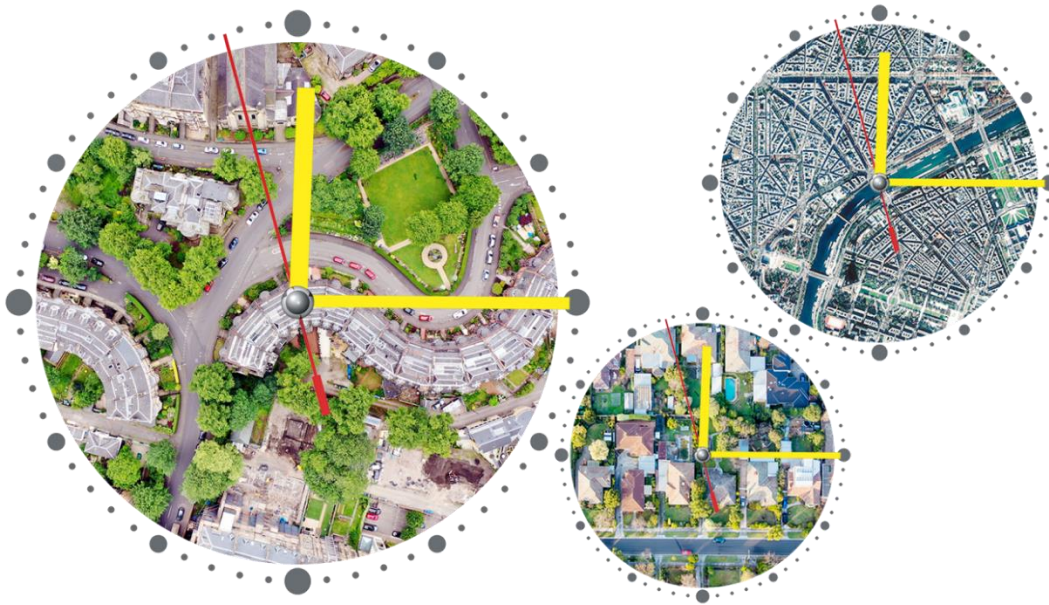


Data Preparation and Spatial Processing for Accessibility Analysis



© Shutterstock; Getty | Aerial views of Glasgow, Paris and Melbourne

| | |
|--------------------|-----------------------------------|
| Author: | Nicky de Theije |
| Student number: | 2783854 |
| Email: | n.de.theije@student.vu.nl |
| Program: | Earth, Economics & Sustainability |
| Faculty: | Faculty of Science |
| Supervisor: | dr. E. Koomen |
| Second Supervisor: | dr. J. Liu |
| Second Assessor: | dr. M. Lankhuizen |
| Date: | May 16, 2025 |

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1. Objective

The 15-minute city is a planning concept that envisions urban environments where residents can enjoy a higher quality of life by effectively fulfilling six essential urban social functions (living, working, commerce, healthcare, education, and entertainment) within a 15-minute walk or bike ride (Moreno et al., 2016). Despite its growing popularity in urban policy and planning, the insight into whether residents' actual travel behaviour aligns with the ideals of the 15-minute city remains limited. Most existing studies focus on developing appropriate indicators to assess the sustainability of neighbourhoods and urban areas, rather than assessing whether people make use of nearby amenities in practice (Khavarian-Garmsir et al., 2023; Papadopoulos et al., 2023).

This research addresses the following main question: *“To what extent does actual travel behaviour align with the spatial distribution and accessibility of amenities, and how does this alignment vary across different socio-demographic characteristics?”*

Assessing whether the concept of the 15-minute city holds true in practice requires studies that link actual mobility patterns with the spatial distribution of amenities. Such analysis requires detailed spatial data on the supply of amenities, the residential locations from which people travel, the network in which people travel, and data on the trips the residents actually make. This report presents the data processing steps performed to prepare a geospatial dataset for the municipality of Alkmaar needed for such an analysis. The municipality of Alkmaar is a mid-sized Dutch Municipality that combines a dense, historic city centre with suburban neighbourhoods and surrounding rural areas. Its spatial diversity makes Alkmaar a suitable case for evaluating the relationship between accessibility and travel behaviour.

To support this analysis, accessibility scores are computed that reflect the number of facilities reachable within a 15-minute walking or cycling distance from residential areas. To achieve this, raw geospatial data, such as Points of Interests (POIs) and travel networks, undergo a series of pre-processing steps. These processes are explained in more detail in the following chapters of the report.

The resulting dataset forms the basis for analysing how variations in observed trip patterns are based on local accessibility. In doing so, this research contributes to bridge the gap between potential access (spatially calculated) and actual travel behaviour (as observed), thereby supporting an evaluation of mobility patterns within the framework of the 15-minute city concept.

