

Fusing Sentinel-2 and Sentinel-1 Data in Google Earth Engine for Road Infrastructure Mapping in Data-Scarce and Conflict Environments

Mali, S. P. A. * and Tokunaga, M.

Department of Civil and Environmental Engineering, Kanazawa Institute of Technology, Japan

E-mail: mwashorg2020@gmail.com*

*Corresponding Author

DOI: <https://doi.org/10.52939/ijg.v22i9.5197>

Abstract

Reliable road network information is a prerequisite for infrastructure planning, humanitarian operations, and disaster response; however, such information often remains incomplete or outdated in conflict-affected and data-scarce regions. In Juba County, South Sudan, decades of conflict, institutional limitations, and environmental challenges have resulted in substantial gaps in road network data. This study introduces a low-cost, cloud-based approach that fuses radar and optical satellite imagery within Google Earth Engine to enhance road visibility and mapping under these conditions. By integrating multi-sensor satellite data with local knowledge and publicly available reference datasets, the approach enables the identification of previously unmapped roads and the correction of outdated road surface classifications. The results show that more than 71 km of undocumented roads were detected, increasing the known road network by approximately 1%, while achieving a connectivity rate of 98.8% with the existing network. These findings demonstrate that multi-sensor data fusion, combined with informed local interpretation, provides a scalable foundation for improving road inventories and generating GeoAI-ready baseline data in fragile and data-scarce environments.

Keywords: Data-Scarce Environments, GeoAI Readiness, Informed Volunteered Geographic Information, Road Infrastructure Mapping, Sentinel Data Fusion

1. Introduction

A well-planned road network is essential for mobility, economic recovery, peacebuilding, disaster response, and humanitarian logistics [1]. Developing countries that have faced long civil wars or are recovering from conflict often struggle with a lack of basic infrastructure data. Reliable geospatial information is crucial for making decisions in infrastructure planning, development, and management [2]. However, in fragile environments, gaps in mapping still exist, despite global progress in Earth observation and volunteered geographic information [3] and [4]. In South Sudan, accurate and up-to-date road data are hard to find, making spatial planning and infrastructure management very challenging. The country went through over two decades of civil war (1983-2005) while still part of the Sudan, during which most of the infrastructure deteriorated and geospatial data collection virtually ceased [5]. After the Comprehensive Peace Agreement and independence in 2011, only limited reconstruction took place before renewed conflict broke out in December 2013, further damaging

infrastructure and breaking apart national institutions [6] and [7]. Because of this, South Sudan is one of the world's most data-scarce places where basic datasets like administrative boundaries and road networks are incomplete, outdated, or absent from global databases [8] and [9].

Local institutions lack the technical infrastructure, cloud-computing resources, and reliable internet needed to process large geospatial datasets. At the same time, international researchers struggle to access reliable ground truth data, navigate security-restricted areas, and obtain verifiable information to validate their models. These challenges create major obstacles for planners, humanitarian partners, and researchers. As a result, the absence of authoritative and current spatial datasets limits the use of technology-based infrastructure management methods and restricts the application of advanced tools like GeoAI and machine learning in South Sudan and similar data-scarce environments [10] and [11].

Field-based road surveys in South Sudan are costly, unsafe, and complicated logistically, especially in areas affected by flooding or conflict. This is made worse by limited institutional capacity and gaps in policy [12]. Constant cloud cover limits the usefulness of optical imagery, while very-high-resolution (VHR) imagery is costly and impractical for wide-area mapping [13] and [14]. Open-source road datasets like OpenStreetMap and Geofabrik offer partial coverage but differ in quality and update frequency, leaving large parts of South Sudan unmapped [15]. These challenges make it difficult to maintain consistent spatial data and weaken the effectiveness of data-driven infrastructure monitoring.

This study presents a cloud-resilient, low-cost fusion approach that combines Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 optical imagery on the Google Earth Engine (GEE) platform for mapping road infrastructure in Juba County. SAR provides all-weather imaging that can penetrate through clouds, while Sentinel-2 offers complementary spectral data that helps distinguish between paved and unpaved surfaces. The approach merges large-scale satellite data processing in GEE with visual interpretation and digitization in Quantum Geographic Information System (QGIS) [16] and [17], enhanced by Informed Volunteered Geographic Information (IVGI) based on the researcher's local knowledge of Juba's road network. This design directly tackles the mapping challenges in South Sudan by using freely available satellite data and cloud-based processing to overcome local computation limitations [18]. It bridges the persistent gap between expensive field surveys and hard-to-access VHR imagery, offering a practical solution for planners, researchers, and international development partners working in data-scarce areas. The integration of IVGI adds context where fusion mapping and surface classification struggle with image noise or urban clutter, ensuring both accuracy and local relevance.

2. Related Work

Mapping road infrastructure using remote sensing has improved significantly over the past decades. This progress comes from the growing availability of open-access satellite data like Sentinel-1 (Synthetic Aperture Radar, SAR) and Sentinel-2 (optical). Traditional mapping methods depend on field surveys or existing vector data, but these can be unreliable or unavailable in conflict-prone, rapidly urbanizing, and cloud-covered areas like Juba County, South Sudan. Several studies show the

potential of fusing Optical and SAR data for extracting infrastructure and mapping land cover [19]. For example, [20] and [21] effectively used the integration of Sentinel-1 and Sentinel-2 to extract built-up areas and impervious surfaces with automated training data sampling. This method showed higher accuracy compared to using images from just one source. Similarly, the advantages of SAR and optical fusion for mapping populations and infrastructure at risk from floods was pointed out by [22]. This approach helps overcome issues caused by persistent cloud cover and surface water reflectance.

However, despite these advancements, fusion-based road extraction remains challenging. Optical imagery becomes less usable during the rainy season due to thick cloud cover [13], while SAR imagery tends to have speckle noise and struggle to distinguish narrow road features [23]. These challenges highlight the need to combine both SAR and optical data to take advantage of their strengths, especially in areas with seasonal changes like Juba County, South Sudan [24]. The use of Volunteered Geographic Information (VGI) and local knowledge has also become a practical way to improve automated mapping. This combination brings context that satellite data alone can't provide. VGI can effectively fill gaps in incomplete datasets, especially when ground surveys are not possible [3][4] and [25]. The researcher's dual perspective as a civil engineer and a Juba resident offered valuable insights into road classification. This formed an Informed Volunteered Geographic Information (IVGI) contribution, enhancing the reliability of the results. This method was particularly helpful for identifying informal and peri-urban roads that are often missing from standard open-source datasets like OpenStreetMap or Geofabrik.

The introduction of Google Earth Engine (GEE) has further changed how geospatial work is done. It allows large-scale, cloud-based data fusion and processing. GEE enables quick, automated analysis of Sentinel imagery, which is especially useful in areas where data is scarce and high-performance computing resources are limited [26] and [27]. In conclusion, the combination of Sentinel-1 and Sentinel-2 imagery, along with Informed Volunteered Geographic Information and implemented in a cloud-based GEE environment, offers a unique and scalable way to map road infrastructure accurately and efficiently in fragile and data-poor regions. This blend of freely accessible satellite data, local expertise, and cloud analytics is the foundation of the current study, as explained in the next section.

Mapping road infrastructure using remote sensing has improved significantly over the past decades due to the increasing availability of open-access Earth observation datasets such as Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 multispectral optical imagery. These datasets provide frequent temporal coverage and moderate spatial resolution suitable for large-scale infrastructure monitoring. Traditional mapping methods depend on field surveys, government institutional records or existing vector data; however, such approaches are often difficult to practice and unreliable in fragile and conflict-prone regions such as Juba County, South Sudan. Rapid urbanization, limited accessibility, persistent cloud-cover and weak infrastructure geospatial data further hinder road inventory development and infrastructure monitoring in these environments.

The increasing availability of Sentinel satellite imagery has encouraged the adoption of remote sensing techniques for infrastructure and land-cover mapping. Sentinel-1 SAR imagery is particularly valuable because of its cloud-penetrating capability and sensitivity to surface roughness and moisture conditions, while Sentinel-2 optical imagery provides rich spectral information useful for land-cover discrimination. The complementary characteristics of SAR and optical datasets have therefore promoted the integration of both sensors for geospatial analysis and classification tasks [19]. Several studies demonstrated that combining Sentinel-1 and Sentinel-2 imagery improves the extraction of built-up areas and impervious surfaces compared to single-sensor approaches. For example, Sentinel-1 and Sentinel-2 imagery were successfully integrated using automated training data sampling techniques and reported improved classification accuracy relative to individual datasets [20] and [21].

Recent developments in machine learning, deep learning, and feature-fusion techniques have further strengthened the integration of SAR and optical imagery for large-scale infrastructure mapping. [28] demonstrated that integrating Sentinel-1 and Sentinel-2 datasets within a Google Earth Engine (GEE) environment significantly improved classification performance through the complementary use of SAR backscatter information and optical spectral reflectance. Similarly, [29] proposed AGF-Net, an adaptive global fusion framework for road extraction in complex terrain environments, which improved road continuity and reduced misclassification through multi-scale feature fusion. [30] further developed a multi-source remote sensing fusion and optimization framework capable

of enhancing road extraction performance using integrated SAR and optical imagery.

Other recent studies have also highlighted the growing capability of freely available Sentinel imagery for extracting rural and peri-urban transportation networks. [31] introduced a spatial relationship-informed road extraction framework capable of generating super-resolution rural road networks from Sentinel-2 imagery. Their findings demonstrated the increasing potential of moderate-resolution satellite data for detailed transportation mapping in spatially complex environments. Likewise, [22] emphasized the advantages of SAR and optical fusion for identifying populations and infrastructure exposed to flooding. Their approach demonstrated the importance of multi-source remote sensing integration in overcoming challenges associated with persistent cloud cover and surface water reflectance.

Despite these advancements, fusion-based road extraction using moderate-resolution imagery remains challenging, particularly in cloud-prone and environmentally heterogeneous regions. Optical imagery becomes significantly less usable during rainy seasons due to persistent cloud cover [13]. Although SAR imagery is resilient to weather conditions, it is frequently affected by speckle noise and geometric distortions that complicate the identification of narrow road features and linear transportation networks [23]. These limitations highlight the importance of hybrid SAR–optical integration approaches capable of leveraging the strengths of both datasets while minimizing their individual weaknesses, especially in seasonally dynamic environments such as Juba County, South Sudan [24].

