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From Space to Society: Integrating Remote Sensing and GIS to Monitor Educational Infrastructure and Social Transformation

Omid Tarashtwal[1*], Abdul Wali Sirat[2], Zabihullah Nadry[3]
[1]University of Nebraska-Lincoln, USA
[2,3]Samangan University, Afghanistan

*Corresponding Author: otarashtwal2@huskers.unl.edu
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Abstract:

Monitoring educational infrastructure in conflict-affected countries such as Afghanistan remains critical for understanding social transformation and guiding evidence-based policy. Indeed, rather vital. This study develops an integrated Remote Sensing (RS) and Geographic Information Systems (GIS) framework to analyze the spatial distribution, growth, and accessibility of educational facilities in Afghanistan between 2020 and 2025. Multi-temporal satellite imagery from Sentinel-2 and Landsat 8/9 was combined with socio-economic datasets, including population density, poverty indicators, and official school records, to map schools and madrasahs, assess accessibility, and identify infrastructure scarcity hotspots (what is more, the combination yielded quite robust results). Accessibility analyses employing urban and rural buffer zones revealed significant disparities, with rural populations facing markedly limited physical access and correspondingly higher educational deprivation. Quite stark, in fact. Multi-criteria hotspot modelling further highlighted those regions where high population demand converges with poor facility quality and teacher shortages, thereby indicating critical service gaps. For that matter, these gaps persist rather stubbornly. Comparative analysis of infrastructure growth versus population expansion demonstrated, quite convincingly, that in many urban and rural areas new school construction has not fully matched demographic demand, thus revealing unmet educational needs. The study emphasises that spatially explicit, data-driven approaches are essential for equitable educational planning and for supporting social transformation in fragile contexts. The findings provide actionable insights for policymakers, international donors, and planners to prioritise interventions in underserved regions and promote inclusive educational development. Future research could usefully integrate real-time geospatial monitoring and participatory approaches to enhance educational planning and social development strategies further.

Key Words: *Remote Sensing, Geographic Information Systems, Educational Infrastructure, Accessibility Analysis*

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INTRODUCTION

Educational infrastructure plays a fundamental role in shaping social development, equity, and long-term human capital formation, particularly in fragile and data-constrained regions. Access to schools is strongly associated with literacy improvement, poverty reduction, and social stability, making educational accessibility a central concern within the Sustainable Development Goals (SDGs), especially SDG 4 on quality education and SDG 10 on reduced inequalities (Dogra Sahni & Chandra Jena, 2024; Manaf et al., 2025; Qu et al., 2024). However, many developing and conflict-affected countries continue to experience severe spatial disparities in educational service provision due to geographic isolation, rapid population growth, and limited monitoring capacity. Reports from international development agencies highlight that reliable spatial information on infrastructure distribution remains insufficient in many regions, preventing evidence-based educational planning and targeted policy intervention (Chipatiso, 2023; Hamza et al., 2023; Huerta et al., 2022). Conventional monitoring approaches relying on field surveys and administrative reporting are often constrained by accessibility, cost, and security limitations. In response, geospatial technologies such as Remote Sensing (RS) and Geographic Information Systems (GIS) have emerged as powerful tools for generating spatially explicit data that support large-scale development monitoring and planning. Satellite-based observations provide continuous, objective measurements of built environments and infrastructure changes, enabling policymakers to evaluate development progress even in areas where ground data collection is difficult or impossible.

Recent scholarly work increasingly emphasizes the role of geospatial technologies in monitoring development outcomes and supporting spatial decision-making. Studies on RS- and GIS-based SDG monitoring demonstrate that spatial analytics enables governments to track infrastructure expansion, assess accessibility, and identify underserved populations across multiple geographic scales (Gelan & Girma, 2022; Hwang & Jung, 2025; Oh & Cho, 2024). Similarly, geospatial big-data approaches have been shown to capture spatiotemporal changes in development indicators and reveal localized inequalities that are often hidden in aggregated statistical datasets (Han et al., 2022; Koh et al., 2022; Zhu et al., 2025). A growing body of research also highlights how satellite imagery combined with machine-learning techniques enables the assessment of infrastructure accessibility and social vulnerability in complex humanitarian environments, offering new opportunities for equitable resource allocation and planning (Agrawal & Petersen, 2021; Gupta & Li Wen, 2023; Prasetyo et al., 2022). Across these studies, three dominant themes emerge: first, the increasing reliance on Earth Observation data for monitoring development indicators; second, the integration of spatial analytics with socio-economic datasets to understand inequality; and third, the expansion of geospatial analysis beyond environmental applications toward social and infrastructure domains.

