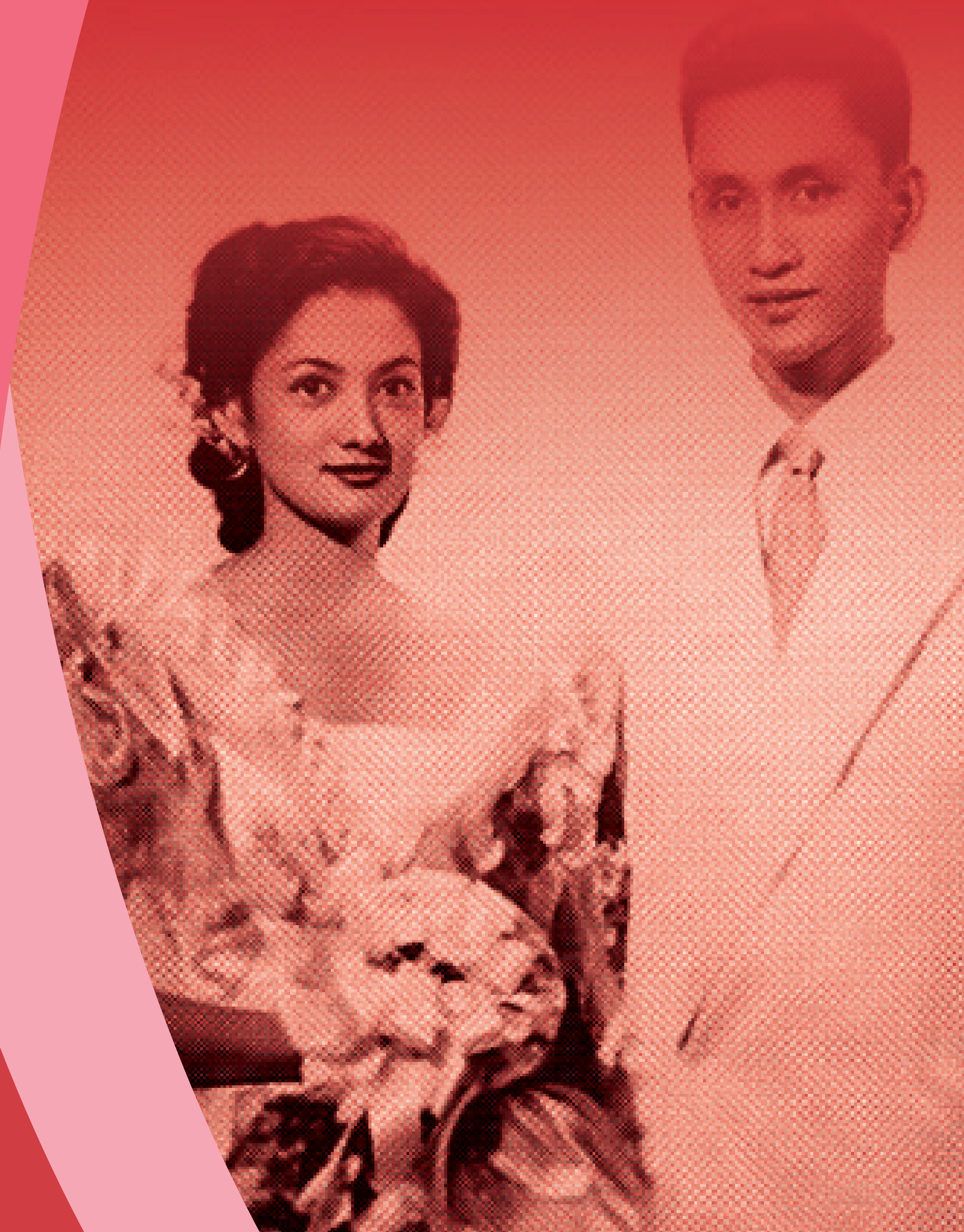


Chapter 5

Geographic Context

Jose Andres F. Ignacio
Jeconiah K. Boongaling
Leo Angelo L. Ocampo

Introduction

The geographical context in which people age can profoundly influence their health, quality of life, and overall ageing experience (Choi, Kwon, and Kim, 2018; Choi, 2020; Wahl, Iwarsson, and Oswald, 2012; Wood et al., 2022). An archipelago of over 7,000 islands, the Philippines encompasses a variety of landscapes, including mountains with rainforests, agricultural plains, coastal areas, and urban metropolises. Because of this diversity of landforms and social spaces, aspects such as the environment, climate, terrain, infrastructure, and access to services can vary widely across the different geographic regions of the country.

Factors such as the ease of access to health facilities, the available modes of transport, and older people support networks are place-based and significantly influence health and well-being (Smith, 2009). Differences in environmental elements such as pollution, soil and water contaminants, extreme weather events, and natural hazards also explain differences in older persons' vulnerability across geographic locations (Di Ciaula and Portincasa, 2020). Regional variations in cultural norms, family structures, and caregiving practices also play a role. Consequently, older persons in isolated rural villages face different challenges than those living in bustling urban areas (Baernholdt et al., 2012). Understanding the risks and realities of ageing in diverse geographic contexts is crucial to ensuring that adequate and appropriate healthcare resources are allocated to meet the unique needs of the ageing population in each milieu (Bacsu et al., 2012; Donovan and Blazer, 2020).

Spatial patterns and clusters of geosocial and geophysical phenomena can determine conditions that may affect the well-being and quality of life of older persons. Geospatial data allows for the integration of physical and human geographic factors, which, when combined with socioeconomic components, provides a more comprehensive and nuanced understanding of the factors influencing healthy ageing (Kwan, 2012). By integrating global positioning system (GPS) data collected from LSAHP respondents with social and environmental data using advanced geospatial technologies, physical factors are combined with the traditional socioeconomic and demographic determinants of health. This provides a more comprehensive understanding of health outcomes.

