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ENHANCING FORCED DISPLACEMENT SIMULATIONS: INTEGRATING HEALTH FACILITIES FOR AUTOMATICALLY GENERATED ROUTES NETWORKS

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ABSTRACT

This paper introduces a novel approach to supporting healthcare accessibility for refugees during their movement to camps in regions with limited infrastructure. We achieve this by integrating the density of healthcare facilities into route networks created by customized pruning algorithms. Through rigorous data analysis and algorithm development, our research aims to optimize healthcare delivery routes and enhance healthcare outcomes for displaced populations. Our findings highlight Visit Tracking route pruning as the most effective method, with an Averaged Relative Difference (ARD) of 0.3837. Particularly in scenarios involving healthcare facility integration, this method outperforms others, including the manual extracted route network (0.4902), Direct Distance pruning (0.3912), Triangle pruning (0.3913), and Sequential Distance pruning (0.7846). Despite the inherent limitations of our proposed method, such as data availability and computational complexity, these quantifiable results underscore its potential contributions to healthcare planning, policy development, and humanitarian assistance efforts worldwide.

1 INTRODUCTION

The movement of populations, particularly refugees fleeing conflict or violence, imposes significant strains on Healthcare Facilities (HFs) (Daynes 2016). As individuals embark on journeys to refugee camps, they encounter hazardous conditions that expose them to various health risks, emphasizing the critical need for accessible and reliable HFs along migration routes (UNHCR. 2018). In regions afflicted by conflict and lacking adequate infrastructure, such as South Sudan, these challenges are exacerbated, leading to severe impacts on refugees' health outcomes (Alarcon 2022; Vesco et al. 2024; OECD. 2021). The availability and accessibility of Hfs are crucial in addressing the health risks and meeting the healthcare demands of displaced populations during their quest for safety (Abbas et al. 2018; WHO. 2019).

The inadequacy of healthcare access during transit emphasizes the pressing need for innovative solutions that incorporate the distribution of HFs into route networks. Such solutions aim to ensure timely access to HFs for refugees along their journey, including upon reaching their final destinations in refugee camps. Therefore, this paper's primary contribution lies in proposing a novel approach that integrates HF density into route weighting calculations during forced displacement simulations. This approach seeks to enhance the accuracy of simulations and raise awareness among decision-makers about the importance of improving healthcare accessibility for refugees during their movement to camps. Another significant contribution of this paper involves leveraging and optimizing advanced route pruning algorithms to establish route networks through which agents navigate towards their final destinations. These efforts collectively address the unique challenges faced by displaced populations and strengthen humanitarian initiatives to deliver essential healthcare services during crises.

The remainder of this paper is structured as follows: section 2 offers an overview of related work concerning location graph construction and route pruning algorithms, highlighting existing methods and their limitations. In section 3, we detail the methodology for integrating healthcare facility density into a forced displacement simulation toolkit and elaborate on the development of customized route pruning algorithms specifically tailored for the South Sudan case study. Section 4 presents the findings from our empirical analysis. It demonstrates how route pruning algorithms effectively enhance healthcare accessibility and reduce the Averaged Relative Difference (ARD) in simulation results when compared to the manually extracted route network, which serves as the ground truth. Finally, section 5 concludes by discussing the implications of our findings and proposing potential avenues for future research in this domain.

2 BACKGROUND

Numerous studies highlight the importance of HFs along migration routes and within refugee camps, concluding that access to healthcare services significantly impacts health outcomes and the resilience of refugee populations (Abbas et al. 2018; Gunst et al. 2019; Lebano et al. 2020; Jackulikova et al. 2022). These findings underscore the critical importance of facility availability, trained personnel, and adequate medical supplies in determining health outcomes (Mears and Chowdhury 1994). Despite advancements and research in this field, challenges persist due to resource constraints, inadequate infrastructure, and political instability. Addressing these issues requires collaboration among governments, humanitarian organizations, and local communities, alongside ongoing empirical research aimed at improving data sources and comprehending migration journeys, focusing on enhancing access to healthcare services.