Despite these advances, significant research gaps remain. Previous studies primarily focus on environmental monitoring, urban expansion, or macro-level SDG assessment, while relatively limited attention has been given to educational infrastructure as a driver of social transformation. Furthermore, many geospatial studies rely exclusively on quantitative spatial analysis, overlooking the contextual socio-economic factors necessary to explain why spatial inequalities persist. The absence of integrated methodological approaches combining spatial analytics with interpretive analysis limits the ability of existing research to connect infrastructure distribution with broader social outcomes. In particular, conflict-affected or data-scarce contexts require methodological frameworks capable of bridging satellite-derived evidence with socio-developmental understanding. Therefore, a mixed-methods geospatial research design offers a critical methodological innovation by integrating quantitative spatial modeling with contextual analysis, allowing researchers to move beyond descriptive mapping toward explanatory insights into infrastructure inequality and social transformation.

In response to these gaps, this study aims to develop and apply an integrated mixed-methods geospatial framework to analyze the spatial distribution, accessibility, and growth dynamics of educational infrastructure and their implications for social transformation. Specifically, the study seeks to (1) map spatial and temporal changes in educational facilities using multi-temporal satellite imagery, (2) evaluate accessibility disparities between urban and rural populations through GIS-based proximity analysis, and (3) identify infrastructure scarcity hotspots by integrating spatial and socio-economic indicators. By combining remote sensing analysis with contextual socio-economic interpretation, this research extends existing geospatial scholarship from infrastructure detection toward understanding development inequality. The study contributes both methodologically, through the integration of quantitative and interpretive spatial analysis, and practically, by providing evidence-based insights for education planning and policy prioritization.

The central argument of this research is that educational inequality is fundamentally a socio-spatial phenomenon shaped by infrastructure availability, demographic pressure, geographic accessibility, and socio-economic conditions. A mixed-methods geospatial research design enables a more comprehensive understanding of these interconnected factors by linking spatial data with development context. Rather than treating geospatial technologies solely as technical mapping tools, this study positions RS and GIS as analytical instruments for examining social transformation processes. Through this approach, spatial patterns of infrastructure expansion are interpreted alongside accessibility dynamics and population demand, allowing deeper exploration of how educational infrastructure contributes to broader development outcomes. The following section outlines the methodological framework employed to operationalize this mixed-methods geospatial approach and ensure systematic, replicable spatial analysis.

RESEARCH METHODS

This study employs a mixed-methods geospatial research design integrating Remote Sensing (RS) and Geographic Information Systems (GIS) to monitor educational infrastructure development and its relationship with social transformation in Afghanistan during the period 2020–2025 (Molina-Azorin & Fetters, 2022; Neuman et al., 2021; Schoonenboom, 2024). The research adopts a spatial–analytical approach combining quantitative geospatial analysis with contextual socio-economic interpretation (Barman & Pradhan, 2025; Ehlert, 2021; Rezaei Soufi et al., 2022). Afghanistan was selected as the study area due to its complex terrain, uneven infrastructure distribution, and limited availability of reliable ground-based data, all of which are affected by prolonged conflict conditions. These characteristics make conventional field-based monitoring challenging, thereby justifying the use of satellite-based observation and spatial modeling as an appropriate methodological approach. The integration of RS and GIS enables large-scale, consistent, and data-driven analysis, allowing for the examination of infrastructure dynamics and accessibility patterns across both urban and rural regions.

Data collection was conducted using multiple complementary sources to ensure spatial and analytical reliability (Botchkaryov, 2022; Jia & Guo, 2022; Zhao et al., 2023). First, *multi-temporal satellite imagery* from Sentinel-2 and Landsat 8/9 for the years 2020 and 2025 was acquired to detect changes in built-up areas and educational facilities. Second, *socio-economic datasets*, including population density data from WorldPop and poverty indicators, were incorporated to contextualize infrastructure availability relative to demographic demand. Third, *ground-truth data* were obtained from official Ministry of Education (MoE) school location records and GPS coordinate points to validate spatial classifications derived from satellite imagery. The integration of these datasets allows triangulation between remotely sensed observations and administrative records, thereby improving analytical accuracy and reducing classification uncertainty.

Data analysis was conducted through a multi-stage geospatial workflow integrating remote sensing processing and GIS-based spatial modeling (Ahuja et al., 2023; Kadhum et al., 2025; Uckardesler & Yomralioglu, 2025). Satellite imagery preprocessing included atmospheric correction, cloud masking, and image compositing using Google Earth Engine (GEE). A Random Forest machine-learning classifier was applied to identify educational infrastructure and distinguish it from other land-cover classes. Change detection analysis was then performed to compare infrastructure distribution between 2020 and 2025. Subsequent GIS analysis involved Kernel Density Estimation (KDE) to identify infrastructure concentration patterns, service-area buffering (3 km for urban areas and 5 km for rural areas) to evaluate accessibility, and network-based proximity analysis to assess spatial service coverage. Comparative urban–rural analysis was finally conducted to examine disparities between infrastructure growth and population demand. The overall methodological workflow applied in this study is illustrated in **Figure 1**.