This chapter aims to use geospatial covariates to describe the geographic locales of older Filipinos using GPS data collected during the LSAHP Wave 2 survey. Geospatial covariates are variables that incorporate the location of survey respondents with ancillary geographic data using geomatics technology (The DHS Program, 2024), more commonly known as mapping and spatial analysis tools. These variables help researchers understand how a person's geographic context might influence the topic being studied. For example, they could show how close a respondent lives to important services or what environmental conditions they experience based on their location.

This novel approach has not been explored in previous ageing research in the Philippines. Desjardins et al. (2023) proposed a research agenda that incorporates longitudinal geospatial health data to better capture risk factors such as ageing, prompting the need for more longitudinal studies in health. Our analysis will determine the proximity of respondents to various social infrastructure characteristics such as health facilities, services, spaces, and networks that affect a community's quality of life and well-being. To illustrate some of these findings, we will provide a series of maps showing the distribution of these indicators, highlighting the LSAHP study areas. We will also provide a map of health facilities per barangay throughout the country using available data from the DOH to validate findings using the LSAHP data.

Our analysis examines the spatial disparities in geospatial covariates by urbanity (urban or rural) and major area group (NCR, Balance Luzon, Visayas, and Mindanao). To offer a better overview of the spread of the computed indicators, quartiles are presented by urbanity and major area groups.

The succeeding sections discuss the methodologies developed to derive geospatial covariates, particularly proximity to various services critical to the well-being of older persons. Subsequently, findings encompassing geospatial covariates for social infrastructures are presented. Finally, we synthesise these results to provide insights into their implications and potential applications for enhancing the quality of life of older persons.

1. Utilising GPS Data and Method for Ageing Research: Issues and Challenges

Our analysis utilises GPS data collected during the LSAHP second wave using Lenovo M10 Plus tablets running on Android 9. Similar data were collected in the LSAHP first wave. To assess the usefulness of the W1 GPS data, we cross-checked the positional quality of the GPS location values with established reference locations (Ignacio, 2023). Based on the W1 data assessment, we made recommendations for improving the quality of GPS data collection for W2, including adopting better geolocation techniques.

For the analysis in this chapter, we employed two main GPS data fields collected by the tablets during the surveys: Longitude (GPS_LONGITUDE) and Latitude (GPS_LATITUDE). We initially considered using the Altitude (GPS_ALTITUDE) data but found that it was not as reliable due to the inherent complexity of calculations needed to capture the Altitude variables. We instead used more reliable data from interferometric synthetic aperture radar digital elevation models (DEMs) accessed from the Department of Science and Technology – University of the Philippines Disaster Risk Exposure Assessment and Mitigation (DOST-UP DREAM) Program in 2017 (DAD-UP DREAM/PHIL-LiDAR 1, 2017). We used the Longitude and Latitude variables to extract the altitude or elevation values for each respondent's location on the DEM.

Geographic information system (GIS) data sourced from OpenStreetMap (OSM) were also used in the analysis. OSM is a collaborative open-source project involving hundreds of thousands of volunteers in mapping the world. OSM data is collected from various sources, such as survey results, aerial photographs, and GPS traces, and is continually updated with new information by the community (OpenStreetMap, 2022). Data from OSM can be downloaded from their website in various geospatial formats, which can then be used in GIS. This allows them to be processed with survey data that contain location characteristics, i.e. latitude and longitude fields.

The LSAHP GPS locational parameters and complementary data were combined to generate social infrastructure variables that make it possible to determine the respondents' proximity to several social infrastructures that may have a significant bearing on their well-being and health. Factors such as distance to several relevant services or facilities indicate their degrees of isolation or exclusion from these services, which, in turn, may significantly affect their health. Additional information from complementary data also provides a more realistic measure of the degree of urbanisation in their milieu, which can be correlated with road density within their local living spaces.

Listed below are the data sources, the corresponding derived variables, and their significance:

1. Major Roads and Highways
   - OSM Data: Thoroughfare locations
   - Derived Variable: Proximity to nearest main road (highway or primary trunk)
   - Significance: Indicates access to critical health and other services
2. Municipal or City Centres
   - OSM Data: Local government point locations
   - Derived Variable: Proximity to municipal or city centre
   - Significance: Represents access to government services and facilities
3. Health Facilities
   - OSM Data: Locations of clinics and hospitals (excluding specialised clinics)
   - Derived Variable: Proximity to nearest health facility
   - Significance: Reflects ease of access to essential healthcare services
4. Pharmacies
   - OSM Data: Pharmacy locations
   - Derived Variable: Proximity to nearest pharmacy
   - Significance: Indicates access to medicines and medical supplies
5. Financial Institutions
   - OSM Data: Locations of banks and automated teller machines (ATMs)
   - Derived Variable: Proximity to nearest financial institution
   - Significance: Ensures access to financial services for health-related needs
6. Road Network
   - OSM Data: Comprehensive road network
   - Derived Variable: Road density within a 500-metre radius of the respondent
   - Significance: Provides a realistic measure of urbanisation in the respondent's immediate environment

Additional Variable:

1. Altitude or Elevation
   - Source: Original GPS position collection
   - Variable: Meters above sea level (MASL)
   - Significance: May influence health due to climate differences and potential isolation in higher areas

These variables allow us to assess respondents' proximity to social infrastructures that may significantly impact their well-being and health. Factors such as distance to services indicate degrees of isolation or exclusion, which can have substantial health implications for older individuals. Although altitude or elevation technically does not represent a social infrastructure geospatial covariate, the original GPS position collection included an altitude variable, the least accurate amongst the three positional variables that included latitude and longitude. Altitude may play a part in the health and well-being of older persons (Liu et al., 2023) because these areas represent cooler climates and less pollution. However, they may also be associated with increased isolation since most of these areas are in remote rural areas, affecting access to healthcare and related services.

2. Mitigating Errors in Mobile-device-based Social Survey Data Collection

This section explores the challenges in collecting GPS data in the LSAHP surveys. We also discuss how these data limitations were managed and mitigated before employing this data for our analysis.

