Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Analysis of distance, poverty and hospital catchment areas for the university hospitals in Sousse, Tunisia

Mohamed Taoufik Bouzidi

mohamedtaoufikbouzidi@yahoo.fr

University of Sousse

Saoussen Ben Ammar

University of Sousse

Research Article

Keywords: hospital catchment, spatial accessibility, distance decay, health equity, planning emergency care, Tunisia

Posted Date: November 17th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11550500/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Analysis of distance, poverty and hospital catchment areas for the university hospitals in Sousse, Tunisia.

Mohamed Taoufik Bouzidi*, Higher Institute of Transport and Logistics of Sousse, University of Sousse, Sousse, Tunisia. mohamedtaoufikbouzidi@yahoo.fr ORCID: 0009-0007-1840-9209

Saoussen Ben Ammar, Higher Institute of Transport and Logistics of Sousse, University of Sousse, Sousse, Tunisia. saoussenbenammar@yahoo.fr

*Corresponding author: Mohamed Taoufik Bouzidi, Higher Institute of Transport and Logistics of Sousse, University of Sousse, Sousse, Tunisia. Email: mohamedtaoufikbouzidi@yahoo.fr

Abstract

Patients of university hospitals in North Africa extend well beyond the borders of the cities where these hospitals are located. Patients from different regions rely on the limited number of specialised university hospitals in a country. The case study of Sousse in Tunisia provides useful insights into the importance of making the specialised health care services of university hospitals accessible to the people who need them the most. Access to services and patients' financial capacity must be considered. Access is also key to geographical distribution and adequacy of university hospitals. From a planning perspective, the results suggest that the hospitals of Sousse are sized appropriately to serve the needs of the region. The first emergency service outside Sousse, preferably in Enfidha, is also supported by the results. This placement would improve the geographical coverage and distribution of university hospitals in Sousse. Considering poverty and the regional development index, the greatest need for specialised health care services is in western, northern and northwestern Tunisia.

Keywords: hospital catchment; spatial accessibility; distance decay; health equity; planning emergency care; Tunisia

1. Introduction

Where patients live and the financial resources they command influence their access to hospital care. Penchansky and Thomas (1981) contended that access consisted of five components: availability, accessibility, accommodation, affordability and acceptability. Guagliardo (2004) showed that spatial measures of potential access must combine supply and demand. Demand and supply combined govern potential access, and empirically, one must take distance and other features of location into account. For example, in an English NHS study, Nicholl et al. (2007) found that the further patients lived from hospitals, the higher was their risk of death following admission via the emergency route. Other studies have shown that patients in the global north living further from hospitals have worse health outcomes (Kelly et al., 2016). Travel times to

the nearest healthcare facility have been estimated for several countries (Weiss et al., 2020). Ouma et al. (2018) found that 29.0% of the population of the countries of sub-Saharan Africa lived more than two hours from the nearest public emergency hospital.

Distance affects who uses a hospital. In England, adjusting for need and supply, the further a patient lived from a hospital, the less likely the patient was to use that hospital (Haynes et al, 1999). Jia et al (2017), observed the same in England and elsewhere. The supply of hospitals and the demand for their services intersect. The distribution of hospital services creates a service area. The geography of a state's hospitals and the availability of hospital beds shows the pulse of a state's health. There is a positive correlation with hospitalization rates and hospital bed supply. University hospitals, like other hospitals, face supply and demand constraints. The catchment area of a university hospital is not restricted to its administration area. Patients travel to university hospitals from a greater geographic area, especially from locations where there is a shortage of medical services.

In Tunisia, patients covered by the social security system are classified in hospital records by their social security fund. The CNSS covers employees in the private sector while the CNRPS covers public sector employees. After the 2004 reform, the Caisse Nationale d'Assurance Maladie (CNAM) took over the health insurance function for both sectors. Patients from low income households are entitled to Free Medical Assistance (AMG). AMG beneficiaries are largely concentrated in public health facilities. Those from high income households utilize health services beyond their health care needs. The state-subsidized health insurance scheme has largely benefited residents of urban areas. Poverty and development are not uniform throughout the country; according to the national poverty map, Kasserine, Le Kef and Kairouan governorates rank the highest in poverty. Similarly, the Regional Competitiveness Index of the Institut Tunisien de la Compétitivité et des Études Quantitatives (ITCEQ) for the years 2020 to 2024 ranks Kasserine, Kairouan and Sidi Bouzid governorates the least competitive.

Urban and regional planning is also impacted by this question. University hospitals are very large public institutions in a city. Patients and staff create inflows and outflows throughout a city and beyond. Consequently, decisions regarding the city's university hospital and its related emergency facilities impact the entire city and its hinterland. Some parts of the governorate (e.g., urban north-west and south-west) are less developed. The rest of the governorate may take a long time to reach the urban area. In regional and urban planning, the location of hospitals and other health centers may respond to the need for medical and health care facilities and emergency services within the area. This is especially the case if the capacity is located away from urban centers.

This study used activity data from the two largest university hospitals (CHUs) in Sousse to define catchment areas and assess the effect of poverty and regional development. It also assessed the effect of insurance schemes on hospital activity. The study assessed the differences in travel time to the nearest hospital (CHU) within the Sousse governorate, and assessed the location of the unmet need for Advanced Emergency Units (AEU) within the governorate. The study used an ecological, descriptive and retrospective design.

2. Literature Review

2.1 Spatial Access and Hospital Catchments

2SFCA is a two-step float catchment area method proposed by Luo and Wang (2003) and was further extended by Luo and Qi (2009). Neutens (2015) explored concepts of health care equity and 2SFCA. Stacherl and Sauzet (2023) discussed the evolution of methods and ideas related to 2SFCA. Accessibility estimates are impacted by the scale of analysis (Apparicio et al. 2008) and hence are less valid at delegation-level. In catchment area analyses, the focus is on determining how far a given hospital can reach (in terms of supply) as opposed to how much a particular location can be supplied from. Distance-decay functions are used to describe catchment areas based on patient flow (Jia et al. 2017). In the absence of patient-level information, Count models are used to analyze the hospital catchment area (Cameron & Trivedi 2013).

2.2 Insurance, Poverty, and Hospital Use

Households in low- and middle-income countries are burdened by out-of-pocket health expenditures (McIntyre et al., 2006). The evidence reviewed by Cookson et al. (2021) supported the presence of the inverse care law, i.e. the highest need for care is met with the least available care. In Indonesia, Johar et al. (2018) showed that access to care is influenced by finance and location. Ismail (2015) reported AMG Type 1 households in Tunisia face higher out-of-pocket costs as compared to CNSS/CNRPS beneficiaries, and explained the situation with the unavailability of local health services in rural Tunisia, which results in the population seeking care in university hospitals. Briki (2022) and Abu-Zaineh et al. (2014) reported income-related and geographic (rural/urban) inequalities in accessing health care. Makhloufi et al. (2015) reported that while there is universal access to health care in Tunisia, poor households may be unable to use care due to financial constraints.

2.3 Emergency Accessibility and Location of Facilities

Thirty minutes of travel time is the planning threshold for providing emergency medical care (Cazacu et al., 2025). Nickol et al. (2007) demonstrated that beyond 2.5 kilometers, the likelihood of death from emergency conditions increases. Varied models of expected travel times show the best-case scenario for access to emergency medical services. In a case study of Dhaka, a failure to consider variability of travel time led to overestimating the coverage of emergency medical services (Ahmed et al., 2019). In Lagos, travel times to emergency obstetric care in the best-case scenario were estimated at 11 minutes, while travel times using actual case scenarios, which involved driving replicas of the patients' routes, estimated travel times at 50 to 52 minutes (Banke-Thomas et al., 2021). Facility location models offer prescription solutions to best address facility siting. These models are varied, including the p-median problem (Hakimi, 1964), location set covering problem (Toregas et al., 1971), and the maximal covering location problem (Church & ReVelle, 1974). The coverage solutions in these models are prescribed to address the greatest demand in a system. Their use in health planning has been described (Ahmadi-Javid et al., 2017; Rahman & Smith, 2000) and health-related studies have documented their integration with other models and geographic information systems (GIS) (Cazacu et al., 2025; Schuurman et al., 2009; Esmaelian et al., 2015). Cazacu et al. (2025)

further demonstrated that adding emergency units to designated hospitals in the case of Romania, reduced the population residing 30 minutes or further from emergency care from 60.28% to 35.63%.

2.4. Composite Indices

Composite Indices combine various components of access into a single Index. Results from these Indices depend on how the components are normalized and weighted (OECD & JRC, 2008; Greco et al., 2019). Entropy weighting, for example, assigns more weight to components that vary more across the subjects being assessed. Entropy weighting, however, does not take into account what the policy makers are trying to assess. In addition, components that take on only a few or no values can affect the weighting as well (Zhu et al., 2020). Qian et al. (2023) and Zhan et al. (2022) assessed healthcare deprivation in Ningbo and Xinjiang, respectively, using Entropy weighting. In addition, Ndonky et al. (2024), used 2SFCA in combination with local indicators of spatial association in rural Senegal, to assess inequities in healthcare. Studies of spatial access in the Maghreb have measured access and described barriers to care in the province of Al Haouz (Salhi et al., 2023). All these works advocate for policy makers to disclose the components of composite Indices, as well as the rankings generated from various weighting schemes.