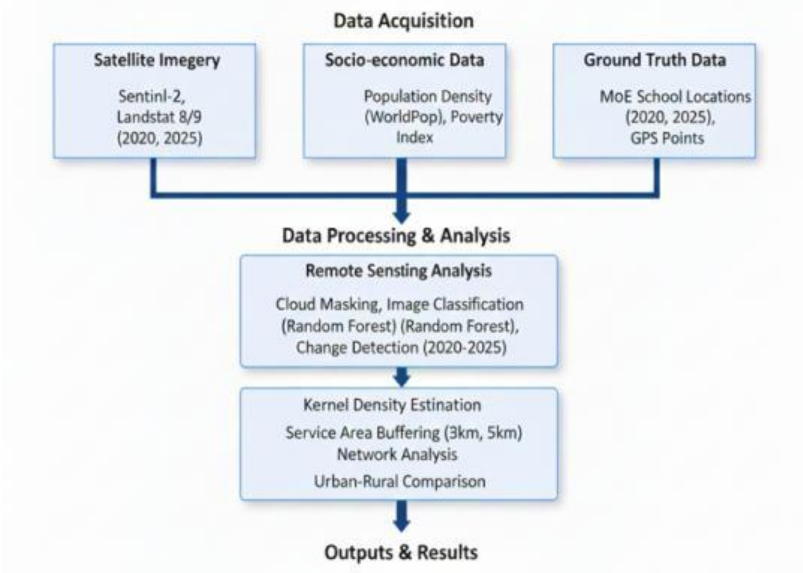

Figure 1. Integrated Remote Sensing and GIS Methodology Framework

RESULTS AND DISCUSSION

Results

The results of this study provide a spatially explicit evaluation of educational infrastructure dynamics in Afghanistan between 2020 and 2025. By integrating multi-temporal satellite imagery with socio-economic datasets, the analysis reveals significant changes in the spatial distribution and accessibility of schools and madrasahs. The application of Remote Sensing (RS) and Geographic Information Systems (GIS) helps address data limitations commonly encountered in conflict-affected environments, providing a quantitative basis for understanding processes of social transformation. The subsequent analyses examine infrastructure growth patterns, assess urban–rural disparities in educational accessibility through proximity modeling, and identify infrastructure scarcity hotspots where population demand exceeds existing educational capacity, the geographical context of which is presented in **Figure 2**.

Figure 2 illustrates the geographical and administrative context of the study area in Afghanistan, presenting provincial boundaries and highlighting key urban centers, including Kabul, Herat, Kandahar, and Mazar-i-Sharif, which function as major demographic and political hubs. The figure also identifies selected provinces, such as Balkh, Nangarhar, and Paktya, designated for detailed spatial analysis. This spatial representation provides an important foundation for understanding regional disparities in educational access and infrastructure development between 2020 and 2025, particularly between urban areas with relatively concentrated facilities and rural or remote regions where access remains limited. Building upon this spatial framework, temporal changes in educational infrastructure distribution between 2020 and 2025 are further illustrated in **Figure 3.**

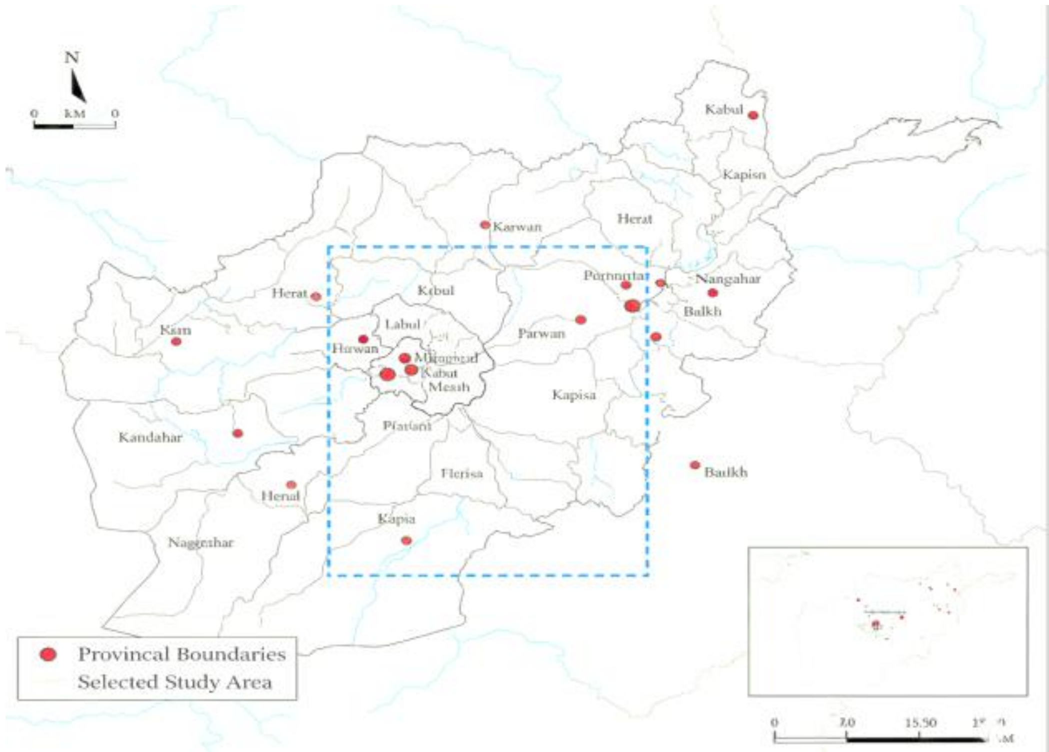

Figure 2. Map of Afghanistan Showing Provincial Boundaries and Selected Study Areas

