9</u>: Thanks for this valuable comment!

- We have described the data in **Section 4.1 (**"Description of the Africa Road Surface Type Dataset"). This is,

"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 include five attribute fields: **road ID, coordinates of the start and end points (see 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

- In Section “Data availability”, we have highlighted the link for acquiring the data. That is,

“The data can be downloaded from the data repository **Figshare at https://doi.org/10.6084/m9.figshare.29424107** (Liu et al., 2025).”

Reviewer2_Comment10

Although the interpretable TabNet model is used, no insights from the model itself (e.g., feature importance rankings for different countries) are discussed. Presenting these findings would significantly strengthen the discussion section.

<u>Reply to Reviewer2_Comment10</u>: Thanks for this valuable comment!

- First of all, <u>we had added a figure (see **Appendix A**) to present the selected proxy indicators for 50 African countries</u>. That is,

"This figure shows the selected proxy indicators for 50 African countries. For each country, each value in the grid represents the mean SHAP of the corresponding proxy indicator (e.g., road class). Darker colors indicate higher contributions to the classification results. Empty values mean that the corresponding proxy indicator was not used for model training, because it has a high correlation (> 0.7) with at least one other proxy indicator but its mean SHAP is lower."

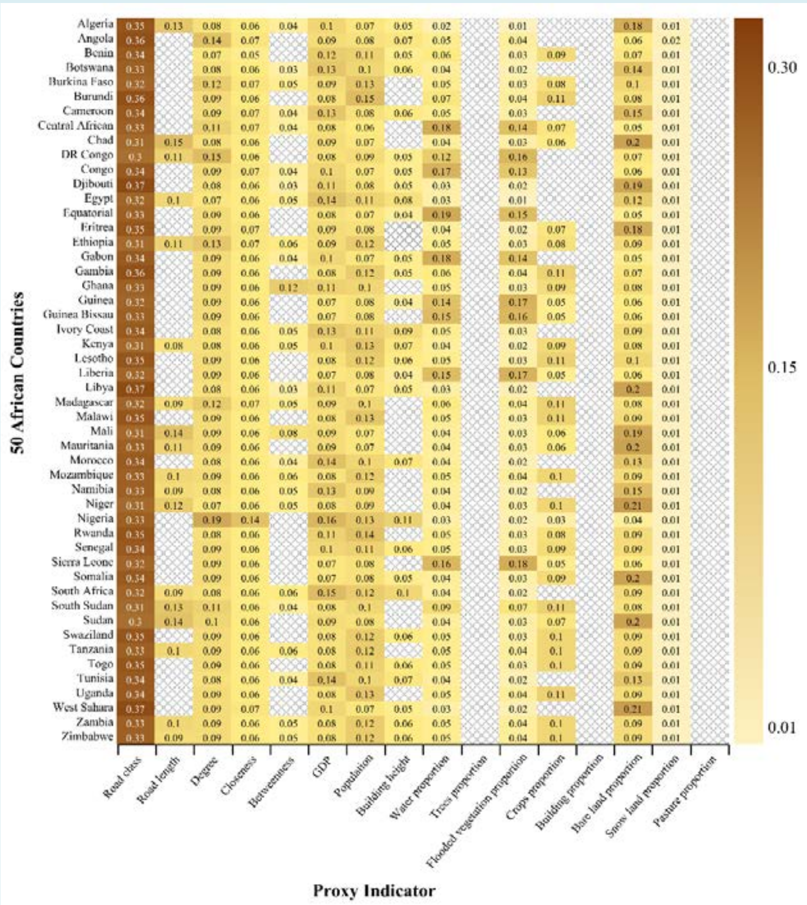

Figure A1. The selected proxy indicators for 50 African countries.

➢ More important, we have presented the finding in the Discussion (see **Section 5.1**). That is,

"This is likely because the proposed approach relies heavily on the proxy indicator "Road class"" (Appendix A), and thus the proportions of various road classes may influence the quality of the developed dataset."

"This finding confirms that the proportions of certain road classes (e.g., "Residential" and "Service") may affect the quality of the road surface type dataset. For instance, the higher the proportion of "Residential" roads (e.g., 78% for Egypt), the lower the corresponding classification accuracy (e.g., 77% for Egypt)."