The simulation of population movements, particularly refugees fleeing conflict or natural disasters, presents complex challenges in ensuring accurate location graphs and route network maps (Warnier et al. 2020). Despite the widespread usage of Geographic Information Systems (GIS) and web mapping tools to visualize, analyze, and model geospatial data, which involves creating location graphs through coordinate importation and route determination (Werner et al. 2000; Wang et al. 2015), they encounter limitations. Specifically, they struggle to automatically generate entire route networks, particularly in regions with sparse geospatial data (Boeing 2017; Kopf et al. 2010; Davies et al. 2006). In the past, location graphs were manually generated as demonstrated by Suleimenova et al. (2017), where the link distances (in kilometers) were estimated using the OpenStreetMap (OSM) route planner for cars, with occasional manual adjustments made to accommodate shorter paths. While regarded as the ground truth and a benchmark for comparison with other algorithms in this paper, this manual approach proved time-consuming. To meet the growing demand for geospatial data mapping, web mapping services like Google Maps, Bing Maps, and OSM have emerged, offering a range of functionalities for inspecting, visualizing, analyzing, and modeling geospatial information (Schweimer et al. 2021). Fu et al. (2023) conducted a comparative study on drive time estimation methods using geospatial data in the USA, assessing six approaches including Google Maps API, Bing Maps API, Esri Routing Web Service, ArcGIS Pro Desktop, OpenStreetMap NetworkX (OSMnx), and Open Source Routing Machine (OSRM). Their findings suggested that OSRM outperforms other methods for longer distances.

In the related work (Schweimer et al. 2021), an automated method for generating location graphs from provided lists of locations is introduced. This method involves a two-step process: first, utilizing OSRM from OSM to compute route distances between all pairs of locations, resulting in a fully connected location graph; second, applying the triangle inequality concept to remove edges representing indirect routes, such as those passing through a third location, from the fully connected graph. Additionally, an extensive review of state-of-the-art route planning algorithms, covering various types including static, dynamic, time-dependent, stochastic, parametric, alternative, and weighted region shortest-path algorithms has been conducted. While detailed discussions on their strengths and limitations were provided, delving into the intricate technical aspects of these algorithms was refrained from, as they fell beyond the scope of this study.

The objective of this paper is to devise customized automated pruning algorithms, including Direct Distance pruning, Visit Tracking route pruning, and Sequential Distance pruning, aimed at extracting route networks and assessing the density of Healthcare Facilities (HFs) within these networks. Acknowledging the critical significance of HFs for refugees, the necessity of integrating them into location graphs by modifying the weighting function for refugee journeys is stressed. Subsequently, the location graphs generated by these algorithms are compared with those derived from Manual extraction and Triangle pruning methods. These initiatives are intended to enhance simulations of forcibly displaced populations.

3 METHOD: INTEGRATING HEALTHCARE FACILITIES WITH ROUTE NETWORKS

To fulfill the research objectives of this paper and examine them within the context of South Sudan as a case study, spatial data on healthcare facility locations and the necessary input data for migration simulation, encompassing locations, conflict events, and relevant populations pertaining to South Sudan, were gathered. Subsequently, OSRM was leveraged to enhance the routing capabilities for refugees moving in conflict-affected areas, focusing on South Sudan and its neighboring countries. The location data were pre-processed to ensure optimization for routing. To provide a tailored and efficient routing experience, Protocolbuffer Binary Format (PBF) data files for the region were downloaded, merged, and processed. Since all OSRM map files are in PBF format, this setup allowed for OSRM to be configured locally, eliminating the reliance on external servers, thus reducing latency and increasing processing speed. Several custom pruning algorithms were developed to automate and optimize the routing process, ensuring that the routes generated are not only efficient but also consider safety and accessibility for the refugees.