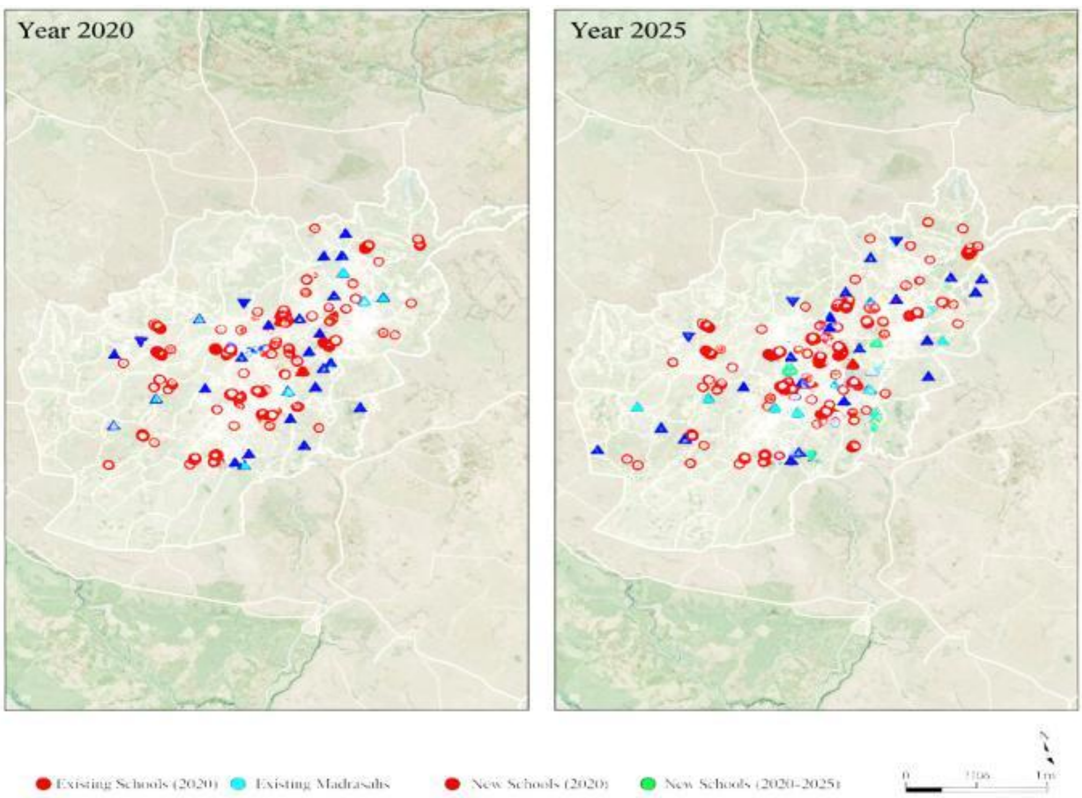

Figure 3. Spatial Distribution and Growth of Educational Infrastructure in Afghanistan (2020 vs. 2025)

Figure 3 presents a comparative spatial analysis of educational infrastructure in Afghanistan for the years 2020 and 2025. The maps depict the distribution of existing schools and madrasahs in 2020 alongside newly established educational facilities developed between 2020 and 2025. The applied symbology enables clear differentiation between facility types (schools and madrasahs) as well as their temporal status (existing versus newly constructed). The comparative visualization reveals distinct spatial patterns of infrastructure development, with growth concentrated in major urban centers such as Kabul, Herat, and Kandahar, while rural provinces exhibit more dispersed or limited expansion. This analysis supports the study's first objective by mapping temporal growth and spatial distribution of educational facilities. The resulting spatial outputs provide a basis for identifying areas of expansion, stability, and infrastructural stagnation, thereby forming a foundational layer for subsequent accessibility and hotspot analyses aimed at assessing disparities in educational service provision. Building on this spatial distribution analysis, accessibility to educational facilities is further examined through urban and rural service buffer modeling, as illustrated in **Figure 4**.

