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Theoretical modelling of spatial accessibility in the management of stroke in Rhône county (France) and comparison with measured data

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Abstract

Introduction. Stroke is a leading cause of death and a major cause of irreversible sequelae. Stroke patients must be transported as fast as possible and their management should be as effective as possible. Firefighters transport a great proportion of these patients. Using a Geographical Information System can be a great tool to measure and predict travel times during stroke patient management.

Methods. This study modeled travel times from the nearest fire station to stroke patient using theoretical data sets in order to compare them. The results were then compared with the on the job data measured by the Departmental Metropolitan Fire and Rescue Service (SDMIS) from 2015 to 2016 for suspected stroke. This comparison assessed the feasibility of using a theoretical model to predict travel times based on real-life data.

Results. A strong correlation was observed between the different theoretical models for measuring accessibility to the nearest fire station, with a Root Mean Square Error (RMSE) about 1.5 minutes and Mean Absolute Percentage Error (MAPE) around 30%. However, when theoretical data sets were compared to measured data, the correlation was lower, the RMSE was six minutes and MAPE from 60% (minimal times) to 25% (median times). This is satisfactory results. Although the coefficients of correlation remain low, due to the high heterogeneity of the measured times. These differences of few minutes represented a very small portion of the stroke patient's care pathway.

Conclusion. Theoretical models were highly correlated and the correlation with the measured data was mostly correct. The few minutes difference between theoretical models and measured data could be explained by traffic hazards and organizational vagaries that always tend to disrupt modeling results. Using measured data was found to be very useful to perform theoretical model and to develop a robust model of stroke transportation.

Keywords : access time, stroke prehospital care, modeled, comparison, GIS

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1. Introduction

Stroke affects 150,000 new patients each year and can affect all major neurological functions: motor skills, sensitivity, language, vision, memory and executive functions (planning, anticipation, activity management (de Peretti et al., 2012)). Stroke is a major public health issue in developed countries, particularly because of their ageing population. France is not immune to the burden of this

45 disease : stroke **was** the leading cause of death among women (18,343 deaths) and
46 the third leading cause of death among men (13,003 deaths) in 2013 (Lecoffre et al.,
47 2017).

48 The **care pathway** of stroke patients consists of several sequences: the pre-
49 hospital phase, with an urgent transfer to a neurovascular unit (PSC), then acute
50 hospitalization, with emergency therapeutic management and, finally, return home
51 directly or after a stay in a generalist or specialized follow-up care and rehabilitation
52 (RRC) service. **Time management is of the essence during** the pre-hospital phase,
53 **as** the patient **needs to arrive** as soon as possible to receive treatment, thrombolysis
54 (within **4.5 hours** after the onset of symptoms) or thrombectomy (within **6-24 hours**)
55 (Powers et al., 2018). In the acute phase of stroke, **the patient** loses **two** million
56 neurons every minute and thus increases his chances of **sustaining** irreversible
57 sequelae (Saver, 2006).

58
59 Good access to health care services for **everyone**, regardless of geography,
60 remains a key objective of governments and societies worldwide (McGrail, 2012).
61 **Access** is essential in the case of stroke: the patient must be treated as soon as
62 possible and it is therefore important to know and optimize **their** trajectory during the
63 pre-hospital phase. Timely access to health services is a major determinant of
64 sequelae. **As per Humphreys definition** (Humphreys, 1998), health service planners
65 need accurate, reliable and rigorous **measures** to determine the spatial variation of
66 accessibility models. McGrail and Humphreys (McGrail and Humphreys, 2014)
67 explain that distance and geographic isolation are the first barriers to accessing
68 health care. Measuring accessibility can be a tool to identify areas to be monitored,
69 especially when the density of care services is low and could lead to inequalities in
70 access to treatment (Páez et al., 2013). **Therefore**, a geographical approach to
71 accessibility in **the case of** stroke is essential.

72 The measurement of accessibility is one of the key **concepts** of health
73 geography. **A** large number of studies **investigated** this concept, **covering** a wide
74 range of topics, **both from a geographical and contextual perspectives** (Page et al.,
75 2018). **Since the 1980s**, a large number of articles have been published on the
76 subject **in the field of access to health care**, and this number has sharply **increased**
77 since the 2000s (Apparicio et al., 2017).

78 Penchansky and Thomas (Penchansky and Thomas, 1981), **defined** the
79 concept of health accessibility **along** five dimensions: availability, geographic
80 accessibility, convenience (i.e. how the structure of care is organized), financial
81 capacity and acceptability. Thus, spatial or geographical accessibility is an important
82 component of the broader concept of access (Penchansky and Thomas, 1981). This
83 approach takes into account the multidimensional aspect of access to care (Wang
84 and Luo, 2005). Due to the complexity of the concept of access and its different
85 components, there are a number of approaches to **measure** access. Talen (Talen,
86 2003) **classified** accessibility measures into five types of approaches: container,
87 coverage, minimum distance, travel costs, and gravity-based measures. Similarly,
88 Guagliardo (Guagliardo, 2004) **summarized** the measurement of spatial accessibility
89 in four categories: provider-to-population ratios, distance to the nearest provider,
90 average distance to a set of providers, gravitational models of provider influence.