Simultaneously, the Overpass API was integrated into the system to enhance the mapping of facilities along the refugee routes. By setting up the Overpass API locally, limitations related to data rate constraints and query frequency were removed, allowing for more frequent and detailed inquiries. This setup was crucial for identifying critical healthcare facilities along the routes. Custom-designed queries were developed to pull relevant facilities data from the locally hosted Overpass database, ensuring that every point of interest could be dynamically updated and accurately represented. This integration not only supports logistical planning but also provides essential information that can be crucial for the safety and well-being of the refugees as they travel through these challenging environments. All the route files as well as the maps are available at https://github.com/mzrghorbani/osrm-tutorial.

Finally, to investigate the integration of healthcare facilities (HFs) with the Flee simulation toolkit, various route networks derived from these algorithms are explored, and the proximity of HFs to each route is determined.

3.1 A Case Study: South Sudan

According to UNHCR. (2023), the South Sudan refugee crisis, Africa's largest and the world's third-largest, stems from the country's descent into conflict since its establishment in 2011. South Sudan gained independence that year, officially separating from Sudan after decades of armed conflict. However, the high hopes for South Sudan's future were soon dashed when fighting broke out in December 2013, leading to widespread violence, economic decline, and food insecurity. This turmoil has prompted nearly 2.32 million South Sudanese to seek refuge in neighboring countries, while 2.22 million remain displaced internally. Over 83% of those fleeing are women and children, with children comprising 65% of the refugee population, often survivors of violence, sexual assault, and family separation. The majority of refugees reside in countries like Sudan, Uganda, Ethiopia, Kenya, and the Democratic Republic of the Congo, with Kenya's Kakuma refugee camp hosting over 148,000 South Sudanese. The humanitarian crisis and continued fighting across the country have exacerbated the situation, leading to large-scale forced displacement. This case study delves into the situation in South Sudan, emphasizing its significance as a major contributor to the ongoing refugee crisis. Within this context, 25 conflict locations were pinpointed using data from the ACLED dataset, and 10 refugee camps were identified through information sourced from the UNHCR data portal Portal. (2024), which provides comprehensive and up-to-date information on global refugee situations and offers access to a wide range of datasets, statistical reports, and interactive visualizations to support humanitarian efforts and policy-making. Finally, all locations were compiled into a CSV file, serving as a primary input for the Flee simulation toolkit.

3.2 Integration of Healthcare Facility Density

Flee, as introduced by Suleimenova et al. (2017), is an agent-based toolkit designed for simulating forced displacement scenarios. It operates by modeling autonomous decision-making agents interacting within their environment based on predefined rules. Within Flee, agents navigate a weighted graph $\mathscr{G} = (V, E, W)$, where V represents geographical locations (e.g., cities, settlements, conflict regions, humanitarian camps), and edges $(\ell, k) \in E$ are associated with weights $w_{\ell,k} \in W$ denoting the distance between locations ℓ and k. Each agent, representing a forcibly displaced person, assesses at each time step whether to remain or move to a neighboring location towards safety zones (e.g., camps), with the decision influenced by the probability $\rho(\ell,t)$ of leaving location ℓ at iteration t. The attractiveness score $\phi(\ell,t)$ further guides the probability of moving to ℓ, with adjustments made by a scaling factor $\kappa(\ell, y_\ell)$ dependent on the population y_ℓ of the vertex. Path selection is facilitated by a weighted probability function, where the weight of each link is determined by the attractiveness value of the destination divided by the length of the link in kilometers (Suleimenova et al. 2021).

In this study, Flee's framework is extended by incorporating the density of HFs alongside each edge $e_{\ell,k}$ into the calculation of edge weights $w_{\ell,k}$. To achieve this, a radius around each edge is first defined, designating the distance within which HFs are considered "close" to the edge. Subsequently, the number of HFs within this radius for each edge is counted and integrated into the weight function as follows:

$$\text{Weight} = \frac{\text{WS} + S_{i,lk,t}^{\rho_{lk}}}{(\text{DS} + d_{lk} + d_{jk}^{\text{DP}}) \times \text{cap}_k}.$$

Here, WS denotes Weight Softening, a constant added to all weights to enhance randomness in route selection. DS represents Distance Softening, which eliminates the unnecessary distinction between very short routes by adding a constant value to every link distance. Distance Power (DP) is a factor that modulates the importance of distance in weight calculations, with the default being linear. S signifies the score for the endpoint of edge $e_{\ell,k}$, used to determine the probability of an agent moving to a given location. ρ represents the calculated density of $e_{\ell,k}$, while cap_k serves to verify whether a given location has reached or is nearing full capacity.