The growing adoption of cloud-based geospatial platforms has further transformed large-scale remote sensing analysis. Google Earth Engine has become one of the most widely used cloud-computing environments for satellite image processing and geospatial analysis because it enables rapid, automated, and scalable processing of large Earth observation datasets [26] and [27]. Recent studies have demonstrated the capability of GEE in infrastructure and disaster-monitoring applications. [32], for instance, utilized Sentinel-1 SAR data and GEE for rapid flood mapping and disaster-response analysis, while [33] implemented automated Sentinel-based workflows in GEE for landslide detection and environmental monitoring. These studies illustrate the increasing role of cloud-based geospatial platforms in handling large Sentinel image archives and supporting automated analysis in data-scarce environments.

Another important advancement in geospatial analysis is the growing integration of Volunteered Geographic Information (VGI) and local contextual knowledge. VGI has become a practical approach for supplementing incomplete geospatial datasets, particularly in regions where field surveys and official mapping infrastructures are limited. Citizen-generated geographic information can significantly improve spatial interpretation and validation processes in data-scarce environments [3][4] and [25]. In the present study, the researcher's dual perspective as both a civil engineer and a resident familiar with the Juba Road environment provided valuable contextual understanding for road classification and interpretation. This contributed to an Informed Volunteered Geographic Information (IVGI) framework that improved the identification of informal, peri-urban, and poorly mapped road segments often missing from conventional datasets such as OpenStreetMap and Geofabrik.

Although considerable progress has been made in SAR-optical fusion, deep learning, cloud computing, and VGI-assisted geospatial analysis, relatively few studies have focused specifically on the development of road infrastructure inventories in fragile and conflict-affected environments such as South Sudan. Existing research is largely concentrated in data-rich and environmentally stable regions with better validation datasets and infrastructure records. Furthermore, limited studies have integrated Sentinel-1 and Sentinel-2 fusion with locally informed geographic interpretation to support road-network enhancement in areas characterized by persistent cloud cover, limited accessibility, and incomplete baseline datasets.

Therefore, this study contributes to the existing body of knowledge by developing a cloud-based geospatial framework implemented in Google Earth Engine that integrates Sentinel-1 SAR imagery, Sentinel-2 optical imagery, and Informed Volunteered Geographic Information for road infrastructure mapping in Juba County, South Sudan. The framework provides a scalable and cost-effective approach for improving road inventories in fragile and data-poor regions while establishing a foundation for future GeoAI-assisted infrastructure mapping applications.

3. Data and Methodology

3.1 Study Area

This study focuses on Juba County, the main administrative and political center of South Sudan. The county covers an area of approximately 18,360 square kilometers, encompassing a mix of dense urban core, peri-urban expansion zones, and extensive rural landscapes. It is located in Central Equatoria State (CES) and includes the national and state capital, Juba, along with its surrounding peri-urban and rural settlements. As a rapidly growing urban area that has emerged from long-standing conflicts, Juba faces significant challenges in developing its infrastructure. These challenges include poor road connectivity, insecurity, lack of road data, and limited road maintenance capability. Juba County is situated along the White Nile and features seasonal rivers, wetlands, and large dry lands. The region experiences extreme wet and dry seasons that affect both satellite image clarity and road access. Because of ongoing urbanization, informal development and protracted conflict, many road networks, particularly feeder roads, remain unmapped or only partially recorded in global databases like Geofabrik and OSM. The study area was defined using administrative boundary data from the Humanitarian Data Exchange (HDX) at the ADM2 level and was processed in QGIS. This defined area offers a manageable yet representative setting for testing the SAR - Optical image fusion and IVGI integration approach. Figure 1 shows the map of the area of interest.

3.1.1 Data sources and tools

Unlike many countries, South Sudan is missing or underrepresented in major global geospatial repositories. These include DIVA GIS, the Global Road Inventory Project (GRIP), and the United States Geological Survey (USGS). As a result, reliable open-source spatial datasets for infrastructure mapping are hard to find and often lack complete information. To address this issue, the study used a mixed data acquisition approach. This method combined open-access Earth Observation archives, humanitarian platforms, and institutionally licensed software. This approach helped collect datasets that are consistent over time and relevant to the context. These datasets were suitable for identifying unmapped roads, improving visibility, connectivity and supporting road surface classification in Juba County.

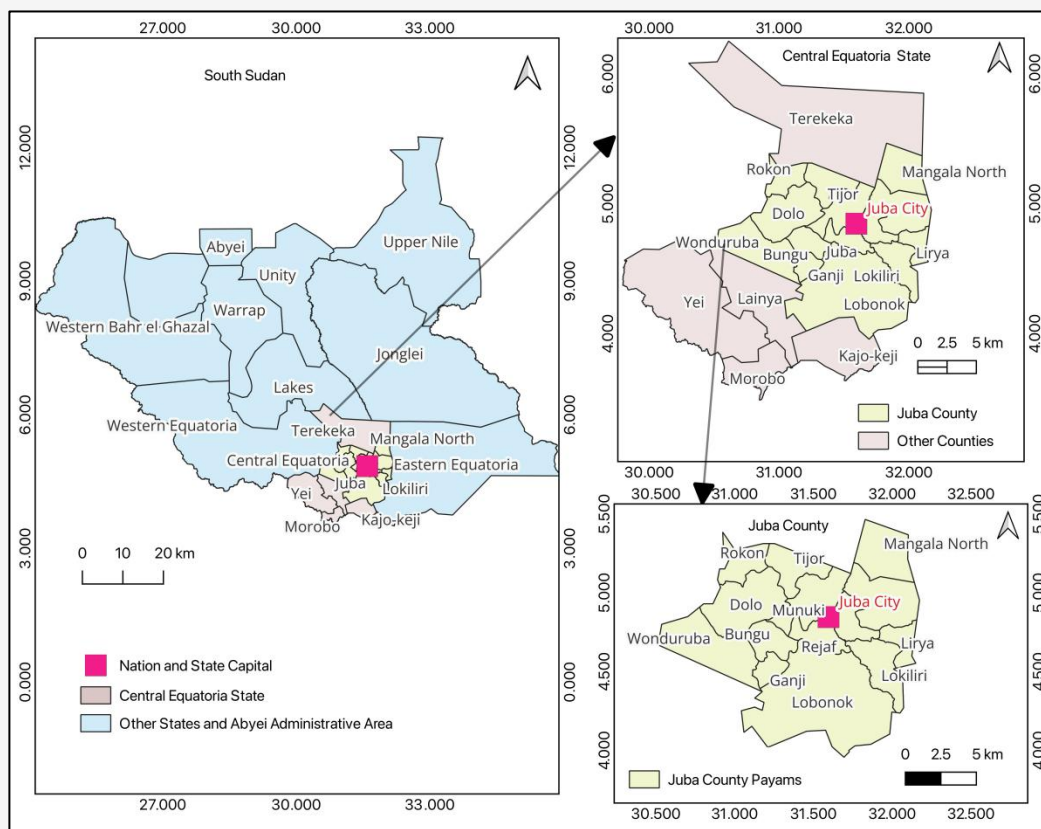


Figure 1: South Sudan, Central Equatoria State, and Juba County

Table 1: Data sources used in the study

Data Source	Data Type	Time Frame	Study Application
ESA Copernicus Open Access Hub	Sentinel-1 Synthetic Aperture Radar (SAR)	Jan - Dec 2024	Cloud-penetrating imagery for enhanced visibility of linear features
ESA Copernicus Open Access Hub	Sentinel-2 optical	Dec 1, 2024 - Mar 31, 2025	Visual enhancement and spectral feature detection
Humanitarian Data Exchange (HDX)	Administrative boundaries (ADM0-2)	April 2025	Defining area of interest (AOI), spatial extent, and map layout
Geofabrik (OSM extracts)	Vector roads data (paved /unpaved)	April 2025	Baseline road dataset for comparison and validation
Google Satellite Imagery	High-resolution imagery	Feb – April 2025	Visual validation of fused imagery and road interpretation
Researcher's VGI Input	Locally digitized road segments	April- July 2025	Supplementing missing roads based on local knowledge of Juba County

Researchers selected datasets based on their availability, reliability, spatial coverage, and how well they fit the study's goals. Spatial visualization, mosaicking, reprojection and vector-raster integration were conducted using QGIS version 3.42.1 (long-term release, LTR). This version was selected to ensure software stability, reproducibility

and full compatibility with GDAL-based raster processing and coordinate reference system handling required for analysis. Table 1 summarizes the satellite and vector data sources, their temporal range, and application in the study and Table 2 lists the software and tools used in the analytical workflow.

Table 2: Software and platforms used in the study

<i>Tool / Software</i>	<i>Type</i>	<i>Purpose in the Study</i>
Google Earth Engine (GEE)	Cloud-based geospatial platform	Satellite data access, median compositing, band stacking (SAR + optical fusion) and export
QGIS (Version 3.42.1)	Desktop GIS software	Manual road visualization and digitization, map layout, validation overlays, and export
Draw.io	Diagram and layout tools	Illustration of methodology and workflow charts
Microsoft edge / Google Chrome and Plugins	Web browser, AI and GEE access	Platform for accessing GEE, java scripts, downloading maps, data processing and analysis

3.1.2 Methodology

This study used a systematic, multi-source remote sensing method by integrating Sentinel-1 and Sentinel-2 images within the Google Earth Engine (GEE), local expert knowledge, and QGIS for visualization and analysis. The workflow aimed to detect and integrate unmapped and fragmented road networks, enhance road visibility, connectivity and road surface classification in urban and peri-urban areas of Juba County, South Sudan. The methodology included six main steps: (1) identifying data sources and analytical tools; (2) acquiring and preprocessing of Sentinel-1 SAR and Sentinel-2 optical images for the study area in GEE; (3) processing, fusion and export of fused image tiles; (4) QGIS - local knowledge integration, processing and analysis; (5) fusion effectiveness evaluation and validation; (6) targeted road surface classification and validation. While this study mainly focused on better visualization and mapping accuracy, the resulting fused datasets provide a foundation for future GeoAI applications, especially in automated road surface detection and classification in the entire road network of South Sudan and other areas with limited data. Figure 2 shows a schematic representation of the methodological workflow.

