Activity-specific mobility of adults in a rural region of western Kenya

Jessica R. Floyd[1], Joseph Ogola[2], Eric M. Fèvre[2,3], Nicola Wardrop[4], Andrew J. Tatem[1], Nick W. Ruktanonchai[1]

[1]WorldPop, Department of Geography and Environmental Science, University of Southampton, Southampton, UK
[2]International Livestock Research Institute, Nairobi, Kenya
[3]Institute of Infection and Global Health, University of Liverpool, UK
[4]Department for International Development, Glasgow, UK

Corresponding Author:
Jessica R. Floyd[1]
University Road, Southampton, SO17 1BJ, UK
Email address: jrf1g15@soton.ac.uk

Abstract

Improving rural household access to resources such as markets, schools and healthcare can help alleviate poverty in low-income settings. Current models of geographic accessibility to various resources rarely take individual variation into account due to a lack of appropriate data, yet understanding mobility at an individual level is key to knowing how people access their local resources. Our study used both an activity-specific survey and GPS trackers to evaluate how adults in a rural area of western Kenya accessed resources in their local area. We calculated the travel time and time spent at six different types of resource and compared the GPS and survey data to see how well they matched. We found links between several demographic characteristics and the time spent at different resources, and that the GPS data reflected the survey data well for time spent at some types of resource, but poorly for others. We conclude that demography and activity are important drivers of mobility, and a better understanding of individual variation in mobility could be obtained through the use of GPS trackers on a wider scale.

Introduction

Population mobility is a complex process with great importance in many fields across the social and health sciences(1–3). Often, people travel because of specific resource needs or activities such as gathering food and water, livelihood and occupational activities, or accessing healthcare. In low-income settings, travel to these resources can be very time-consuming or expensive meaning that people may forego healthcare, employment, or other resources. As a result, the geographic inaccessibility of vulnerable populations can lead to worse health outcomes, a poorer economic outlook, and can widen spatial inequalities(4–6). In Kenya, resource access is particularly important for poverty reduction in rural populations, as people often have to travel further for resource-related activities than their urban counterparts. It is widely accepted that people in rural areas spend more time accessing resources than people in urban areas, and that this likely contributes to poverty in these areas. For example, market access is important for several household activities such as gathering food, selling crop surpluses and buying medicine, and studies have shown that poor market access contributes to poverty in rural areas(7). Similarly, poor water source access means reduced time for making money elsewhere and therefore contributes to household poverty, as well as being linked to poor health(8,9).

Geographic inaccessibility of healthcare is also a known driver of poor health outcomes, particularly in rural settings(10,11). Government policies in Kenya have responded accordingly, through measures designed to ensure that everyone lives within 5km of basic healthcare services. In 2003 it was estimated that 82% of the population live within 5km of a primary healthcare and referral service(12). Because geographic accessibility is vitally important for ensuring vulnerable populations can utilise healthcare, a significant body of recent research focuses on modelling accessibility across national scales. Often, these accessibility models assume that people visit their nearest clinic(13), using accessibility surfaces or straight-line distances to predict clinics used and associated travel times. In reality, geographic accessibility remains highly heterogenous

60 across the country despite new clinics in resource-poor areas(14), and straight-line distance is not
61 the only factor that impacts whether people can access healthcare in a reasonable time without
62 undue expense. Other factors such as poor road quality and lack of public transport options can
63 severely impact mobility and therefore healthcare access in rural areas where the most vulnerable
64 populations live(15,16). In Kenya, recent studies have found that people often visit clinics other
65 than their nearest one, for reasons such as the availability of medicines or the perceived
66 effectiveness of the facility(17). One study found that only 54-63% of people surveyed visited
67 their nearest facility, with the rest visiting other clinics(18).

68

69 Moreover, resource-related movement is quantitatively different from other types of mobility, so
70 accessibility models that predict general mobility patterns may not accurately reflect resource
71 seeking behaviour. For example, a recent study in Iquitos, Peru found that residents moved
72 significantly further for commercial and familial reasons than for healthcare(19).
73 Sociodemographic factors could also influence mobility and resource-specific movement:
74 household income, rural/urban context(20) and gender are all important determinants of
75 mobility, but spatial models of access often lack this demographic information, assuming that all
76 adults access resources such as markets and health facilities identically, regardless of
77 socioeconomic context. More detailed movement datasets could help improve these models by
78 providing evidence to support or reject these key assumptions and better understand how
79 movements driven by different activities vary.

80

81 Additionally, mobility studies typically focus on single types of resource access without
82 comparing against travel of other types(21)·(22), particularly in a rural context where activity-
83 dependent mobility models could provide a richer picture of how people spend their time, and
84 how resource-specific movement could exaggerate or mitigate geographic inaccessibility.
85 Traditionally, studies of individual mobility have relied on survey methods, which may be
86 affected by recall bias(23). In recent years, specialised tools such as personal Global Positioning
87 System (GPS) tracking devices employed at a household level have facilitated the collection of
88 detailed movement information(24–26). Personal GPS trackers have been used in urban and rural
89 settings to document the movements of both humans and animals in a variety of contexts, from
90 investigating the diving behaviour of certain species of birds(27,28) to the social structures of
91 cattle in pastoral communities(29) to detailed human movements in urban settings(25). With
92 good portability, weight and battery life, this type of tracker has also been used in research into
93 healthcare access(30) and vector-borne disease(24,25). Given the growing populations in rural
94 areas of lower-income countries, detailed knowledge of activity spaces and health facility access
95 in a rural context could have benefits for better understanding specific types of resource access.

96

97 Here, we use surveys of people in a rural area of western Kenya to capture movements to and
98 time spent on different types of activity, and examine links between these and demographic
99 characteristics. We use GPS trackers to explore where the same people spent their time outside

100 of their households. We then compare these two sources of data to see how well they capture
101 proportions of time spent on different types of activity. . The results from this study shed light on
102 the activity spaces of people in relation to resource access in a resource-poor setting and provide
103 evidence for how well GPS trackers are able to capture daily activities compared to survey
104 methods. They also help quantify the importance of including sociodemographic and activity-
105 specific movement into geographic accessibility models, particularly for healthcare
106 infrastructure.
107
108

Materials & Methods

Study area and population

This study was conducted in the densely populated county of Busia in the Lake Victoria basin
region of western Kenya (*Fig. 1*). Busia county has a population of just under one million
people(31), of whom approximately 80% live in rural areas (as defined by the latest DHS survey)
and practice smallholder subsistence farming, mainly operating mixed crop-livestock systems
with 60% of households in rural areas owning cattle(32).

We used a clustered random sampling strategy to select 55 households to visit and survey in
Busia county. Of the 181 sublocations in the county, 11 were selected at random and within these
we selected five households for participation in the study, by randomly generating coordinates
within each sublocation, and choosing the household closest to each of the coordinates, up to 200
metres. A surplus of coordinates (up to ten) were generated in each sublocation, so that if a
household could not be identified within 200 metres, the next set of coordinates were used. We
used QGIS software tools(33) for the random selection of sublocations and coordinates. Due to
the lack of appropriate data to base a sample size calculation on, we chose to sample 55
households from a broad geographical range based on the manpower and time available for
fieldwork while optimising the use of the limited number of GPS trackers. We selected 30 of the
55 households for GPS tracking because this was the maximum number of people that could be
tracked for a full week with the resources available.