Reviewer2_Comment11

The use of source data from "around 2020" is acknowledged, but the potential impact of minor temporal misalignments between different datasets (e.g., GDP from 2019, population from 2020) on model performance is not discussed. A brief comment on this would be valuable.

Reply to Reviewer2_Comment11: Thanks for this valuable comment!

In the revised manuscript, we have highlighted this point in **Section 5.3** ("Limitations and future work"). This is,

"This is because the source data were all obtained from 2020 or nearby years (i.e., 2018 or 2019). **Although existing studies have reported that GDP and building**

height data change little within a period of 1–2 years (African Development Bank Group, 2020; Ali et al., 2025), inconsistencies in the years may still affect the quality of our dataset. Therefore, it is worthwhile to investigate whether the quality of the road surface type dataset could be improved by using source data obtained from the same year."

Reference:

1) African Development Bank Group. African Economic Outlook 2020: Developing Africa's Workforce for the Future. African Development Bank, 2020.

2) Ali, S., Alireza, D., Parviz, A. Volumetric insights into urban growth analysis: Investigating vertical and horizontal patterns. Sustainable Cities and Society. Volume 130, 106589, ISSN 2210-6707, 2025.

Reviewer2_Comment12

The analysis does not break down the classification accuracy by OSM road class (e.g., 'motorway' vs. 'residential'). A stratified accuracy assessment would help identify if performance is biased towards certain road types.

<u>Reply to Reviewer2_Comment12</u>: Thanks for this valuable comment!

In the revised manuscript, <u>the classification accuracy for each of main road classes has also been given out</u> (see **Section 5.1**). This is, "In order to verify this, Figure 8 shows the classification accuracies for nine main road classes in the 50 African countries. For each country and each road class, 100 sampling points were randomly selected for analysis. As shown, most classification accuracies for these road classes are close to or exceed 80%, with some classes—specifically "Motorway", "Trunk" and "Primary"—achieving accuracies above 95%. These results demonstrate the effectiveness of the road surface type dataset, which is consistent with the finding in Figure 4. However, the classification accuracies for the four road classes— "Residential", "Service", "Track" and "Unclassified"—are generally lower than those of other road classes. This is probably because high-class roads are predominantly paved and can be easily identified; in contrast, low-class roads may consist of a mix of paved and unpaved surfaces, making road surface classification more difficult." (see **Section 5.1**)

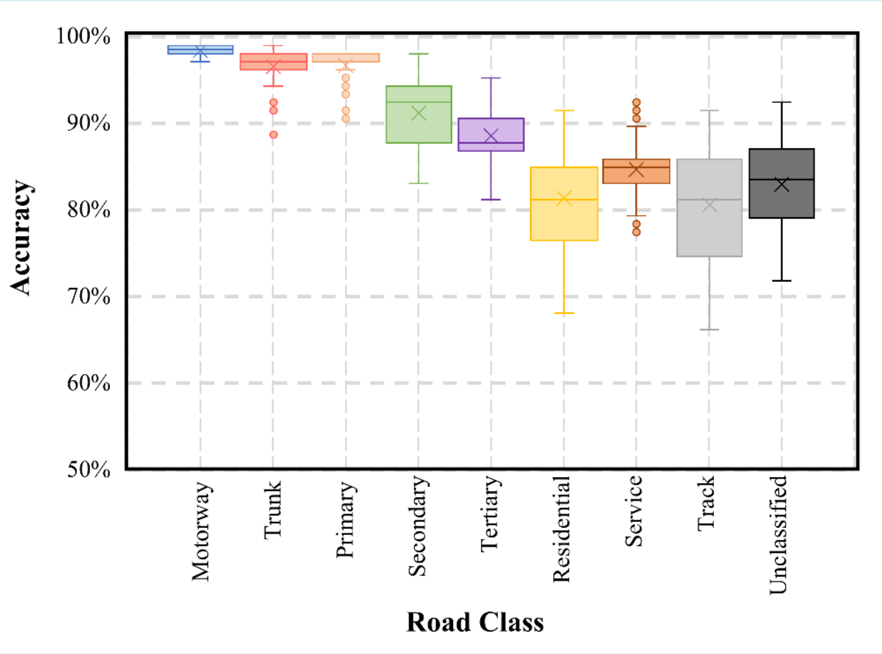

Figure 8. The box plot to show the classification accuracy for each of main road classes for 50 African countries.