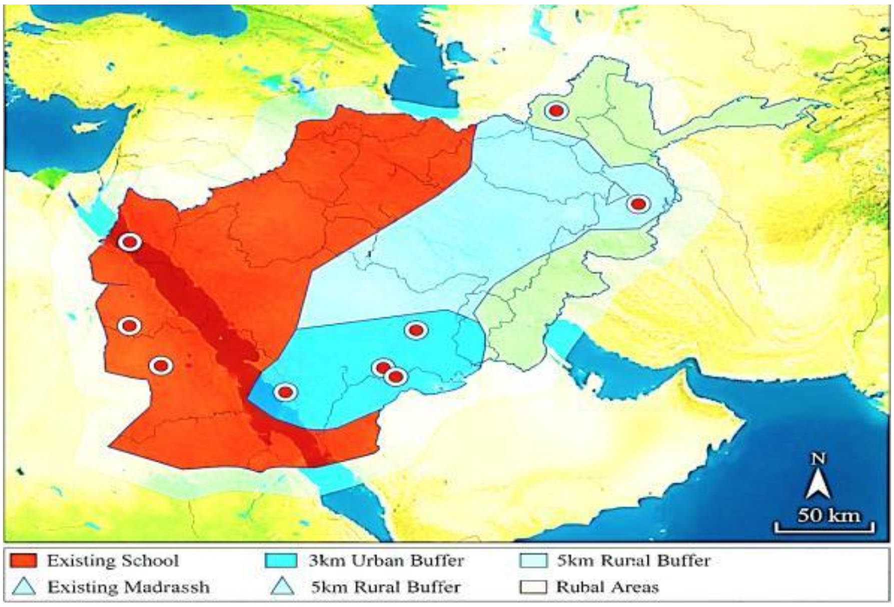

Figure 4. Accessibility Analysis of Educational Facilities

Figure 4 illustrates the methodology for assessing physical access to educational facilities across Afghanistan's diverse landscapes through a geospatial buffer analysis. It differentiates between urban and rural contexts by applying two distinct service area thresholds: a 3-kilometer buffer around facilities in urban centers and a more expansive 5-kilometer buffer for rural areas. This distinction is critical, as it acknowledges the practical realities of travel shorter, more feasible distances in densely populated cities versus longer, often more challenging journeys in remote regions. The map visually represents these buffer zones radiating from the locations of existing schools and madrassahs, providing a clear, spatial depiction of the areas theoretically serviced by current infrastructure.

The analysis derived from this figure is central to the study's second objective, which seeks to evaluate educational accessibility and identify spatial disparities. By overlaying service buffer zones with population density data, the analysis estimates the proportion of both urban and rural populations residing within a reasonable travel distance of educational facilities. Areas located beyond these buffers are identified as potential "accessibility deserts," indicating communities facing significant physical barriers to education. Furthermore, comparison between the 2020 and 2025 scenarios enables assessment of whether newly constructed infrastructure has effectively expanded service coverage or primarily reinforced existing accessibility patterns in already-served areas. Consequently, the buffer analysis transforms a simple spatial representation of facility locations into a diagnostic framework for detecting spatial inequality and informing targeted infrastructure planning aimed at reducing urban–rural disparities in educational access. Building upon this accessibility assessment, regions experiencing compounded educational disadvantages are further identified through a multi-criteria hotspot analysis, as presented in **Figure 5**.