A major problem affecting the collection of quality data is poor connectivity. Tablets usually collect GPS data and rely on mobile data or Wi-Fi signals to obtain a satellite fix for determining geographic coordinates (Barzilay, 2019). Without cellular networks to assist GPS, it can take over 12.5 minutes for a tablet to download the necessary ephemeris data directly from GPS satellites[1] (Langley, 2015). This data is essential for accurate position capture. In remote rural locales and areas obstructed by buildings or thick vegetation and plagued with intermittent cell connectivity and multipath GPS signal errors, it is difficult for mobile devices to accurately log locations (Abdalla, 2016). These errors were evident in the LSAHP W1 survey, where almost 25% of the raw positional data from the tablets used either had null values or were positioned far from their designated barangay locations or the centroid of the clusters of respondents in their respective community groups (Ignacio, 2023).

Technological advancements and a better understanding of cell-assisted GPS significantly mitigated the positional errors in the LSAHP Wave 2 survey compared to Wave 1. We also provided comprehensive training for field interviewers, which included tips on checking the strength or presence of cell signals, allotting more time to gather positional readings in areas with poor or non-existent signals, and seeking areas with minimal obstructions to the sky. Additionally, we modified the software coding used in the survey rounds to ensure improved collection of positional data. As a result, only 3.3% of W2 raw positional data were erroneous, an improvement of 22 percentage points from W1.

3. Error Correction for Wayward GPS Positions

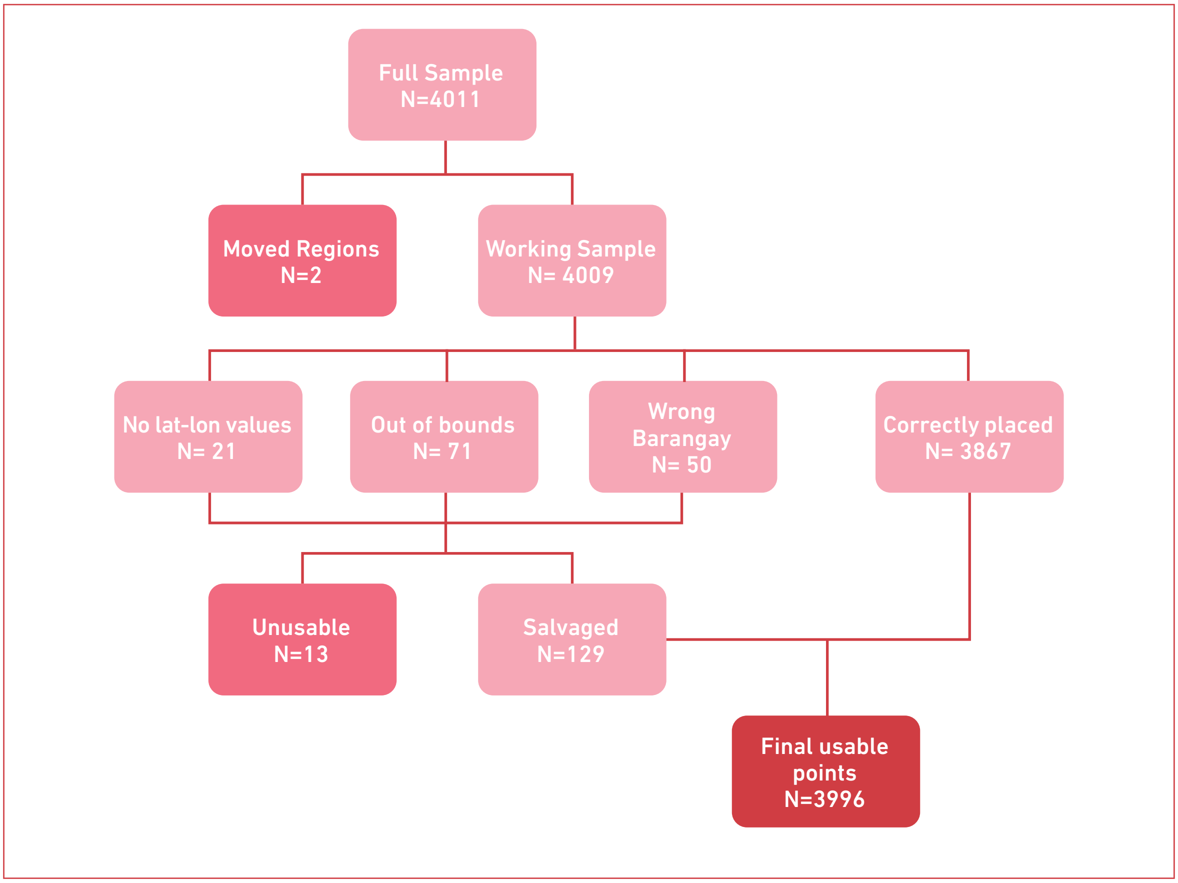
Part of assessing the validity of the LSAHP point locations was to reference it with an established polygon GIS dataset of barangays (villages) of the Philippines, available through the United Nations Office for the Coordination of Humanitarian Affairs. This dataset possesses real Philippine Standard Geographic Codes (PSGC) for the barangays, which can be cross-referenced with the raw plot of the individual LSAHP survey points (Humdata, 2023). The PSGCs of the barangays, which uniquely identify local governance geographic areas, were used to match the LSAHP and OCHA polygon datasets.

[1] Ephemeris data is a table or data file that provides the calculated positions of a celestial object, such as a GPS satellite, at regular intervals throughout a period. This table is crucial to rapidly establishing satellite references, which is the entire basis for GPS positioning.

The analysis focuses on the 4,011 respondents from Wave 1 who were reinterviewed in Wave 2. Eighty-seven respondents changed their residence between W1 and W2, crossing the boundaries of their original barangays. Of these, two respondents moved across regional boundaries and outside the original LSAHP study area. These cases were excluded from the analysis, leading to an analytical sample of 4,009 cases.