To compute ρ, the density of HFs, datasets from the South Sudan Ministry of Health and World Bank Health Facility Mapping 2009 (Humanitarian Data Exchange. 2018) were used. Subsequently, the density of HFs for various route networks derived from different pruning algorithms was determined. This involved employing geodesic distance calculations through the geopy library in Python.

3.3 Route Pruning Algorithms

Several route pruning algorithms have been used to see the effect of healthcare facilities integration in different route networks. As depicted in Figure 1, which shows the location graphs for South Sudan as a case study, different algorithms produce varying graphs that consequently affect the simulation results. Here is a brief description of each pruning algorithm.

3.3.1 Direct Distance Pruning

The Direct Distance pruning algorithm is designed to manage and optimize routing between various geographic locations by ensuring that unique and meaningful routes are processed and visualized. It achieves this by maintaining a set of processed location pairs, which prevents redundancy and unnecessary recalculations. For each unique pair, the algorithm requests route data from an OSRM service and calculates the total route distance. This approach not only helps in visualizing the geographic distribution of routes but also aids in strategic planning by providing a clear overview of the shortest and most direct routes between points. The resulting 1226 routes and their respective distances are stored in both visual and numerical formats, enabling comprehensive analysis and optimization. This approach proves particularly beneficial in applications necessitating efficient route planning and network optimization, such as logistics, urban planning, and emergency response scenarios.

3.3.2 Visit Tracking Route Pruning

The Visit Tracking route pruning algorithm optimizes the processing of routing information between geographical points by ensuring that routes are calculated only once for each unique pair of locations. This is achieved by maintaining a set of processed pairs, preventing redundant route calculations. The algorithm fetches and visualizes routes using OSRM, calculating total route distances and visualizing these on a map. Each route is only processed once, even if requested multiple times in different contexts, due to the use of a set to store and check already processed pairs. Although not a conventional clustering method that groups data points based on proximity or similarity, the term "clustering-based" is applied to this algorithm due to its efficacy in handling large datasets. This method generated 1226 routes, the same as the Direct Distance method. This approach proves particularly effective in mitigating computational burden and network requests when dealing with extensive location and route data, which holds paramount importance in applications such as logistics planning, disaster response, and transportation management.

3.3.3 Sequential Distance Pruning

The Sequential Distance pruning algorithm predominantly performs a route optimization task by linking each location to its subsequent neighbor to form a continuous loop. This routing strategy utilizes the OSRM API to compute and visualize routes between consecutive locations, effectively generating a circular path that initiates and concludes at the same location. The method involves storing and mapping each computed route, resulting in a total of only 51 routes, which are then displayed interactively on a map. While it iteratively establishes connections between locations and records distances, it does not adhere to traditional clustering principles based on proximity or other similarities. Instead, it systematically links each point to the next, aligning more closely with path optimization in a predetermined order rather than clustering. This approach proves particularly advantageous in scenarios where a sequential visit to each location is planned, such as in logistics routes or daily delivery schedules where the starting and ending points remain constant.

3.3.4 Triangle Pruning

The Triangle pruning algorithm applies a selective process to prune routes between locations based on a simple yet effective distance threshold mechanism. This method evaluates each pair of locations and retains only those connections that fall within a specified distance limit, effectively reducing the number of routes and focusing on the most relevant or shortest paths. This pruning is performed by initially calculating the geodesic distances between all pairs, sorting these distances, and then applying a cutoff based on the threshold or the specified number of nearest neighbors. The resulting pruned routes, which were 151 routes, are then visualized on a map, showing only the most pertinent routes that meet the criteria. This approach is particularly useful in scenarios where reducing computational complexity or focusing on significant routes is necessary, such as in logistics, routing optimization, or simplifying network analysis in GIS.