Households were selected if they were the main residence of at least one consenting adult present
at the time of the visit. Inclusion criteria for participation were consenting adults aged 18 years
or over who were present at the time of the visit. Some demographic characteristics of the study
population are given in *Table 1*. If the household declined to participate in the study, the next
household closest to the coordinates was visited. All adults within a household were selected for
participation in the survey, but only the adult who spent most time looking after livestock
(determined from survey responses and verbal discussion) was selected for participation in the
GPS tracking. If the household had no livestock, the head of the household (determined by
verbal communication) was selected instead. These choices enabled analysis of the activities of
populations that spent time with livestock and therefore may be at higher risk of some zoonotic

140   diseases. This limits the representativeness of the sample population, but we felt this was
141   acceptable given the small sample size.
142
143   *Data collection - survey*
144   A structured survey with closed and open questions was administered to all consenting members
145   aged 18 years or over present in the household at the time of visiting (see supplementary
146   information). The survey included questions on demographic characteristics, regular movements
147   outside of the household and activities involving livestock. For movements to places outside the
148   household, we asked about the type of place visited (e.g. school, water source, place of worship,
149   market etc.), how often the respondents visited, the mode of transport used and time spent
150   travelling, and how long they usually spend there. The types of places were pre-defined based on
151   information from previous studies in this area(34,35), and the survey included open-ended
152   questions to identify any other significant types of place. A village elder was present to facilitate
153   introduction to the household and explanation of the study. The survey was written in English
154   and administered through an interpreter. The survey included 10 closed-ended questions from the
155   Poverty Probability Index for Kenya(36). The answers to these questions were scored to obtain a
156   basic index of household wealth which was used to compare relative wealth between households.
157   The answers to the survey, including collection of GPS coordinates to determine household
158   location, were collected on a tablet using a custom-designed survey built with OpenDataKit
159   (ODK)(37) software and uploaded to a secure server once an internet connection could be
160   established.
161
162   *Data collection – GPS data*
163   During the same visit, the consenting participant was given a GPS tracker (i-gotU GT-600 by
164   Mobile Action(38)) to wear for one week, fitted to a lanyard, which could be worn around the
165   neck or carried in a pocket. We chose this length of time based on previous studies(39,40) and to
166   maximise the use of our limited number of GPS trackers. The time interval used on the trackers
167   was one minute and the devices were programmed to power off if stationary for two minutes,
168   then turn on again when movement was detected. At the end of the week, the researchers
169   returned to the household to collect the trackers and download the data.
170
171   The data collection was conducted in two phases: household survey and GPS tracking in
172   July/August 2016, followed by GPS tracking only in November/December 2016. In phase two,
173   the same households were visited as in phase one and the GPS tracking was repeated with the
174   same participants where possible, in order to capture potential differences in movement patterns
175   during different seasons, henceforth called the short rainy season (July/August 2016) and the dry
176   season (November/December 2016) in accordance with climate classifications for this region of
177   Kenya(41). Of the 26 trackers given out in each season, one device was unrecoverable and two
178   suffered battery issues during the week (these weeks were therefore repeated).
179

180 *Data analysis*
181 The survey and GPS data were downloaded in .csv format, then cleaned and analysed using R
182 version 3.1.1 software(42). Erroneous points in the GPS data were identified by their unlikely
183 speeds and deleted using functions from the *trip*(43) package. A linear interpolation algorithm
184 was then applied to obtain locations at regular intervals. Erroneous points can occur due to
185 changing atmospheric conditions and building obstructions, and accounted for less than 1% of
186 the dataset. We used survey response, GPS points collected in the field and publicly available
187 datasets of health facilities (44) to group the places where people spent time into six categories:
188 household or residential places;, shops and markets; places of worship; health facilities; places
189 where livestock activities occurred; and places where activities related to water (but not
190 livestock) occurred. A central GPS point was identified for each of the places, and a 25-metre
191 radius around that point was used to determine when that place was visited by a person, defined
192 as 5 minutes or more spent within that radius. Due to their larger size, a radius of 50 metres was
193 used for market centres.
194
195 We conducted univariable analyses using linear mixed models for the three movement measures
196 calculated from survey responses (frequency of visits, time spent travelling and time spent at
197 places). We log transformed these data to ensure an approximately normal distribution and used
198 linear models to examine their relationships with the covariates. Because of the hierarchical
199 nature of the data (individuals nested in clusters, with repeat measurements per individual), we
200 used linear mixed models (LMMs) which had the individual household nested within the
201 sublocation as a random effect, to account for variation between individuals from different
202 households and within different sublocations. Variables were chosen for analysis in line with
203 those found to be important to movement metrics in previous studies in the area(34,35,45).
204
205 **Ethics statement**
206 This study was approved by the Institutional Research Ethics Committee and the Institutional
207 Animal Care and Use Committee of the International Livestock Research Institute (IDs: ILRI-
208 IREC2016-11; IACUC-RC2016-14; committees approved by the Kenya National Commission
209 for Science, Technology and Innovation (NACOSTI)) and the Ethics and Research Governance
210 board at the University of Southampton (ID:18984). All participants provided signed, informed
211 consent for their participation in the study and the data were stored securely in accordance with
212 the University of Southampton data storage policy.
213
214 # Results
215
216 We used the survey data to explore where people spent most of their time, how long they took to
217 get there and how long they stayed when visiting places outside of the household. When
218 examining the places people travelled to regularly, we found substantial variation in the
219 frequency of visits to different types of places compared to healthcare visits (*Fig. 2*). As

220   expected, participants visited health facilities less often than other types of locations, the mode
221   being three to six visits a year with very few visiting more often than monthly. Visits to areas
222   where livestock activities occurred (such as grazing pastures) and to water sources were the most
223   polarised out of all types of travel, with most visits occurring daily or not at all.
224
225   We asked participants about how long they spent travelling to different places and found that
226   mean one-way travel times to health facilities ranged from 4 minutes to 2 hours. Participants
227   reported spending the shortest time travelling when tending to livestock (median 9 minutes one
228   way), and the longest times when visiting a market (median 34 minutes one way). We found the
229   greatest range of travel times for visits to health facilities, markets and places of worship, while
230   visits to livestock areas, water sources and other households tended to have shorter travelling
231   times (*Fig. 3*).
232
233   We also asked about the amount of time people spent at different places. Participants reported
234   spending the longest times at health facilities and places of worship (median 3 hours for both),
235   and the shortest times at other households (median 45 minutes) and water sources (median 9
236   minutes). *Figure 4* shows how the time spent by participants varied by type of place.
237
238   We used the three movement measures (frequency of visits, time spent travelling and time spent
239   at places) and the demographic characteristics collected in the survey to conduct a univariable
240   analysis to explore correlations (*Table 2*). We found that men reported spending more time at
241   and making more frequent visits to places where livestock activities occurred compared to
242   women (p = 0.017 and p = 0.007, respectively), while women reported spending more time at
243   and making more frequent visits to health facilities than men did (p = 0.019 and p < 0.001,
244   respectively). Women also made more frequent visits to water sources than men but did not
245   spend significantly more time there (p = 0.075). Older people tended to visit health facilities and
246   water sources less often (p = 0.041 and p < 0.001, respectively) and spend less time at places of
247   worship (p = 0.003) than younger people. No significant relationships were observed between
248   time spent travelling to places and any of the demographic characteristics tested; these results are
249   reported in the supplementary information.
250
251
252   *GPS validation*
253   Lastly, we used the GPS data to explore the time participants spent outside of their households,
254   and measure how variable overall movements were in our study population. We found that
255   people spent between 5% and 52% of their time outside of their households over the week that
256   they were tracked. For each GPS dataset, we were able to identify the type of place visited for
257   between 2% and 97% of the time recorded outside of the household;some movements could not
258   be characterised because not all locations in the local area were identifiable through the survey or
259   mapping techniques. We selected GPS datasets where the season tracked was the same as when
260   the survey was conducted and where over a third of minutes were identified, resulting in 27 GPS