91 Many of these approaches simultaneously take into account the notion of
92 geographical accessibility and availability of the care service. This is the case, for
93 example, for gravitational models, the Two Step Floating Catchment Area (2SFCA)
94 method (McGrail, 2012) or Kernel density models (Guagliardo, 2004). These
95 calculation methods are often used for their high level of satisfaction in measuring
96 accessibility (Page et al., 2018). However, **it remains essential to measure** the
97 geographical accessibility of the nearest health care service, not associated with
98 availability. Since spatial accessibility is affected by factors such as the location of
99 the patient, the location of health care services and the road network used to travel
100 (Gharani et al., 2015), accessibility to the nearest service is an appropriate method.
101 Thus, "key spatial variables include distance and travel time between the residential
102 locations of potential patients in a region and the locations of health centers in their
103 region" (Joseph and Bantock, 1982).

104 Despite its many uses, measuring travel time to the nearest service has some
105 limitations because it only takes into account the proximity of a population to a
106 resource, regardless of the availability of that resource (depending on the number of
107 beds available for example and the size of the population pool concerned) (McGrail
108 and Humphreys, 2009). Since the **issue** of availability in our analyses of emergency
109 stroke treatment is only a secondary one, the measurement of access to each
110 potential community where a patient is cared for from the nearest **fire station** has
111 been selected.

112 **As** defined by Joseph and Phillips (Joseph and Phillips, 1984), **measured**
113 **accessibility** "refers to prospective levels of accessibility based on the analysis of
114 spatial patterns of physical access to services (rather than on patterns of service use;
115 accessibility "achieved")", thus informing "policy makers of potential disparities [...] **identifying areas where levels of accessibility are poor and targeted interventions needed**".
117

118
119 **This** study **modeled** travel times from the nearest fire station to **the** stroke
120 patient using data sets from different sources in order to compare them. The results
121 of these models are then compared with the **on the job** data measured by the
122 Departmental Metropolitan Fire and Rescue Service (*Service Départemental*
123 *Métropolitain d'Incendie et de Secours* (SDMIS)) in 2015 and 2016. This comparison
124 **was used to** assess the feasibility of using a theoretical model to predict travel times
125 based on **real-life data**. **Based on the results of this study, we hope in the long term**
126 **to provide the best possible picture of the current state of care with reliable travel**
127 **time data, in order to identify areas at risk of delayed care and access to treatment**
128 **and provide recommendations for the organization of the prehospital care at all**
129 **points of the network**.

130 However, **modeling** travel time to the nearest fire station raises the question of
131 the representativeness of the road network. Indeed, road networks are more or less
132 accurately **mapped** and detailed according to the service providers. In stroke care,
133 where every minute counts, it is essential to have the most efficient network analysis
134 model possible. Two main road networks **were available** (IGN *BDCarto* and *Multinet*
135 *TomTom*, **described** in the **methods** section), each with its own advantages and
136 disadvantages. The **second** section presents the **methods**, describing the selected
137 road networks, the procedures for modeling and creating isochrones, the SDMIS **jobs**

138 database of measured travels and the procedures for comparing modeling and
139 measurement results. The third section focuses on the results and their analysis,
140 while making recommendations for a better organization of stroke management.