3.2 Data used and Data Acquisition

The data acquisition, preprocessing, processing and fusion of Sentinel-2 and Sentinel-1 satellite imagery were conducted on the Google Earth Engine (GEE) platform. This aimed to improve road visibility, reduce cloud interference, and allow for surface differentiation across Juba County, South Sudan. The process combined optical and radar data to address the limitations of each sensor and ensure complete spatial coverage. Sentinel-2 Level-2A surface reflectance images from December 1, 2024, to March 31, 2025 and Sentinel-1 Ground Range Detected (GRD) products from January 1, 2024, to December 31, 2024 were accessed from the Copernicus Open Access Hub through GEE's public data catalog. The Area of Interest (AOI) was defined using a boundary

shapefile of Juba County, which was obtained from the Humanitarian Data Exchange (HDX). Using both datasets ensured that structural and spectral road characteristics were captured, even in places often hidden by clouds or shadows.

3.3 Data Processing

3.3.1 Preprocessing and band selection

Standard preprocessing operations were carried out within Google Earth Engine (GEE) to ensure consistent radiometric properties and proper spatial alignment before data fusion. The Sentinel-2 images were filtered for the period from December 1, 2024, to March 31, 2025 (dry season) for a maximum cloud cover threshold of 20% to reduce cloud interference while retaining sufficient temporal coverage. The Sentinel-1 SAR data were retrieved for the entire 2024 calendar year to provide all-weather backscatter information that supports the optical imagery. At the same time, we used Sentinel-2 Level-2A imagery, which has been corrected for atmospheric and radiometric effects to provide Bottom-of-Atmosphere (BOA) surface reflectance using ESA's Sen2Cor processor. Using Level-2A products ensured that surface reflectance values accurately represented true ground conditions, reducing atmospheric effects and improving the reliability of subsequent optical-SAR integration. For Sentinel-1 Ground Range Detected (GRD) products, we applied radiometric calibration to sigma-naught σ^0 and performed orthorectification with terrain correction through GEE's standard SAR processing pipeline. These steps ensured comparable backscatter values across the study area and reduced distortions caused by terrain. The analysis focused on the VV and VH polarization bands acquired in descending orbit. These provided stable surface backscatter signatures important for analyzing road-related features. We selected six Sentinel-2 spectral bands based on their relevance to detecting road surfaces: B2 (Blue, 490 nm), B3 (Green, 560 nm), B4 (Red, 665 nm), B8 (Near-Infrared, 842 nm), B11 (SWIR-1, 1610 nm), and B12 (SWIR-2, 2190 nm).

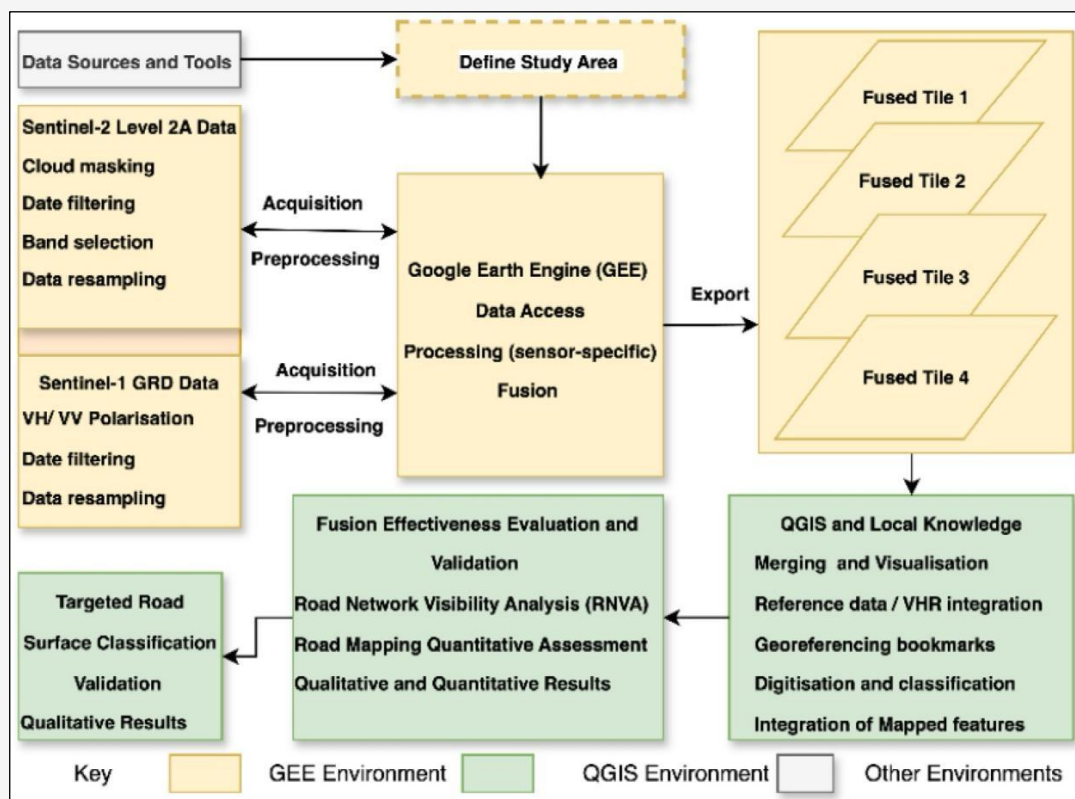


Figure 2: Road mapping using sentinel imagery fusion workflow

The visible bands (B2-B4) improve surface color contrast and highlight feature boundaries. B8 helps distinguish between bare soil and vegetation, while B11 and B12 are sensitive to surface moisture and compaction, which are crucial for telling apart paved and unpaved road surfaces. These bands provide complementary spectral information that improves road visibility. After preprocessing specific to each sensor, we resampled both Sentinel-1 and Sentinel-2 datasets to a common spatial resolution of 10 m. This step ensured pixel-level correspondence before fusion. At this point, all corrections and normalization steps were finished, and the datasets were ready for integration using the empirical fusion model described in Section 3.3.2.

3.3.2 Imagery fusion processing

This section describes the processing stage, including temporal compositing, polarization selection and empirical pixel-level integration of Sentinel-1 and Sentinel-2 data following prior sensor specific preprocessing. The Sentinel-1 and Sentinel-2 fusion took place in Google Earth Engine (GEE) using an empirical non-parametric band-stacking fusion model aimed at improving linear road features in areas with frequent clouds and limited data. Previously preprocessed Sentinel-1 GRD data, generated using GEE's standard SAR processing

pipeline and cloud minimized Sentinel-2 Level-2A composites were used as inputs for the fusion process. The fusion process had two main stages: first, pixel-wise median compositing specific to each sensor, and second, multi-sensor band stacking. Initially, Sentinel-2 Level-2A imagery underwent temporal compositing using pixel-wise median reduction to create cloud-minimized surface reflectance composites for the chosen spectral bands (B2, B3, B4, B8, B11, and B12). At the same time, Sentinel-1 GRD data were processed with GEE's standard SAR preprocessing pipeline. This included orbit correction, radiometric calibration, and terrain correction, leading to the generation of a pixel-wise median composite. While both VV and VH polarizations were initially available, only the VV channel was kept for fusion due to its greater sensitivity to surface roughness and linear infrastructure features. In contrast, VH is more affected by volume scattering from vegetation and urban clutter.

After the specific preprocessing for each sensor, an empirical pixel-level fusion model was applied through band stacking. This fusion process combines SAR backscatter and optical reflectance information at corresponding pixel locations, shown in Equation 1:

$$F(x, y) = \text{Median}[S1(x, y), S2(x, y)]$$

Equation 1

Where:

$F(x, y)$ = Fused pixel vector (intensity)
 $S1(x, y)$ = Sentinel-1 VV backscatter
 $S2(x, y)$ = Sentinel-2 spectral reflectance from
 bands (B2, B3, B4, B8, B11, B12)

In GEE, this fusion was done with the `ee.Image.addBands()` function. This function adds the Sentinel-1 VV band to the Sentinel-2 median composite while keeping the band metadata and spatial alignment intact. The resulting fused stack is defined in Equation 2:

$$F_{Stack} = [B2, B3, B4, B8, B11, B12, VV]$$

Equation 2

All bands were resampled to a common spatial resolution of 10 m before stacking to ensure pixel-level correspondence. The final output was a seven-band fused composite designed for better road visibility, smooth export, and further visualization, digitization, and analysis in QGIS. This empirical fusion model offers a cost-effective and repeatable method that uses the combined strengths of optical

and SAR data. It keeps interpretability for road network visibility and improves the analysis of road networks and future GeoAI-based applications.

3.3.3 Export and merging of fused tiles

Given the size of Juba County and the limitations of exporting large images from Google Earth Engine (GEE), the final fused composite was divided and exported as four GeoTIFF image tiles at a 10 m spatial resolution and the final fused composite was exported in WGS 84/ UTM Zone 36N for subsequent processing and analysis as shown in Figure 3(a). This export approach improved data handling, reduced processing errors, and allowed for quality control during mapping and analysis. The four fused Sentinel-1 and Sentinel-2 tiles exported from GEE were then merged into a single seamless mosaic using the Raster → Miscellaneous → Merge tool in QGIS. All tiles had the same spatial resolution, coordinate reference system, band structure, and radiometric scaling. This kept pixel-level radiometric consistency and ensured spatial continuity across the Juba County boundary. The resulting merged composite created a georeferenced, radiometrically continuous dataset suitable for easy visualization, digitization, and comparison with OpenStreetMap, Geofabrik, and Google Satellite imagery as depicted in Figure 3(b).