3.4 Model Validation and Evaluation

The proposed approaches will undergo validation and evaluation using real-world data on refugee movements and healthcare accessibility in South Sudan. The ARD, developed by the Flee team as detailed by Suleimenova et al. (2017), will be used to assess the accuracy of the simulations. This metric computes the mean score, representing the ARD between the simulated camp arrival numbers and validation data provided by UNHCR. Notably, the ARD avoids squaring arrival differences, aligning with the humanitarian principle that every human life should carry equal importance. The ARD is calculated according to the following formula:

$$\text{Averaged Relative Difference} = \frac{\sum_{x \varepsilon S}(|n_{sim,x,t} - n_{data,x,t}|)}{N_{data,all}}.$$

4 RESULTS AND DISCUSSION

The study examined how integrating Healthcare Facilities (HFs) affects the performance of four distinct route pruning algorithms, Direct Distance pruning, Visit Tracking route pruning, Sequential Distance pruning, and Triangle pruning, compared to the manually extracted route network within a simulation framework. Each algorithm underwent two evaluations: one with HF integration and one without. To validate and assess the real-world impact on refugee movements and healthcare accessibility in South Sudan, the primary metric used was the ARD.

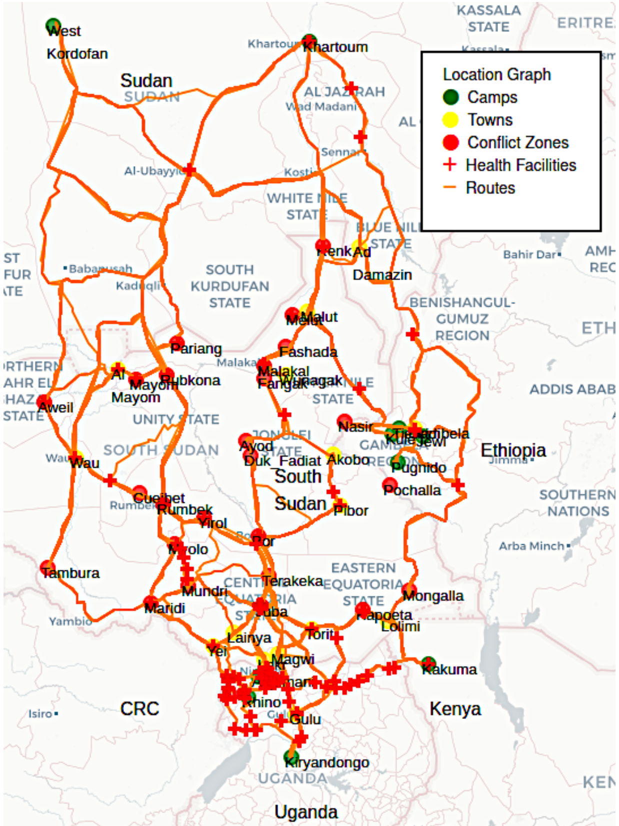
Table 1 provides the details of the achieved ARDs from the mentioned instances. Among the assessed algorithms, Visit Tracking route pruning demonstrated superior effectiveness, particularly in scenarios integrating HFs. With an ARD of 0.3837, this algorithm surpassed its counterparts: the manual extracted route network (ARD: 0.4902), Direct Distance pruning (ARD: 0.3912), Triangle pruning (ARD: 0.3913), and Sequential Distance pruning (ARD: 0.7846). These results suggest that Visit Tracking route pruning efficiently optimized routes, potentially enhancing accessibility to healthcare services within the simulated environment. Notably, the only exception observed was in the case of Sequential Distance pruning, where the ARD without HF integration was lower than that with HF integration.

Table 1: Averaged relative difference results.