141

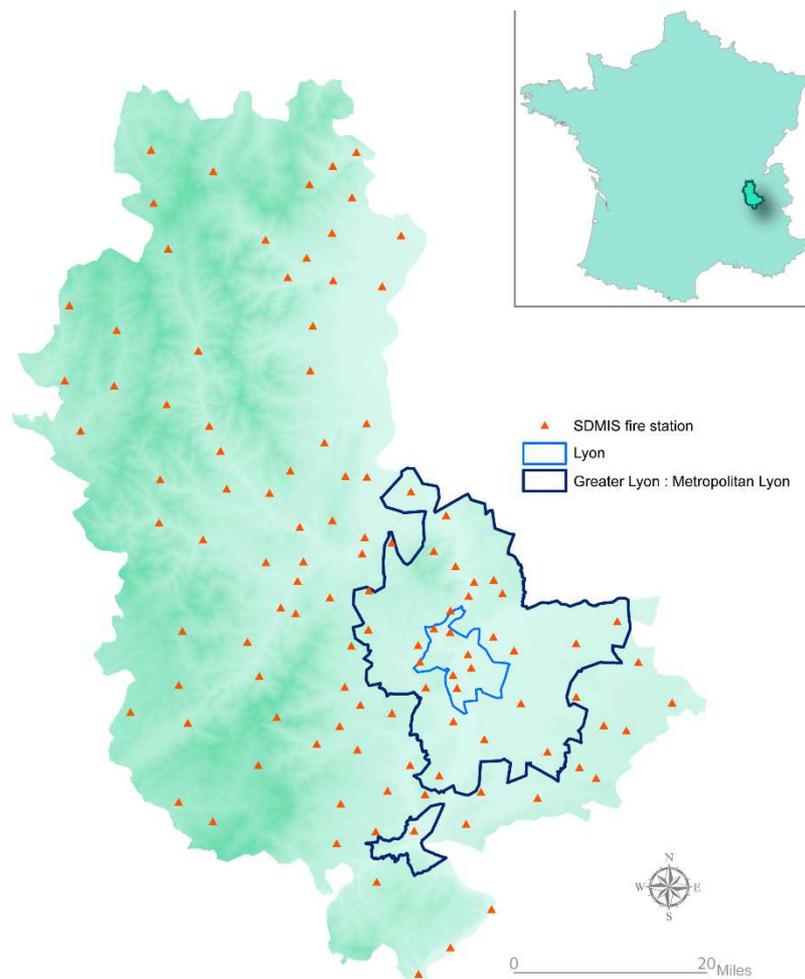
142 2. Material and methods

143 2.1. Study area

144

145 The analytical framework for this study was the Rhône department (one of the
146 96 administrative divisions of metropolitan France) (fig. 1), which corresponds to the
147 SDMIS service area. However, accessibility from each fire station took into account
148 the side effects linked to neighboring departments. The fire stations located in border
149 departments were taken into account for the calculation of isochrones. According to
150 the latest available census, the Rhône department had 1,798,511 inhabitants in 2014
151 (source: *Institut national de la statistique et des études*) for an area of 3,249 km². The
152 Rhône county is mainly composed by metropolitan Lyon, with 1,300,000 inhabitants,
153 organized into 59 municipalities (fig. 1), representing the most densely populated
154 territory in the department. It is the second largest urban area in France and a major
155 economic center in Southeastern France.

156



157

158 Figure 1: The Rhône department and its location in France – source: IGN

159

160 2.2. Stroke care by the SDMIS

161
162 In France, fire brigades are organized into SDIS (*Service Départemental*
163 *d'Incendie et de Secours*) at the department level. According to Article L1424-2 of the
164 General Code of Local Authorities, the SDIS provides emergency assistance to
165 victims of accidents and, natural disasters, as well as their evacuation. In addition,
166 according to article L1424-42, the SDIS can intervene at the request of the dispatch
167 centre of the Emergency Medical Service (EMS) (*Service d'Aide Médicale Urgente*
168 *SAMU*) when private health transporters are not available. In the Rhône department,
169 SDIS is called SDMIS because it covers the Rhône department and metropolitan
170 Lyon. The SDIS are classified into three categories, according to population size:
171 category A for a population \geq 900,000 inhabitants; category B for a population \geq
172 400,000 inhabitants and $<$ 900,000 inhabitants; category C for a population $<$
173 400,000 inhabitants. The SDMIS belongs to category A. The SDMIS has 110 fire
174 stations (fig. 1), divided into seven territorial groupings. Each territorial grouping is in
175 charge of one operational speciality, such as wildfire or rescue-clearing.

176
177 In the specific case of stroke management, 27% of patients were transported to
178 hospital by the fire brigade, compared to 36% by private ambulance or taxi, 20% by
179 their own means, 2% by EMS, and 15% undetermined (DREES, 2015). Dispatch is
180 typically decided by the EMS. Patients were transported by the closest provider
181 available. Firefighters transport many though not most patients. Patient transport is a
182 challenge for firefighters because of the increasing numbers of patients they manage,
183 as fire is no longer their main activity. We did not investigate private ambulances and
184 taxis because the relevant databases are not searchable.

185 186 2.3. Databases: modeling and jobs measures

187
188 The aim of our study was to compare different theoretical accessibility models
189 with measured jobs data to determine their validity, and, if applicable, which one is
190 the most relevant to measure access for a stroke patient.

191 192 2.3.1. Theoretical databases for spatial accessibility modeling: *BDCarto* 193 (IGN) and *Multinet TomTom* (ESRI)

194
195 The measurement of travel time over the network was complex and required
196 "the use of geometric network files containing traffic directions, speed limits,
197 turnaround restrictions and delays for each road segment" (Apparicio et al., 2008).
198 Two different types of road network databases were used in this framework. The
199 databases differed in their financial accessibility and exploitation.

200 201 2.3.1.1. *BDCarto*

202
203 *BDCarto* is an open access dataset for non-commercial use, which was
204 developed by the National Institute for Geographical and Forestry Information (*Institut*
205 *National de l'information Géographique et forestière* (IGN)). *BDCarto* maps all French
206 roads, with more than one million kilometers of network represented: highways,
207 national and departmental roads, residential and urban sections. However, this

208 dataset does not specify the speed limit allowed on each section. As speed limit
 209 could not be estimated from road type (Mao and Nekorchuk, 2013), a two-step
 210 process was carried out. Firstly, the *OpenStreetMap* collaborative database was
 211 used to extract the speed limit of 87% of roads in the Rhône department as listed in
 212 the *BDCarto* database. An estimation based on land use was made to complete
 213 missing data (13% of roads). We used the European land use database *CORINE*
 214 *Land Cover*: we attributed a speed limit of 50 kph (31 mph) to urban roads and 90
 215 kph (56 mph) to rural roads (Author et al., 2018).