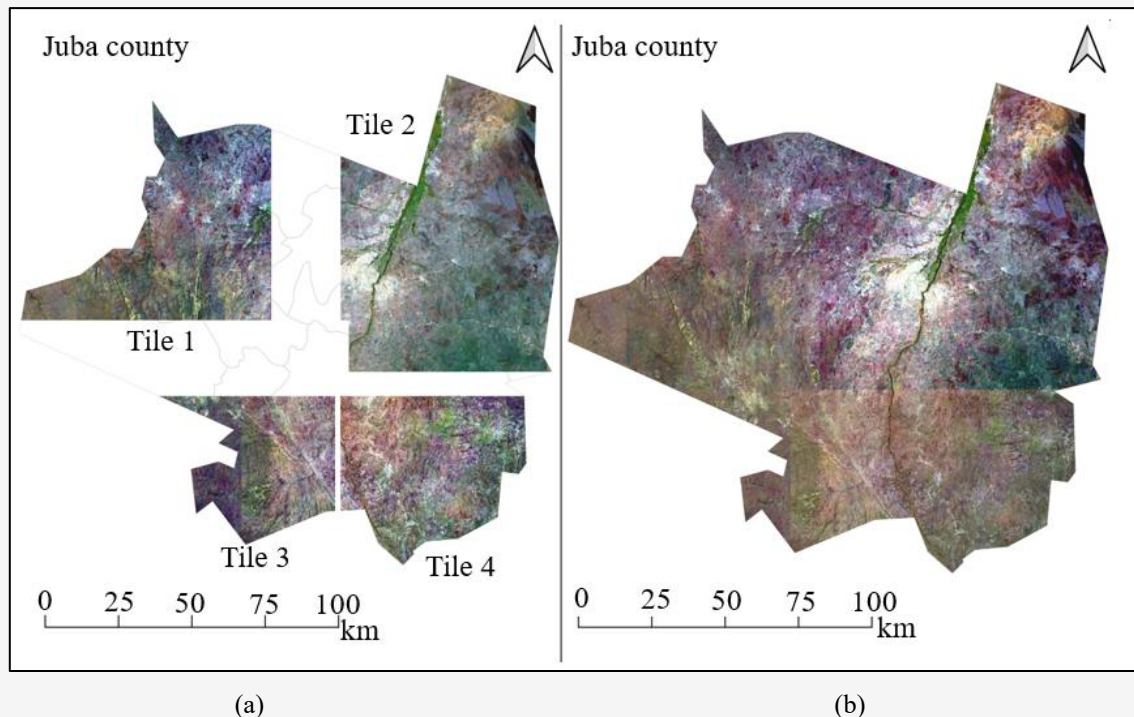


Figure 3: Sentinel imagery fusion: (a) four fused sentinel-1/2 tiles exported from GEE, and (b) seamlessly merged composite mosaic

3.4 Visualization Digitization and Road Verification Process

The visualization and digitization workflow supported by Informed Volunteered Geographic Information (IVGI) derived from the researcher's local knowledge of Juba County integrated four complementary spatial datasets. These included the QGIS merged composite mosaic, OpenStreetMap (OSM), Geofabrik roads, and Google Satellite imagery. All datasets were imported into QGIS. The fused Sentinel-1/2 composite (QGIS merged composite mosaic) served as the main reference layer. The OSM layer provided an initial view of mapped road segments. The Geofabrik dataset acted as an additional tool for spotting inconsistencies and missing features. High-resolution Google Satellite imagery allowed for independent checks on road continuity, alignment, and surface type. Using IVGI, the researcher carefully examined the fused image. They recalled road locations and features based on their experiences in Juba. A road segment was marked as unmapped when:

- (1) It was clearly visible in the fused composite
- (2) It was not present in either OSM or Geofabrik,
- (3) Its existence, alignment, and surface type (paved or unpaved) were confirmed through Google

Satellite imagery and local expert knowledge.

Each confirmed unmapped segment was given a georeferenced bookmark in QGIS. This process was carried out repeatedly across the entire county. All bookmarked locations were later digitized as polyline features, classified by surface type and compiled into a complete road-gap inventory.

3.5 Fusion Effectiveness Evaluation and Validation

To evaluate the effectiveness of the fused Sentinel-1 and Sentinel-2 imagery in enhancing road detection in a data-scarce and conflict-affected setting, a Road Network Visibility Analysis (RNVA) and quantitative analysis were conducted. The objective of the former was twofold: (1) to demonstrate the fusion ability to enhance road visibility, (2) to confirm the existence of unmapped roads, classify by surface type and validate road mapping outcomes through detailed visual interpretation and comparative analysis of the mapping results. The second step aimed at assessing the contribution of the fusion in enhancing the growth of road network, connectivity and updating mapped road surface classification of recently upgraded roads.

The study focused on three illustrative RNVA case scenarios covering varied environmental conditions throughout Juba County. The RNVA used the well-established "Select-Zoomed-In" method where spatially bookmarked and digitized road

segments obtained in the initial mapping phase were assessed at a cartographic scale of 1:5000. These road segments were purposively chosen to cover both paved and unpaved roads that are missing from existing open-source reference datasets. The unmapped roads analyzed were chosen for areas in and close to Juba City that are moderately built-up, since reduced visibility was observed in the densely built urban core and transitional peri-urban areas, in which mapping difficulty is common under sensor limitations, landscape complexity and insecurity. To improve the poor visibility of roads in congested built-up environments in Juba City, expert judgment was used, where tracing a road to its origin was deemed necessary for the study.

3.5.1 RNVA case 1

The first instance of RNVA case focused on the previously spatially bookmarked unmapped paved and unpaved road segments within inner urban and peri-urban areas. The merged image achieved better linear clarity and contrast that enabled better delineation of the road geometry than either Sentinel-1 or Sentinel-2 images [13] and [14]. This RNVA case shows the fusion's enhancement aspect in moderately built-up regions where traditional mapping sources encountered challenges, and in areas that are vulnerable to insecurity in the mapping domain.

3.5.2 RNVA case 2

The focus of this case was validating the unmapped road existence for inner-urban and peri-urban road segments mentioned in RNVA Case 1. For the RNVA case 2, the merged image was analyzed with the Geofabrik datasets to confirm physical existence of the selected road segments through the overlay of the reference road datasets.

3.5.3 RNVA case 3

Case 3 conducted a continuation of RNVA case 2 to cross-verify the physical existence and surface classification of the unmapped roads through a high-resolution Google Satellite overlay as a base-layer. Road segments unrepresented in standard datasets were classified as paved or unpaved by integrating spectral and textural characteristics from Sentinel-2, back-scatter properties from Sentinel-1, and contextual interpretation of Google satellite imagery. Classification was based on the expert visual interpretation of tone, texture, and geometric patterns, creating a labeled dataset. Through analysis of the fusion imagery, these road segments were visible with distinct surface features and structurally continuous, validating the robustness of the approach in semi-urban and peripheral environments.

3.6 Quantitative Assessment of Road Network Enhancement

In this paper, we formulated a comprehensive spatial metrics framework for the quantitative evaluation of Sentinel-1/2 fusion approach for road feature detection. Specifically, QGIS 3.42.1 was used to perform this analysis, using multiple indicators to assess network expansion, connectivity improvement, and classification accuracy through a systematic geospatial approach.

3.6.1 Network expansion metrics

To ensure accurate calculation of road network lengths across the study area, all spatial layers imported for visualization and analysis in QGIS were double-checked and confirmed to match the project coordinate reference system (CRS), WGS 84/UTM Zone 36N (EPSG:32636). The total lengths of the Geofabrik road network ($L_{Geofabrik}$) and the newly detected roads (L_{New}) were calculated using QGIS' field calculator with the \$length function as modeled by Equation 3 and Equation 4, respectively:

$$L_{Geofabrik} = \sum_{i=1}^n \frac{\text{Length}(R_i)}{1,000} \quad \text{Equation 3}$$

$$L_{New} = \sum_{i=1}^n \frac{\text{Length}(r_i)}{1,000} \quad \text{Equation 4}$$

Where:

L_{new} = Total length of newly detected roads (km)

$L_{Geofabrik}$ = The reference road length from Geofabrik (km)

R_i = Individual road segments derived from Geofabrik

r_i = Individual Road segments derived from fusion imagery

The proportional network expansion ($P_{Expansion}$) representing the contribution of newly detected roads to the integrated network was calculated from Equation 5:

$$P_{Expansion} = \frac{L_{New}}{L_{Geofabrik} + L_{New}} \quad \text{Equation 5}$$

3.6.2 Connectivity analysis

This step aimed to determine the number of unmapped roads that would be connected to the existing reference road network within a standardized selected buffer.

Connectivity measurement is done with geometric proximity analysis for network integration in QGIS. The distance threshold of 200 meters was determined by sensitivity analysis considering the widths and positional accuracy of rural road corridors. Connected roads were selected by spatial selection based on 200-meter distance, in order to determine directly the functional connectivity of the network, and not using the geometric buffer overlap. The length-based approach to obtain the connectivity index (CI) is given by Equation 6:

$$CI = \frac{\sum L_{Connected}}{\sum L_{New}} \times 100 \quad \text{Equation 6}$$

Where:

$\sum L_{Connected}$ = Total length of new roads within 200 meters of the existing network

$\sum L_{New}$ = Complete length of newly detected roads

3.7 Targeted Road Surface Classification and Validation

The extensive presence of paved road segments in Juba County increasingly originates from the urban core of Juba City, many of them freshly upgraded and still inconsistently represented in the existing georeferenced datasets. After the connectivity analysis conducted in the previous section 3.6.2, we performed a targeted road surface classification validation to verify the applicability of the Sentinel-1 and Sentinel-2 fusion, backed by Informed Volunteered Geographic Information (IVGI), for the delivery of timely and robust updates on road surface information. The key challenge that this validation aimed to address was to demonstrate how the fusion-IVGI approach can be used to resolve Sentinel fusion mapping gaps encountered in the urban core of Juba City and identify discrepancies in mapped road surface types - a persistent challenge in conflict-affected and data-scarce environments where datasets such as Geofabrik and OpenStreetMap tend to be outdated. A set of representative road segments was chosen along mapped primary corridors linking Juba County to neighboring counties, states, and international borders, where recent upgrades from unpaved to paved surfaces were already known to have taken place. This also helped to produce valid road surface classification information on pre-existing road networks to facilitate data refreshing, logistics planning, and infrastructure management.

Furthermore, the validated road segments provide a systematic and credible sample dataset for modeling to train machine learning models in upcoming GeoAI-based road surface classification studies.

4. Results

4.1 Fusion Based Visualization and Identification of Mapping Gaps

Using fused Sentinel-1 and Sentinel-2 imagery, we found numerous road segments in Juba County that are not included in the current georeferenced road datasets. The fusion images made it easy to identify and manually digitize continuous paved and unpaved road segments in both urban and peri-urban areas as shown in Figure 4(a). When we overlaid the Geofabrik road network onto the digitized roads, distinct mapping gaps appeared. Many road segments visible in the fusion images were missing from the Geofabrik dataset, as shown in Figure 4(b). This was especially true in the urban core of Juba City and along major corridors leading to neighboring counties, states, and international borders. These gaps show differences between the actual road conditions and the existing road datasets. Unmapped road segments tend to cluster in areas with recent infrastructure development. This suggests that some road networks have been improved or newly built, but not updated in

commonly used open-source road databases. The fusion-based visualization provides clear evidence of missing road information in these datasets.