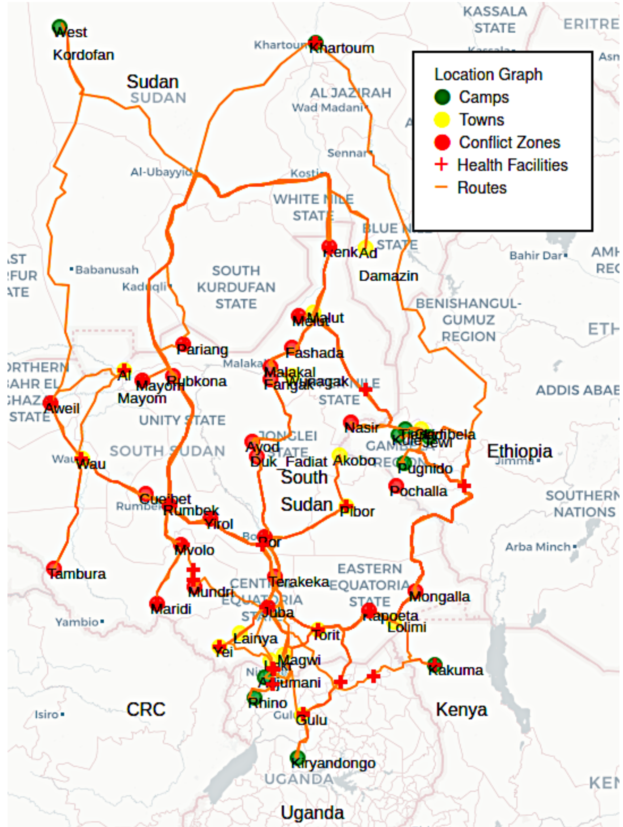
Algorithms	**Averaged Relative Difference**	
	Without HF	*With HF*
Manual Extracted Route Network	0.5101	0.4902
Direct Distance Pruning	0.4021	0.3912
Visit Tracking Route Pruning	0.4015	0.3837
Sequential Distance Pruning	0.7546	0.7846
Triangle Pruning	0.4023	0.3913

However, it is essential to interpret these findings cautiously. While lower ARD values indicate lower simulation errors, they do not inherently imply superior forecasting capabilities. Other factors, such as moving vehicles, geographical constraints, and demographic dynamics, may influence the actual efficacy of the routing algorithms beyond the simulated environment. Therefore, as ARD alone may not comprehensively indicate the quality of route pruning algorithms, the analysis was extended to include a visual comparison of the location graphs generated by these algorithms with the manually extracted route network. This comparison, depicted in Figure 1, provides a more holistic understanding of the efficacy of the pruning algorithms. Notably, it was observed that the route networks generated from the pruning algorithms not only exhibit a greater diversity of routes but also encompass a broader array of HFs compared to the manually extracted route network. This expanded scope suggests that the pruning algorithms not only optimize routes more effectively but also offer increased access to vital healthcare services within the simulated environment.

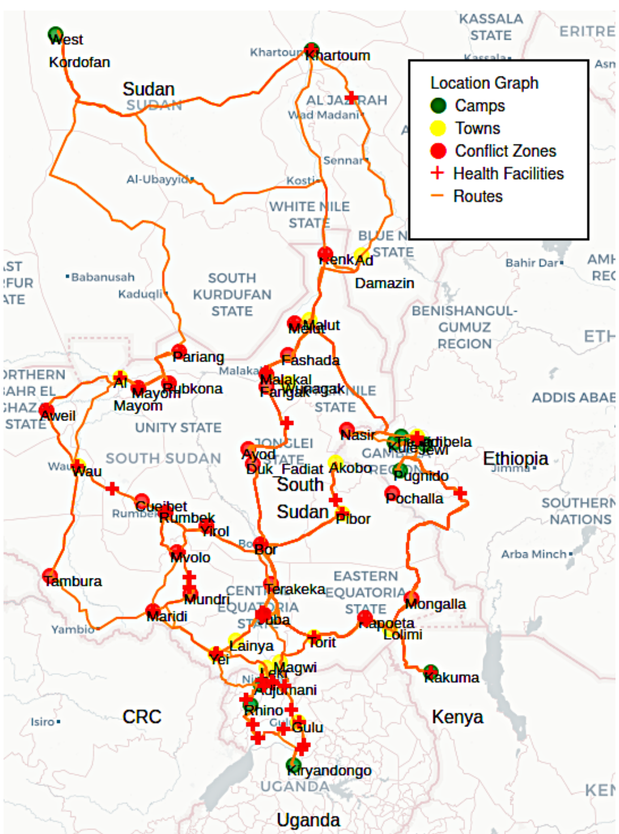
The results revealed a notable influence of HF integration on the performance of the route pruning algorithms. In general, simulations incorporating HF integration exhibited lower ARD values compared to those without such integration. This suggests that the presence of HFs influenced routing decisions, leading to more efficient routes being identified. In Figure 2, a comparison of the simulation ARD obtained from various simulation instances of route networks generated by different pruning algorithms described in Section 3.1, incorporating HFs, with the ground truth, which comprises the manually extracted route network, is illustrated. As depicted in this figure, the Visit Tracking pruning algorithm yielded a lower ARD compared to other methods. Furthermore, concerning the manually extracted route network, the instance integrated with HFs exhibited a lower ARD than the one without such integration.