216 In addition, it is physically impossible to maintain constant speed on the road,
 217 even with an SDMS vehicle which is allowed to disregard the highway code. Thus,
 218 we modeled four scenarios corresponding to different traffic conditions, management
 219 mode and weather conditions (Table 1). Scenario 1, corresponds to compliance to
 220 national speed limits. This was the basic scenario. For scenario 2, average
 221 ambulance speed was based on measured travel times compiled from the Rhône
 222 department's EMS registry, i.e. an average speed of 20 km/h above speed limit
 223 (Table 1).
 224

Scenario	Modeling	Speed	Justification of speed adaptations
Scenario 1	Initial database	Compliance to national speed limits	Private car complying to French Highway Code
Scenario 2	Emergency transport	20 kph (12 mph) above speed limit throughout the road network	Analysis based on the Rhône department's SAMU stroke jobs between 2012 and 2016, and Petzäll et al (2011) (Petzäll et al., 2011) study
Scenario 3	Difficult weather conditions (rain, fog, snow)	20 kph (12 mph) below speed limit throughout the	Compliance to Article R413-2 of the French Highway Code in the

		road network	case of severe weather conditions
Scenario 4	Emergency transport with traffic congestion in metropolitan Lyon	20 kph (12 mph) below speed limit in metropolitan Lyon network (59 municipalities), 20 kph (12 mph) higher than speed limit elsewhere	Petzäll et al (2011) (Petzäll et al., 2011) study and SAMU jobs analysis for 20 kph above speed limit and SAMU jobs analysis during traffic congestion for 20 kph below speed limit

225 Table 1: Scenarios built from the open access database for non-commercial use
226 *BDCarto*

227

228

2.3.1.2. Multinet Tomtom

229

230 The second source for theoretical road network data used was the *Multinet*
231 *Tomtom* database (MultiNet® EUR 2015.06, Version - V1.0) (Esri - GIS Mapping), a
232 commercial data set developed by ESRI. This dataset covers the entire road network
233 in France. In addition, it contains a traffic history (weekday, weekend, precise
234 schedules) as well as speed limits depending on different modes of transport (private
235 car, taxi, bus, bicycle, walking). As with the *BDCarto* database, scenarios were
236 calculated based on traffic conditions (Table 2).

237

Scenario	Modeling	Speed
Scenario A	Weekday (Monday to Friday) with heavy traffic (06:00 – 09:00 et 16:30 – 18:30)	Lower than the usual limit due to traffic congestion. Speed varies depending on the

		traffic history reported in Multinet. E. g. a section of road with a speed limit of 90 kph (56 mph) can have a reported speed of 50 kph (31 mph), especially in urban areas.
Scenario B	Weekday (Monday to Friday) with normal traffic (09:00 – 16:30)	Speed varies depending on the traffic history reported in Multinet for Monday to Friday outside of rush hours.
Scenario C	Weekend	Speed varies depending on the traffic history reported in Multinet for Saturday to Sunday.

238 Table 2: Scenarios built from *Multinet Tomtom* commercial database

239

240 The models from the two databases were then compared with the data measured in
241 the field during SDMIS in the field.

242

243 2.3.2. Measured data of travel times in SDMIS jobs

244

245 The models of travel times were compared with the SDMIS in the field
246 measures. These measurements were performed as part of SDMIS jobs for
247 suspected stroke between January 1, 2015 and December 31, 2016 inclusive. A total
248 of 2,886 measures were identified. For each job compiled in the register, the
249 departure fire stations and the municipality of arrival were known as well as the travel
250 time. Each trip was made with a Victim Assistance and Rescue Vehicle (*Véhicule de*
251 *Secours et d'Assistance aux Victimes* (VSAV)). This type of vehicle can transport a

252 patient with medical equipment and is not subject to traffic regulations (speed limits,
253 traffic lights, right of way, etc.).

254

255 2.4. Comparing modeled data with measured data: spatial and statistical
256 analysis

257 2.4.1. Spatial analysis with GIS

258 This part aimed to model access times at any point in the territory from the 110
259 fire stations of the Rhône department's SDMIS. Initially, the fire stations were
260 geolocated according to their exact postal address using a Geographical Information
261 System (GIS). The GIS software used for this project was Environmental Systems
262 Research Institute (ESRI) ArcMap, version 10.5.1 ("Esri - GIS Mapping Software,
263 Solutions, Services, Map Apps, and Data," n.d.). All accessibility measures were
264 calculated using the network analyst extension available in ArcGIS™. Then, the
265 modeling was carried out using isochrones, i.e. lines representing areas of equal
266 travel time from the fire stations of the study area (fig. 2), using the existing road
267 network. For each model, we drew a 1-minute travel time isochrone for each fire
268 station in the department (§ 2.3.1.1.1 and 2.3.1.2).