3. Data and Methods

3.1 Study Area

The governorate of Sousse covers 16 Delegations (Fig.1). A developed and urbanized coastal area (Sousse Medina, Sousse Jaouhara, Sousse Riadh, Sousse Sidi Abdelhamid, Hammam Sousse, Akouda and Kalaa Sghira) is in stark contrast with a remote, less developed and equipped hinterland (Enfidha, Bouficha, Kondar, Sidi El Heni, Hergla and Sidi Bou Ali). M'saken, Kalaa Kebira and Zaouiet Ksibet Thrayet are less developed and equipped than the coastal area but more developed and equipped than the hinterland. CHU Sahloul and CHU Farhat Hached provide tertiary care in the governorate. Public hospitals at the basic level of care are found in Enfidha and Sousse.

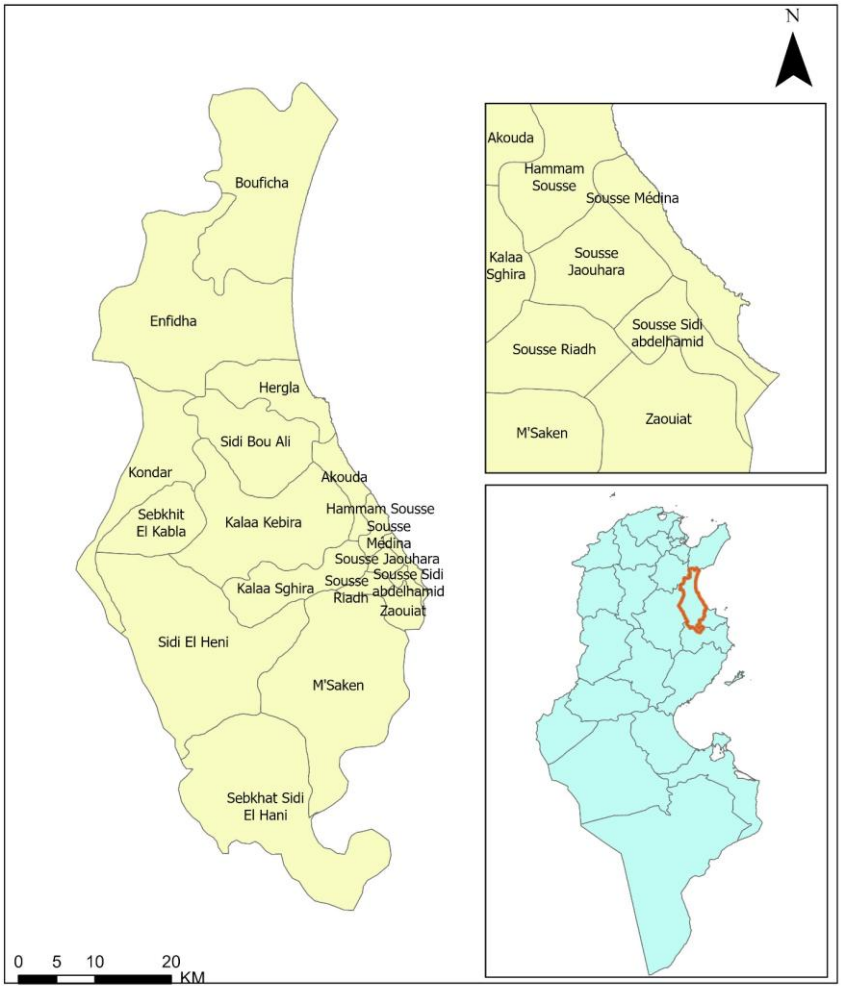


Fig. 1: Location of the study area: the 16 delegations of the Sousse Governorate and the position of the governorate in Tunisia.

3.2 Data

The data is shown in Table 1. For both CHUs, the information systems produced synthesized activity tables for the 2024 exercise, and no individual case records were made available. For CHU Farhat Hached, tables included data on admissions by governorate of residence, by insurance scheme and department and sex, and by age, as well as outpatient consultations by insurance scheme, and ambulatory care. For CHU Sahloul, tables included outpatient consultations by department, scheme and sex, and age, and ambulatory care by governorate. Admissions to CHU Sahloul were not available. Poverty data are from the national poverty map that integrates the 2015 household budget survey and the 2014 census (Institut National de la Statistique (INS), 2020) and the 2024 census (INS, 2024). The Regional Development Index (IDR) is from Instutit Tunisien de la Compétitivité et des études Quantitatives ITCEQ (2024). The IDR ranges from 0 to 1. Data on the location and transport distances to each health facility (ArcGIS Pro, Network Analyst) are from the Regional Health Directorate Sousse. Personal and health staff data by delegation, and health facilities of the private sector by the Regional Health Directorate Sousse were from the Regional Health Directorate Sousse (DRS, 2024).

Governorate and Delegation limits are from geoBoundaries (Runfola et al., 2020) and Governorate capitals from GeoNames (http://www.geonames.org).

Table 1. Data sources

Data	Content	Source	Unit
Admissions, CHU Farhat Hached	40,372 admissions by governorate, insurance scheme, department × sex, department × age group	Hospital information system	Governorate / hospital
Ambulatory care, both CHUs	Outpatient and emergency visits by governorate of residence	Hospital information systems (2024)	Governorate
Outpatient consultations by scheme	CHU Farhat Hached (393,609); CHU Sahloul by department and by sex × age group	Hospital information systems	Hospital
Population	2024 census, governorates and delegations	INS (2024)	Governorate, delegation
Poverty	Poverty rate (%), census-based and survey estimates	INS (2020)	Governorate
Regional development	Regional development index (IDR), 2024; 2021 edition; 2015 and 2018 for sensitivity	ITCEQ (2024)	Governorate
Travel times	Car distance (km) and time (min) from each delegation to each CHU	Measured by the authors	Delegation
Health workforce	Public and private general practitioners and specialists; pharmacies	DRS Sousse (2024)	Delegation
Geography	Capitals, delegation seats, boundaries	GeoNames; geoBoundaries	–

3.3 Regional catchment, distance and poverty

The utilization rates for the other 23 governorates, other than Sousse, were calculated for the three following indicators: the total number of admissions to CHU Farhat Hached, total number of visits in the emergency departments of the two CHUs, and total number of visits in the outpatient departments of the two CHUs. We used the great circle distance from the city of Sousse to each of the remaining 23 gouvernerates to represent distance. The counts were modelled using a negative binomial regression, with the 2024 population as an offset. Equation (1) represents the model.

$$\log E[Yg] = \log Pg + \beta 0 + \beta 1 \log dg + \beta 2\, Povg/10 \quad (1)$$

E[Yg] represents the count for governorate g and Pg its population. dg is the distance from the capital, and Povg represents poverty in governorate g, expressed as a percentage (INS 2024). We first estimated the model with distance only and compared two other functions (log d and d) in the context of the AIC. We then added poverty to the model. Reported herein are the relative rates $2\beta 1$ associated with a doubling of distance and the relative rate $\exp(\beta 2)$ associated with an increase of 10 percentage points in the poverty rate. We created a second model and replaced poverty with IDR. The model was estimated for governorates where IDR is less than a specified value. Because of high correlation (Pearson $r = -0.88$) between the two measures of poverty, we compared the models by using the AIC and estimated them simultaneously. Large count overdispersion is modeled by using the negative binomial distribution. Deviance of the Poisson distribution in each of the models estimated was greater than 1000 (Cameron and Trivedi, 2013). In a pooled model with outcome-specific slopes and intercepts, we tested if the slope associated with distance was the same for all other variables.

Sensitivity analyses pertained to the survey-based poverty estimates for 2015 and 2018 anddropped one governorate at a time. It employed the unadjusted Kairouan value andestimated the distances from hospitals rather than from Sousse (from CHU Farhat Hached for admissions, and from the two nearest hospitals for Emergency and outpatient visits, respectively). The ratio of the observed to expected value, from the full model, helped identify governorates that showed extreme cases of patients' absence or excess relative to their expected cases, based on distance poverty level and other factors. Analyses employed Python 3.13, with statsmodels 0.15 (Seabold & Perktold 2010) and geopandas 1.2.

3.4 Insurance mix

We analyzed the distribution of insurance schemes for the admissions, outpatient consultations and outpatient at CHU Farhat Hached and at CHU Sahloul. In the case of the CHU Sahloul, the table by sex and scheme gives the distribution of AMG by age.

3.5 Local access within the governorate

For each delegation, Ti is the shorter of the measured car travel times to the two CHUs. We classified delegations into four accessibility groups (10 minutes or less, 10-20 minutes, 20-30 minutes, and more than 30 minutes) and calculated the 2024 census population for each group. The local access index (LAI) uses Ti and three supply indicators (per 10,000 inhabitants) of the private sector, that is, private practitioners and private pharmacies. Based on the travel time data, we expected 415 of the 449 public sector specialists and 1261 of the 1692 public sector nurses, posted to university hospitals (located in Sousse Jaouhara), to join the staff of university hospitals, and thus, travel time data reflects public sector staff postings. Each of the supply and travel time components was rescaled to the range [0, 1] by min-max normalization, and travel time was inverted, that is, longer travel times were assigned lower values.

$$LAI_i = \Sigma_j w_j x_{ij} \quad (1)$$

where $x_{ij} = (X_{ij} - \min_i X_{ij}) / (\max_i X_{ij} - \min_i X_{ij})$, and equal weights ($w_j = 0.25$) were used for the main index. We examined LAI in relation to Shannon's entropy, and an index in which travel time was given twice the weight (Shannon, 1948). We also examined an index in which components were ranked using percentile instead of min-max, and assessed the Spearman correlation of rankings.