261   datasets with matching survey data. We compared these to explore how well the GPS data were
262   able to mirror how people spent their time at different places. For this comparison, we only
263   selected types of places that at least 50% of people with GPS data visited at least once a week,
264   apart from the health facility locations, which we included for their public health importance.
265   Unsurprisingly since not all GPS points could be identified, participants reported spending more
266   time at all place types than captured by the GPS (hours reported in survey minus hours recorded
267   by GPS was positive). In most cases, this difference was less than 1 hour of difference per day
268   for each type of place.

269

270   Because the GPS data consistently underreported the absolute amount of time spent at different
271   places compared to the survey data, we also compared how well the survey and GPS data were
272   able to capture the proportions of time spent at the different place types. *Figure 5* shows how
273   GPS data found very similar proportions of time spent compared to those reported in the survey
274   for some types of places, such as shops and places where livestock-related activities occurred.
275   Other types of places had large differences in proportion of times spent between the two datasets
276   – specifically, time spent at places of worship and visits to other households and health facilities.
277   Using a paired t-test we found significant differences in the mean proportions of time spent at
278   other households and places of worship (p = 0.002 and p = 0.041, respectively) between the
279   survey and GPS datasets. The GPS datasets recorded more trips to other households than
280   recounted in the survey, while the survey had more trips to places of worship than recorded in
281   the GPS, potentially due to a recall bias effect: people may be more likely to recall movements
282   that they place higher intrinsic value on. There is also the possibility of a 'social desirability'
283   bias: participants may be tempted to overstate the amount of time spent at more desirable
284   locations such as places of worship, particularly as the survey was conducted in the presence of
285   village elders.

286

287   Discussion

288   Geographic inaccessibility is a primary factor for many poor communities that are unable to
289   easily use important infrastructure and natural resources, particularly in rural areas(4,7,46). Even
290   within these communities, accessibility can vary between individuals and can manifest
291   differently when people are traveling for various types of resources(19,21). Better understanding
292   of how accessibility varies with type of activity and with an individual's socioeconomic context
293   could help inform future analyses on geographic accessibility. This socioeconomic and activity-
294   based understanding of mobility can also help with identifying populations in communities at
295   especially high risk of being unable to access healthcare and other services.

296

297   When comparing accessibility to a variety of resources we found that time people spent
298   accessing different resources was not homogenous and had some links to demographic
299   characteristics. Specifically, we observed that mobility related to livestock-related activities and
300   health facilities were correlated with factors such as occupation, age and gender, while other

301 types of activities like household visits and market visits were not. The small sample size and
302 bias towards rural households mean that the representativeness of these results is limited, but
303 nevertheless, combined with evidence of social differences in resource access from previous
304 studies in this area(47), they suggest further research into inequalities in resource access could be
305 beneficial for improving individual and thus population welfare.
306
307 Broadly, we also found that people access different resources with variable frequencies and spent
308 varying amounts of time there. For example, people visited places where livestock-related
309 activities occurred and water sources either frequently or not at all, while other types of places
310 like health facilities and places of worship were visited by most participants on a regular basis.
311 The time spent at each type of place also showed large variation, with people spending the
312 longest times at health facilities and places of worship, and the shortest times at other households
313 and water sources. These findings, while unsurprising, demonstrate a heterogeneity in resource
314 access between individuals. Travel times to health facilities in our study were longer than to
315 other types of places – a finding which differs from results in Iquitos, Peru, where people
316 travelled less far for health reasons than for commercial and household reasons(19). This
317 highlights how health facilities in rural communities such as our study area are likely more
318 inaccessible than other resources when compared to access in an urban area such as Iquitos.
319
320 Notably, when comparing health facility visits and water source visits (two resources widely
321 regarded as fundamental human rights), we observed that people spent longer both travelling to
322 and at health facilities compared to water sources. However, travelling time to health facilities
323 suggest that most people live within the government target of 5km from a health facility, and
324 previous evidence from rural Kenya found that travel time to health facilities did not affect child
325 mortality in areas with many facilities(48), leading to calls for more focus on social determinants
326 and quality of care and other factors that influence healthcare access and use. Our findings
327 underscore this, as people reported having to spend a mean of 3 hours waiting at health facilities,
328 compared to under 10 minutes to access water.
329
330 We also found some significant gender disparities in the amount of time people spent at different
331 places, which could influence healthcare utilisation patterns. Men reported spending longer than
332 women on livestock-related activities, while women spent longer than men at health facilities
333 and water sources. Women reported visiting health facilities more frequently than men, possibly
334 because they are usually responsible for their children's healthcare as well as their own(49). The
335 differences in time spent by gender suggests that women are having to wait longer to access
336 healthcare than their male counterparts. Previous studies in rural communities in Kenya and
337 neighbouring Tanzania have found that waiting times, like time spent travelling to the facility,
338 are a major barrier to accessing care and can result in delayed care-seeking behaviour,
339 particularly for women due to the opportunity cost of accessing care over their domestic
340 responsibilities(50–52). Since women both visit more often on behalf of their families and spend

341 more time at health facilities, measures to reduce waiting times could have a direct benefit to
342 both their and their families' health.
343
344 Finally, we compared the travel times and frequencies reported in GPS and survey data, to
345 quantify potential biases in each and address the potential value of both datasets. The survey
346 results are likely affected by recall bias and a social desirability bias. Notably, the GPS data were
347 limited by the short data collection period and the small sample size, failing to capture visits to
348 health facilities in the time available. Nevertheless, for places frequently visited during the data
349 collection period, they more objectively reflected proportions of time spent compared to the
350 survey data. Compared to surveys, GPS tracking technology could give a more complete picture
351 of activity spaces in rural contexts, but require long data collection periods and a thorough
352 knowledge of the local area. This knowledge could be obtained through a variety of methods,
353 such as a participatory mapping approach, and could help to reduce recall bias effects. Future
354 studies may be able to overcome the time and cost issues of increasing the data collection period
355 by utilising smartphone technology, which already capture GPS locations of individuals under
356 certain conditions. The collection of smartphone data in combination with GPS trackers has
357 recently been piloted in an urban area of the UK and showed that location histories from
358 smartphones can be valid datasets for exploring individual movements(53). In low-income areas
359 of sub-Saharan Africa, this method would have a substantial bias towards wealthy people and is
360 dependent on reliable cell phone network coverage, but smartphone ownership and demand for
361 data plans have both been increasing in recent years(54), making this a viable option for similar
362 studies in the future.
363