2. Data Preparation

To analyse whether the concept of the 15-minute city holds true in practice, this study requires geospatial data that captures where people live, the transport networks they use, and the distribution of amenities. The general approach involves calculating accessibility scores for residential locations based on the number of facilities reachable within a 15-minute walk or bike ride. To achieve this, several spatial datasets are combined and processed to ensure consistency and compatibility.

The analysis relies on five key spatial data layers, which are summarised in Table 1.

Table 1 Data input layers

| Data layer | Source | Description |
|-----------------------------|---|---|
| Walkway Network | OpenStreetMap (OSM) | Links that can be used for walking (e.g., “footway”, “pedestrian”, “steps”, “track”). |
| Bicycle Network | OSM | Links that allow for cycling, including dedicated cycling lanes and other types of shared routes (e.g., “cycleway”, “living_street”, “residential”, “track”). |
| Points of Interests (POIs) | OSM | Includes a wide range of amenities such as shops, school, recreational areas etc.. |
| 500-by-500m grid | Statistics Netherlands (CBS) | Grid cells of 500-by-500 metre containing demographic and socio-economic data. |
| Residential building points | Basisregistratie Adressen en Gebouwen (BAG) | Locations of all residential buildings in the Netherlands |

Three main datasets were selected for this study: OpenStreetMap (OSM), the 500-by-500m grid, and the Residential building points. OSM is a widely used open-source geospatial database that is regularly updated and has been applied in many previous studies focused on the 15-minute city concept (Papadopoulos et al., 2023). Its comprehensive tagging system makes it well-suited for mapping both transportation networks and Points of interests (POIs). Additionally, OSM is easily accessible to everyone, making it a practical and transparent choice for this analysis.

The Statistics Netherlands (CBS) 500-by-500m grid data was selected for its uniform size of the cells and its inclusion of demographic and socio-economic information. In contrast, administrative boundaries such as postal codes or neighbourhoods, which vary in size and shape and may not accurately reflect the actual distribution of the population. Previous analyses have often relied on the central points of such administrative units, yet this approach can introduce exposure bias, particularly when population densities vary significantly within a unit. Moreover, the 100-by-100m grid data was not used due to the lack of many relevant demographic attributes, which are omitted under privacy regulations (Knap et al., 2023).

To more precisely identify residential locations within each grid cell, residential building points from the Basisregistratie Adressen en Gebouwen (BAG) were used. The BAG dataset, maintained by Dutch municipalities, contains highly accurate information on all registered buildings, including their function, size, and location (Ministerie van Binnenlandse Zaken en Koninkrijksrelaties, n.d.).

To define the spatial extent of the analysis, Figure 1 shows the case study area: the municipality of Alkmaar, including a surrounding buffer zone. A buffer of 3750 metres is applied around the municipal boundaries to account for the maximum distance that can be covered within 15 minutes of cycling. This approach ensures that the residential locations located near the municipal edges are not artificially excluded from amenities located just outside the official boundary.

Before computing accessibility scores, all data layers were standardised to ensure consistency in projection and spatial extent. The next paragraphs describe in more detail how each dataset was processed and integrated into the final geospatial dataset used for accessibility analysis.