269

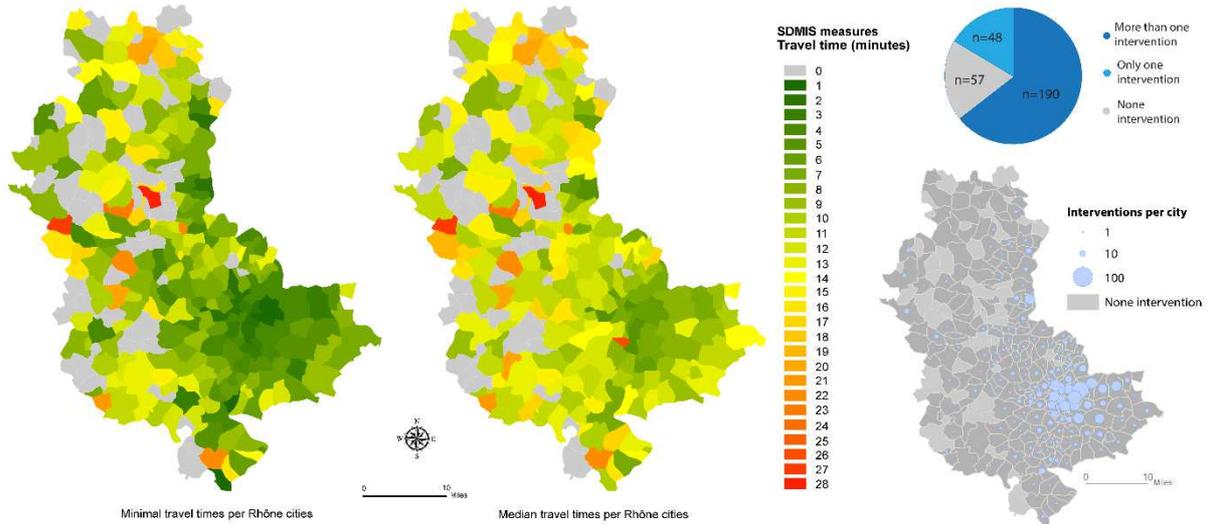


270

271 Figure 2: The Rhône department's accessibility measure from fire stations to patients
272 with acute stroke (BD Carto maps: 1. Compliance to speed limit, 2. emergency
273 transport, 3. difficult weather conditions, 4. emergency transport with traffic
274 congestion; and Multinet Tomtom maps: A. weekday heavy traffic, B. weekday free-
275 flowing traffic, C. weekend regular traffic)

276

277 Then, the modeled isochrones **were** compared with the measured travel times.
 278 From 1 January 2015 to 31 December 2016, several **jobs** were compiled for the
 279 same municipality. As a result, there **were** several measured **travel times** for **each**
 280 municipality. **We used** the minimum travel time and the median travel time. Finally,
 281 **we compared** the modeled travel times for each of the municipalities where
 282 measured time information **was** available (i.e. 238 out of the 295 municipalities in the
 283 **department**; fig. 3). For the comparison, **we used** the isochron located on the centroid
 284 of the **municipality**.
 285



286
 287 Figure 3: Minimum and median travel time measured by municipality on the basis of
 288 2886 SDMIS **jobs**.
 289

290 2.4.2. Statistical comparison of models to measures

291
 292 To **compare** accessibility models to measured, **we used** a correlation
 293 coefficient (Apparicio et al., 2008). Normality was **checked** using the Shapiro-Wilk
 294 test (Shapiro and Wilk, 1965). "The correlation coefficient gives an indication of the
 295 level of good fit" between the different measurement models (Apparicio et al., 2003).
 296 **As our sample was not normally distributed, we used** the Spearman coefficient, a
 297 non-parametric test. The Spearman coefficient **uses** the observations' rows and thus
 298 **makes** it possible to measure the level of linear relationship between rows. **The**
 299 correlation coefficient **varied from -1 to 1**, a positive value **indicating** a positive
 300 correlation, **while a** negative value **indicates** a negative correlation. A value close to
 301 zero **indicates an** absence of linear correlation. **A p-value < 0.05 was considered**
 302 **statistically significant**.
 303

304 In addition to the correlation coefficient, performance of the different models
 was assessed using the following three measures (Willmott, 1981) :