364 ## Conclusions
365 These results suggest that demography and activity are important drivers of mobility, influencing
366 how scientists should quantify geographic accessibility to resources such as health facilities.
367 Because different types of mobility manifest in different ways and occur with various
368 frequencies, data such as GPS and survey data could be used to quantify mobility for specific
369 types of activities, taking into account the advantages of each. Since healthcare-related mobility
370 was particularly time-consuming and appears to be linked to several demographic characteristics
371 in our small study, further research in this area could shed light on how people from different
372 demographic and socioeconomic contexts access healthcare and therefore help to improve access
373 in low-income settings.
374
375

376 ## Acknowledgements

377 The authors are grateful to the county commissioner, the chiefs, assistant chiefs and village
378 elders of Busia County, Kenya for facilitating the fieldwork. We would also like to thank the
379 people of Busia County, Kenya for participating in the study.

380

381

382

383

384 **References**

385

386 1.   Wesolowski A, Eagle N, Tatem AJ, Smith DL, Noor AM, Snow RW, Buckee CO.
387   Quantifying the Impact of Human Mobility on Malaria. Science (80-). 2012 Oct
388   12;338(6104):267–70.
389 2.   Prothero RM. Disease and Mobility: A Neglected Factor in Epidemiology. Int J
390   Epidemiol. 1977 Sep 1;6(3):259–67.
391 3.   Bajardi P, Poletto C, Ramasco JJ, Tizzoni M, Colizza V, Vespignani A. Human Mobility
392   Networks, Travel Restrictions, and the Global Spread of 2009 H1N1 Pandemic. Perc M,
393   editor. PLoS One. 2011 Jan 31;6(1):e16591.
394 4.   Pearce J, Witten K, Hiscock R, Blakely T. Regional and Urban–Rural Variations in the
395   Association of Neighbourhood Deprivation with Community Resource Access: A
396   National Study. Environ Plan A Econ Sp. 2008 Oct 1;40(10):2469–89.
397 5.   Alegana VA, Maina J, Ouma PO, Macharia PM, Wright J, Atkinson PM, Okiro EA, Snow
398   RW, Tatem AJ. National and sub-national variation in patterns of febrile case
399   management in sub-Saharan Africa. Nat Commun. 2018 Dec 26;9(1):4994.
400 6.   Macintyre S, Maciver S, Sooman A, Anderson A, Blane D, Ecob R, Ford G, Forsyth A,
401   Green G, Kelly M, Mullen K, Phillimore P, Wight D. Area, Class and Health: Should we
402   be Focusing on Places or People?*. NETSCC, on. 2019;22:213–34.
403 7.   Chamberlin J, Jayne TS. Unpacking the Meaning of 'Market Access': Evidence from
404   Rural Kenya. World Dev. 2013 Jan 1;41:245–64.
405 8.   Whittington D, Mu X, Roche R. Calculating the value of time spent collecting water:
406   Some estimates for Ukunda, Kenya. World Dev. 1990 Feb 1;18(2):269–80.
407 9.   Cook J, Kimuyu P, Whittington D. The costs of coping with poor water supply in rural
408   Kenya. Water Resour Res. 2016;52(2):619–1539.
409 10.   Noor AM, Zurovac D, Hay SI, Ochola SA, Snow RW. Defining equity in physical access
410   to clinical services using geographical information systems as part of malaria planning and
411   monitoring in Kenya. Trop Med Int Heal. 2003 Oct 1;8(10):917–26.
412 11.   Ruktanonchai CW, Ruktanonchai NW, Nove A, Lopes S, Pezzulo C, Bosco C, Alegana
413   VA, Burgert CR, Ayiko R, Charles AS, Lambert N, Msechu E, Kathini E, Matthews Z,
414   Tatem AJ. Equality in Maternal and Newborn Health: Modelling Geographic Disparities
415   in Utilisation of Care in Five East African Countries. Ali M, editor. PLoS One. 2016 Aug
416   25;11(8):e0162006.
417 12.   Noor A., Gikandi P., Hay S., Muga R., Snow R. Creating spatially defined databases for
418   equitable health service planning in low-income countries: the example of Kenya. Acta
419   Trop. 2004 Aug 1;91(3):239–51.
420 13.   Alegana VA, Wright JA, Pentrina U, Noor AM, Snow RW, Atkinson PM. Spatial
421   modelling of healthcare utilisation for treatment of fever in Namibia. Int J Health Geogr.
422   2012 Feb 15;11(1):6.
423 14.   Kenya Ministry of Medical Services and Ministry of Public Health & Sanitation.
424   HEALTH SECTOR STRATEGIC AND INVESTMENT PLAN (KHSSP) [Internet].
425   2013.

426   15.   Tanser F, Gijsbertsen B, Herbst K. Modelling and understanding primary health care
427   accessibility and utilization in rural South Africa: An exploration using a geographical
428   information system. Soc Sci Med. 2006 Aug 1;63(3):691–705.
429   16.   Airey T. The impact of road construction on the spatial characteristics of hospital
430   utilization in the Meru district of Kenya. Soc Sci Med. 1992 May 1;34(10):1135–46.
431   17.   Mwabu GM. Health care decisions at the household level: Results of a rural health survey
432   in Kenya. Soc Sci Med [Internet]. 1986;
433   18.   Mwabu G, Mwanzia J, Liambila W. User charges in government health facilities in
434   Kenya: effect on attendance and revenue. Health Policy Plan. 1995 Jun 1;10(2):164–70.
435   19.   Perkins TA, Garcia AJ, Paz-Soldan VA, Stoddard ST, Reiner RC, Vazquez-Prokopec G,
436   Bisanzio D, Morrison AC, Halsey ES, Kochel TJ, Smith DL, Kitron U, Scott TW, Tatem
437   AJ. Theory and data for simulating fine-scale human movement in an urban environment.
438   J R Soc Interface. 2014 Aug 20;11(99):20140642–20140642.
439   20.   Molyneux CS, Mung'ala-Odera V, Harpham T, Snow RW. Maternal responses to
440   childhood fevers: a comparison of rural and urban residents in coastal Kenya. Trop Med
441   Int Heal. 1999 Dec 1;4(12):836–45.
442   21.   Schröder L, Flägel K, Goetz K, Steinhäuser J. Mobility concepts and access to health care
443   in a rural district in Germany: a mixed methods approach. BMC Fam Pract. 2018 May
444   2;19(1):47.
445   22.   Kanuganti S, Sarkar AK, Singh AP, Arkatkar SS. Quantification of accessibility to health
446   facilities in rural areas. Case Stud Transp Policy. 2015 Sep 1;3(3):311–20.
447   23.   Wesolowski A, Stresman G, Eagle N, Stevenson J, Owaga C, Marube E, Bousema T,
448   Drakeley C, Cox J, Buckee CO. Quantifying travel behavior for infectious disease
449   research: a comparison of data from surveys and mobile phones. Sci Rep. 2015 May
450   14;4(1):5678.
451   24.   Searle KM, Lubinda J, Hamapumbu H, Shields TM, Curriero FC, Smith DL, Thuma PE,
452   Moss WJ. Characterizing and quantifying human movement patterns using GPS data
453   loggers in an area approaching malaria elimination in rural southern Zambia. R Soc Open
454   Sci. 2017 May 3;4(5):170046.
455   25.   Vazquez-Prokopec GM, Bisanzio D, Stoddard ST, Paz-Soldan V, Morrison AC, Elder JP,
456   Ramirez-Paredes J, Halsey ES, Kochel TJ, Scott TW, Kitron U. Using GPS technology to
457   quantify human mobility, dynamic contacts and infectious disease dynamics in a resource-
458   poor urban environment. PLoS One. 2013 Jan 8;8(4):e58802.
459   26.   Parsons MB, Gillespie TR, Lonsdorf E V, Travis D, Lipende I, Gilagiza B, Kamenya S,
460   Pintea L, Vazquez-Prokopec GM. Global positioning system data-loggers: a tool to
461   quantify fine-scale movement of domestic animals to evaluate potential for zoonotic
462   transmission to an endangered wildlife population. PLoS One [Internet]. 2014
463   Jan;9(11):e110984.
464   27.   Browning E, Bolton M, Owen E, Shoji A, Guilford T, Freeman R. Predicting animal
465   behaviour using deep learning: GPS data alone accurately predict diving in seabirds.
466   McPherson J, editor. Methods Ecol Evol. 2018 Mar 1;9(3):681–92.
467   28.   Ryan PG, Petersen SL, Peters G, Gremillet D. GPS tracking a marine predator: the effects
468   of precision, resolution and sampling rate on foraging tracks of African Penguins. Mar
469   Biol. 2004 Aug 10;145(2):215–23.
470   29.   Moritz M, Galehouse Z, Hao Q, Garabed RB. Can One Animal Represent an Entire Herd?
471   Modeling Pastoral Mobility Using GPS/GIS Technology.