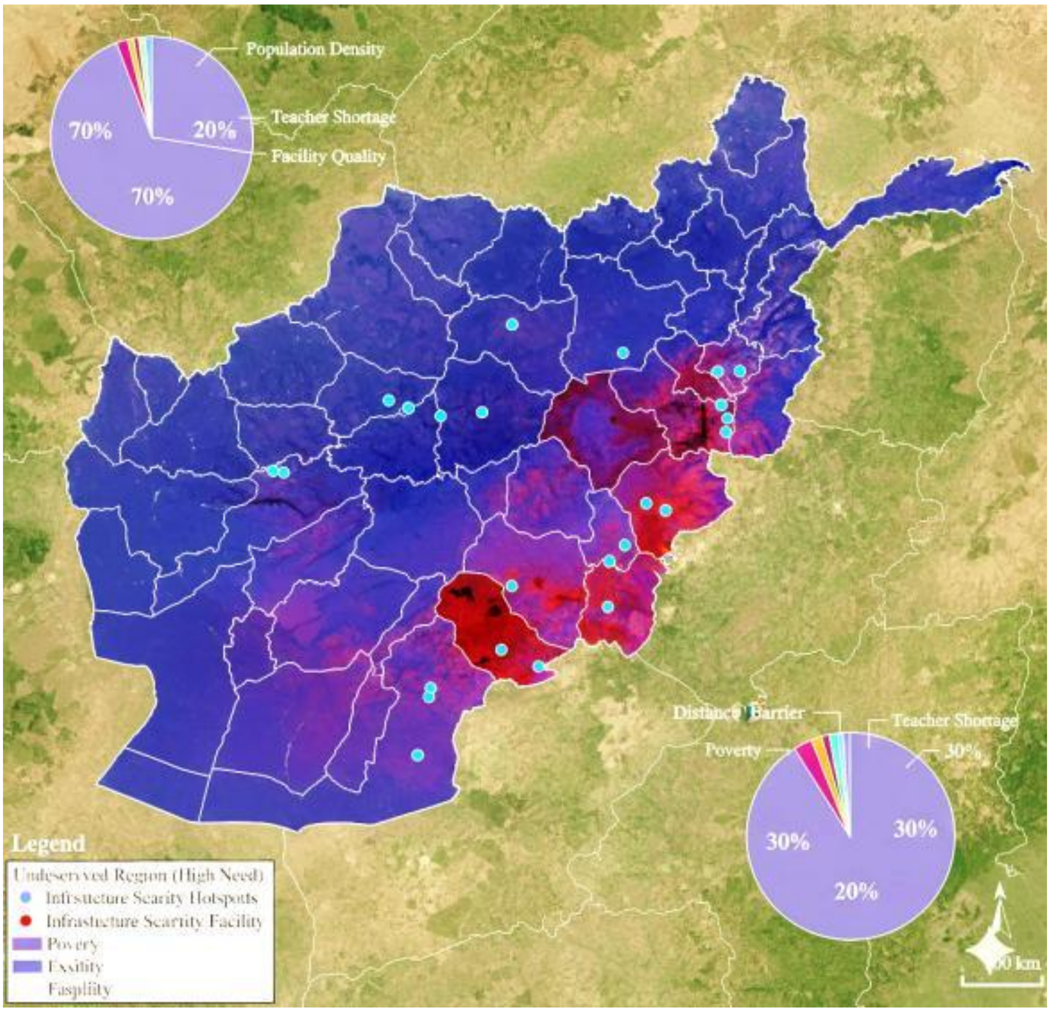

Figure 5. Multi-Criteria Hotspot Analysis for Identifying Underserved Educational Regions

Figure 5 presents the synthesis of a multi-criteria geospatial analysis used to identify underserved regions and infrastructure scarcity hotspots across Afghanistan. It moves beyond simple proximity by integrating multiple, overlapping thematic layers that collectively define educational need and service gaps. The diagram illustrates how factors such as high population density (demand), poverty (socio-economic barrier), poor facility quality, and teacher shortages are combined with the core metric of physical distance to existing schools. The pie chart visualizations highlight the weighted contribution of each criterion, such as poverty and teacher shortage each accounting for significant portions (e.g., 30%) of the composite index used to define a "high-need" area.

The output of this analytical process is a map identifying "Infrastructure Scarcity Hotspots" regions where a convergence of high demand and multiple supply-side deficiencies creates severe educational deprivation. These hotspots are critical for understanding the nuanced spatial patterns of educational inequality that simple buffer analysis cannot reveal. For instance, an area might fall within a 5km service buffer but still be classified as a hotspot due to extreme poverty, overcrowded classrooms, or a lack of qualified teachers. By quantitatively comparing infrastructure growth against this multi-dimensional measure of population demand and service quality over time, the study fulfills its objective of assessing unmet needs. This figure thus represents a key analytical outcome, transforming diverse datasets into a targeted, evidence-based map that can directly inform policy formulation and prioritize international support for the regions most in need of educational investment and social development interventions.

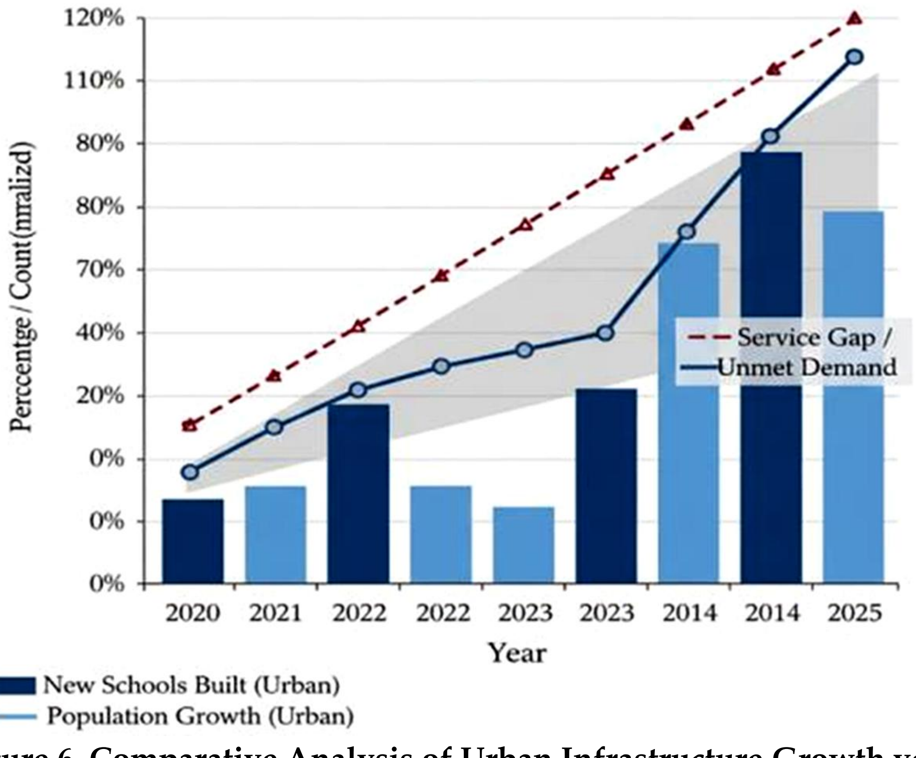

Figure 6. Comparative Analysis of Urban Infrastructure Growth versus Population Demand (2020–2025)