305 Mean **squared** error (MSE) = $\frac{1}{W-p*} \sum_{i=1}^n w_i (y - \hat{y}_i)^2$

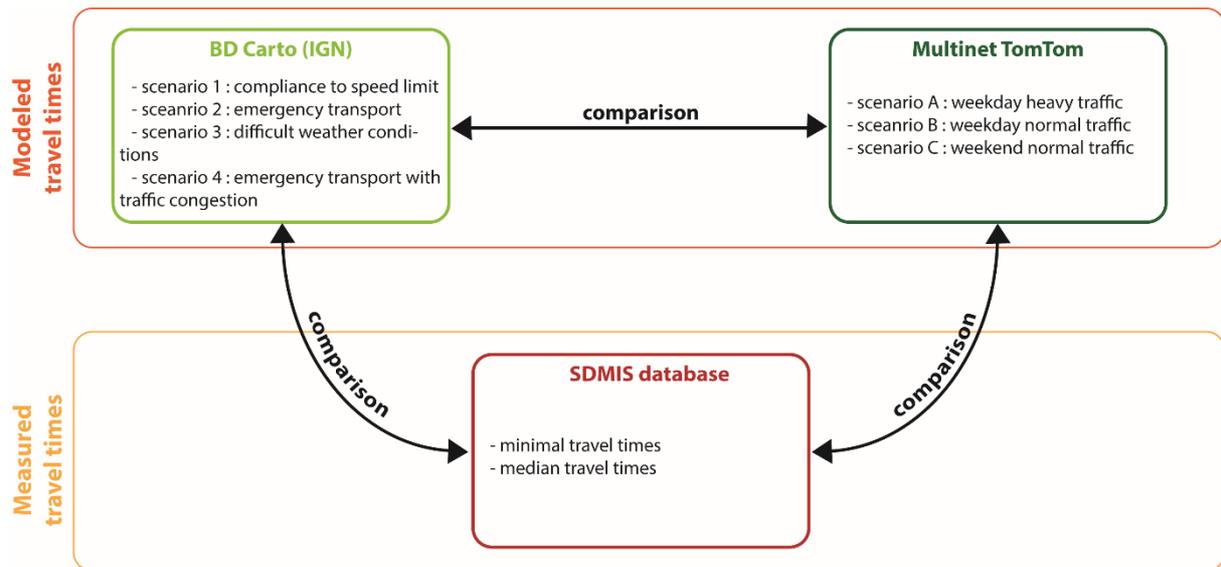
306 Root Mean Square Error (RMSE) = $\sqrt{\frac{1}{W-p*} \sum_{i=1}^n w_i (y - \hat{y}_i)^2}$

307 Mean Absolute Percentage Error (MAPE) = $\frac{100}{W} \sum_{i=1}^n w_i \left| \frac{y_i - \hat{y}_i}{y_i} \right|$

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Where y = model predicted value (real time), y_i = observed value (measured theoretical time), n = number of observations.

Models performance **was** evaluated against the measured data. In a complementary way, the modeled results from the two databases **were** compared with each other (fig. 4). Statistical analyses were carried out using XLSTAT software, version 2019.1.2 (Addinsoft (2019). XLSTAT statistical and data analysis solution. Long Island, NY, USA. <https://www.xlstat.com>).



317
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Figure 4: Diagram of database analysis

320 As traffic conditions outside Lyon **are** not **similar to those** in dense urban areas,
321 statistical analyses were carried out on a global scale throughout the Rhône
322 **department, as well as** on a more local scale (metropolitan Lyon).

323
324

3. Results

325
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3.1. Comparison of the results from the two theoretical models

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Our study **aimed** to compare different theoretical accessibility models with measured SDMIS **jobs** data. Before meeting this objective, a first comparison was made between the models in order to evaluate the performance of the model founded on the open access dataset for non-commercial use *BDCarto* compared to the *Multinet TomTom* commercial model. For this purpose, the performance indicators described above were used (Table 3). *Multinet TomTom*'s three scenarios were compared to the four scenarios from *BDCarto*, on the scale of the Rhône **department** and **Greater Lyon**.

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A strong correlation was observed between the models measuring theoretical accessibility at the **scale of the department** (Table 3). The maximum RMSE between the scenarios of the two models **was** 2.2 minutes for scenario 4 of the IGN when compared to scenarios **A** to **C** of Multinet. Similarly, the lowest Spearman coefficient **was** found for the latter, with values between 0.62 and 0.63. The other scenarios **were** very strongly correlated with RMSEs about 1.5 minutes (e.g. scenarios 1, 2 and

341 3 and scenario A) and Spearman's rho of about 0.85 (Table 3). On the scale of
342 Greater Lyon, the observation was similar with very small differences between the
343 models (RMSE of about 1.5 minutes) and high Spearman's rho around 0.7 (table 3).
344 From 25 to 30 %, MAPE confirmed the results of RMSEs and Spearman's rho.
345 For Greater Lyon models and for scenario four (both scales), correlations were lower.
346 This was due to the heterogeneity of dense traffic. MAPEs were also worse for
347 scenario 4, explained by the traffic.

			Rhône department				Greater Lyon			
			BD Carto modeling							
			scenario 1 (compliance)	scenario 2 (+12 mph)	scenario 3 (-12 mph)	scenario 4 (traffic congestion)	scenario 1 (compliance)	scenario 2 (+12 mph)	scenario 3 (-12 mph)	scenario 4 (traffic congestion)
Multinet TomTom modeling	Scenario A (weekday heavy traffic)	MSE	2.1	2	2.4	4.8	2.3	2.4	2.2	2.8
		RMSE	1.4	1.4	1.5	2.2	1.5	1.5	1.5	1.7
		MAPE	24.4	27.1	26.5	46.1	28.2	31.6	25.2	35
		Spearman coefficient	0.86	0.85	0.84	0.63	0.73	0.74	0.73	0.67
	Scenario B (weekday normal traffic)	MSE	2	1.9	2.3	4.7	2.1	2.2	2.0	2.5
		RMSE	1.4	1.4	1.5	2.2	1.4	1.5	1.4	1.6
		MAPE	24	26.1	26.2	46.2	27.6	30.8	25.3	33
		Spearman coefficient	0.87	0.86	0.85	0.63	0.73	0.73	0.71	0.67
	Scenario C (weekend)	MSE	2	2	2.3	4.8	2.4	2.6	2.1	2.8
		RMSE	1.4	1.4	1.5	2.2	1.5	1.6	1.5	1.7
		MAPE	24.3	26	26.5	47.3	27.4	30.8	24.9	32.5
		Spearman coefficient	0.87	0.86	0.85	0.62	0.75	0.74	0.74	0.68