3.6 Location of Emergency Units

As travel times between delegations were not given, we estimated these from the measured times of delegations to CHUs. The Delegations' seats are known and given in lat/long coordinates in GeoNames. For the Sousse delegations, we used polygon centers. The two CHUs are at Sahloul, 35.8363° N, 10.5896° E, and Farhat Hached, 35.8296° N, 10.6278° E; the distance between the two CHUs is 3.5 km. Estimated travel times to the CHUs are 1.17 times the straight-line distances. The model is in the form, $t = a + bd$, where d is the straight line distance in Kms and t is travel time in minutes. The RMSE of the model is 4.5 minutes.

Demand points represent 16 delegations to the 2024 Census. Two Constituent Unit (CHU) facilities and their measured times are listed. Nine candidate sites are Bouficha, Enfidha, Hergla, Kondar, Sidi El Heni, Sidi Bouali, Kalaa Kebir, Kalaa Sghira, and M'saken. For each candidate, measured time to the nearest CHU is compared to estimated time to the candidate site (time is zero for the candidate site's own delegation). Because there are only nine candidate sites, we considered all possible cases. For each case, we identified the population that is within 30 minutes and represented the results in terms of the maximal covering location problem (Church & ReVelle, 1974) and the population weighted mean (Hakimi, 1964). To account for the uncertainty in the estimates, we increased and decreased the estimates by one standard deviation and recalculated coverage.

We repeated the siting on the road network with the Location–Allocation solver of ArcGIS Pro 3.5.2 (Network Analyst) . The network is the road graph of the governorate extracted from OpenStreetMap through BBBike in March 2025, with car travel time as impedance. Demand points and candidate sites were the same as above, and the two CHUs were entered as required facilities. We solved three problems: Minimize Impedance with one new facility (scenario 1, the p-median problem), Minimize Facilities with a 30-minute cutoff (scenario 2, the location set covering problem of Toregas et al., 1971) and Maximize Coverage with a 30-minute cutoff and a fixed number of new facilities (scenario 3, the maximal covering problem of Church & ReVelle, 1974). These runs do not use our estimated travel times, so they show whether the choice of site holds under a different model of travel.

4. Results

4.1 Origin of patients

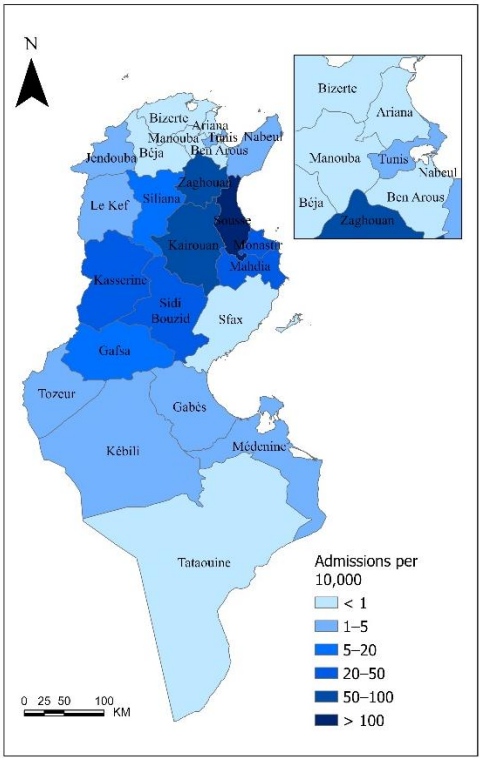
Of the 40,368 patients admitted to CHU Farhat Hached with known residence, 26,550 (65.8%) were from Governorate Sousse, 13,608 (33.7%) from other Governorates, and 210 (0.5%) from abroad (Table 2). From other Governorates, 29.1% and 24.6% of admissions, respectively, to

CHU Farhat Hached and CHU Sahloul, were of an emergency nature, compared to 42.0% and 38.2% of all outpatient visits, respectively, to the two CHUs.

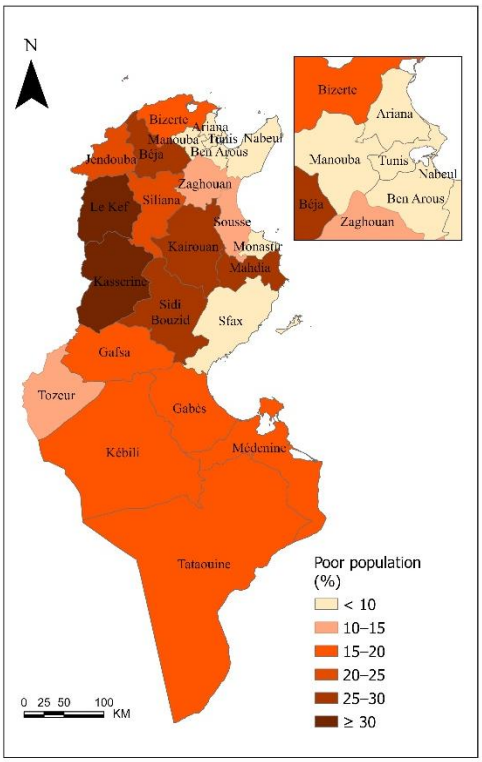
Table 2. Origin of patients by hospital and type of activity, 2024.

Activity	**Total**	**Sousse, n (%)**	**Other governorates, n (%)**	**Abroad (%)**	**Main other origins (%)**
Admissions, Farhat Hached	40,368	26,550 (65.8)	13,608 (33.7)	0.5	Kairouan 11.0; Kasserine 5.3; Sidi Bouzid 4.0
Outpatient visits, Farhat Hached	246,151	141,405 (57.4)	103,424 (42.0)	0.5	Kairouan 14.0; Kasserine 6.1; Mahdia 5.0
Emergency visits, Farhat Hached	142,338	98,384 (69.1)	41,478 (29.1)	1.7	Kairouan 9.7; Kasserine 2.8; Sidi Bouzid 2.3
Outpatient visits, Sahloul	182,504	112,000 (61.4)	69,801 (38.2)	0.4	Kairouan 12.1; Kasserine 5.1; Monastir 4.4
Emergency visits, Sahloul	133,681	99,120 (74.1)	32,942 (24.6)	1.2	Kairouan 8.5; Kasserine 2.7; Monastir 2.0

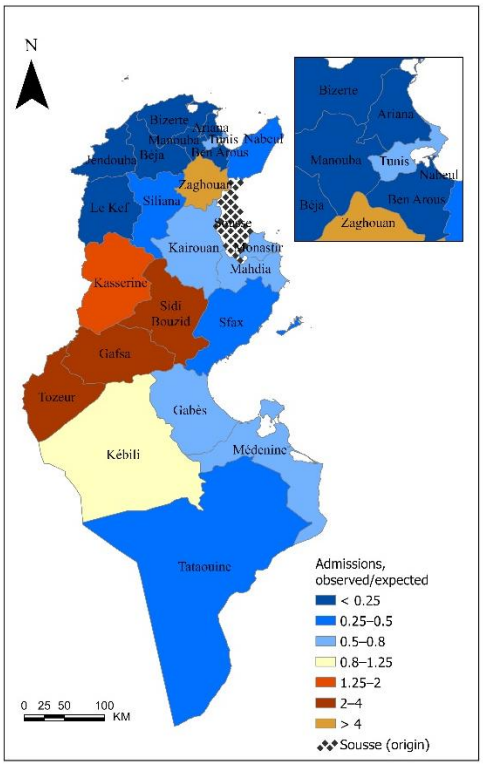
Annual admission rates (per 10,000 population) were 348 in Sousse, 74 in Kairouan, 61 in Zaghouan, 43 in Kasserine, 33 in Sidi Bouzid, 30 in Mahdia and 23 in Monastir (figure 2 a). They were below 2 in Greater Tunis, Bizerte, Nabeul and Sfax. Rates in other governorates (especially interior governorates located to the west and northwest of Sousse) are comparatively higher (see figure 2b) and also correspond to the higher poverty rates in the country (see figure 2c).



a) **Admission Rate**



b) **Poverty Rate**



c) **Observed / expected**

Figure 2. (a) Admissions to CHU Farhat Hached per 10,000 inhabitants by governorate of residence; (b) poverty rate; (c) ratio of observed to expected admissions from Negative Binomial regression model of distance and poverty.

4.2 Distance, poverty and usage

In the case of distance only, usage (admissions and emergency visits) to CHU Farhat Hached progressively decreased (See Table 3) and the admission rate to the CHU was multiplied by 0.44 (95% confidence interval, CI: 0.23 to 0.87) and the emergency visit rate was multiplied by 0.52 (0.31 to 0.87). Usage was also progressively multiplied by 0.47 (0.25 to 0.87) for outpatient visits. Power and exponential forms yielded nearly identical results. The three forms did not differ from each other (pair wise $p \geq 0.73$). Residuals were positively related to poverty. The correlation coefficient between the governorate poverty rate and the ratio of observed to expected admissions was 0.62 ($p = 0.002$).

Adding poverty to the models improved them (AIC decreased by 8.6 to 12.4 points). Accounting for distance, relative to the base case, a 10 percentage point increase in the poverty rate was associated with a 3.25-fold (95% CI 1.60-6.61) relative increase in admission, a 2.68-fold (1.66-4.33) relative increase in emergency, and a 3.28-fold (1.87-5.76) relative increase in outpatient visit rate. The distance gradient was unchanged (rate ratios for 2nd distance order = 0.39, 0.51 and 0.43). The association was similarly observed for survey based poverty estimates (rate ratios = 2.52, 2.22 and 2.67) and in the presence of governorate of Le Kef (rate ratios for emergency and outpatient visits = 2.64, 2.95 respectively). Excluding a single governorate in the analysis did not alter the association (admission rate ratios = 2.94-3.91; emergency and outpatient visit rate ratios = 2.47-3.26 and 3.01-3.77, respectively). Without correcting Kairouan, the distance slope for emergency visits was -1.20 compared to -0.95. Measuring distance to the hospitals did not materially alter the rate ratios for poverty (3.25 and 2.66, 3.25 and 2.27, and 3.25 and 2.70 for admissions, emergency and outpatient visits respectively). Correcting Kairouan did not change the rate ratios for poverty (3.25 and 2.70, 3.25 and 2.66, and 3.25 and 2.70 for admissions, emergency and outpatient visits respectively).