Figure 6 presents a comparative line-graph analysis of urban educational infrastructure development in relation to demographic change in Afghanistan between 2020 and 2025. The graph tracks two primary indicators over time: the number of newly constructed schools in urban areas and the corresponding rate of urban population growth. The divergence or convergence of these trend lines illustrates the relationship between educational service provision and population demand. The shaded area between the lines, labeled "Service Gap / Unmet Demand," represents the discrepancy between infrastructure expansion and demographic needs, reflecting pressures such as classroom overcrowding, increased student-to-teacher ratios, and reduced access to quality education.

This analysis is central to the study's objective of quantitatively comparing infrastructure growth with population demand in order to assess educational service gaps. When the population growth trend exceeds the rate of new school construction, it indicates an increasing deficit in educational service capacity, suggesting that infrastructure expansion is insufficient to meet rising demand. Conversely, periods in which school construction outpaces population growth may reflect a phase of capacity recovery or targeted investment strategies. Extending this comparative framework to rural contexts further highlights disparities in resource allocation and planning efficiency between urban and rural regions. This temporal, data-driven perspective moves beyond static spatial mapping by demonstrating how the relationship between infrastructure development and demographic change evolves over time, providing critical evidence for forecasting future needs, evaluating past policy effectiveness, and supporting proactive, demand-responsive planning within Afghanistan's education sector. **Table 1** presents a provincial-level overview of school distribution, infrastructure growth rates, and population coverage between 2020 and 2025.

Table 1. Provincial Distribution of Schools, Growth Rate, and Population Coverage in Afghanistan (2020–2025)

Province	Schools (2020)	Schools (2025)	Growth (%)	Population Coverage (%)
Kabul	1,200		+20.8%	85%
Herat	950	1,080	+13.7%	72%
Kandahar	800	890	+11.2%	60%
Rural	---	---	+5.4%	42%

Table 1 presents a comparative overview of educational infrastructure growth and population coverage across selected provinces in Afghanistan between 2020 and 2025, highlighting significant spatial disparities between urban centers and rural areas. The data indicate that Kabul experienced the most substantial expansion in educational facilities, with the number of schools increasing from 1,200 in 2020 to 1,450 in 2025, representing a growth rate of 20.8%. This expansion corresponds with a relatively high population coverage of 85%, reflecting Kabul's status as the country's primary urban and administrative hub, where infrastructure investments are more concentrated and accessible.

Herat also demonstrates notable progress, with schools increasing from 950 to 1,080 over the same period, yielding a growth rate of 13.7% and population coverage of 72%. Although this reflects steady development, the lower coverage compared to Kabul suggests emerging pressures from population growth and urban expansion. Kandahar shows more modest growth, with an increase from 800 to 890 schools (+11.2%) and population coverage limited to 60%. This indicates persistent challenges related to accessibility, security constraints, and uneven spatial distribution of facilities.

In contrast, the rural average reveals a critical development gap. With an average growth rate of only 5.4% and population coverage of just 42%, rural areas remain significantly underserved. The absence of detailed school counts further reflects limitations in data availability and monitoring capacity in remote regions. Overall, **Table 2** underscores the imbalance between urban and rural educational development and highlights the urgent need for targeted, GIS-informed planning strategies to improve equitable access to education across Afghanistan.

Table 2. Multi-Criteria Hotspot Analysis for Underserved Regions

Province/Area	High Population Density	Poverty Level	Poor Facility Quality	Teacher Shortages	Hotspot Priority
Kabul	Medium	Low	Medium	Low	Low
Herat	Medium	Medium	Medium	Medium	Medium
Kandahar	High	High	Medium	High	High
Rural Areas	High	High	High	High	Very High

Table 2 presents a comparative analysis of educational infrastructure growth relative to population changes across Afghanistan between 2020 and 2025. Kabul demonstrates the highest school growth at 20.8%, slightly outpacing its population growth of 18%, resulting in a positive service gap of 2.8%, indicating that infrastructure expansion has somewhat kept pace with demand. Herat and Kandahar, however, exhibit lower school growth rates of 13.7% and 11.2%, respectively, compared with higher population growth, leading to negative service gaps of -2.3% and -3.8%. This suggests that infrastructure development in these provinces has lagged behind demographic pressures, potentially causing overcrowding and limited access to quality education. Rural areas face the most significant disparity, with only 5.4% school growth versus 12% population growth, producing a service gap of -6.6%, highlighting severe under-provision of educational facilities. At the national level, Afghanistan's average service gap is -2.2%, emphasizing the persistent need for targeted, demand-responsive educational planning to reduce inequities.