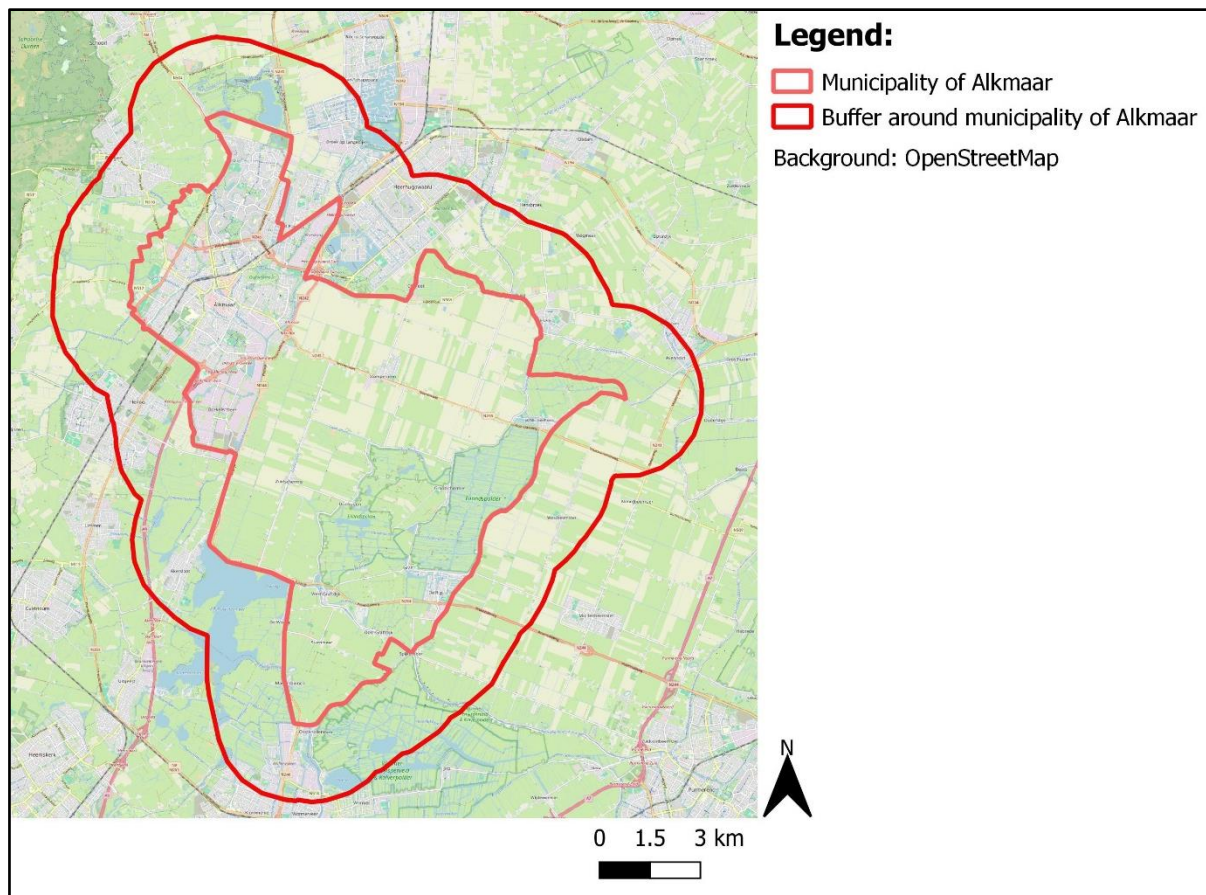


Figure 1 Case study area: municipality of Alkmaar and buffer zone

2.1 Walkway and Cycleway Networks

To ensure a topologically correct and usable transport network for accessibility calculations, the raw OSM data required several preprocessing steps. The general approach involved breaking down complex road geometries into basic units, assigning connectivity attributes, identifying and resolving inconsistencies, and extracting relevant subsets for walking and cycling.

The raw OSM data initially consisted of arcs (a stretch of road, that could contain multiple points). To improve topological clarity, these arcs were split into simple segments, each defined by exactly two endpoints (nodes). This step allowed for a precise representation of the network's structure and facilitated the detection of connectivity between segments.

Next, a comprehensive node set was created by extracting all individual coordinate points in the dataset. These nodes served as the basis for assigning from and to relationships to each segment, enabling the identification if two segments were topologically connected. Using this structure, the network was then analysed to find and isolate unconnected subnetworks or segments. Where appropriate, manual corrections were applied to address small gaps, misalignments, or overlaps in geometry. Subsequently, only those segments connected to the main network were retained, while isolated or dangling links (those not connected to any meaningful part of the network) were removed. This step ensured that accessibility calculations would not be distorted by unreachable links.

Establishing a clean and connected network structure, a subset of segments was selected to represent walkable and cyclable infrastructure. This selection was based on the *fclass* attribute from OSM, which categorises roads and paths by function. The classification into pedestrian and bicycle networks was performed manually, guided by domain knowledge and practical criteria (e.g., inclusion of “cycleway”, “footway”, etc.).

Finally, the network underwent a manual inspection and cleaning phase to remove or correct problematic segments that would affect accessibility results. For example, roads that technically existed in the data but were inaccessible by bike or on foot (e.g., gas stations) were either removed or logically reconnected to the main network when appropriate. This cleaning process resulted in a topologically consistent and realistic representation of the pedestrian and bicycle infrastructure in the study area, as shown in Figure 2.