Of the three outcomes, the association of regional development with admission, emergency visit, and outpatient visit rates was comparatively better than the association of poverty with these rates (AIC 304.8, 313.3, 378.8, and 409.8, respectively, against 382.2, 384.2, 409.8, and 413.3). After adjusting for the distance to the site, an IDR unit decrease was estimated to increase admission rate by a factor of 3.29 (95% CI 2.06, 5.24), emergency visit rate by a factor of 2.30 (1.64, 3.23), and outpatient visit rate by a factor of 2.75 (1.84, 4.11). The results were similar for the 2015 and 2018 IDR values and when any one of the governorates was excluded (Table 3). When both IDR and poverty were included in the same model, the association of IDR with admission rate was 3.59 (1.59, 8.09), with emergency and outpatient visits corresponding association being 2.10 and 2.33, respectively. The association of poverty with admission, emergency, and outpatient visits was 0.88, 1.26, and 0.91, respectively, with comparatively wide confidence intervals.

Table 3. Negative binomial regression analysis of selected state utilization rates based on residence in 23 other governorates (22 for emergency and outpatient visits) relative to Sousse.

	Admissions (Farhat Hached)	**Emergency visits (both CHUs)**	**Outpatient visits (both CHUs)**
Distance only			
Rate ratio per doubling of distance	0.44 (0.23–0.87)	0.52 (0.31–0.87)	0.47 (0.25–0.87)
AIC	321.9	393.3	425.7
Rate ratio per doubling of distance	0.39 (0.23–0.64)	0.51 (0.35–0.75)	0.43 (0.28–0.66)
Rate ratio per +10 points of poverty	3.25 (1.60–6.61)	2.68 (1.66–4.33)	3.28 (1.87–5.76)
AIC	313.3	382.2	413.3
Dispersion parameter α	1.36	0.78	1.01
Rate ratio per doubling of distance	0.37 (0.25–0.55)	0.49 (0.35–0.69)	0.40 (0.27–0.58)
Rate ratio per 0.1 lower IDR	3.29 (2.06–5.24)	2.30 (1.64–3.23)	2.75 (1.84–4.11)
AIC	304.8	378.8	409.8
Survey-based poverty estimates	2.52 (1.27–5.00)	2.22 (1.41–3.52)	2.67 (1.52–4.66)
Range when dropping one governorate	2.94–3.91	2.47–3.26	3.01–3.77
IDR 2018 values	3.19 (2.07–4.91)	2.22 (1.62–3.06)	2.65 (1.83–3.86)
IDR 2015 values	2.97 (2.01–4.37)	2.08 (1.56–2.79)	2.46 (1.75–3.45)
Range when dropping one governorate	3.03–3.52	2.16–2.93	2.57–3.40
Joint model with poverty: IDR	3.59 (1.59–8.09)	2.10 (0.97–4.55)	2.33 (1.00–5.44)
Joint model with poverty: poverty (+10 points)	0.88 (0.32–2.37)	1.14 (0.42–3.05)	1.26 (0.43–3.68)

Values are rate ratios with 95% confidence intervals. Distance: great-circle distance from Sousse to the governorate. Poverty: census-based estimate of the poverty rate (%) (INS, 2020). IDR: regional development index, 0–1 (ITCEQ, 2024).

We found ratios of observed to expected admissions using our full model (shown in Figure 2c) to be highest in Zaghouan (6.7), Gafsa (2.9), Tozeur (2.8), Sidi Bouzid (2.1), and Kasserine (1.4) and lowest in Bizerte and Béja (0.05), Manouba (0.06), Ariana (0.09), Ben Arous (0.10), Le Kef (0.11), and Jendouba (0.14). Monastir (0.68) and Mahdia (0.51) sent fewer patients than expected, based on distance and the poverty index. Kairouan (0.73), which also has a university hospital, sent fewer patients than expected (0.73), as well. Among all Governorates, Kairouan was the highest contributor, based on the absolute value. In the model that includes the IDR, Sidi Bouzid (1.30) and Kasserine (0.97) were closest to expected value, while Zaghouan (2.80) and Tozeur (2.30) were far above expected value, and Gafsa (3.50) was also above expected value.

4.3 Insurance mix

At CHU Farhat Hached, 19.5% of inpatients and 19.0% of outpatients, and 16.1% of outpatients at CHU Sahloul, were covered by the AMG (see Table 4). The CNSS covered between 40.6 and 50.1% of the users in all tables. The full fee-paying group covered 13.6% of inpatients and 20.6% of outpatients at CHU Sahloul. Of all users of CHU Sahloul, the AMG covered 14.7% to 19.0% of the users in all age groups, except users aged 90 years and older, for whom the AMG covered 29.7% of the users. The AMG covered 17.7% of the users of CHU Sahloul, who were between 20 and 29 years, while the AMG covered 14.4% of the users of CHU Sahloul, who were between 1 and 19 years.

Table 4. Activity by insurance scheme (%).

Scheme	**Admissions, Farhat Hached**	**Consultations, Farhat Hached**	**Consultations, Sahloul**
CNSS	50.1	41.0	40.6
CNRPS	13.2	8.3	7.9
AMG Type 1	10.0	11.1	9.1
AMG Type 2	8.1	6.3	6.2
AMG, blind and disabled persons	1.4	1.6	0.8
Full fee	13.6	15.2	20.6
Other schemes	3.5	16.4	14.9
All AMG	**19.5**	**19.0**	**16.1**
N	40,155	393,609	312,373

Other schemes include personnel from public health (10.0% of consultations at Farhat Hached), personnel from the military and security services, detainees and social cases. The cases from Sahloul are included in their respective departments.

4.4 Local Access Within The Governorate

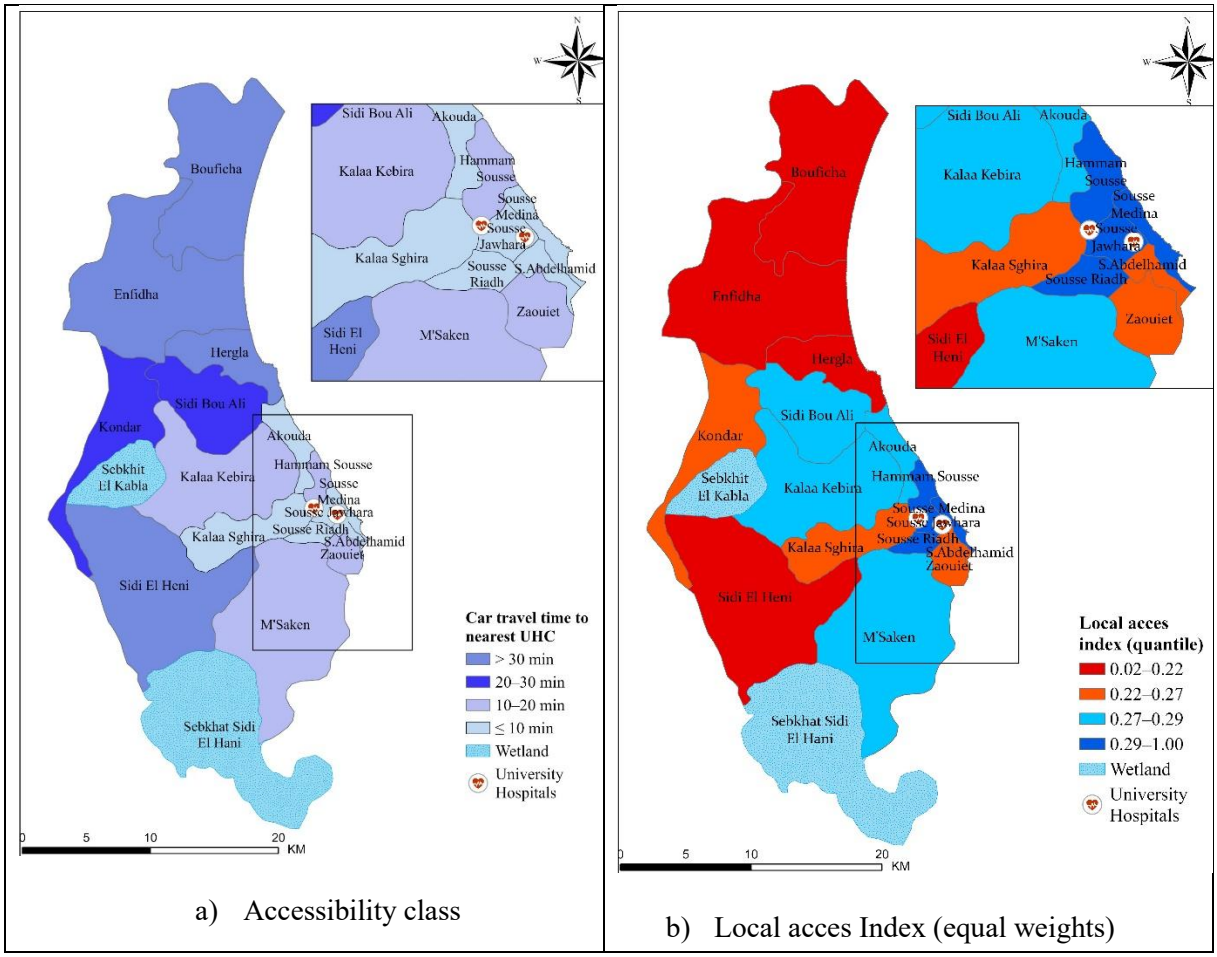
The four delegations that are beyond 30 minutes away have the lowest averages for the LAI, 2.3 general practitioners per 10,000 inhabitants (Table 5, figure 3a). Sousse Medina and Sousse Jaouhara, the two most accessible delegations, in travel time, have the highest weights. The two most remote delegations in travel time, Sidi Bou Ali and Kondar, had the second highest weights, while Sidi El Heni was the fourth most remote. using the weights of the existing specialities and private practice, Enfidha and Sidi El Heni were the two most remote, and Sousse Sidi Abdelhamid and Sousse Riadh were the least remote (figure 3b). The other two weighting schemes were the same as the equal weighting scheme in terms of correlations (ρ = 0.87, 0.89 and 0.95, respectively) with the travel time weighting scheme giving the lowest correlations. The travel time weighting scheme gave the highest rank correlations, and with the other components of the LAI the correlations remained the same or close (ρ = 0.89 to 0.99). Travel time had the largest effect on the rank order of the LAI (Table 5).