472   30.   Siedner MJ, Lankowski A, Tsai AC, Muzoora C, Martin JN, Hunt PW, Haberer JE,
473   Bangsberg DR. GPS-measured distance to clinic, but not self-reported transportation
474   factors, are associated with missed HIV clinic visits in rural Uganda. AIDS. 2013 Jun
475   1;27(9):1503–8.
476   31.   Kenya National Bureau of Statistics. Busia County Statistical Abstract [Internet]. 2017.
477   32.   Statistics KNB of, Health/Kenya M of, Council/Kenya NAC, Institute KMR,
478   Development/Kenya NC for P and. Kenya Demographic and Health Survey 2014
479   [Internet]. 2015 [cited 2018 Feb 22].
480   33.   QGIS Development Team. QGIS Geographic Information System. Open Source
481   Geospatial Foundation Project.; 2019.
482   34.   Fèvre EM, de Glanville WA, Thomas LF, Cook EAJ, Kariuki S, Wamae CN. An
483   integrated study of human and animal infectious disease in the Lake Victoria crescent
484   small-holder crop-livestock production system, Kenya. BMC Infect Dis. 2017 Dec
485   30;17(1):457.
486   35.   Floyd JR, Ruktanonchai NW, Wardrop N, Tatem AJ, Ogola J, Fèvre EM. Exploring fine-
487   scale human and livestock movement in western Kenya. One Heal [Internet]. 2019;7.
488   36.   Kenya | PPI [Internet]. Poverty Probability Index. 2011.
489   37.   Brunette W, Sundt M, Dell N, Chaudhri R, Breit N, Borriello G. Open data kit 2.0. In:
490   Proceedings of the 14th Workshop on Mobile Computing Systems and Applications -
491   HotMobile '13. New York, New York, USA: ACM Press; 2013. p. 1.
492   38.   i-gotU GT-600 GPS logger [Internet]. Taiwan: Mobile Action Technology Inc.; 2018.
493   39.   Bohte W, Maat K. Deriving and validating trip purposes and travel modes for multi-day
494   GPS-based travel surveys: A large-scale application in the Netherlands. Transp Res Part C
495   Emerg Technol. 2009 Jun 1;17(3):285–97.
496   40.   Stopher PR, Daigler V, Griffith S. Smartphone app versus GPS Logger: A comparative
497   study. Transp Res Procedia. 2018 Jan 1;32:135–45.
498   41.   Thuranira-McKeever C, Shaw A, Machila N, Eisler M, Welburn S, Maudlin I. Seasonal
499   influences on livestock keeping in a sedentary crop–livestock system. Trop Anim Health
500   Prod. 2010 Apr 7;42(4):705–17.
501   42.   Team RC. R: A language and environment for statistical computing. [Internet]. Vienna,
502   Austria: R Foundation for Statistical Computing; 2017.
503   43.   Sumner MD. trip: Tools for the Analysis of Animal Track Data. R package version 1.5.0.
504   [Internet]. 2016.
505   44.   Noor AM, Alegana VA, Gething PW, Snow RW. A spatial national health facility
506   database for public health sector planning in Kenya in 2008. Int J Health Geogr. 2009 Mar
507   6;8(1):13.
508   45.   Wardrop NA, Thomas LF, Cook EAJ, de Glanville WA, Atkinson PM, Wamae CN, Fèvre
509   EM. The Sero-epidemiology of Coxiella burnetii in Humans and Cattle, Western Kenya:
510   Evidence from a Cross-Sectional Study. Vinetz JM, editor. PLoS Negl Trop Dis. 2016 Oct
511   7;10(10):e0005032.
512   46.   Clark GL, Gertler MS, Feldman MP. The Oxford handbook of economic geography
513   [Internet]. Oxford University Press; 2003. 742 p.
514   47.   Okwi PO, Ndeng'e C G, Kristjanson P, Arunga M, Notenbaert A, Omolo A, Henninger N,
515   Benson T, Kariuki P, Owuor J. Spatial determinants of poverty in rural Kenya [Internet].
516   2007.
517   48.   Moïsi JC, Gatakaa H, Noor AM, Williams TN, Bauni E, Tsofa B, Levine OS, Scott JAG.

518   Geographic access to care is not a determinant of child mortality in a rural Kenyan setting
519   with high health facility density. BMC Public Health. 2010 Dec 17;10(1):142.
520 49. M P, M B, JC T. Womens agricultural work child care and infant diarrhea in Rural Kenya.
521   [Internet]. Boulder Colorado Westview Press 1989.; 1989 [cited 2019 Jan 29]. p. 217–36.
522 50. Thaddeus' S, Maine D. Too far to walk: Maternal Mortality in context [Internet]. Vol. 38,
523   Sm. Sci. Med. 1994.
524 51. Mason L, Dellicour S, Ter Kuile F, Ouma P, Phillips-Howard P, Were F, Laserson K,
525   Desai M. Barriers and facilitators to antenatal and delivery care in western Kenya: a
526   qualitative study. BMC Pregnancy Childbirth. 2015 Dec 13;15(1):26.
527 52. Mubyazi GM, Bloch P, Magnussen P, Olsen ØE, Byskov J, Hansen KS, Bygbjerg IC.
528   Women's experiences and views about costs of seeking malaria chemoprevention and
529   other antenatal services: a qualitative study from two districts in rural Tanzania. Malar J.
530   2010 Dec 17;9(1):54.
531 53. Ruktanonchai NW, Ruktanonchai CW, Floyd JR, Tatem AJ. Using Google Location
532   History data to quantify fine-scale human mobility. Int J Health Geogr [Internet].
533   2018;17(1).
534 54. World Bank. The transformational use of information and communication technologies in
535   Africa [Internet]. 2012.
536

Individual and household characteristics of sample population

* PPI Kenya: Poverty Probability Index for Kenya 2011 [36].