4.2 RNVA Based Evaluation of Fusion Effectiveness and Road Surface Interpretation

Combining Sentinel-1 and Sentinel-2 images made it easier to spot and assess roads, even in challenging environments and areas with heavy cloud cover. Fusing these datasets made roads clearer and more continuous, and provided better contrast than using either Sentinel-1 or Sentinel-2 alone. Roads stood out more, regardless of their surroundings, which helped in areas with mixed land cover or limited data. With improved visibility, it became possible to see what kind of surface a road had. Differences in tone and texture in the fused images made it easier to tell whether an unmapped road segment was paved or unpaved. This applied to both new and older roads, showing the fusion approach classifies road surfaces well. These newly identified road segments were verified using OpenStreetMap, Geofabrik datasets, and high-resolution Google satellite imagery. Roads that appeared in both fusion and high-resolution images and followed a logical path were confirmed as real infrastructure, even if they were missing from reference maps.

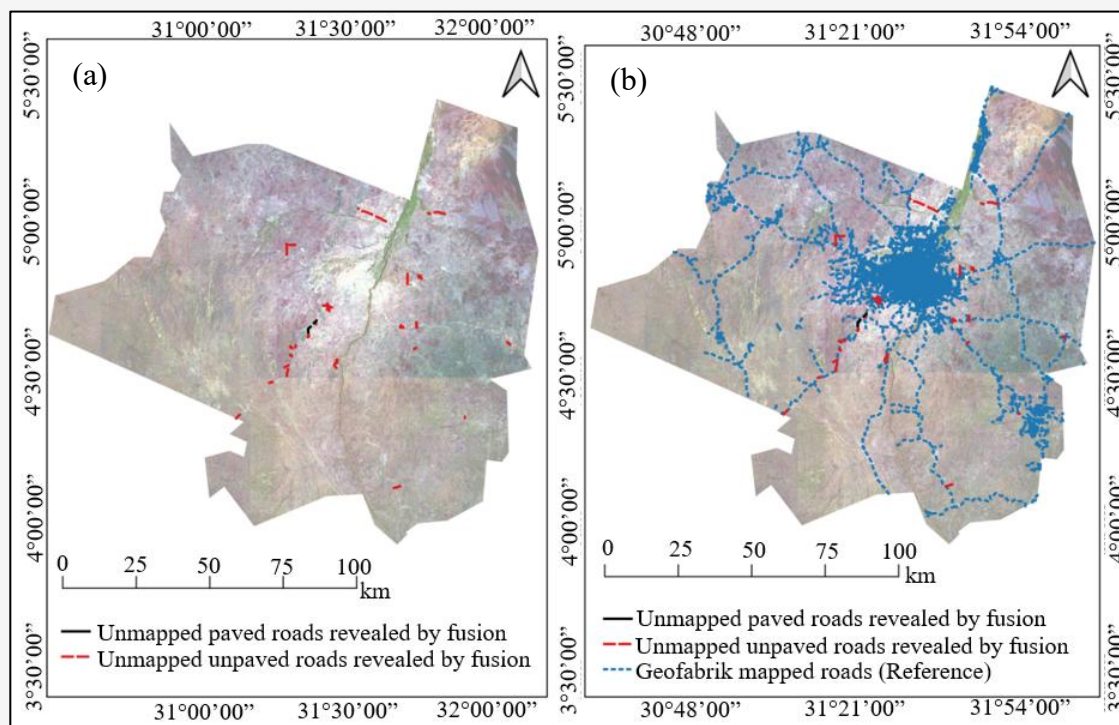


Figure 4: Sentinel imagery fusion mapping (a) unmapped roads detected from fusion, and (b) existing reference road networks overlay

Local knowledge from Juba County provided through Informed Volunteered Geographic Information helped confirm very new roads or those in complex city layouts. Overall, the Road Network Visual Assessment shows that fusing Sentinel-1 and Sentinel-2 data is a powerful way to make roads easier to see, classify their surfaces, and identify missing roads in areas where traditional data is hard to obtain, or conflict makes mapping difficult as illustrated by the three subsequent Road Network Visibility Analysis cases discussed in Sections 4.2.1–4.2.3.

4.2.1 RNVA Case 1: Enhanced visibility of unmapped roads in urban and peri-urban settings

The first RNVA example highlights how fusing Sentinel-1 and Sentinel-2 imagery significantly improves the visibility of road features. This is demonstrated with two road types: an unmapped unpaved road in a peri-urban area and nearby paved and unpaved roads within Juba City's urban core. Notably, neither of these road segments appeared in existing reference datasets such as OpenStreetMap (OSM) or Geofabrik. In the peri-urban area, the fused imagery revealed the unpaved road with clear linear

continuity and sharper edge contrast. While surface heterogeneity and vegetation often made this road appear fragmented or hidden in single-sensor images, it stood out clearly in the fusion product Figure 5(b). In the urban core, the fusion allowed both paved and unpaved road segments to be distinguished despite challenges like building shadows, narrow alignments, and dense surrounding infrastructure. As Figure 5(c) shows, the fusion reduced spectral ambiguity by blending SAR backscatter sensitivity to structural features with optical spectral reflectance, especially from bands B4, B8, B11, and B12.

As a result, both road types were clearly distinguishable from their surroundings in the fused imagery. This improved separability increased confidence in visual interpretation, enabled more reliable road surface classification, and allowed for accurate manual digitization of unmapped road segments. The RNVA results show that Sentinel-1 and Sentinel-2 fusion effectively overcomes visibility challenges often found in built-up and peri-urban environments, where cloud cover, spectral confusion, and structural obstacles typically hinder road mapping quality.

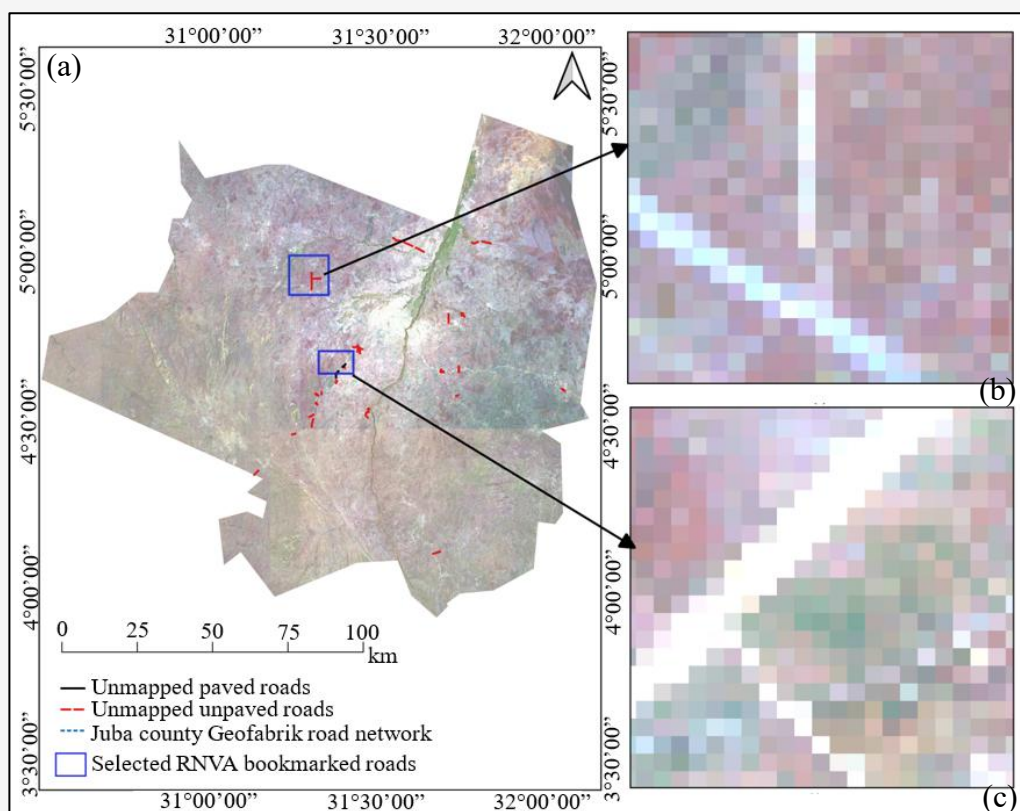


Figure 5: Road network visibility analysis case 1:(a) selected unmapped roads (b) unmapped peri-urban unpaved road (c) unmapped paved and unpaved road within Juba city

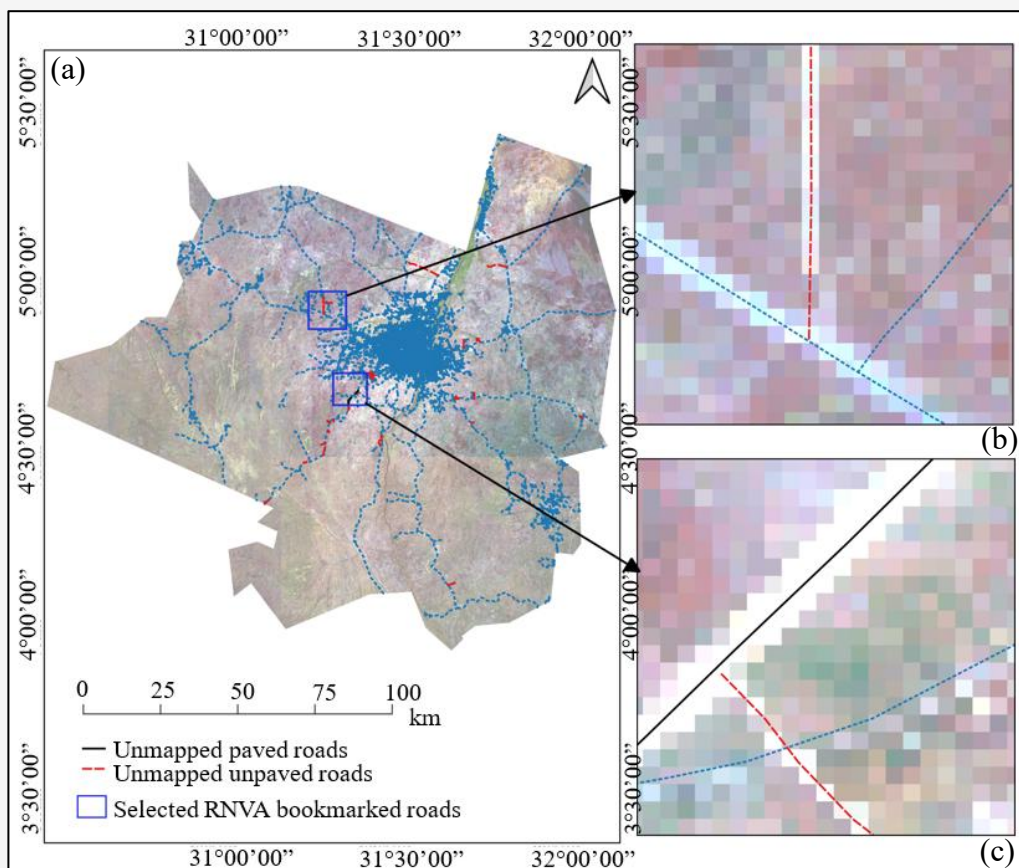


Figure 6: Road network visibility analysis case 2: (a) selected unmapped roads with overlaid reference road network (b) overlay of reference road network on peri-urban unpaved road, and (c) overlay of reference road network on unmapped paved and unpaved road within Juba city