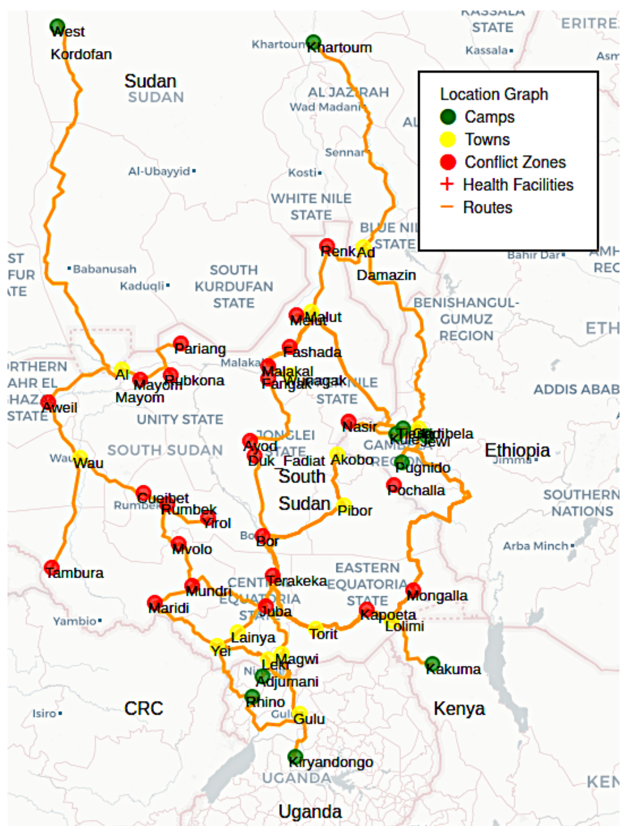
(a) Direct Distance Pruning



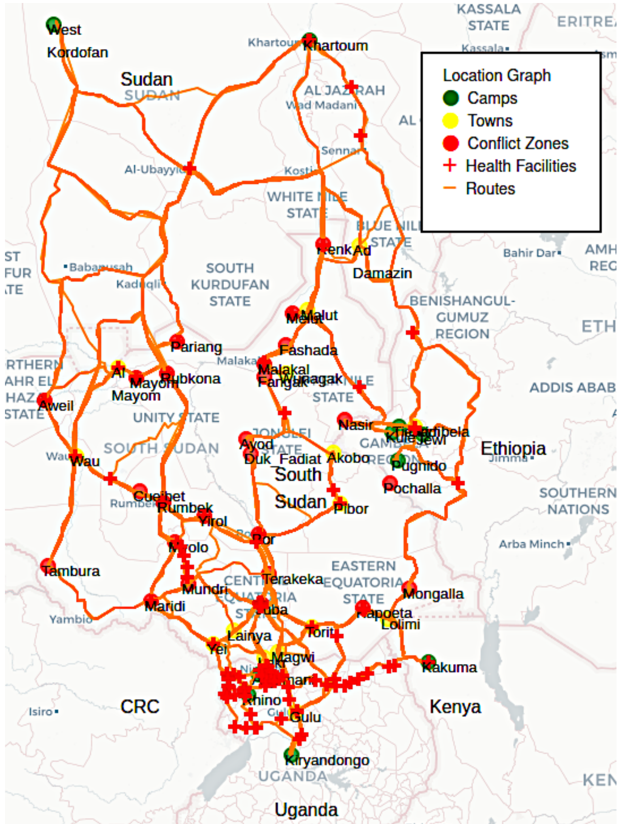
(b) Sequential Distance Pruning



(c) Triangle Pruning



(d) Manual Extracted - Without HFs



(e) Visit Tracking Route Pruning

Figure 1: South Sudan location graphs based on the proposed route pruning algorithms.

5 CONCLUSION

In conclusion, our study presents key findings regarding the role of route pruning algorithms in simulating forced displacement and integrating HFs. Notably, Visit Tracking route pruning emerges as a promising approach, although further validation across diverse settings is warranted. Moreover, by automating route extraction, these algorithms mitigate the need for manual intervention, saving substantial time and effort, particularly in scenarios involving large datasets. Furthermore, their automated nature ensures consistency and accuracy in route generation, enhancing efficiency across various applications, including forced displacement simulations.

In summary, our proposed method introduces an innovative approach to supporting healthcare accessibility for refugees during migration to camps in regions with limited infrastructure. Also, it supports decision-makers in designing