Table 5: Travel time, health workforce and local access index (LAI) by delegation.

Delegation	**Population 2024**	**T_i (min)**	**GPs per 10,000**	**Private specialists per 10,000**	**Pharmacies per 10,000**	**LAI (equal weights)**	**Rank: equal / entropy / percentile**
Sousse Médina	32,220	6	16.1	35.7	11.2	1.00	1 / 1 / 1
Sousse Jaouhara	97,535	5	15.2	30.6	1.7	0.73	2 / 2 / 2
Hammam Sousse	48,899	13	4.3	4.9	2.5	0.34	3 / 3 / 3
Sousse Riadh	71,464	8	3.8	0.7	1.7	0.31	4 / 7 / 4
M'saken	97,312	19	5.0	1.8	1.6	0.29	5 / 5 / 5
Akouda	39,174	9	2.6	0.3	2.0	0.28	6 / 10 / 6
Kalaa Kebira	67,108	14	4.3	0.6	1.5	0.28	7 / 6 / 8
Sidi Bou Ali	20,647	22	5.3	1.9	1.5	0.27	8 / 4 / 6
Zaouiet Ksibet Thrayet	49,130	12	1.8	0.0	2.2	0.26	9 / 11 / 10
Kalaa Sghira	45,743	8	2.0	0.2	1.3	0.26	10 / 12 / 13

Sousse Sidi Abdelhamid	57,691	7	2.4	0.3	0.5	0.26	11 / 13 / 12
Kondar	15,491	29	3.9	0.0	1.9	0.22	12 / 9 / 10
Hergla	10,652	32	4.7	0.0	1.9	0.22	13 / 8 / 9
Sidi El Heni	14,508	35	2.8	0.0	1.4	0.16	14 / 14 / 14
Enfidha	58,613	36	1.7	0.2	1.5	0.14	15 / 15 / 15
Bouficha	36,094	63	2.5	0.0	0.8	0.02	16 / 16 / 16

Travel time to the nearest CHU measured by car. GPs = public and private general practitioners. Ties in percentile ranks have the same value. Population data: INS (2024) (DRS Sousse (2024).



a) Accessibility class

b) Local acces Index (equal weights)

Figure 3: (a) Classification of accessibility by car travel time to nearest CHU; (b) local access index in quartiles.

4.5 Emergency unit siting

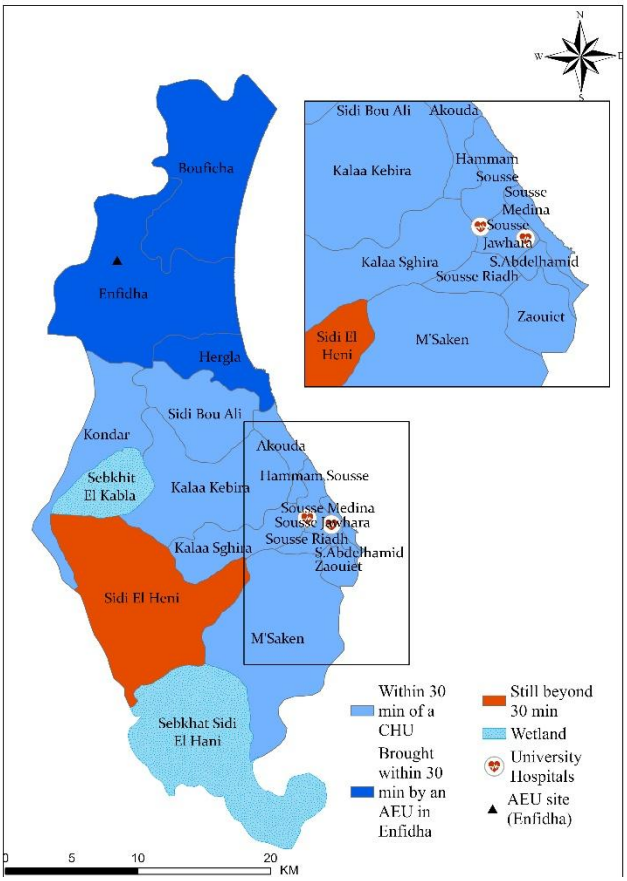
The 2 CHUs considered serve 642,414 (84.3%) of the total population with a population-weighted mean travel time of 16.4 min (figure 4a and b). If considered as single units, an AEU

in Enfidha (the best alternative) serves the population of Enfidha, Bouficha and Hergla, and increases the coverage to 98.1% (see Table 6).

Table 6. Impact of One AEU on 30-minute Coverage by Candidate Site.

Candidate site	Inhabitants newly within 30 min (range)	Coverage (%)	Mean travel time (min)	Delegations newly within 30 min
None (two CHUs)	–	84.3	16.4	–
Enfidha	105,359 (69,265–105,359)	98.1	11.8	Enfidha, Bouficha, Hergla
Bouficha	94,707 (36,094–94,707)	96.7	12.7	Enfidha, Bouficha
Hergla	69,265 (69,265–69,265)	93.4	13.6	Enfidha, Hergla
Sidi Bou Ali	69,265 (10,652–69,265)	93.4	14.0	Enfidha, Hergla
Sidi El Heni	14,508 (14,508–14,508)	86.2	15.8	Sidi El Heni
Kalaa Kebira	10,652 (10,652–10,652)	85.7	14.6	Hergla
Kondar	10,652 (0–69,265)	85.7	14.8	Hergla
M'saken	0 (0–14,508)	84.3	13.9	–
Kalaa Sghira	0 (0–25,160)	84.3	15.4	–
Enfidha and Sidi El Heni	119,867	100.0	11.1	All four delegations beyond 30 min

Range: coverage with all estimated travel times increased (lower bound) or decreased (upper bound) by one RMSE (4.5 min). Mean travel time: population-weighted mean over the 16 delegations.



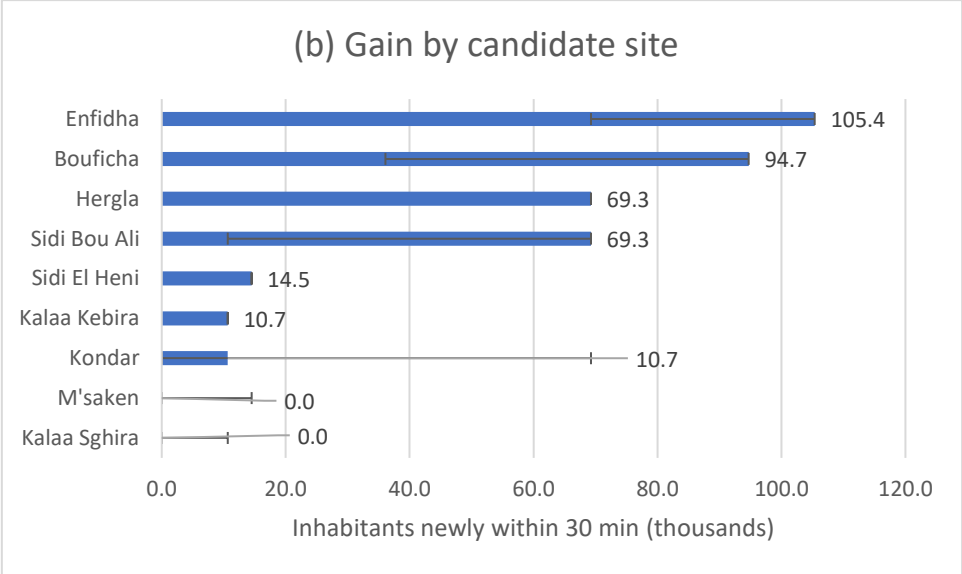


Figure 4 (a): (i) Areas within 30 minutes of a CHU, brought within 30 minutes by an AEU at Enfidha; (ii) areas beyond 30 minutes. (b) Range within which the entire population of Sousse is brought within 30 minutes by a candidate site, if estimated travel times are increased by one RMSE.

It has the lowest mean travel time (11.8 minutes), so according to both methods, coverage, and p-median, Enfidha is the best option. Its catchment area covers 69,265 persons, though, if all the estimated times are considered the best that can be obtained, that is, if the estimated travel time from Enfidha to Bouficha is considered (26.3 minutes), the catchment area would cover

all persons. Sidi El Heni remains beyond 30 minutes with an AEU in Enfidha (estimated travel time is 59.5 minutes). The best option is to locate one unit in Enfidha and the other in Sidi El Heni, which brings the entire population within 30 minutes.