Demographic covariates	Number of participants: Survey & GPS	Number of participants: GPS only
Gender		
Male	33 (43.4%)	18 (69.2%)
Female	43 (56.6%)	8 (30.8%)
Age		
18-29	22	7
30-49	26	8
50-69	23	7
70+	5	4
Main occupation		
Farming/agriculture	45	18
Hunting	2	2
Trading	3	1
Other	18	4
Unemployed	8	1
Relative wealth score (PPI Kenya*) of participant's household		
Less than 30	16	9
30 to 50	24	9
51 or more	12	8
Ruminant ownership of participant's household		
No ruminants	12	6
Ruminants	40	20

Relationships between movement metrics and demographic characteristics of the surveyed population for different types of activity.

Univariable analysis of movement metrics using beta regression in a linear mixed model. Estimates are given with 95% confidence intervals in square brackets. *** p < 0.001, ** p < 0.01, * p < 0.05.

Activity type	Explanatory variable	Estimate	p-value
Livestock activity	Visits per week	Gender: male [Ref = female]	15.78 [2.10, 109.68]	0.007 **
		Occupation: non-farmer [Ref = farmer]	0.08 [0.01, 0.65]	0.022 *
		Household wealth	0.17 [0.01, 3.69]	0.263
		Age	1.04 [0.97, 1.11]	0.245
	Time spent	Gender: male [Ref = female]	5.33 [1.41, 20.22]	0.017 *
		Occupation: non-farmer [Ref = farmer]	0.68 [0.17, 2.79]	0.591
		Household wealth	5.46 [0.95, 31.05]	0.063
		Age	1.03 [0.99, 1.07]	0.206
Health facility	Visits per week	Gender: male [Ref = female]	0.12 [0.04, 0.36]	< 0.001 ***
		Occupation: non-farmer [Ref = farmer]	2.96 [0.93, 9.44]	0.069
		Household wealth	0.25 [0.06, 1.10]	0.071
		Age	0.97 [0.93, 1.00]	0.041 *
	Time spent	Gender: male [Ref = female]	0.65 [0.46, 0.92]	0.019 *
		Occupation: non-farmer [Ref = farmer]	0.88 [0.60, 1.28]	0.504
		Household wealth	0.70 [0.42, 1.18]	0.193
		Age	0.99 [0.98, 1.01]	0.338
Place of worship	Visits per week	Gender: male [Ref = female]	0.50 [0.24, 1.00]	0.054
		Occupation: non-farmer [Ref = farmer]	1.01 [0.48, 2.14]	0.984
		Household wealth	0.65 [0.23, 1.84]	0.425
		Age	1.01 [0.98, 1.03]	0.617
	Time spent	Gender: male [Ref = female]	0.81 [0.65, 1.00]	0.051
		Occupation: non-farmer [Ref = farmer]	1.03 [0.82, 1.28]	0.812
		Household wealth	0.72 [0.54, 0.96]	0.032 *
		Age	0.99 [0.98, 1.00]	0.003 **
Market	Visits per week	Gender: male [Ref = female]	1.09 [0.37, 3.09]	0.875
		Occupation: non-farmer [Ref = farmer]	0.43 [0.14, 1.36]	0.135
		Household wealth	1.29 [0.27, 6.13]	0.753
		Age	0.97 [0.95, 1.00]	0.121
	Time spent	Gender: male [Ref = female]	1.24 [0.54, 2.87]	0.611

		Occupation: non-farmer [Ref = farmer]	0.64 [0.28, 1.47]	0.299
		Household wealth	0.98 [0.34, 2.84]	0.970
		Age	0.99 [0.96, 1.01]	0.316
Household visits	Visits per week	Gender: male [Ref = female]	1.39 [0.38, 4.85]	0.612
		Occupation: non-farmer [Ref = farmer]	0.92 [0.24, 3.55]	0.909
		Household wealth	1.12 [0.16, 7.49]	0.908
		Age	0.97 [0.93, 1.01]	0.122
	Time spent	Gender: male [Ref = female]	1.22 [0.78, 1.93]	0.387
		Occupation: non-farmer [Ref = farmer]	0.83 [0.51, 1.33]	0.438
		Household wealth	0.87 [0.46, 1.62]	0.655
		Age	1.00 [0.98, 1.01]	0.663
Water activity	Visits per week	Gender: male [Ref = female]	0.02 [0.00, 0.12]	< 0.001 ***
		Occupation: non-farmer [Ref = farmer]	4.80 [0.47, 49.31]	0.191
		Household wealth	0.10 [0.00, 2.66]	0.176
		Age	0.87 [0.81, 0.92]	< 0.001 ***
	Time spent	Gender: male [Ref = female]	2.52 [0.92, 6.65]	0.075
		Occupation: non-farmer [Ref = farmer]	0.86 [0.34, 2.13]	0.755
		Household wealth	0.69 [0.22, 2.17]	0.535
		Age	1.00 [0.97, 1.03]	0.976

Figure 1

Map of the study area.

(A) Kenya with Busia county highlighted in yellow. (B) Busia county with the 11 selected