and deciding where to place the HFs. Our research contributes valuable insights into healthcare logistics and transportation planning, with implications for global policy development and humanitarian assistance.

However, it's essential to acknowledge the limitations of our method, including constraints related to data availability, quality, and computational complexity. Factors such as spatial data resolution and availability can affect the accuracy of the route pruning algorithm. Moreover, the applicability of our method may vary across regions with different healthcare infrastructure and migration dynamics. The observed variations in performance among routing algorithms emphasize the importance of careful algorithm selection in simulation studies. Future research should explore additional performance metrics beyond ARD, such as computational efficiency, scalability, and robustness to varying input parameters. Additionally, incorporating

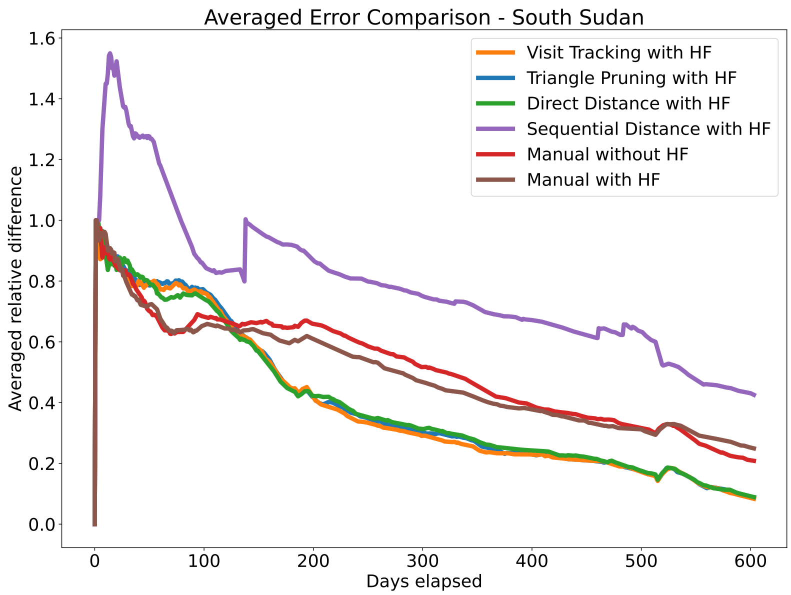


Figure 2: Averaged relative difference comparison.

sensitivity analyses could enhance the reliability and generalizability of our findings, providing further insights for future studies.

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