The location-allocation analyses performed on the road network comply with the results of the first site's enumeration. In Scenario 1 (which minimizes the population-weighted travel time) Enfidha was chosen (see Figure 5). In Scenario 2 (which determines the minimum number of facilities to satisfy the demand within 30 minutes) Enfidha was also chosen (see Figure 6). Finally, in Scenario 3 (which determines the optimal locations of five facilities) the selected sites were Enfidha, Sidi Bou Ali, Kalaa Kebira, Kalaa Sghira and M'saken (see figure 7). Among the remaining sites, Bouficha, Kondar and Sidi El Heni, were never selected. Scenario 2 of this study also did not require the second site for Sidi El Heni.

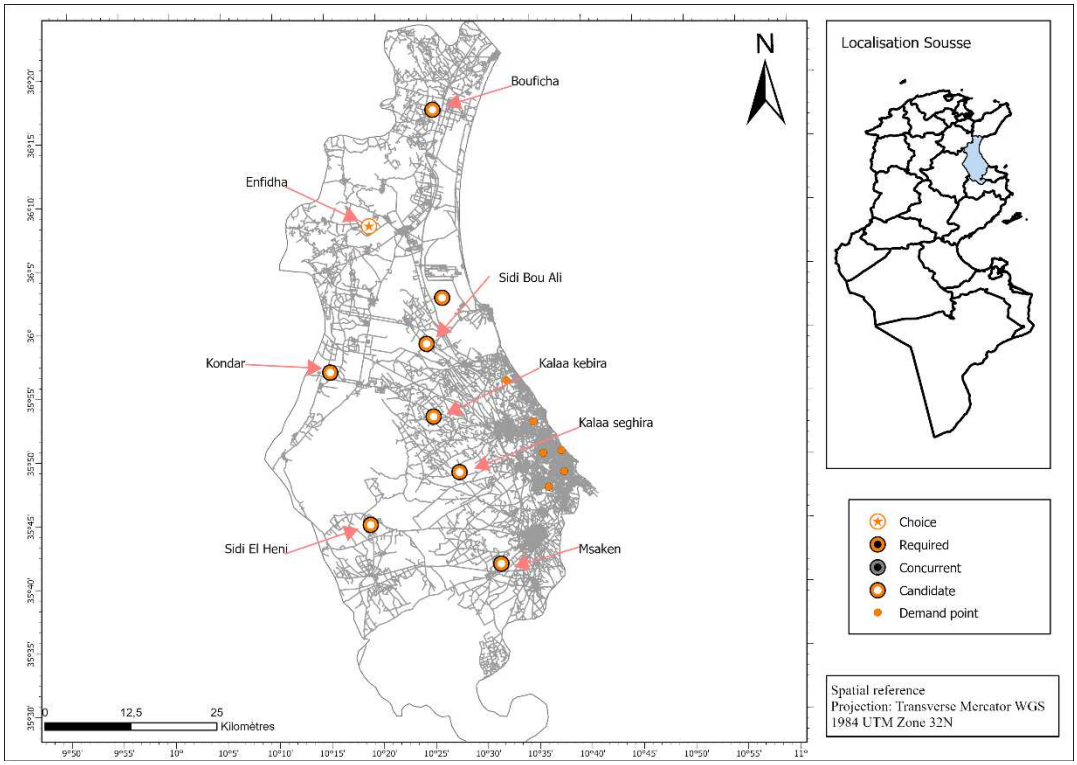


Figure 5. Location–allocation on the road network, scenario 1: lowest population-weighted travel time (Minimize Impedance). Star: selected site; circles: candidate sites; dots: demand points.

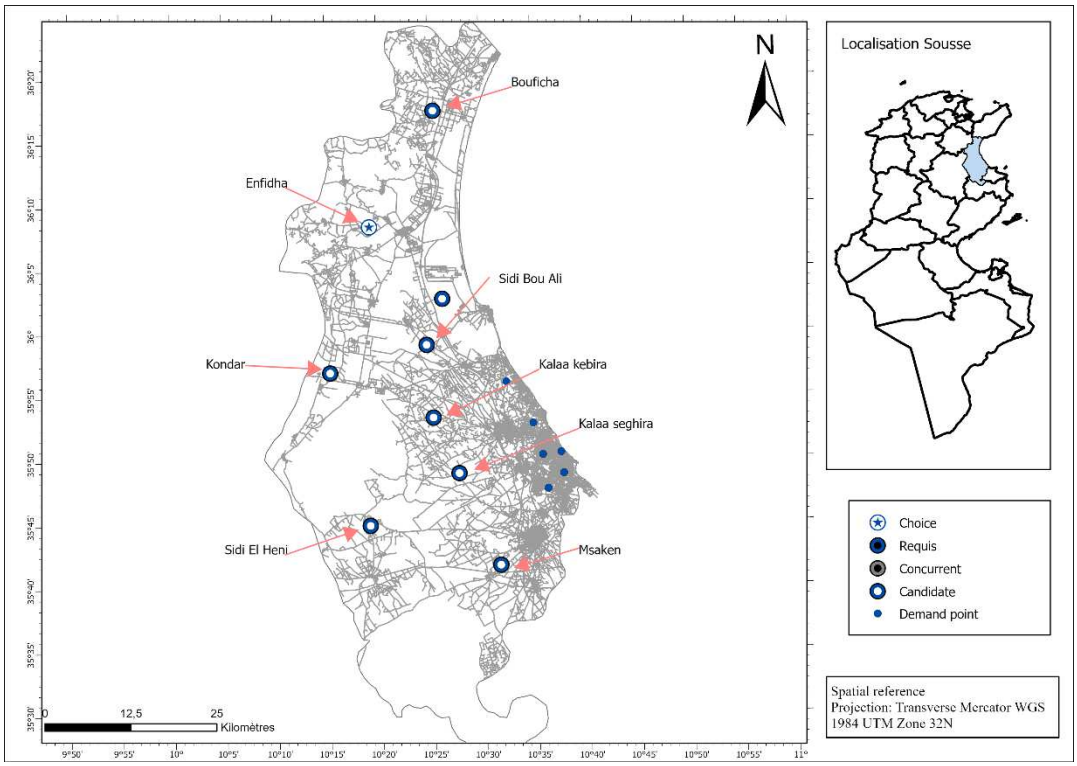


Figure 6. Location–allocation on the road network, scenario 2: fewest facilities covering the demand within 30 minutes (Minimize Facilities). Symbols as in Figure 6.

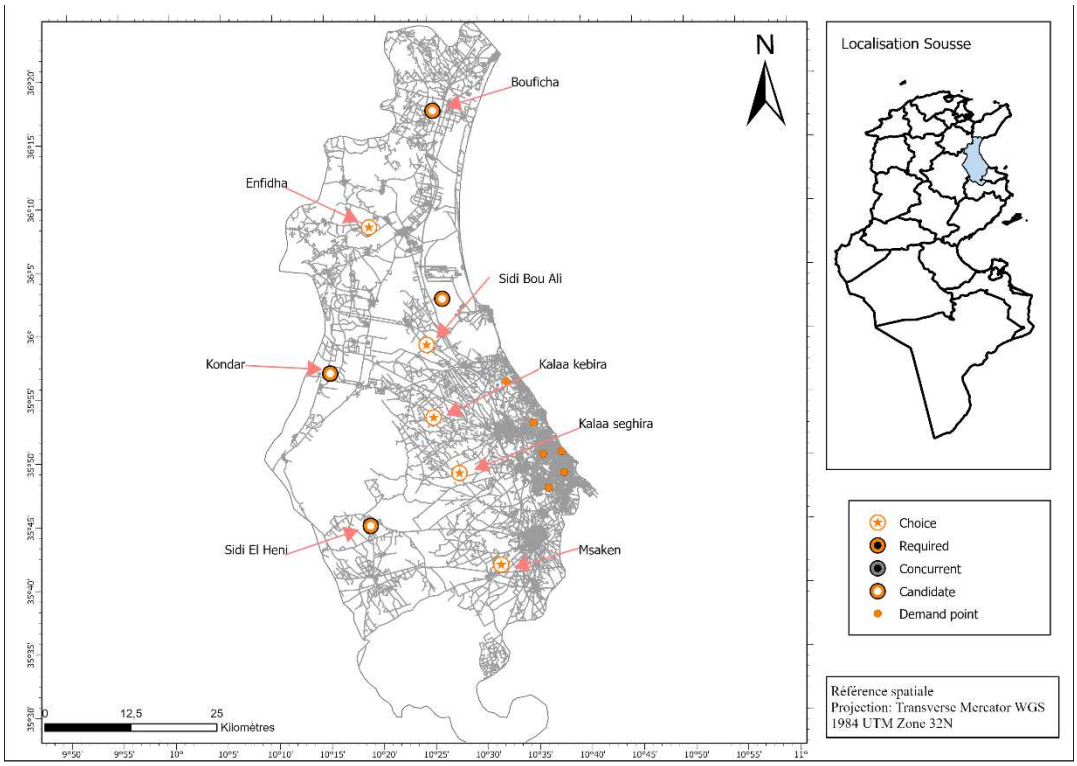


Figure 7. Location–allocation on the road network, scenario 3: largest demand covered within 30 minutes (Maximize Coverage). Symbols as in Figure 6.