Reviewer2_Comment13

The future work section is somewhat generic. Please provide more specific, testable hypotheses or planned methodologies for incorporating terrain data or finer surface type classifications.

Reply to Reviewer2_Comment13: Thanks for this valuable comment! We have highlighted this point in the revised manuscript (see Section 5.3). That is,

"In the future, additional data sources, such as terrain data, could be incorporated, **as unpaved roads are likely common in mountainous areas due to high construction costs. Thus, additional proxy indicators (e.g. elevation and slope) may be considered to determine whether they can enhance the classification accuracy of the data product.**"

Supplement Materials

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 the United Nations Sustainable Development Goal (SDG) 9.1. Existing research indicates that Africa generally ~~have~~ has a low road paved rate, ~~limiting~~ which limits 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~~countries nor specifies the surface type of individual roads, making it challenging to ~~offer~~support decision-making ~~support~~ for improving Africa's road infrastructure. To ~~fill~~address 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~~OpenStreetMap 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~~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~~the Human Development Index (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 revealed an average paved rate of only 17.4% across the 50 countries and regions. A distinct “pattern emerged, with higher paved rates in the north and south~~,~~ and lower rates in the central region”~~ pattern emerged, ~~; the average paved rate north of the Sahara is approximately three times that of Sub-Saharan Africa (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 toward SDG 9.1 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~~affect 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~~durable structure and are resistant to erosion, allowing them to ~~be~~remain passable ~~all-season, while~~year-round. In contrast, unpaved roads ~~may be affected~~are often impacted by natural factors such as rain and snow, making them typically difficult to ~~pass all-season.~~traverse throughout the year. The proportion of the rural population living within 2 kilometers of an all-season road has ~~also~~ been adopted by the World Bank as ~~an important~~a key indicator for evaluating road infrastructure~~, and this~~. This indicator was incorporated by the United Nations into ~~the~~ Sustainable Development Goal (SDG) 9.1 in 2017. ~~Road~~Data on road surface ~~type data~~types are considered ~~one of the key data sources~~essential for assessing progress toward SDG 9.1.

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 Africa, 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~~a major bottleneck 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~~endorsed by multiple African countries, also sets goals to improve residents' quality of life and enhance infrastructure ~~in African nations~~across the continent (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~~ global data on road surface types are primarily statistical~~ data~~, and most analyses of road surface types ~~are also based~~rely 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-Saharan Africa, the proportion of "all-season ~~road~~roads" (e.g., paved roads) does not exceed 30%. Kresnanto (2019) used statistical data on paved road ~~length data~~lengths 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 Africa. 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 only 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 of data from various sources (Turner, 2015; CIA, 2025), making it ~~still~~ impossible to accurately ~~identify~~determine 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~~ researchers 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. Harikrishnan et al. (2017) collected vehicle speed data using the XYZ three-axis accelerometer of smartphones and established road surface type identification 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~~ researchers 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~~ globally 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, which inevitably ~~requiring~~demands significant manpower, ~~material~~materials, 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 only in a ~~few~~limited number of countries or specific regions within countries, making it challenging to identify the surface types of all roads nationwide. Therefore, although datasets 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~~whereas the multisource data method achieves accuracy exceeding 85% 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 only 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. (2024) ~~only providing~~provided a road surface type dataset only for Kenya, leaving a gap in data products covering ~~different~~other countries and regions ~~in~~across Africa.