Furthermore, 21 points lacked latitude and longitude values, 71 cases were out of bounds, e.g. in bodies of water or other countries, and 50 cases were misclassified in a different barangay. To allow for the possibility of using cases with no positional values or erroneous readings for geospatial analysis, the centroids or average positions of correctly placed barangay cluster respondents were calculated and used as substitute values for the errant cases for that barangay. After implementing these corrections, only 13 cases remained unlocatable and were excluded from geospatial analysis. As a result, the analytical sample size was further reduced to 3,996 cases for analysis involving the use of GPS locations (Figure 5.1).

Figure 5.1. Derivation of the Analytical Sample



Source: Calculated by DRDF using original LSAHP W2 data.

We used the following open-source software for the GIS processing and mapping: PostgreSQL, PostGIS, and QGIS. PostgreSQL is a robust relational database management system whilst PostGIS is an extension that adds support for geographic objects and spatial functions in PostgreSQL. It allows the storing, analysing, and querying of spatial data within a PostgreSQL database. The first two are scripting-based applications, whilst QGIS is a graphical GIS application that is one of the most popular open-source GIS projects.

4. Geospatial Covariates for Social Infrastructures

The geospatial data revealed various insights into the accessibility of important social infrastructures to older persons. Table 5.1 summarises the estimated distances to the nearest main roads, municipal or city centres, health facilities, pharmacies, and financial institutions, along with estimated measures for road density and elevation. Note that the distances computed were straight line Euclidean distances between the respondents and the points of interest and do not represent the actual distances travelled using existing road networks and travel times.

Table 5.1. Geospatial Covariates for Social Infrastructures by Urbanity and Major Area Group

Geospatial Covariates	URBANITY			MAJOR AREA GROUP					TOTAL
	Rural	Urban	Sig.	NCR	Balance Luzon	Visayas	Mind-anao	Sig.	
Distance to the nearest main road (km)									
Quartile 1	0.38	0.21		0.24	0.35	0.11	0.29		0.24
Quartile 2 (Median)	1.82	0.48	**	0.47	0.71	0.49	0.85	*	0.62
Quartile 3	5.74	0.81		0.67	2.55	6.84	4.12		2.65
Distance to the municipal or city centre (km)									
Quartile 1	2.13	0.66		2.04	1.39	0.50	1.68		1.39
Quartile 2 (Median)	4.71	2.06	*ns*	2.60	2.66	5.99	3.22	*	2.98
Quartile 3	11.72	3.89		3.09	5.48	12.65	8.33		7.39
Distance to the nearest health facility (km)									
Quartile 1	1.59	0.22		0.22	0.67	0.21	1.15		0.54
Quartile 2 (Median)	4.03	0.62	*	0.37	1.25	5.60	3.76	***	1.44
Quartile 3	9.22	1.27		0.58	4.00	13.26	8.45		6.58

Geospatial Covariates	URBANITY			MAJOR AREA GROUP					TOTAL
	Rural	Urban	Sig.	NCR	Balance Luzon	Visayas	Mind-anao	Sig.	
Distance to the nearest pharmacy (km)									
Quartile 1	2.10	0.22		0.20	0.56	0.42	1.59		0.45
Quartile 2 (Median)	9.09	0.52	***	0.37	1.38	12.93	9.33	***	1.78
Quartile 3	13.81	1.57		0.47	4.95	18.84	20.95		12.48
Distance to the nearest financial facility (km)									
Quartile 1	2.19	0.18		0.15	0.63	0.25	1.47		0.42
Quartile 2 (Median)	4.55	0.51	***	0.37	1.60	9.60	3.06	***	1.96
Quartile 3	13.86	1.59		0.57	3.96	20.79	11.47		8.55
Road density (m/ha)									
Quartile 1	16.76	70.44		209.64	27.75	14.60	20.61		22.67
Quartile 2 (Median)	26.97	150.81	***	244.47	82.74	25.63	31.37	***	63.71
Quartile 3	52.12	223.26		244.47	115.65	118.36	56.37		157.16
Elevation (m)									
Quartile 1	10.42	7.04		9.22	9.13	6.79	11.89		8.98
Quartile 2 (Median)	20.43	11.66	*ns*	12.28	15.40	13.10	26.52	*ns*	15.47
Quartile 3	64.84	28.48		31.07	31.60	52.33	113.38		37.48
N	*2,269*	*1,727*		*398*	*1,228*	*1,170*	*1,200*		*3,996*

*p < .05, **p < .01, ***p < .001, ns = not significant.

Source: Calculated by the DRDF using original LSAHP W2 data.

The analysis of median distances estimates that at least half of the older persons reside within 0.6 km of the nearest main road, within 3.0 km of their municipal or city centres, within 1.4 km of the nearest health facility, within 1.8 km of the nearest pharmacy, and within 2.0 km of the nearest financial institution. Conversely, the remaining half of older persons reside farther away from these infrastructures.

At least half of the older persons reside in areas with a road density of 63.7 m per hectare or less, whilst the remaining half experience higher road density. Similarly, at least half of the older persons live in areas with elevations of 15.5 m or less above sea level, with the remaining half at higher elevations. Although there are no established limits or cutoffs for road density and elevation and their relationships to the older persons' health, the literature suggests that higher road densities are negatively correlated with older persons' health (Zhang et al., 2021). Studies have consistently reported that proximity to roads and higher road densities are linked to increased levels of traffic-related air pollutants such as nitrogen dioxide (NO2) and particulate matter (PM2.5 and PM10). These pollutants are known to impair cognitive function and increase the incidence of neurological disorders in adults (Yuchi et al., 2020). People living at higher altitudes reported higher physical and social quality of life (Liu et al., 2023).

Statistically significant differences are observed across urbanity and major area groups, underscoring disparities in accessibility. However, it is notable that the distance to municipal or city centres does not show significant variation across urbanity, suggesting a more consistent distribution regardless of urban or rural settings. Moreover, variations in elevation across urbanity and major area groups lack statistical significance.