4.2.2 RNVA Case 2: Identification of missing roads using Geofabrik overlay and select-zoomed-in method

In RNVA Case 2, applying the select-zoomed-in approach revealed limitations in the completeness of existing road datasets through overlay comparison of Geofabrik road vectors with fusion-detected road segments from RNVA Case 1. The analysis showed that several road segments clearly visible in the fused Sentinel imagery were missing from the Geofabrik dataset. For example, Figure 6(b) displays a clearly identifiable unpaved peri-urban road, while Figure 6(c) highlights distinct paved and unpaved road segments that were conspicuously absent from the overlaid Geofabrik data. These results indicate that relying solely on open-source road datasets can lead to incomplete representation of road infrastructure, especially in data-poor or rapidly changing environments. The observed discrepancies demonstrate that fused Sentinel imagery can reveal road infrastructure not captured in existing reference datasets. Thus, the results highlight the value of Sentinel-1 and Sentinel-2 fusion as an effective

complementary source for identifying missing road segments and supporting more robust, up-to-date road mapping.

4.2.3 RNVA Case 3: Validation through Google Satellite overlay using select-zoomed-in method

Using the Select-Zoomed-In approach, RNVA scenario three validated RNVA case 2 by comparing fused Sentinel imagery and Geofabrik road data with high-resolution Google Satellite imagery. Overlaying the fused imagery on the Geofabrik dataset revealed missing and partially mapped road segments, consistent with earlier RNVA findings Figure 6. Comparing these findings with Google Satellite imagery confirmed the existence, alignment, and surface characteristics of these segments. Visual inspection of the Google Satellite overlays revealed distinct differences in road surface brightness, width, and connectivity. These differences enabled the confirmation of both unmapped peri-urban roads and paved or unpaved segments within the urban core. As illustrated in Figures 7(b) and 7(c), these comparisons demonstrate that fusion-detected road

features correspond to actual on-the-ground infrastructure. These results confirm the reliability of the fusion process and highlight the value of integrating fusion-based imagery with high-resolution reference data and local expert visual interpretation. The Select-Zoomed-In approach proved effective for validating road features in regions with limited authoritative road data.

4.3 Enhanced Road network mapping through multi-sensor fusion

The integration of Sentinel-1 SAR and Sentinel-2 optical imagery, along with informed Volunteered

Geographic Information (IVGI), enabled the identification of 71.39 km of previously unmapped road infrastructure in Juba County. This expanded the known network by approximately 1%, from 7,336 km to 7,407 km as shown in Figure 8. Similarly, compositional analysis revealed that 94% (67 km) of these new roads were unpaved tracks and 6% (4 km) were paved roads. These results demonstrate that the method is effective for accurately mapping both urban and informal rural infrastructure often missing from established reference data as shown in Figure 9.

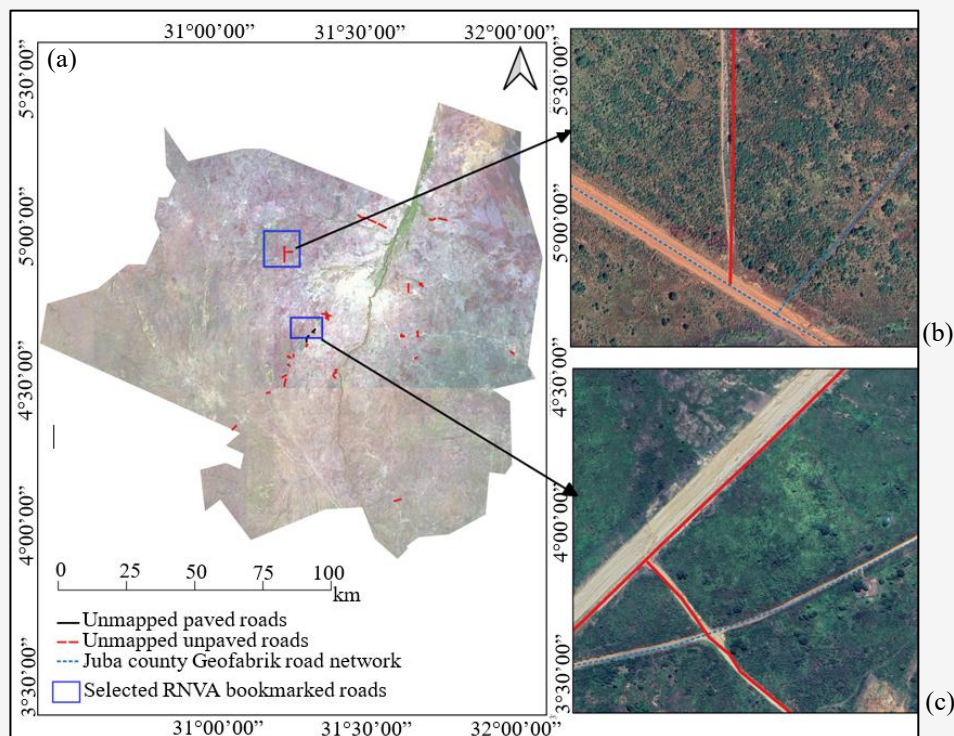


Figure 7: Road network visibility analysis case 3 (a) selected unmapped roads (b) overlay of reference road network and Google satellite imagery on unmapped peri-urban unpaved road, and (c) overlay of reference road network and Google satellite imagery on unmapped paved and unpaved road within Juba city

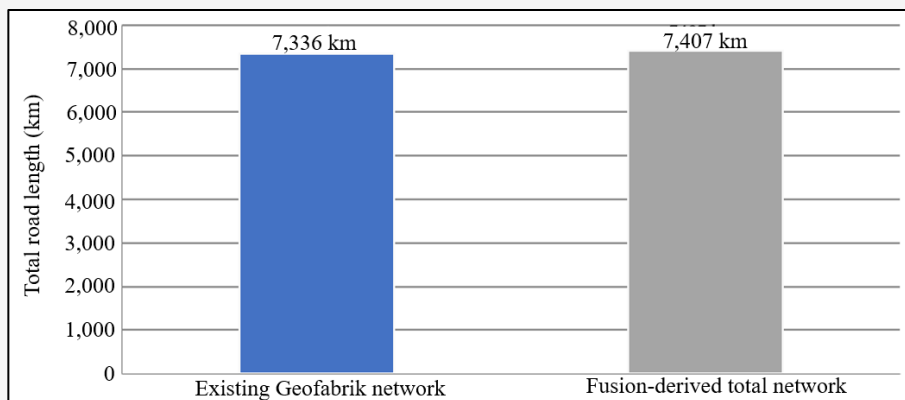


Figure 8: Fusion enhanced road network expansivity in Juba County

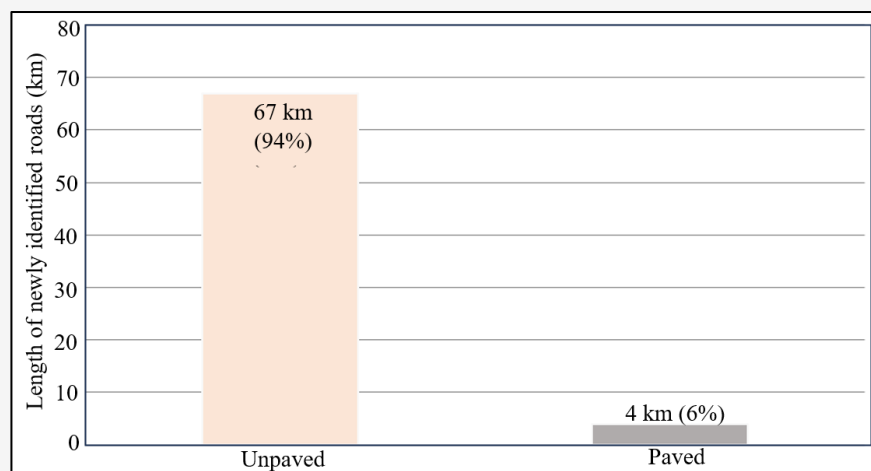


Figure 9: Road surface conditions of newly identified roads

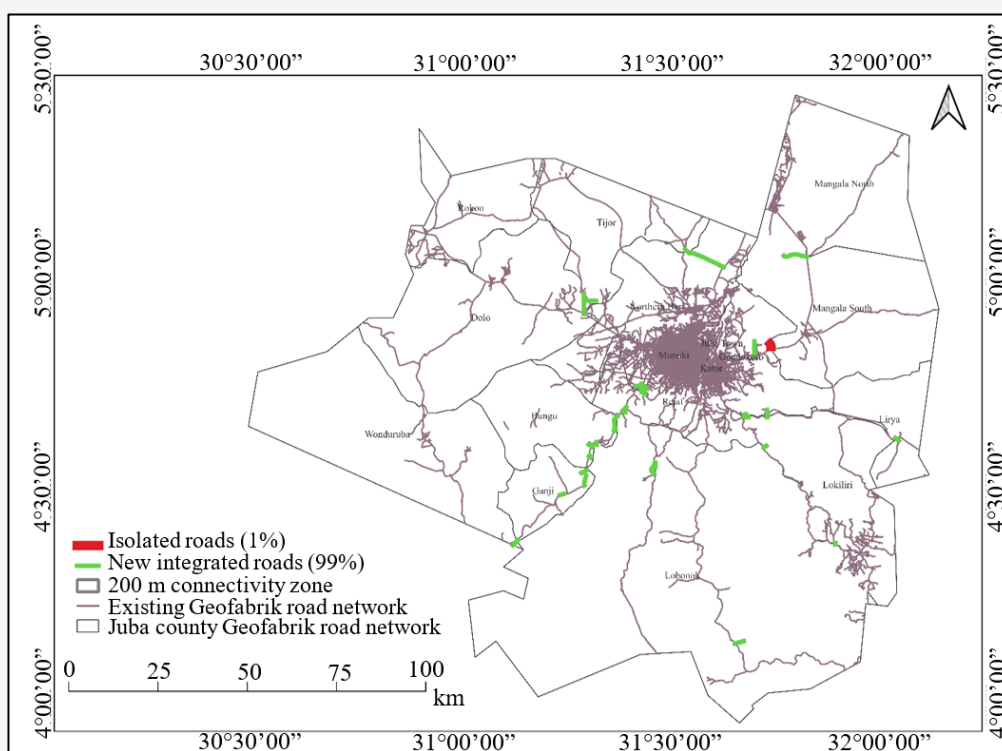


Figure 10: Enhanced road network map of Juba County derived from sentinel imagery fusion