349 Table 3: Spearman correlation and performance metrics of open access database model v. commercial database model

351 3.2. Comparison of the results from the two theoretical models to measured data

352

353 From the outset, Spearman's coefficients were low between the models and
354 the measured times, both at the scale of Rhône department or that of Greater Lyon.
355 However, the RMSE study for the Rhône department indicated that all the differences
356 between the modeled and measured minimum and median times ranged between
357 5.6 and 5.8 minutes (Table 4). The MAPEs at the scale of Rhône department were
358 around 57% for the measured minimum times, but for the median measured times
359 they were around 26%. While the RMSEs were similar between minimum and
360 median measures, the MAPE suggested that the percentage error between
361 theoretical models and median travel times was lower. The RMSEs for Greater Lyon
362 were even lower, with Spearman's rho slightly higher. The RMSEs for modeled vs.
363 minimum measured travel time were 2.9 or three minutes. The RMSEs for median
364 times ranged between three and 3.1 minutes. For MAPEs, the observation is
365 identical that at the scale of Rhône department. Regardless of scale, the differences
366 in estimates between the models were minimal.

		Rhône department							Greater Lyon						
		BD Carto modeling				Multinet TomTom modeling			BD Carto modeling				Multinet TomTom modeling		
		scenario 1 (compliance)	scenario 2 (+12 mph)	scenario 3 (-12 mph)	scenario 4 (traffic congestion)	scenario A (weekday heavy traffic)	scenario B (weekday normal traffic)	scenario C (weekend)	scenario 1 (compliance)	scenario 2 (+12 mph)	scenario 3 (-12 mph)	scenario 4 (traffic congestion)	scenario A (weekday heavy traffic)	scenario B (weekday normal traffic)	scenario C (weekend)
SDMIS (minimal traveltime)	MSE	31.4	31.4	31.5	31.5	31.5	31.5	31.5	8.7	8.7	9	8.9	9	8.9	9
	RMSE	5.6	5.6	5.6	5.6	5.6	5.6	5.6	3	2.9	3	3	3	3	3
	MAPE	56.6	56.3	57.4	57.8	57.5	57.4	57.4	63	62.6	62.8	62	63.2	63.4	62.9
	Spearman coefficient	0	0.04	-0.04	-0.07	0.02	0.02	0.02	0.1	0.2	-0.01	-0.1	-0.01	0.01	0
SDMIS (median traveltime)	MSE	34	34	34	34	33.9	33.9	33.9	9.2	9.1	9.7	9.9	9.9	9.8	9.9
	RMSE	5.8	5.8	5.8	5.8	5.8	5.8	5.8	3	3	3,1	3,1	3,1	3,1	3,1
	MAPE	26.9	26.9	26.8	26.7	26.6	26.6	26.6	27	26	26.5	25.7	26.3	26.4	26
	Spearman coefficient	0.04	0,07	0	-0.02	0.03	0,03	0.03	0.2	0.23	0.07	-0.03	0.02	0.04	0.02

368 Table 4: Spearman correlation and performance metrics of database models compare to SDMIS travel times (minimal and median)

4. Discussion

Measuring accessibility is a complex concept. The study compared travel time for stroke management in models using two databases vs as measured on the job, with the aim of generalizing a theoretical model to a territory that does not have reliable field surveys. We investigated travel times from the nearest fire station to stroke patient, complementing our previous study (Author and al, 2018) on time of care, time to dispatch and time spent on scene. The present study compared theoretical models with actual data to determine the feasibility of using theoretical databases to estimate travel time. So, only one travel time out of the total duration of the care was sufficient, since the purpose of this study was to estimate the travel time of a vehicle. The first step of this study was to measure theoretical accessibility. We compared theoretical models to assess the performance and validity of using a model based on open access data for non-commercial use. In the second step, we measured the performance of the theoretical accessibility models against the SDMIS data.

The theoretical model built from *BDCarto* was strongly correlated to the commercial model. The most correlated scenario was that of a 12 mph increase in speed compared to the commercial scenario of normal traffic on a weekday, with a RMSE of 1.4 minutes in the Rhône department. However, all the scenarios were very similar. This may seem surprising but the small size of the study area combined with relatively small differences in scenarios explains this homogeneity. The theoretical model developed from *BDCarto* was found to be a reliable tool for modelling theoretical spatial accessibility and a good alternative to a paid model.