Building on this, a comparable analysis can be conducted using the first and third quartiles, providing additional insights into the distribution of distances and other related measures amongst older persons. This perspective helps capture the range of experiences, highlighting not only the median but also the spread of various measures for key social infrastructures.

Whilst median estimates provide single summary measures of how older persons fare in terms of the accessibility of social infrastructures, the experiences of those in more extreme situations should not be overlooked. Tables 5.2 to 5.8 further emphasise this, presenting the percent distribution of older persons across categorical measures related to the same social infrastructures outlined in Table 5.1, by urbanity and major area groups.

As shown in Table 5.2, 11% of older persons reside 10 km or more from the nearest main road. This situation applies to 4% of older persons in urban areas and 17% of older persons in rural areas. In Visayas, 22% of older persons find themselves in this circumstance, contrasting sharply with the zero percentage in the NCR, where nearly all reside within a 10 km radius of the nearest main road.

Table 5.2. Percent Distribution of Older Persons by Distance in Kilometres from Residence to the Nearest Main Road by Urbanity and Major Area Group

Distance	URBANITY			MAJOR AREA GROUP					TOTAL
	Rural	Urban	Sig.	NCR	Balance Luzon	Visayas	Mind-anao	Sig.	
Distance to the nearest main road									
Less than 0.5 km	30.2	51.3	**	52.1	33.7	50.8	38.9	**	40.5
0.5 to less than 1 km	10.9	27.8		39.3	22.5	6.8	13.3		19.2
1 to less than 10 km	41.7	16.4		8.6	39.4	20.5	27.1		29.4
10 km or more	17.1	4.5		0.0	4.4	22.0	20.7		10.9
N	*2,269*	*1,727*		*398*	*1,228*	*1,170*	*1,200*		*3,996*

**$p < .01$, ns = not significant.

Source: Calculated by the DRDF using original LSAHP W2 data.

For about one out of five (21%) older persons, their municipal or city centre is more than 10 km away from their residence. This condition also applies to 11% of older persons in urban areas and 31% of older persons in rural areas. In the Visayas, 36% of older persons face this scenario, followed by Mindanao at 24% (Table 5.3).

Table 5.3. Percent Distribution of Older Persons by Distance in Kilometres from Residence to the Municipal or City Centre by Urbanity and Major Area Group

Distance	URBANITY			MAJOR AREA GROUP					TOTAL
	Rural	Urban	Sig.	NCR	Balance Luzon	Visayas	Mind-anao	Sig.	
Distance to the municipal or city centre									
Less than 0.5 km	4.1	15.9	**	0.9	7.6	25.0	4.0	*	9.9
0.5 to less than 1 km	5.5	19.1		8.5	14.6	7.9	13.0		12.1
1 to less than 10 km	59.6	53.7		90.6	59.2	31.1	59.4		56.7
10 km or more	30.8	11.3		0.0	18.7	36.1	23.6		21.3
N	*2,269*	*1,727*		*398*	*1,228*	*1,170*	*1,200*		*3,996*

*p < .05, **p < .01.

Source: Calculated by the DRDF using original LSAHP W2 data.

Similarly, according to Table 5.4, 16% of older persons live 10 km or more from the nearest health facility. A significant rural–urban disparity is noted, with 23% of rural residents in such locations compared to 9% of the urban population. Across major area groups, the disadvantageous condition in Visayas and Mindanao is evident in the significant proportion of older persons residing more than 10 km from the nearest health facility. The situation in the Visayas region shows an intraregional disparity: 30% reside within half a kilometre of the nearest health facility, slightly less than the 38% living more than 10 km away. This differs from the situation in the Mindanao region, where only 11% are within half a kilometre of the closest health facility. Due to the more archipelagic characteristic of the Visayas region, the population tends to be more concentrated along the coastal zones of the islands. Hence, the closer proximity of health facilities to the respondents.

Table 5.4. Percent Distribution of Older Persons by Distance in Kilometres from Residence to the Nearest Health Facility by Urbanity and Major Area Group

Distance	URBANITY			MAJOR AREA GROUP					TOTAL
	Rural	Urban	Sig.	NCR	Balance Luzon	Visayas	Mind-anao	Sig.	
Distance to the nearest health facility									
Less than 0.5 km	4.9	42.7	***	66.3	15.2	30.5	10.7	***	23.4
0.5 to less than 1 km	10.6	21.1		28.4	22.6	0.8	8.6		15.8
1 to less than 10 km	61.3	27.3		5.2	54.7	30.8	58.5		44.7
10 km or higher	23.1	8.8		0.0	7.5	37.9	22.3		16.1
N	*2,269*	*1,727*		*398*	*1,228*	*1,170*	*1,200*		*3,996*

***p < .001.

Source: Calculated by the DRDF using original LSAHP W2 data.

Table 5.5 reveals that 29% reside at least 10 km away from the nearest pharmacy. Additionally, according to Table 5.6, 24% are situated 10 km or more from the nearest financial institution. Similar to previous findings, the data reveal the significant urban–rural disparity and disadvantageous situation in the Visayas and Mindanao areas relative to the main island of Luzon.

Table 5.5. Percent Distribution of Older Persons by Distance in Kilometres from Residence to the Nearest Pharmacy by Urbanity and Major Area Group

Distance	URBANITY			MAJOR AREA GROUP					TOTAL
	Rural	Urban	Sig.	NCR	Balance Luzon	Visayas	Mind-anao	Sig.	
Distance to the nearest pharmacy									
Less than 0.5 km	5.3	49.1	***	80.2	23.2	27.7	3.6	***	26.7
0.5 to less than 1 km	12.9	13.2		19.7	17.8	3.8	8.1		13.1
1 to less than 10 km	37.4	24.4		0.1	43.3	13.0	39.1		31.0
10 km or more	44.3	13.4		0.0	15.7	55.5	49.2		29.2
N	*2,269*	*1,727*		*398*	*1,228*	*1,170*	*1,200*		*3,996*

***p < .001.

Source: Calculated by the DRDF using original LSAHP W2 data.