sublocations highlighted in red.
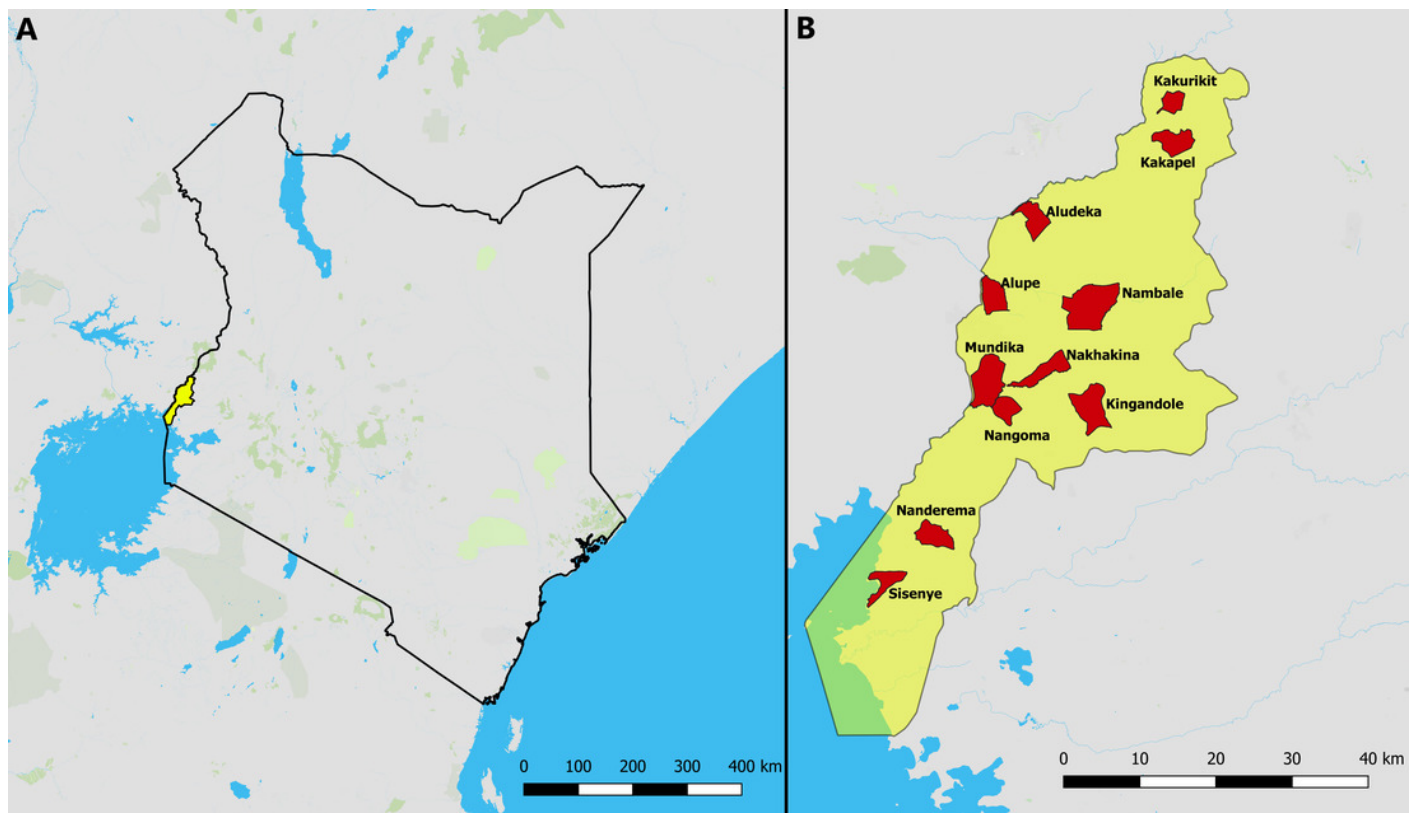
Figure 2

Frequencies of visits to different types of places.
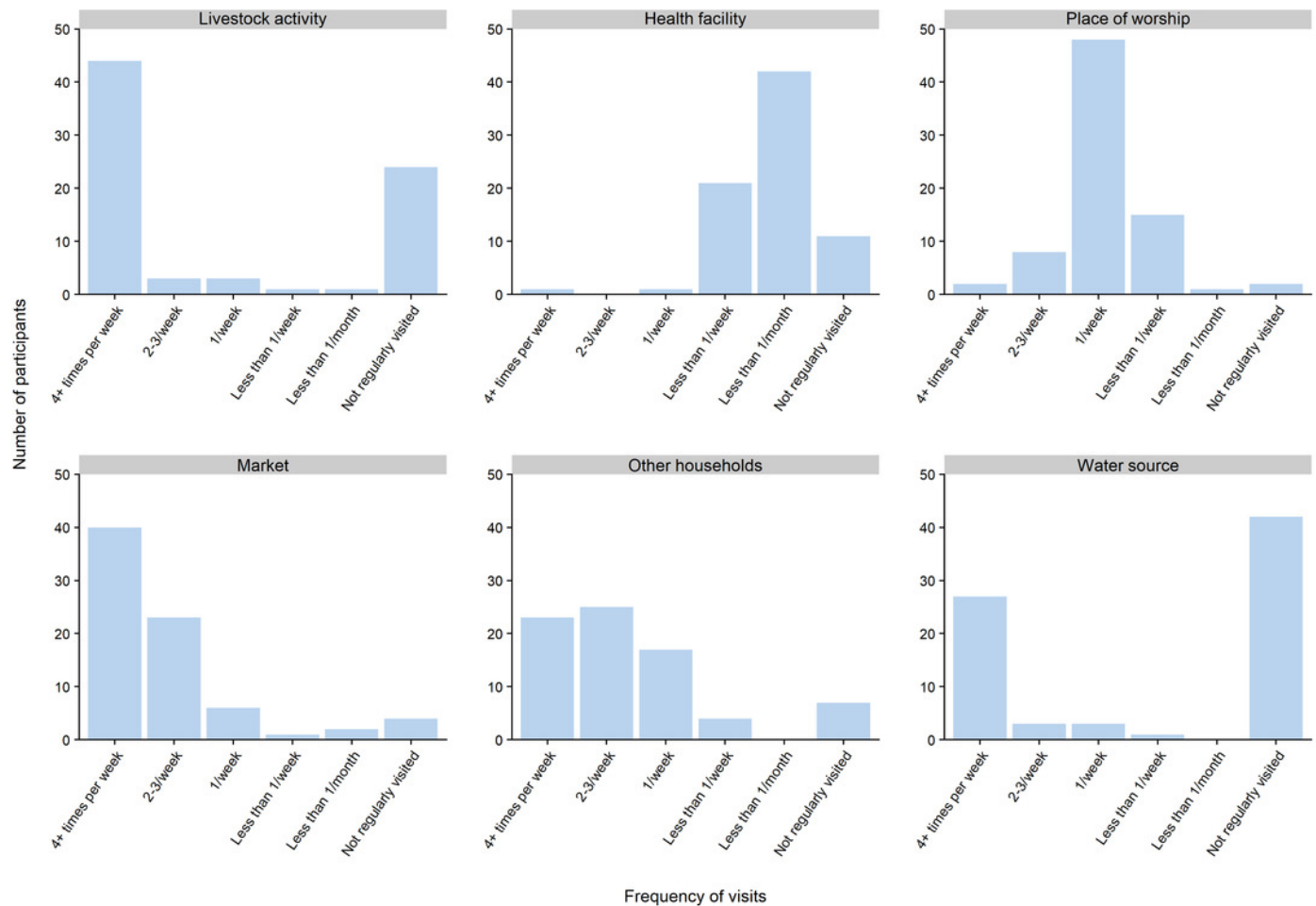
Figure 3