5. Discussion

5.1 Main findings

The admission and outpatient figures for the two university hospitals in Sousse demonstrate a significant patient flow out of the governorate. Approximately a third of admissions and up to two fifths of outpatient visits are attributed to patients residing outside of the governorate. The use of the hospitals falls with distance, at similar rates for admissions, emergency visits and outpatient visits. Of equal importance is the rate of poverty in the governorate of origin. A governorate with a poverty rate 10 points higher than the average sends, on average, three times the patient flow per capita to the hospitals. The 15.7% of the population living outside the catchment area of the two hospitals (more than 30 minutes away) are clustered in the northern and westernmost areas of the governorate. These areas also have the lowest density of general practitioners. The introduction of an emergency unit in Enfidha would make the most of the population within the 30 minute catchment area.

5.2. A referral role for the more deprived interior

Results relating to the distance gradient are expected based on earlier work showing hospital use diminishes with distance (Haynes et al., 1999), as well as with respect to the use of distance-decay logic to determine hospital catchment areas (Jia et al., 2017). The association with poverty includes a regional dimension. Governorates in the interior, especially those which send the highest number of patients (Kairouan, Kasserine and Sidi Bouzid) as well as those which send more patients than the model predicts (Zaghouan, Gafsa and Tozeur) also lie in the interior. Governorates in the coastal region and in Greater Tunis, which house several university hospitals, also send less patients. This situation has been illustrated by the inverse care law (Cookson et al., 2021) and is documented by the case of AMG beneficiaries in Tunisia (Ismail, 2015) who rely on the university hospitals for healthcare. The study by Abu-Zaineh et al. (2014) as well as other studies by Makhloufi et al. (2015) also document the relationship where higher social and economic deprivation leads to higher use of healthcare. Results are consistent with the research design, and the relationship is likely to represent the situation and not the individuals. We expect that the local poverty level indicates, among other things, the local healthcare supply, the type of health insurance and/or previously established healthcare referral.

The regional development index demonstrates stronger evidence and creates a better fit. It incorporates the excess use of Kasserine and Sidi Bouzid and, along with poverty, loses its significance in joint models. CHUs of Sousse reflect the governorate's overall potential and opportunities. The IDR also represents access to health services and other social and economic conditions of the labor market and society. In this case, access to health services reflects the overall context of a governorate. Once again, because of the data constraints, it is not possible to confirm this association, but the data suggest that it is appropriate to integrate the analysis of the regional development context and the health system reforms in this case.

It is worth noting that there are similar distances for the three types of activities covered by the model. However, given that the focus is on the distance from the places of residence, emergency visits are the most local. Thousands of residents from the most remote governorates still utilize health care services offered by the region. There is evidence to assume that some of these

emergency visits are the result of referral/transfer from higher-level regional health facilities. Answers to these assumptions can be found in patient referral/transfer data.

5.3 Insurance mix

Approximately one in five calls concern an AMG patient. This ratio is the same for inpatient and outpatient consultations at CHU Farhat Hached. The ratio is lower for CHU Sahloul. Full-pay patients are more frequent at CHU Sahloul. A higher proportion of AMG beneficiaries in the younger age bracket and a lower proportion in the older age bracket may reflect income and age-related needs. AMG beneficiaries may also be more in the poorer governorates. However, the tables do not indicate AMG beneficiaries' place of residence, and we cannot determine whether AMG beneficiaries are more in poorer governorates.

5.4 Local access and the location of an emergency unit

There is a strong relationship between the longest travel times to the PHC and Delegation levels. Four of the most remote delegations (a 30-minute or more travel time to the nearest primary care facility) had 2.3 general practitioners per 10,000 population compared to 6.0 in the other delegations. The bottom of the LAI ranking was the same for all weighting schemes; therefore, the observations for Bouficha, Enfidha, and Sidi El Heni would not change, regardless of the weighting scheme. The entropy weighting scheme demonstrated the threat described by Zhu et al. (2020); it assigned almost no weight to travel time and changed the position of the scheme's mid-ranking units. Reporting the components and several weighting schemes would provide transparency to these effects, in accordance with best practices for composite indices (OECD & JRC, 2008; Greco et al. 2019).

Enfidha presents the best options for both cover. It is on the main corridor between Bouficha and Sousse, and has a public hospital, so it may be less costly to improve emergency care there. A site assessment should be made to determine if it is viable to establish an emergency unit at that location. Sidi El Heni lies to the southwest of Sousse. A unit located to the north would require a longer travel time. For the improvement of MTOs, our figures (MTO of 18 minutes from 84.3% to 98.1% coverage with one unit) would be better than the figures presented by Cazacu et al. (2025) for the national level of Tunisia, because the uncovered population of Sousse is concentrated in a few adjacent delegations. These coverages are based on the assumption of car travel times and ArcGis Pro data and Location-Allocation methods (Polo et al., 2015). The times may be longer during peak hours (Ahmed et al., 2019; Banke-Thomas et al., 2021). It should be kept in mind, however, that an emergency unit does not preclude the need for the transfer of patients to a higher level unit.

5.5 Limitations

Results show three government planning concerns. First, with about 30% of admissions at the University Hospitals coming from outside of their governorate, the planning of the capacity and staffing of the University Hospitals should consider the needs of a broader regional population. For example, the governorates of Kairouan, Kasserine and Sidi Bouzid, which all have specialised hospitals, send the bulk of the patient traffic to University Hospitals in Sousse. Developing such specialised services in the aforementioned governorates may reduce the need

for residents to travel to University Hospitals in Sousse. Second, the planning of the first specialised emergency unit outside of the University Hospitals should be located along the Northern Corridor. A public hospital in Enfidha is located along this corridor. A public hospital in Sidi El Heni needs the first specialised emergency unit to be located in Sousse, or other specialised transport services. Finally, the travel times used in the analysis do not consider peak hour travel. Special management of peak hour travel may reduce the travel times for residents and other patients accessing the hospital from the outlying areas of the prefecture. Management of access to both CHU Farhat Hached and CHU Habib Bourguiba should be addressed in the same regional plan. Management of access to these hospitals should be addressed prior to any major changes or expansions.

5.6. Conclusions

University hospitals in Sousse admit patients from beyond their governorate. About 70% of admissions come from elsewhere, especially from the poorer and less developed governorates of the interior. Each of these governorates sends about three times more patients to Sousse than inhabitants of Sousse governate. Scheduling of workforce and capacity of both CHUs should consider forecast and control demand in the neighboring governorates. It has been proven in other similar programs that improving the level of specialization in the health centers of the internal governorates can reduce the need for patients of these governorates to travel to Sousse for specialized care.

An emergency center in Enfidha would bring 87% of their population within 30 minutes. Sidi El Heni requires a different solution. To verify these conclusions for individual cases, we can utilize the various types of data, including the patient's residence, type of insurance, and the referring unit.

Author contributions

M T B: conceptualisation, methodology, spatial analysis, writing (original draft) writing (review and editing).

S B A: data curation, statistical analysis. supervision, writing (original draft).

All authors read and approved the final manuscript.

Funding

This research did not receive any funding.

Competing Interest

The authors have no competing interests to declare.

Ethics approval and Consent to Participate

No individual case records were analyzed in this study.

Consent to Publish

Not applicable.

Availability of Data and Material

The aggregated tables by governorate and by delegation are included in the article. The complete case activity records are available from the corresponding author. The scripts used for the analysis are available from the corresponding author.

Acknowledgements

The authors thank the directors and the information-system staff of CHU Farhat Hached and CHU Sahloul, and the Regional Directorate of Health of Sousse, for providing the aggregated data used in this study.

Declaration of generative AI use

During the preparation of this work, the authors used Grammarly Inc. to restructure the manuscript and edit the English. The authors checked all analyses and text and take full responsibility for the content of the article.

References

Abu-Zaineh, M., Arfa, C., Ventelou, B., Ben Romdhane, H., & Moatti, J.-P. (2014). Fairness in healthcare finance and delivery: What about Tunisia? *Health Policy and Planning, 29*(4), 433–442. https://doi.org/10.1093/heapol/czt029

Ahmadi-Javid, A., Seyedi, P., & Syam, S. S. (2017). A survey of healthcare facility location. *Computers & Operations Research, 79*, 223–263. https://doi.org/10.1016/j.cor.2016.05.018

Ahmed, S., Adams, A. M., Islam, R., Hasan, S. M., & Panciera, R. (2019). Impact of traffic variability on geographic accessibility to 24/7 emergency healthcare for the urban poor: A GIS study in Dhaka, Bangladesh. *PLOS ONE, 14*(9), e0222488. https://doi.org/10.1371/journal.pone.0222488

Apparicio, P., Abdelmajid, M., Riva, M., & Shearmur, R. (2008). Comparing alternative approaches to measuring the geographical accessibility of urban health services: Distance types and aggregation-error issues. *International Journal of Health Geographics, 7*, 7. https://doi.org/10.1186/1476-072X-7-7

Banke-Thomas, A., Wong, K. L. M., Ayomoh, F. I., Giwa-Ayedu n, R. O., & Benova, L. (2021). "In cities, it's not far, but it takes long": Comparing estimated and replicated travel times to reach life-saving obstetric care in Lagos, Nigeria. *BMJ Global Health, 6*(1), e004318. https://doi.org/10.1136/bmjgh-2020-004318

Briki, I. (2022). Le système de santé en Tunisie : indicateurs, inégalités et perceptions. *Revue Recherches et Études en Développement, 9*(2), 322–343. https://asjp.cerist.dz/en/article/215438

Cameron, A. C., & Trivedi, P. K. (2013). *Regression analysis of count data* (2nd ed.). Cambridge University Press. https://doi.org/10.1017/CBO9781139013567