Table 5.6. Percent Distribution of Older Persons by Distance in Kilometres from Residence to the Nearest Financial Facility by Urbanity and Major Area Group

Distance	URBANITY			MAJOR AREA GROUP					TOTAL
	Rural	Urban	Sig.	NCR	Balance Luzon	Visayas	Mind-anao	Sig.	
Distance to the nearest financial facility									
Less than 0.5 km	5.9	49.4	***	67.6	23.8	29.1	10.0	***	27.1
0.5 to less than 1 km	5.0	12.5		28.6	8.0	1.1	7.3		8.7
1 to less than 10 km	53.5	26.8		3.9	52.8	20.2	53.9		40.5
10 km or more	35.6	11.3		0.0	15.4	49.6	28.7		23.7
N	*2,269*	*1,727*		*398*	*1,228*	*1,170*	*1,200*		*3,996*

***p < .001.

Source: Calculated by the DRDF using original LSAHP W2 data.

These extreme distances are more prevalent in rural areas compared to urban ones and in Visayas and Mindanao compared to the NCR and Balance Luzon. The observed differences are statistically significant.

Exploring measures other than distances, Table 5.7 indicates that nearly half (46%) of older persons live in areas where the road network density within a 500 m radius is less than 50 m per hectare. An urban–rural disparity is evident, with three quarters (75%) of older persons in rural areas residing in areas with low road density compared to only 16% amongst their urban counterparts. A similar finding in China reveals that more older persons reside in rural areas, which also have lower road densities (Gu et al., 2022). Across major area groups, limited access to road networks presents a notable challenge for older persons in Visayas and Mindanao, with 66% and 72%, respectively, living in areas with minimal road density. This sharply contrasts with the situation in the NCR, where the majority (82%) reside in areas with a road density of 200 m per hectare or higher. Differences across urbanity and major area groups are statistically significant.

Table 5.7. Percent Distribution of Older Persons by Road Density by Urbanity and Major Area Group

Road Density	URBANITY			MAJOR AREA GROUP					TOTAL
	Rural	Urban	Sig.	NCR	Balance Luzon	Visayas	Mind-anao	Sig.	
Density of road network within a 500 m radius									
Less than 50 m/ha	74.7	16.5	***	0.0	37.4	66.2	72.1	***	46.0
50 to less than 100 m/ha	17.9	20.4		30.0	30.0	2.8	21.3		19.1
100 to less than 200 m/ha	7.4	31.4		17.8	27.5	13.4	6.5		19.3
200 m/ha or more	0.0	31.6		82.2	5.1	17.5	0.1		15.6
N	*2,269*	*1,727*		*398*	*1,228*	*1,170*	*1,200*		*3,996*

***p < .001.

Source: Calculated by the DRDF using original LSAHP W2 data.

Table 5.8 shows that 43% of older persons live 20 m above sea level or higher, potentially facing increased vulnerability to natural disasters like landslides, along with challenges in accessing essential services and infrastructure in remote or mountainous areas. In contrast, 8% of older persons live in areas 5 m above sea level, exposing them to risks associated with floods and coastal hazards such as storm surges, as well as potential impacts on agriculture and livelihoods. Differences across urbanity and major area groups are also shown in Table 5.8, but they are not statistically significant.

Table 5.8. Percent Distribution of Older Persons by Elevation by Urbanity and Major Area Group

Distance	URBANITY			MAJOR AREA GROUP					TOTAL
	Rural	Urban	Sig.	NCR	Balance Luzon	Visayas	Mind-anao	Sig.	
Elevation									
Less than 5 m above sea level	6.5	9.5	ns	3.5	8.7	11.8	4.6	ns	7.9
5 to less than 10 m above sea level	15.7	30.5		28.2	22.6	27.7	15.5		22.9
10 to less than 20 m above sea level	27.3	25.9		34.2	26.9	27.3	20.9		26.6
20 m above sea level or more	50.6	34.2		34.1	41.9	33.2	59.0		42.5
N	*2,269*	*1,727*		*398*	*1,228*	*1,170*	*1,200*		*3,996*

ns = not significant.