Therefore, this study aims not only ~~aims~~ to evaluate ~~whether~~ the universal applicability of a method ~~of~~for developing road surface type dataset based on multisource big data and deep learning models ~~has universal applicability~~ but also ~~uses~~to apply this method to ~~develop~~create the first dataset of road surface types (paved and unpaved) for 50 countries and regions in Africa. The dataset 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~~describes the study area and the source data used for developing and evaluating the road surface type data. Section 3 ~~introduces~~outlines the methods employed for data development and evaluation. Section 4 ~~reports~~presents the evaluation results of the road surface type data. Section 5 discusses the implications and limitations of ~~this~~the study. The ~~last~~final two sections ~~provide~~detail the data acquisition methods and provide 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 was selected as the study area ~~is that~~primarily because existing research ~~shows that the~~ indicates a high proportion of unpaved roads ~~in Africa is high~~ across the continent (Biber-Freudenberger et al., 2025~~), while~~). However, the IRF only provides statistics on ~~the length of~~ paved ~~roads~~road lengths and ~~the road paved rate~~paving rates for some African countries. Due to the lack of ~~spatialized~~a spatially detailed road surface type dataset, it is ~~difficult~~challenging to ~~provide~~offer decision support for improving road infrastructure in Africa.

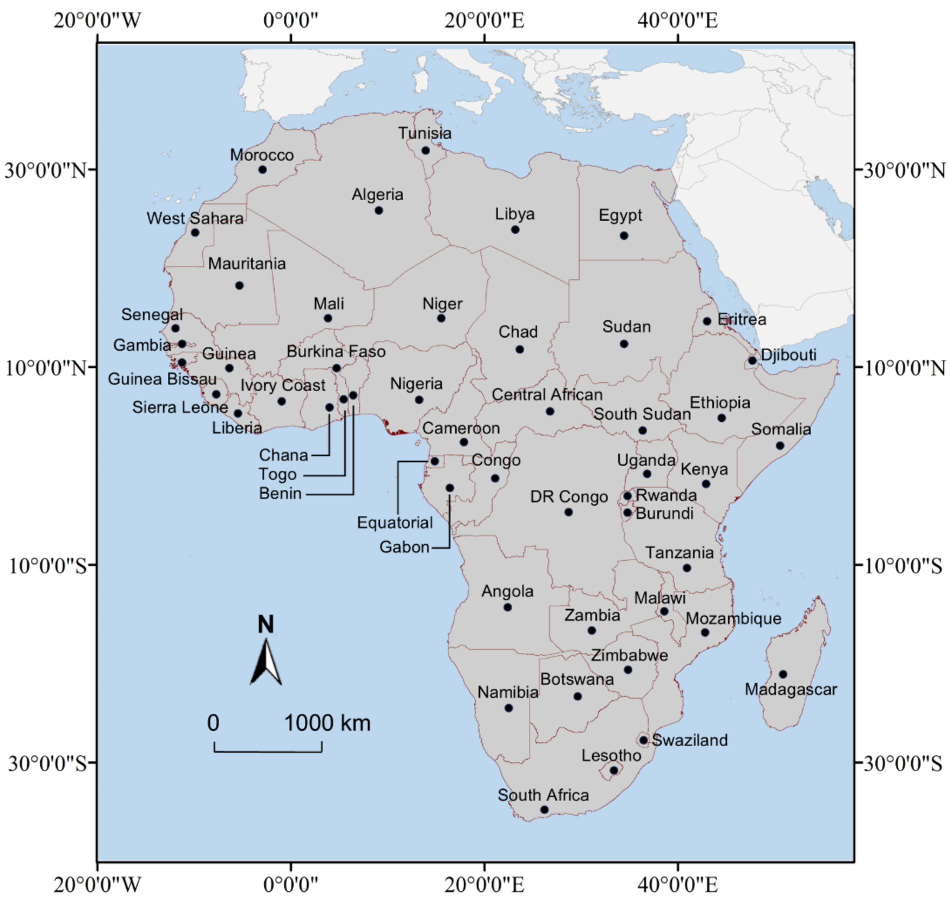

Figure 1. Study area

2.2 Data

2.2.1 Geospatial data

(1) OpenStreetMap road data: OpenStreetMap (OSM) is an open geospatial dataset contributed ~~provided online~~ by global volunteers and made available online (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 information on road surface ~~type information~~types, 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~~highlighting an urgent need for 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 accurately captures~~can precisely depict~~ the spatial heterogeneity of economic activities. The dataset covers the period~~spans~~ from 1992 to 2019;~~, and~~ this study utilized~~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