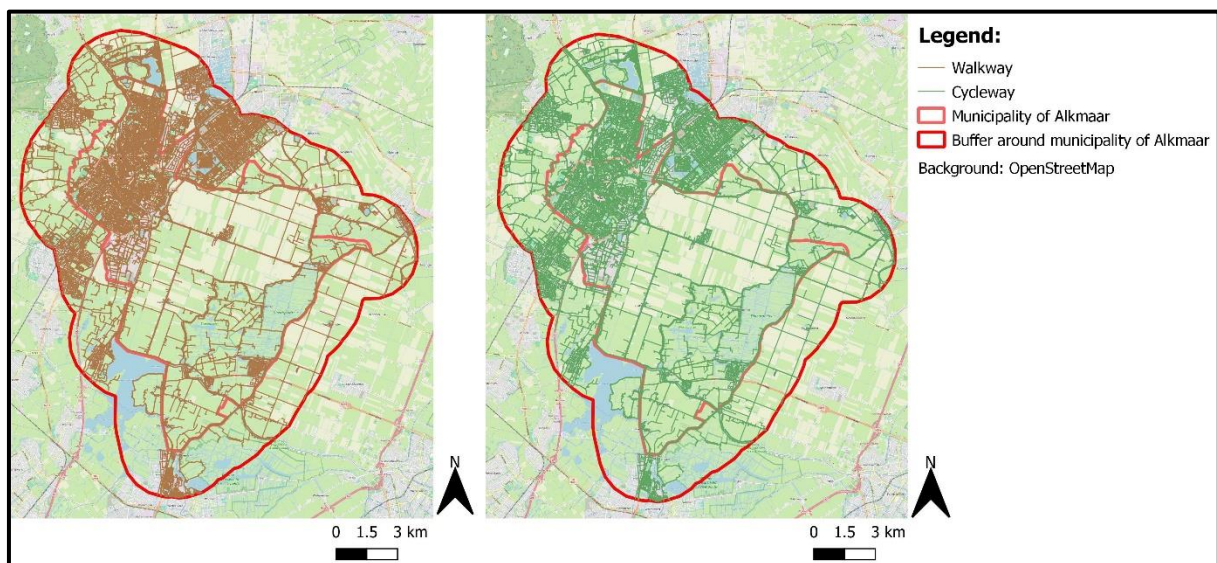


Figure 2 Walkway and Cycleway Networks in municipality of Alkmaar and buffer zone

2.2 Population-Weighted Centroids

This study uses population-weighted centroids derived from a combination of two spatial datasets: the 500-by-500 metre grid dataset provided by Statistics Netherlands (CBS) and the Basic Registration of Addresses and Buildings (BAG). The CBS grid includes detailed demographic and socio-economic data, such as age groups, household characteristics, gender, and income for each cell, while the BAG provides precise geolocations of residential buildings.

By integrating the CBS grid data with the residential point data from BAG, it is possible to determine not only how many people live in each cell, but also where exactly they are located. Using geometric centroids could lead to biased results, particularly if the centroid falls into an uninhabited area (e.g., a park or body of water). To avoid this, population-weighted centroids were adopted, as they more accurately represent the residential location within each cell. This is particularly important when calculating accessibility, as the population is rarely evenly distributed.

The centroids were computed using the ‘mean coordinate(s)’ function in QGIS, which determines the average location within each 500-by-500 metre cell. While this method does not apply explicit population weights, it effectively accounts for population concentration by relying on the actual distribution of residences. As a result, the computed centroids are more likely to fall within inhabited areas and better represent the true residential sites of each cell. Cells with zero population were excluded from the dataset, as these areas are assumed to generate no trips. The outcome of this process is visualised in Figure 3.