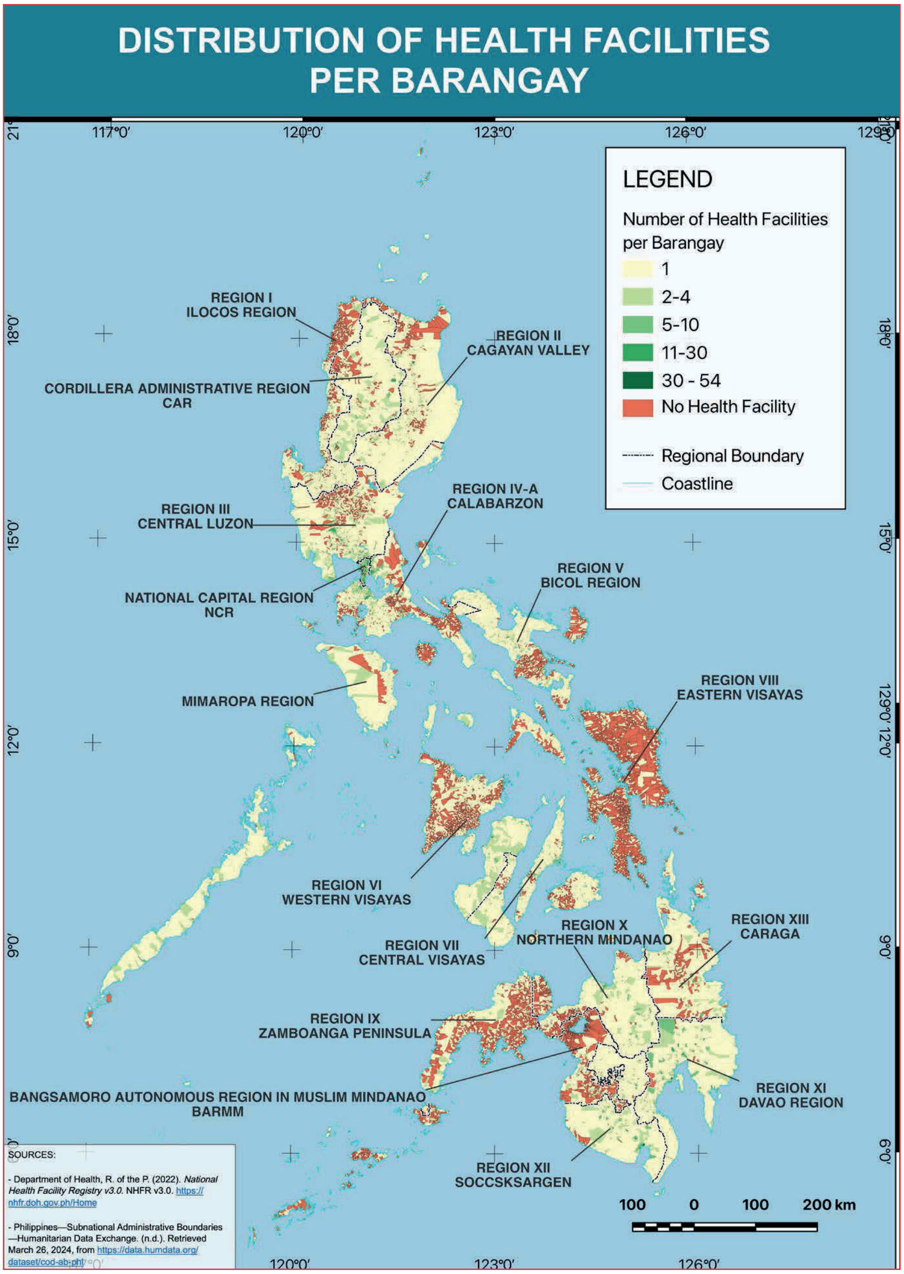
Source: Calculated by the DRDF using original LSAHP W2 data.

5. Independent Validation from Available Data

The foregoing findings were validated with the data using a map, in cartographic form, showing the distribution of OSM health facilities from DOH data, financial institutions, and major roads used for selected LSAHP sample areas. Figure 5.2 presents the 2022 nationwide distribution of health facilities registered under the DOH National Health Facility Registry. This map plots all health facilities at the barangay level using standard PSGC. The map contains a total of 40,232 health facilities, including barangay health stations, rural health units, birthing homes, hospitals, clinics, general clinic laboratories, medical outpatient clinics, dialysis clinics, infirmaries, and blood centres (DOH, 2022).

Results demonstrate the significant geographic disparity in the distribution of health facilities in the country. Health facilities are particularly inadequate in regions such as Eastern Visayas, as shown by the red areas in Figure 5.2. The severe lack of health facilities in Eastern Samar, one of the LSAHP study areas, corroborates the LSAHP finding that the Visayas region has the highest proportion of older persons (38%) residing more than 10 km away from the nearest health facility. Their situation is further aggravated by poor transportation access, with the region having the highest proportion of older persons residing at least 10 km away from the nearest main road. About two-thirds of older people in the Visayas region report very low road density (< 50 m/ha). This is in contrast with older persons living in the NCR, who have the best access to health facilities, as shown by their proximity to health facilities and the main road network and their having the highest road density across major areas in the country.

Figure 5.2. Map of the Distribution of Health Facilities per Barangay: Philippines, 2022



Cartography: Jose Andres F. Ignacio.

Data Source: Department of Health National Health Facility Registry (DOH, 2022).

6. Summary, Conclusions, and Recommendations

This chapter highlights the power of incorporating the geographical context into the analysis of the overall ageing experience of older persons. Such spatial data help identify patterns and clusters of geosocial and geophysical phenomena for a better understanding of the factors affecting older persons' well-being and quality of life. This is particularly relevant in the Philippines, where diverse landscapes and varying degrees of infrastructure development across the archipelagic terrain can significantly affect the experiences of ageing.

Older persons in remote areas of rural settings face challenges that are quite different from those in urban areas. Rural residents have poor access to the nearest social infrastructures such as main roads, municipal or city centres, health facilities, pharmacies, and financial facilities. Fewer road networks and higher elevations in rural areas exacerbate the poorer access to social infrastructures. These findings highlight the higher vulnerability of older persons living in rural areas compared to those in urban areas. By understanding these diversified contexts, resource allocation in healthcare and tailored interventions can be effectively developed to meet the unique needs of older populations in each area.

Our findings also demonstrate how advances in geolocation technologies have improved the quality of GPS data for analysis. Despite these improvements, challenges persist in achieving precise GPS data coverage, particularly in remote and obstructed areas. This underscores the need to enhance methods and technologies for data collection for future research.

The foregoing analysis, integrating geospatial and sociodemographic data, has important implications for future policies, programmes, and research aimed at improving the lives of older persons in the Philippines. These include the need for improved healthcare resource allocation. Rural areas, where access to health facilities is relatively poor, may benefit from mobile health clinics or telemedicine setups to bridge the gap. Infrastructure improvements, particularly in rural and isolated areas, need to be prioritised to ensure better access to facilities and services for older persons.

Considering the increasing natural hazards in the country, health interventions should include disaster preparedness and risk reduction, particularly in high-risk regions. Locality-specific disaster preparedness and risk reduction measures should ensure the protection of older populations. Health programme interventions must also be sensitive to the cultural norms and family structures that vary by region. Our analysis likewise highlights the need to continue improving the accuracy of geospatial data collection through better technology and training for field data gatherers.