Discussion

The integration of Remote Sensing (RS) and Geographic Information Systems (GIS) in this study has provided a spatially explicit understanding of educational infrastructure development and its link to social transformation in Afghanistan between 2020 and 2025. The results reveal notable spatial disparities, with urban centers such as Kabul, Herat, and Kandahar experiencing more substantial infrastructure growth compared to rural provinces. Kabul, for instance, saw a 20.8% increase in schools, covering 85% of the population, whereas rural regions exhibited an average growth of only 5.4% with 42% population coverage. This urban–rural divide highlights persistent inequalities in educational access and underscores the challenges of delivering equitable services in fragile and conflict-affected settings (Bergman, 2025; Ferrario et al., 2025; Pattanshetty et al., 2023).

Accessibility analyses indicate that urban populations are relatively well served, with the majority within 3 km of educational facilities. In contrast, rural populations often reside beyond the 5 km buffer, creating "accessibility deserts" that exacerbate educational exclusion. These findings align with prior research emphasizing the importance of spatial proximity for effective service delivery and the socio-political implications of uneven infrastructure distribution (Ding & Wu, 2025; Fajgelbaum et al., 2023; Patience & Nel, 2021). By overlaying population density, poverty, and teacher availability data, the multi-criteria hotspot analysis further illustrates that physical access alone does not ensure educational equity. Regions with adequate school density may still experience high levels of deprivation due to overcrowding, under-resourced facilities, or insufficient numbers of qualified teachers, underscoring the multidimensional nature of educational inequality.

The comparative analysis of infrastructure growth versus population demand highlights significant service gaps, particularly in fast-growing urban areas where population increases outpace school construction. Such imbalances suggest that despite investments in infrastructure, the Afghan education system remains under pressure, potentially limiting quality education outcomes and social transformation (Atif, 2024; Frugh & Naseri, 2025; Thomas et al., 2021). These findings reinforce the need for data-driven, spatially informed planning approaches that prioritize both underserved rural areas and urban regions facing demographic pressure. Methodologically, the use of RS and GIS has proven essential in conflict-affected contexts, enabling continuous monitoring where ground surveys are limited or unsafe (Baytiyeh, 2021; Hammoudeh et al., 2021; Huang, 2022). The combination of satellite imagery, machine learning classification, and geospatial modeling provides a replicable framework for assessing not only educational infrastructure but also broader social and developmental indicators. Moreover, integrating qualitative dimensions, such as policy and governance considerations, with geospatial data enhances the relevance of findings for evidence-based decision-making (Alajmi & Worthington, 2021; Sarjito, 2024; Van Rooy, 2024).

This study contributes to the growing body of research linking geospatial technologies with social development by demonstrating how the integration of Remote Sensing and GIS can move beyond descriptive spatial mapping toward explanatory analysis of educational inequality in fragile contexts. The findings provide a conceptual and empirical bridge between infrastructure monitoring and social transformation by showing that educational access is shaped not only by physical infrastructure expansion but also by spatial accessibility, demographic dynamics, and socio-economic conditions. Methodologically, the study advances the application of multi-source geospatial data and multi-criteria analysis as a scalable framework for monitoring public service provision in data-constrained and conflict-affected environments. Substantively, the research highlights the persistent urban–rural imbalance as a central thread connecting infrastructure distribution, accessibility disparities, and service gaps, thereby emphasizing that equitable educational development requires integrated, demand-responsive planning rather than isolated infrastructure investment. In this way, the study positions spatially explicit evidence as a critical foundation for policy formulation aimed at fostering inclusive education systems and supporting broader processes of social transformation in Afghanistan and comparable fragile settings.

CONCLUSION

This study demonstrates the critical role of integrating Remote Sensing (RS) and Geographic Information Systems (GIS) in monitoring educational infrastructure and examining its relationship with social transformation in Afghanistan between 2020 and 2025. The findings reveal substantial spatial disparities in school distribution and accessibility, with urban centers such as Kabul, Herat, and Kandahar experiencing faster infrastructure growth and higher population coverage, while rural regions remain significantly underserved. Accessibility and hotspot analyses further indicate that physical proximity to educational facilities alone does not guarantee equitable access, as socio-economic constraints, facility quality, and teacher shortages continue to intensify inequalities, particularly in rural and remote areas. The comparative assessment of infrastructure expansion relative to population growth also highlights persistent service gaps, suggesting that educational development has not consistently kept pace with demographic change, thereby limiting broader social development outcomes in conflict-affected and resource-constrained contexts.

The study provides a spatially explicit and data-driven framework that integrates demographic, socio-economic, and infrastructural dimensions to support evidence-based educational planning and policy formulation. The results emphasize that achieving equitable educational access requires not only infrastructure expansion but also consideration of socio-spatial dynamics and population needs.

By demonstrating the practical value of RS and GIS for addressing data limitations and guiding strategic decision-making, this research contributes to more inclusive, demand-responsive development planning in fragile settings. Future research should incorporate real-time geospatial monitoring, policy evaluation, and participatory community-based approaches to further strengthen the role of education as a driver of social transformation and to support progress toward the Sustainable Development Goals in Afghanistan and comparable contexts.

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