The comparison of the theoretical models' performance with real SDMIS job data led to several interesting conclusions. First, the RMSEs between the models and the minimum measured times were low: about 5.6 minutes at the scale of the Rhône department and three minutes at the scale of Greater Lyon. The same was true for median times, with very slightly higher RMSEs. This can be explained by the higher variability of median travel times compared to minimum times. Indeed, to get to a given place, travel time can vary by up to a factor of two, which explains the better performance of the models with regard to minimum times, which are the optimal times for jobs. MAPEs confirmed that minimum times are optimal times for jobs, because the percentage error is higher (60%) for minimal times than median times (26%). However, the differences between modeled and measured travel times remain acceptable from the point of view of patient management. Indeed, a maximum approximation of six minutes when managing a patient as part of his care pathway (transport, imaging and treatment) remains minimal.

The coefficients of correlation were low because, for many municipalities, the modeling was different from the measured value. In some municipalities, there was a wide dispersion of time in relation to a given interval of access time. However, compared to the RMSEs and MAPE, this low correlation should be put into perspective, as dispersion of travel times was found in RMSEs of around six minutes. The correlations might have been better if we had sampled the measured data in weekdays (48 %, n= 2035), weekend (20 %, n= 827) and days of difficult weather (32

415 %, n= 1350) and compared the corresponding theoretical models. However,
416 modeling reality remains challenging.

417 Secondly, it appears that the differences between the different scenarios of the
418 theoretical models compared to the measured data were low. This can be explained
419 similarly with the small size of the study area and small differences between traffic
420 speeds.

421
422 In order to optimize modeling results, a number of additional factors should be
423 taken into account. These are mainly related to traffic conditions and vehicle type.
424 The random aspect of traffic conditions is part of the measured data of travel time on
425 the field of the SDMIS, which is an inherent limitation of the theoretical models.
426 Considering the difficulty of predicting traffic incidents, one possible improvement of
427 the theoretical model from *BDCarto* could be to develop a scenario based on an
428 estimate of the average traveling speed of an SDMIS vehicle.

429
430 However, there are limitations regarding representativeness and
431 exhaustiveness of the travel times measured by SDMIS. Indeed, there is a wide
432 dispersion of travel times to access the same municipality (see above). This variation
433 can be explained by the large fluctuation in traffic conditions over time, and it cannot
434 be easily anticipated.

435
436 Furthermore, the quality of the measures also raises concerns. Some of the
437 data in the SDMIS jobs register seems to be improper. Delays seem unusually high.
438 For example, the municipality of Oullins was reached in 23 minutes, while the median
439 time was nine minutes and the minimum time was four minutes. For Rillieux-la-Pape,
440 the minimum time was three minutes, the median seven minutes and the maximum
441 time 25 minutes. However, these differences could be explained by very difficult
442 traffic conditions at certain times, such as traffic incidents.

443
444 In addition, the method used to measure travel time is debatable. Travel time
445 was measured from the moment the vehicle was started. A delay between the start of
446 the measurement, i.e. when the vehicle is started, and the movement of the vehicle
447 could exist. This time is thus added to the real travel time on network between fire
448 station and patient location. So, in some case, the time analyzed in our study was not
449 exact.

450
451 Another explanation for this variability may lie in the very organization of the
452 SDMIS in the Rhône department. Outside of urban areas, firefighters are volunteers
453 and most of them are not on call at the fire station. The high extreme values of the
454 sample could be explained by the time it may take for some firefighters to reach the
455 response vehicle at the fire station.

456
457 Finally, the size of the sample and its representativeness must be taken into
458 consideration. Indeed, the SDMIS jobs data analyzed are those of two calendar
459 years. While 2886 measures may seem a relatively representative sample, 57
460 communes did not have associated measured data and 48 communes had only one
461 measure. All these communes are located outside Greater Lyon, with lower

462 residential densities, which reduces the probability of an SDMIS jobs and thus
463 decreases the representativeness of the measures.

464

465 5. Conclusion

466

467 The primary objective of this study was to model travel times from the nearest
468 fire station to a stroke patient using different data sets. The results of the models
469 were compared with the data measured in the field during jobs by SDMIS. The
470 purpose of this comparison was to evaluate the performance of the models in relation
471 to the reality of the field when managing stroke patients.

472

473 The results of the two theoretical models were very strongly correlated with
474 each other, with modeling based on open access data playing equal parts with the
475 commercial model, with travel time differences of around one minute. Comparing of
476 modeled isochrones to measured times provided satisfactory results with differences
477 of only a few minutes, which represents a very small portion of time during the stroke
478 patient's care pathway. However, Spearman's correlations were low because the
479 modeled travels were different from the measured values in some municipalities. This
480 is explained by the dispersion of these times. But this dispersion is not very important
481 since the RMSEs are about six minutes. A discretization of the real data according to
482 the different scenarios (weekend, weekday, weather conditions) modeled could
483 improve the correlation. Modeling reality remains a very complex exercise as traffic
484 hazards and organizational imponderables disrupt modeling results. Collecting and
485 relying on real travel time data such as that of the SDMIS is essential to developing
486 and validating a relevant predictive model of stroke management travel times.

487

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