4.4 Connectivity

Figure 10 demonstrates improved road network detection and connectivity by combining Sentinel-1 (SAR) and Sentinel-2 (optical) imagery. This fusion strengthens the continuity of linear road features, enabling new road segments to connect with the existing network in Juba County. A connectivity analysis using a 200 m geometric proximity threshold reveals that 98.8% (70.53 km) of newly identified road segments connect to the existing OpenStreetMap (Geofabrik) network, while just 1.2% (0.86 km) remain isolated. This high

connectivity occurs along both recently upgraded corridors and unimproved roads. Many unmapped roads function as feeder or access routes, providing strong geometric and functional connections to the broader network, even though they are not part of reference datasets. Most unmapped road segments are found in peri-urban areas, mainly in the southern part of Juba County, where gradual development, limited institutional mapping capacity, and security issues limit traditional field mapping. Here, road infrastructure grows slowly and often remains undocumented, even when it is important for local

connectivity. The fusion-based approach is effective at identifying both upgraded and non-upgraded roads, supporting network continuity. Few unconnected road segments serve as local access in informal or low-density neighborhoods. These roads meet community mobility needs but do not connect to main transport routes, so they fall outside the connectivity threshold. Their limited integration signals ongoing mapping gaps in informal and insecure areas, not misdetection, as their networks grow without formal planning.

4.5 Fusion - IVGI for Updating Road Surface Attributes

The results in Figure 11 show that several road segments mapped in existing datasets have outdated or undefined surface attributes. This remains true even though these roads have recently been paved. The geometric data for these roads is available in the Geofabrik network. However, their surface conditions have not been updated to reflect on-the-ground changes. Informed Volunteered Geographic

Information (IVGI) provided background knowledge about these upgrades along key transport routes connecting Juba City to neighboring regions. The combined Sentinel-1 and Sentinel-2 imagery provided independent spatial evidence to support this knowledge. It showed surface features typical of paved roads, like improved linear continuity and a uniform surface response. High-resolution Google Satellite imagery confirmed the width, alignment, and continuity of the pavement along these segments.

These findings suggest that the fusion and IVGI approach is particularly good for updating information on existing road networks, not just for finding new roads. In areas with limited data and those affected by conflict, where field surveys and regular database updates are difficult, this ability enables locally known but undocumented infrastructure improvements to be verified and mapped as verified information. The results highlight how fusion imagery and IVGI work together to reduce delays in road surface datasets and improve the accuracy of road infrastructure inventories.

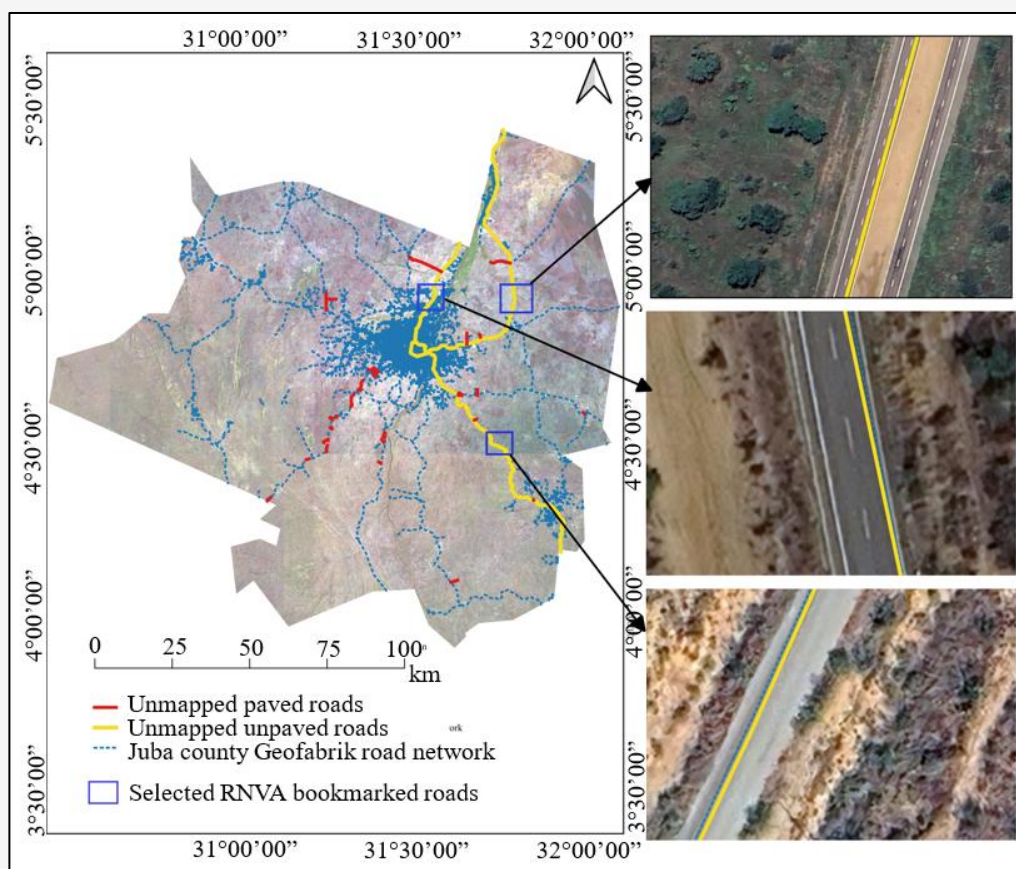


Figure 11: Validation of mapped road network with currently upgraded road surfaces in Juba County

5. Discussion

This paper explores the feasibility of combining Sentinel-1 SAR and Sentinel-2 optical imagery for road infrastructure mapping in data-scarce, conflict-affected areas, using Juba County as a case study. The fusion-based algorithm improved road visibility and connectivity across urban, peri-urban, and peripheral environments, as corroborated by the Road Network Visibility Analysis (RNVA) samples and the quantitative outcomes reported in Section 4. The recognition of 71.39 km of previously undiscovered roads and a 98.8% integration rate with connectivity showcases the usage of multi-sensor fusion in practice, where authoritative datasets (such as OpenStreetMap and Geofabrik) are still incomplete or outdated. These results suggest that, rather than isolating a feature or introducing a spurious one, the proposed approach primarily detects functionally relevant infrastructure, thereby helping build confidence in map outputs. We integrated Informed Volunteered Geographic Information (IVGI) to enhance contextual accuracy, especially in informal settlements and peri-urban areas where road development is rapid and poorly documented. However, IVGI is inherently conditional on the provider's reliability and spatial familiarity. In this study, potential subjectivity was mitigated through standardized cross-validation using Google Satellite imagery and relevant reference datasets.

Subsequent deployments might continue to improve robustness by including additional local contributors or formalized, community-based validation structures. Road detectability was also affected by the seasonal vegetation regime. In wetter conditions, vegetation invasion and surface moisture can reduce optical visibility, while radar backscatter variability can mask fine-angle linear features. While the application of dry-season Sentinel-2 imagery, supplemented with year-round Sentinel-1 data, reduced these effects somewhat, road detection in densely developed urban cores and heavily vegetated corridors remained difficult. This means that multi-temporal analysis will be crucial in future development. Notwithstanding these limitations, the proposed fusion framework excelled in semi-urban and peripheral landscapes, where traditional field surveys and high-resolution images are not viable. Currently, the process is largely guided by human image interpretation, as determined by experts, and digitized, but the higher-quality visual representation from fused images lays a strong foundation for future semi-autonomous and GeoAI-enhanced road extractions. In general, our findings validate that integrating free satellite imagery, cloud-based data processing, and well-informed local knowledge is a

pragmatic and scalable approach to enriching road infrastructure inventories in fragile, data-poor areas.

6. Conclusion

The study presents a practical and innovative framework for mapping road infrastructure in data-scarce and conflict-affected environments by integrating Sentinel-1 SAR and Sentinel-2 optical imagery with the cloud-based Google Earth Engine, supplemented by informed volunteered geographic information. This approach addresses persistent challenges such as cloud cover, insecurity, limited institutional capacity, and restricted field access by relying exclusively on freely available satellite data and cloud computing technologies. Our findings demonstrate that multi-sensor fusion significantly enhances the visibility and continuity of roads, successfully identifying 71.39 km of previously unknown roads in Juba County and expanding the known road network by approximately 1%. Additionally, this approach uncovered outdated road surface classifications in the existing dataset, highlighting its utility for both discovering missing infrastructure and updating road inventories essential for planning, logistics, and disaster response. A notable methodological advancement is the structured human-in-the-loop fusion framework, which seamlessly integrates cloud-based satellite processing with local expertise and open reference datasets. This enables the deployment of GeoAI-ready baseline datasets optimized for both technical robustness and contextual accuracy, making them suitable for training automated road extraction and classification models. The framework paves the way for (1) expanding workflows to multi-seasonal and multi-year analyses of vegetation dynamics and surface moisture variability, and (2) developing semi-automated and fully automated GeoAI models trained on validated fusion outputs to reduce reliance on manual digitization. Future research could also explore community-based validation methods to enhance scalability and objectivity. Overall, our proposed procedure offers a pragmatic, cost-effective, and reproducible approach to improving road infrastructure data in South Sudan and other geospatial contexts facing similar constraints.