Cazacu, C., Dumitrache, L., Mareci, A., Cioclu, A., & Petre, A.-A. (2025). Geospatial analysis of emergency healthcare accessibility: Bridging urban–rural disparities in Romania. *Land, 14*(12), 2321. https://doi.org/10.3390/land14122321

Church, R., & ReVelle, C. (1974). The maximal covering location problem. *Papers of the Regional Science Association, 32*(1), 101–118. https://doi.org/10.1007/BF01942293

Cookson, R., Doran, T., Asaria, M., Gupta, I., & Parra Mujica, F. (2021). The inverse care law re-examined: A global perspective. *The Lancet, 397*(10276), 828–838. https://doi.org/10.1016/S0140-6736(21)00243-9

Esmaelian, M., Tavana, M., Santos Arteaga, F. J., & Mohammadi, S. (2015). A multicriteria spatial decision support system for solving emergency service station location problems. *International Journal of Geographical Information Science, 29*(7), 1187–1213. https://doi.org/10.1080/13658816.2015.1025790

Greco, S., Ishizaka, A., Tasiou, M., & Torrisi, G. (2019). On the methodological framework of composite indices: A review of the issues of weighting, aggregation, and robustness. *Social Indicators Research, 141*(1), 61–94. https://doi.org/10.1007/s11205-017-1832-9

Guagliardo, M. F. (2004). Spatial accessibility of primary care: Concepts, methods and challenges. *International Journal of Health Geographics, 3*, 3. https://doi.org/10.1186/1476-072X-3-3

Hakimi, S. L. (1964). Optimum locations of switching centers and the absolute centers and medians of a graph. *Operations Research, 12*(3), 450–459. https://doi.org/10.1287/opre.12.3.450

Haynes, R., Bentham, G., Lovett, A., & Gale, S. (1999). Effects of distances to hospital and GP surgery on hospital inpatient episodes, controlling for needs and provision. *Social Science & Medicine, 49*(3), 425–433. https://doi.org/10.1016/S0277-9536(99)00149-5

Institut National de la Statistique (INS). (2020). *Carte de la pauvreté en Tunisie*. INS. https://ins.tn/sites/default/files-ftp3/files/publication/pdf/Carte%20de%20la%20pauvret%C3%A9%20en%20Tunisie_final_0.pdf

Institut National de la Statistique (INS). (2024). *Recensement général de la population et de l'habitat (RGPH) 2024*. INS.

Institut Tunisien de la Compétitivité et des Études Quantitatives (ITCEQ). (2022). *Indicateur de développement régional 2021*. ITCEQ.

Ismail, S. (2015). *Évaluation économique de la réforme de l'assurance maladie en Tunisie* [Doctoral dissertation, Université Paris Dauphine]. HAL Thèses. https://theses.hal.science/tel-01300569

Jia, P., Wang, F., & Xierali, I. M. (2017). Using a Huff-based model to delineate hospital service areas. *The Professional Geographer, 69*(4), 522–530. https://doi.org/10.1080/00330124.2016.1266950

Johar, M., Soewondo, P., Pujisubekti, R., Satrio, H. K., & Adji, A. (2018). Inequality in access to health care, health insurance and the role of supply factors. *Social Science & Medicine, 213*, 134–145. https://doi.org/10.1016/j.socscimed.2018.07.044

Kelly, C., Hulme, C., Farragher, T., & Clarke, G. (2016). Are differences in travel time or distance to healthcare for adults in global north countries associated with an impact on health outcomes? A systematic review. *BMJ Open, 6*(11), e013059. https://doi.org/10.1136/bmjopen-2016-013059

Luo, W., & Qi, Y. (2009). An enhanced two-step floating catchment area (E2SFCA) method for measuring spatial accessibility to primary care physicians. *Health & Place, 15*(4), 1100–1107. https://doi.org/10.1016/j.healthplace.2009.06.002

Luo, W., & Wang, F. (2003). Measures of spatial accessibility to health care in a GIS environment: Synthesis and a case study in the Chicago region. *Environment and Planning B: Planning and Design, 30*(6), 865–884. https://doi.org/10.1068/b29120

Makhloufi, K., Ventelou, B., & Abu-Zaineh, M. (2015). Have health insurance reforms in Tunisia attained their intended objectives? *International Journal of Health Economics and Management, 15*(1), 29–51. https://doi.org/10.1007/s10754-014-9157-6

McIntyre, D., Thiede, M., Dahlgren, G., & Whitehead, M. (2006). What are the economic consequences for households of illness and of paying for health care in low- and middle-income country contexts? *Social Science & Medicine, 62*(4), 858–865. https://doi.org/10.1016/j.socscimed.2005.07.001

Ndonky, A., Loum, S., & Ndour, M. M. M. (2024). Geographical accessibility to basic infrastructures and services in rural Senegal: The case of the Niakhar area. *Journal of Geographic Information System, 16*(5), 343–366. https://doi.org/10.4236/jgis.2024.165021

Neutens, T. (2015). Accessibility, equity and health care: Review and research directions for transport geographers. *Journal of Transport Geography, 43*, 14–27. https://doi.org/10.1016/j.jtrangeo.2014.12.006

Nicholl, J., West, J., Goodacre, S., & Turner, J. (2007). The relationship between distance to hospital and patient mortality in emergencies: An observational study. *Emergency Medicine Journal, 24*(9), 665–668. https://doi.org/10.1136/emj.2007.047654

OECD & JRC. (2008). *Handbook on constructing composite indicators: Methodology and user guide*. OECD Publishing. https://doi.org/10.1787/9789264043466-en

Ouma, P. O., Maina, J., Thuranira, P. N., Macharia, P. M., Alegana, V. A., English, M., Okiro, E. A., & Snow, R. W. (2018). Access to emergency hospital care provided by the public sector in sub-Saharan Africa in 2015: A geocoded inventory and spatial analysis. *The Lancet Global Health, 6*(3), e342–e350. https://doi.org/10.1016/S2214-109X(17)30488-6

Penchansky, R., & Thomas, J. W. (1981). The concept of access: Definition and relationship to consumer satisfaction. *Medical Care, 19*(2), 127–140. https://doi.org/10.1097/00005650-198102000-00001

Polo, G., Acosta, C. M., Ferreira, F., & Dias, R. A. (2015). Location-allocation and accessibility models for improving the spatial planning of public health services. *PLOS ONE, 10*(3), e0119190. https://doi.org/10.1371/journal.pone.0119190

Qian, Y., Qiao, G., Li, T., & Ma, R. (2023). Measuring the healthcare spatial deprivation in multiple perspectives: A case study of Ningbo city. *Frontiers in Sustainable Cities, 5*, 1260892. https://doi.org/10.3389/frsc.2023.1260892

Rahman, S., & Smith, D. K. (2000). Use of location-allocation models in health service development planning in developing nations. *European Journal of Operational Research, 123*(3), 437–452. https://doi.org/10.1016/S0377-2217(99)00289-1

Runfola, D., Anderson, A., Baier, H., Crittenden, M., Dowker, E., Fuhrig, S., Goodman, S., Grimsley, G., Layko, R., Melville, G., Mulder, M., Oberman, R., Panganiban, J., Peck, A., Seitz, L., Shea, S., Slevin, H., Youngerman, R., & Hobbs, L. (2020). geoBoundaries: A global database of political administrative boundaries. *PLOS ONE, 15*(4), e0231866. https://doi.org/10.1371/journal.pone.0231866

Salhi, S., Bouirbiten, S., & Benhsain, W. (2023). Accès aux soins de santé : freins, défis et exigences d'équité territoriale. Le cas de la province d'Al Haouz, Maroc. *Geografares, 3*(37), 234–258. https://doi.org/10.47456/geo.v3i37.41510

Schuurman, N., Bell, N. J., L'Heureux, R., & Hameed, S. M. (2009). Modelling optimal location for pre-hospital helicopter emergency medical services. *BMC Emergency Medicine, 9*, 6. https://doi.org/10.1186/1471-227X-9-6

Seabold, S., & Perktold, J. (2010). Statsmodels: Econometric and statistical modeling with Python. In *Proceedings of the 9th Python in Science Conference* (pp. 92–96). https://doi.org/10.25080/Majora-92bf1922-011

Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal, 27*(3), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Stacherl, B., & Sauzet, O. (2023). Gravity models for potential spatial healthcare access measurement: A systematic methodological review. *International Journal of Health Geographics, 22*, 34. https://doi.org/10.1186/s12942-023-00358-z

Toregas, C., Swain, R., ReVelle, C., & Bergman, L. (1971). The location of emergency service facilities. *Operations Research, 19*(6), 1363–1373. https://doi.org/10.1287/opre.19.6.1363

Weiss, D. J., Nelson, A., Vargas-Ruiz, C. A., Gligorić, K., Bavadekar, S., Gabrilovich, E., Bertozzi-Villa, A., Rozier, J., Gibson, H. S., Shekel, T., Kamath, C., Lieber, A., Schulman, K., Shao, Y., Qarkaxhija, V., Nandi, A. K., Keddie, S. H., Rumisha, S., Amratia, P., … Gething, P. W. (2020). Global maps of travel time to healthcare facilities. *Nature Medicine, 26*(12), 1835–1838. https://doi.org/10.1038/s41591-020-1059-1

662 Zhan, L., Li, N., Li, C., Sang, X., & Ma, J. (2022). Evaluation method of equalization of basic
663 medical services from the spatial perspective: The case of Xinjiang, China. *ISPRS*
664 *International Journal of Geo-Information, 11*(12), 612. https://doi.org/10.3390/ijgi11120612

665 Zhu, Y., Tian, D., & Yan, F. (2020). Effectiveness of entropy weight method in decision-making.
666 *Mathematical Problems in Engineering,*