Time spent travelling one-way to different types of places.
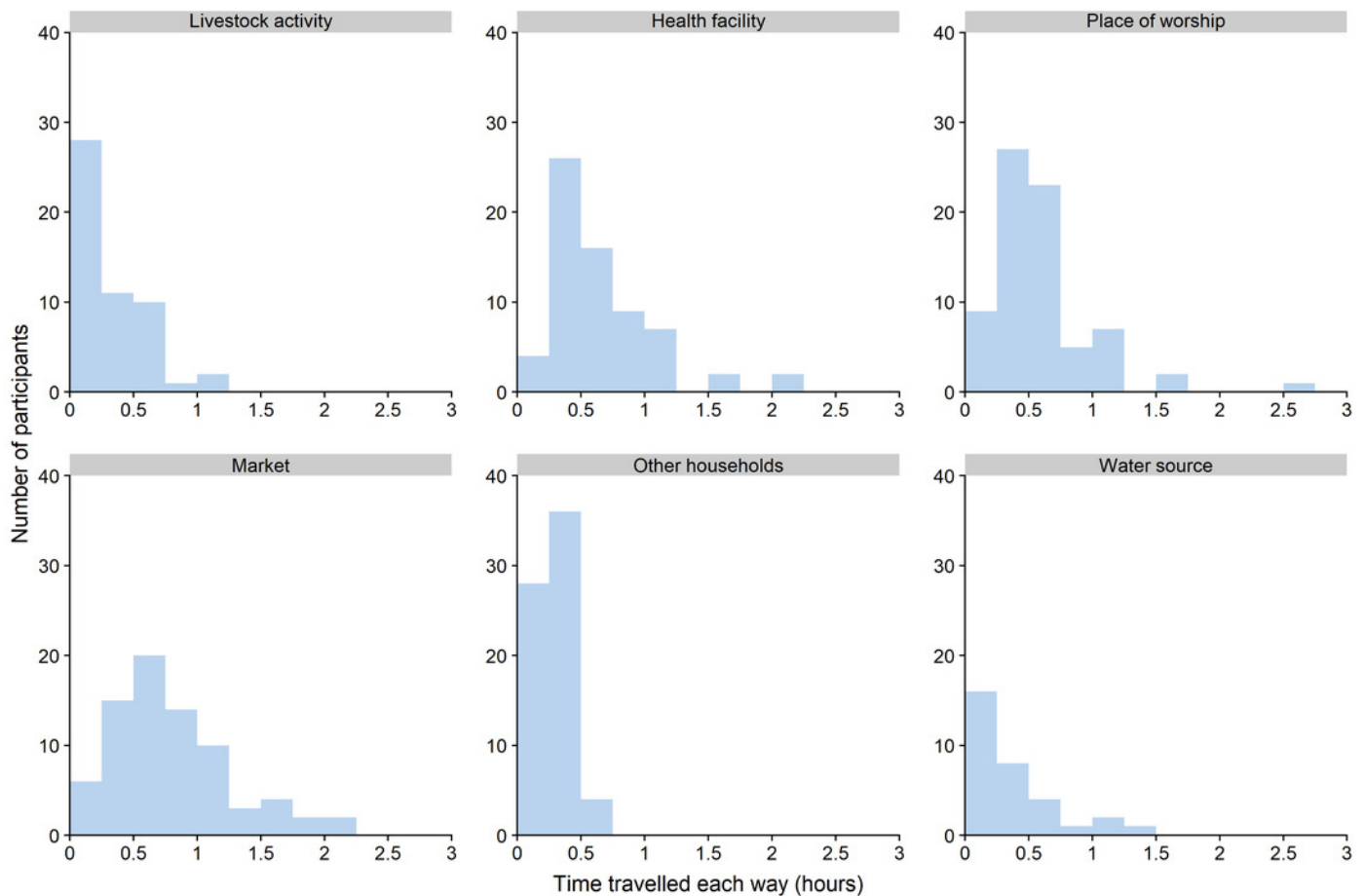
Figure 4

Time spent by participants at different types of places.
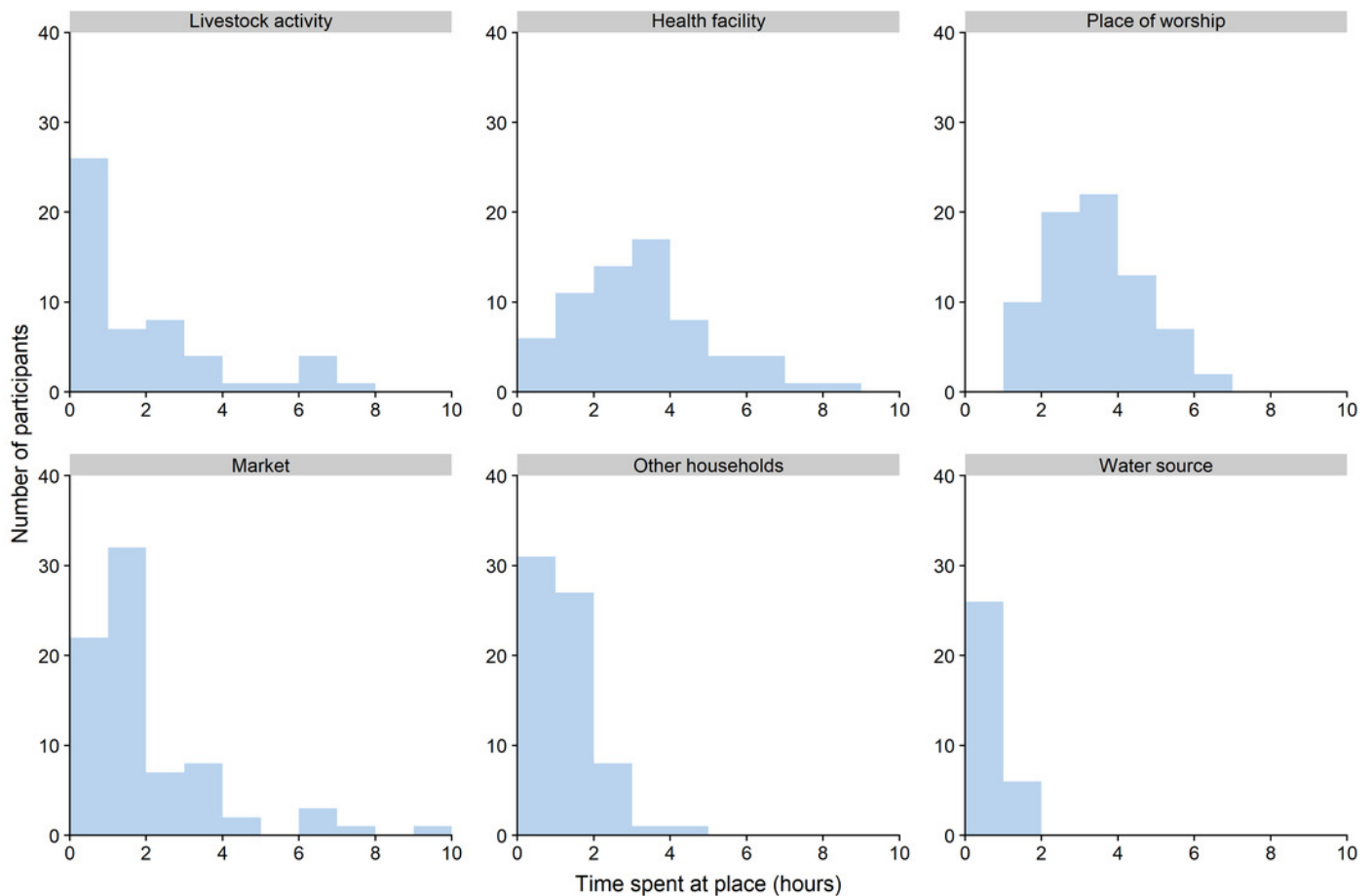
Figure 5

Network representation of mean proportions of time spent in different types of places.

Mean proportions of time spent from GPS (orange) and survey (blue) data.