Acknowledgements

This research was made possible by the generous support of the Japan International Cooperation Agency (JICA), in collaboration with Kanazawa Institute of Technology and the Government of South Sudan (GoSS), under the Knowledge Co-Creation Program for Long-Term Participants in Road Assets Management program (JICA KCCP-RAMP). I gratefully acknowledge this sponsorship, and the

continued encouragement from my home institution, the University of Juba.

References

- [1] World Food Program (WFP). *South Sudan Logistic Cluster Operation Update 2024*, Rome, Italy. [Online]. Available: <https://logcluster.org>. [Accessed: Jan. 20, 2026].
- [2] United Nations Development Programme. *South Sudan Human Development Report (2023): Infrastructure and Resilience in Fragile States*, UNDP, New York, USA, 2023. [Online]. Available: <https://www.undp.org> [Accessed: May 12, 2026].
- [3] See, L., Olteanu -Raimond, A. M. and Fonte, C. C., (2025). Recent Advances in Volunteered Geographic Information (VGI) and Citizen Sensing. *International Journal of Digital Earth*, Vol. 18. <https://doi.org/10.1080/17538947.2025.2480220>.
- [4] Opach, T., Navarra, C., Rod, J., Neset, T., Wilk, J., Cruz, S. and Joling, A., (2023). Identifying Relevant Volunteered Geographic Information about Adverse Weather Events in Trondheim using the Citizen Sensing Participatory System. *Environment and Planning B: Urban Analytical City Science*, Vol. 50. <https://doi.org/10.1177/23998083221136557>.
- [5] World Bank Group. *South Sudan Digital Economy Assessment*, (2022). [Online]. Available: <https://www.worldbankgroup.org> [Accessed: Nov. 11, 2025].
- [6] World Bank Group. *South Sudan Economic Monitor: Towards a Jobs Agenda*, 2022. [Online]. Available: <https://www.worldbank.org> [Accessed: Nov. 10, 2025].
- [7] Jundi, S., (2024). The Impact of Armed Conflict on Economic Growth and Sustainability in South Sudan. *Journal of Developing Countries Studies*, Vol. 8(2); 58-73. <https://doi.org/10.47604/jdcs.2826>.
- [8] Ibisch, P. L., Hoffmann, M., Kreft, S., Pe`Ere, G., Kati, V., Biber-Freudenberger, L., DellaSala, D., Vale, M., Hobson, P. and Selva, N., (2016). A Global Map of Roadless Areas and their Conservation Status. *Science*, Vol. 354. <https://doi.org/10.1126/science.aaf7166>.
- [9] United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA). *South Sudan Humanitarian Needs and Response Plan 2024*, Geneva, Switzerland. [Online]. Available: <https://www.unocha.org> [Accessed: May 12, 2026].
- [10] Ramm, F., (2025). OpenStreetMap Data in Layered GIS Format. [Online]. Available: <http://wiki.openstreetmap.org/>. [Accessed: Oct. 21, 2025].
- [11] Guo, H., Wang, L. and Liang, D., (2016). Big Earth Data from Space: A New Engine for Earth Science. *Science Bull*, Vol. 61. <https://doi.org/10.1007/s11434-016-1041-y>.
- [12] Paul, G. C., (2023). Road Maintenance Challenges: The Greatest Obstacle to Sustainable Development in South Sudan. *Journal of Sustainable Social Change*, Vol. 15. <https://doi.org/10.5590/jssc.2023.15.1.03>.
- [13] Meraner, A., Ebel, P., Zhu, X. and Schmitt, M., (2020). Cloud Removal in Sentinel-2 Imagery Using a Deep Residual Neural Network and SAR-Optical Data Fusion. *ISPRS Journal of Photogrammetry and Remote Sensing*, Vol. 166. <https://doi.org/10.1016/j.isprsjprs.2020.05.013>.
- [14] Yun, Y., Jung, J. and Han, Y., (2024). Cloud Restoration of Optical Satellite Imagery Using Time-Series Spectral Similarity Group. *GIScience & Remote Sensing*, Vol. 61. <https://doi.org/10.1080/15481603.2024.2324553>.
- [15] Barrington-Leigh, C. and Millard-Ball, A., (2017). The World's User-Generated Road Map is More than 80% Complete. *PLoS One*, Vol. 12. <https://doi.org/10.1371/journal.pone.0180698>.
- [16] QGIS Development Team. *QGIS Geographic Information System, Open Source Geospatial Foundation Project*, 2025. [Online]. Available: <https://www.qgis.org> [Accessed: May 12, 2026].
- [17] Qiu, C., Schitt, M., Geib, C., Chen, T. K. and Zhu, X. X., (2020). A Framework for Large-scale Mapping of Human Settlement Extent from Sentinel -2 Images via Fully Convolutional Neural Networks. *ISPRS Journal of Photogrammetry and Remote Sensing*, Vol 163; 152-170. <https://doi.org/10.1016/j.isprsjprs.2020.01.028>.
- [18] Gargiulo, M., Dell'aglio, D., Iodice, A, Ricco, D. and Ruello, G., (2023). Intergration of Sentinel -1 and Sentinel -2 data for Earth Surface Classification using Machine Learning Algorithms Implemented on Google Earth Engine. *Sensors (Switzerland)*, Vol. 20(22). <https://doi.org/10.1109/InGARSS59135.2023.10490344>.
- [19] Zhang, Z., Liu, Q. and Wang, Y., (2018). Road Extraction by Deep Residual U-Net. *IEEE Geoscience and Remote Sensing Letters*, Vol. 15. <https://doi.org/10.1109/LGRS.2018.2802944>.

- [20] Li, Y., Matgen, P. and Chini, M., (2025). Extraction of Built-up Areas using Sentinel-1 and Sentinel-2 Data with Automated Training Data Sampling and Label Noise Robust Cross-Fusion Neural Networks. *International Journal of Applied Earth Observation and Geoinformation*, Vol. 139. <https://doi.org/10.1016/j.jag.2025.104524>.
- [21] Shrestha, B., Ahmad, S. and Stephen, H., (2021). Fusion of Sentinel-1 and Sentinel-2 Data in Mapping the Impervious Surfaces at City Scale. *Environ Monit Assess*, Vol. 193. <https://doi.org/10.1007/s10661-021-09321-6>.
- [22] Nazir, U., Waseem, M., Khan, F., Saeed, R., Hasan, S., Uppal, M. and Khalid, Z., (2023). Improved Flood Mapping for Efficient Policy Design by Fusion of Sentinel-1, Sentinel-2, and Landsat-9 imagery to Identify Population and Infrastructure Exposed to Floods. *Lahore University of Management Science (LUMS), Lahore Pakistan* [online]. Available: <http://arxiv.org/abs/2306.06074>. [Accessed on May 12,2026]
- [23] Sebastianelli, A., Rosso, M., Ullo, S. and Gamba, P., (2022). A Speckle Filter for Sentinel-1 SAR Ground Range Detected Data Based on Residual Convolutional Neural Networks. *IEEE Journal of Selected Topics in Applied Earth Observation and Remote Sensing*, Vol. 15. <https://doi.org/10.1109/JSTA RS.2022.3184355>.
- [24] Sengani, D., Ramoelo, A. and Archer, E., (2023). A Review of Fusion Framework using Optical Sensors and Synthetic Aperture Radar Imagery to Detect and Map Land Degradation and Sustainable Land Management in the Semi-arid Regions. *Taylor and Francis Ltd*, Vol 38. <https://doi.org/10.1080/10106049.2023.2278325>.
- [25] Usmani, M., Francesca, A., Fondazione, B., Kessler B., Maurizio, C. and Fondazione, N., (2024). Fusion of Remote Sensing and Citizen Science Information through Machine Learning for Geospatial Analysis. *Doctoral Dissertation. Department of information Engineering and Computer Science. ICT International Doctoral School. Athesina Studiorum Universitas*.
- [26] Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D. and Moore, R., (2017). Google Earth Engine: Planetary-Scale Geospatial Analysis for Everyone. *Remote Sensing of Environment*, Vol. 202. <https://doi.org/10.1016/j.rse.2017.06.031>.
- [27] African Development Bank (AfDB). African Infrastructure Development Index Report 2024, Abidjan, Cote d'Ivoire, 2024. [Online]. Available: <https://www.afdb.org> [Accessed: May 12, 2026].
- [28] Razzano, F., Iandolo, M. R., Zarro, C. G., Yogesh, S. and Ullo, S. L., (2023). *Integration of Sentinel-1 and Sentinel-2 Data for Earth Surface Classification using Machine Learning Algorithms Implemented on Google Earth Engine*. [Online]. Available: <http://arxiv.org/abs/2308.11340> [Accessed: May 12, 2026]
- [29] Zhang, Y., Zhang, L., Wang, Y. and Xu, W., (2024). AGF-Net: Adaptive Global Feature Fusion Network for Road Extraction from Remote-Sensing Images. *Complex and Intelligent Systems*, Vol. 10. <https://doi.org/10.1007/s40747-024-01364-9>.
- [30] Fu, L., Chai, H. and Lv, X., (2024). Enhancing Road Extraction in Large-Scale Complex Terrain through Multi-Source Remote Sensing Image Fusion and Optimization. *Remote Sensing (Basel)*, Vol. 16. <https://doi.org/10.3390/rs16020297>.
- [31] Jia, Y., Zhang, X., Xiang, R. and Ge, Y., (2023). Super-Resolution Rural Road Extraction from Sentinel-2 Imagery Using a Spatial Relationship-Informed Network. *Remote Sensing (Basel)*, Vol. 15. <https://doi.org/10.3390/rs15174193>.
- [32] Singh G. and Rawat, K. S., (2024). Mapping Flooded Areas Utilizing Google Earth Engine and Open SAR Data: A Comprehensive Approach for Disaster Response. *Discover Geoscience*, Vol. 2. <https://doi.org/10.1007/s44288-024-00006-4>.
- [33] Yang, Y. E., Yu, T. T. and Chen, C. Y., (2024). Automatic Detection of Landslide Impact Areas using Google Earth Engine. *Terrestrial, Atmospheric and Oceanic Sciences*, Vol. 35. <https://doi.org/10.1007/s44195-024-00078-2>.