References

Abdalla, R. (2016), *Introduction to Geospatial Information and Communication Technology* (GeoICT). Springer International. https://doi.org/10.1007/978-3-319-33603-9_2

Bacsu, J., B. Jeffery, S. Johnson, D. Martz, N. Novik, and S. Abonyi (2012), 'Healthy Aging in Place: Supporting Rural Seniors' Health Needs', *Online Journal of Rural Nursing and Health Care,* 12(2), pp.77–87. https://doi.org/10.14574/ojrnhc.v12i2.52

Baernholdt, M., G. Yan, I. Hinton, K. Rose, and M. Mattos (2012), 'Quality of Life in Rural and Urban Adults 65 Years and Older: Findings from the National Health and Nutrition Examination Survey', *The Journal of Rural Health,* 28(4), pp.339–47. https://doi.org/10.1111/j.1748-0361.2011.00403.x

Barzilay, M. (2019), Data Collection and Mobile Technologies. Research proposal. London: London Metropolitan University. https://doi.org/10.13140/RG.2.2.31541.93929

Choi, Y.J. (2020), 'Age-friendly Features in Home and Community and the Self-reported Health and Functional Limitation of Older Adults: The Role of Supportive Environments', *Journal of Urban Health,* 97(4), pp.471–85.

Choi, Y., Y.-H. Kwon, and J. Kim (2018), 'The Effect of the Social Networks of the Elderly on Housing Choice in Korea', *Habitat International,* 74, pp.1–8.

DAD-UP DREAM/PHIL-LiDAR 1 (2017), Philippines IfSAR 10m Digital Elevation Model [dataset]. https://lipad.dream.upd.edu.ph/layers/?limit=100&offset=0&keywords__slug__in=sar

Department of Health (DOH), Republic of the Philippines (2022), National Health Facility Registry v3.0 [dataset]. https://nhfr.doh.gov.ph/Home

Desjardins, M.R., E.T. Murray, G. Baranyi, M. Hobbs, and S. Curtis (2023), 'Improving Longitudinal Research in Geospatial Health: An Agenda', *Health & Place,* 80, 102994. https://doi.org/10.1016/j.healthplace.2023.102994

The DHS Program (2024), Spatial Data Repository – Geospatial Covariates. May. https://spatialdata.dhsprogram.com/covariates/

Di Ciaula, A. and P. Portincasa (2020), 'The Environment as a Determinant of Successful Aging or Frailty', *Mechanisms of Ageing and Development,* 188, 111244. https://doi.org/10.1016/j.mad.2020.111244

Donovan, N.J. and D. Blazer (2020), 'Social Isolation and Loneliness in Older Adults: Review and Commentary of a National Academies Report', *The American Journal of Geriatric Psychiatry,* 28(12), pp.1233–44. https://doi.org/10.1016/j.jagp.2020.08.005

Gu, Z., X. Luo, Y. Chen, X. Liu, C. Xiao, and Y. Liang (2022), 'Density, Diversity, and Design: Evaluating the Equity of the Elderly Communities in Three Measures of the Built Environment', *Land*, 11(11), 1976. https://doi.org/10.3390/land11111976

Humdata (2023), Philippines – Subnational Administrative Boundaries [Shapefile]. United Nations Office for the Coordination of Humanitarian Affairs. https://data.humdata.org/dataset/cod-ab-phl

Ignacio, J.A.F. (2023), A Deriving Geospatial Covariates on Social Infrastructures for LSAHP Data. Paper presented at the 2023 Philippine Population Association Scientific Conference, 27 April, Iloilo City, Philippines. https://sites.google.com/view/2023ppaconference/programme?authuser=0

Kwan, M.-P. (2012), 'The Uncertain Geographic Context Problem', *Annals of the Association of American Geographers,* 102(5), pp.958–68. https://doi.org/10.1080/00045608.2012.687349

Langley, R. (2015), 'Innovation: Faster, Higher, Stronger', *GPS World - The Business and Technology of Global Navigation and Positioning.* https://www.gpsworld.com/innovation-faster-higher-stronger/

Liu, S., F. Wang, S. Sha, H. Cai, C.H. Ng, Y. Feng, and T. Xiang (2023), 'A Comparison of Quality of Life Between Older Adults Living in High and Low Altitude Areas', *Frontiers in Public Health,* 11. https://doi.org/10.3389/fpubh.2023.1184967

OpenStreetMap (2022), About OpenStreetMap—OpenStreetMap Wiki, January. https://wiki.openstreetmap.org/w/index.php?title=About_OpenStreetMap&oldid=2310396

Smith, A.E. (2009), *Ageing in Urban Neighbourhoods: Place Attachment and Social Exclusion.* Bristol: Bristol University Press. http://www.jstor.org/stable/j.ctt9qgmn1

Wahl, H.-W., S. Iwarsson, and F. Oswald (2012), 'Aging Well and the Environment: Toward an Integrative Model and Research Agenda for the Future', *The Gerontologist,* 52(3), pp.306–16.

Wood, G., J. Pykett, P. Daw, S. Agyapong-Badu, A. Banchoff, A.C. King, and A. Stathi (2022), 'The Role of Urban Environments in Promoting Active and Healthy Aging: A Systematic Scoping Review of Citizen Science Approaches', *Journal of Urban Health,* 99(3), pp.427–56.

Yuchi, W., H. Sbihi, H. Davies, L. Tamburic, and M. Brauer (2020), 'Road Proximity, Air Pollution, Noise, Green Space, and Neurologic Disease Incidence: A Population-based Cohort Study', *Environmental Health,* 19(1), p. 8. https://doi.org/10.1186/s12940-020-0565-4

Zhang, R., S. Liu, M. Li, X. He, C. Zhou (2021), 'The Effect of High-density Built Environments on Elderly Individuals' Physical Health: A Cross-sectional Study in Guangzhou, China', *International Journal of Environmental Research and Public Health*, 18(19), 10250. https://doi.org/10.3390/ijerph181910250