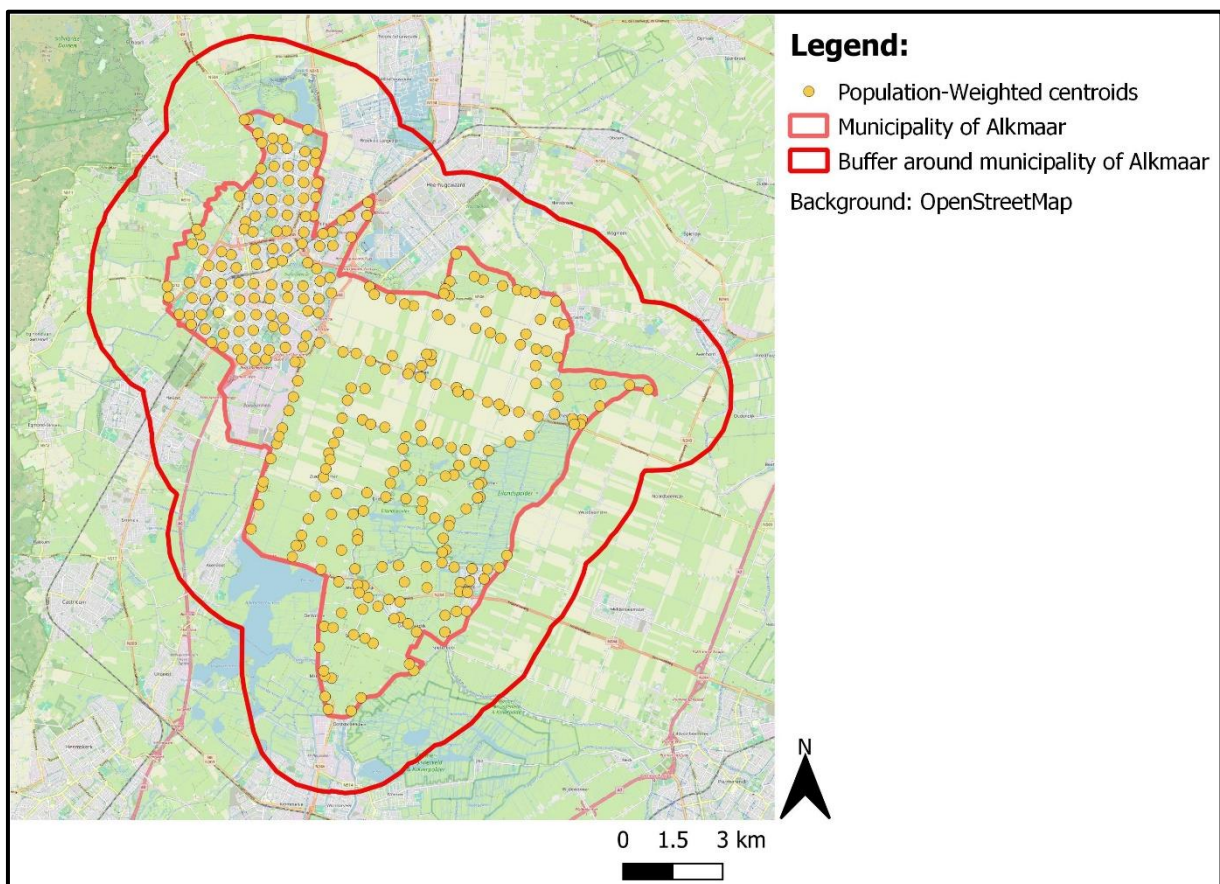


Figure 3 Population-Weighted Centroids in municipality of Alkmaar

2.3 Points of Interest

Points of interest (POIs) refer to the specific locations where facilities are situated, such as shops, schools, and recreational areas. In the context of this study, POIs are used to represent potential destinations for daily activities. The categorization and spatial processing of these POIs are outlined below.

2.3.1 Defining Amenity Types

The POIs were classified into six broad amenity categories based on the main purpose or function. This categorization reflects common types of activities that support daily life, such as grocery shopping and participating in leisure or sporting activities. The six categories were chosen based on their frequent inclusion in previous 15-minute city studies (e.g., Papadopoulos et al., 2023), and their relevance to the travel motives from the mobility data. Table 2 present the amenity categories and the main function with some examples.

Table 2 Amenity categories

| Amenity category | Description |
|---------------------------|--|
| Education | Educational institutions like kindergartens, libraries, schools and universities. |
| Entertainment and leisure | Places for free-time and cultural activities like cinemas, museums, etc. |
| Grocery and shopping | All types of retail stores (e.g., supermarkets, clothing stores, and electronics shops). |
| Healthcare | Professional services and products for preventing or treating illness (and or health) conditions (complains) |
| Service | General public or private service providers such as banks, post offices, and hairdressers. |
| Sports | Facilities for physical activity and exercise, such as gyms, swimming pools, and sports fields. |

2.3.2 POIs Processing

The POI data were extracted from the OSM geospatial database. OSM offers a comprehensive, public, and regularly updated dataset with standardized tagging conventions. These tags allow for consistent identification of facility types.

In QGIS, a new field called *Amenity* was created in the attribute table to assign each POI to one of the six categories. This was accomplished using the Field Calculator and a rule-based expression referencing the *fclass* attribute (an OSM-specific field that denotes the functional classification of each feature). A full mapping of *fclass* values to amenity categories is included in Appendix A1. POIs that could not be clearly assigned to one of the six categories, such as a graveyard, were classified as “Other” and excluded from the final output.

For polygon-based POIs representing larger areas (e.g., parks, sport fields), the geometric centre of each polygon was calculated using the “mean coordinates” function. In cases where a single clear entrance was visible (e.g., Golf & padel Sluispolder), the centroid was manually adjusted to better reflect the main point of access. However, such corrections were only applied when necessary, as the centroid generally provided a reliable representation of the POI’s location.

Figure 4 shows the outcome of this process, illustrating the spatial distribution of the categorized POIs.

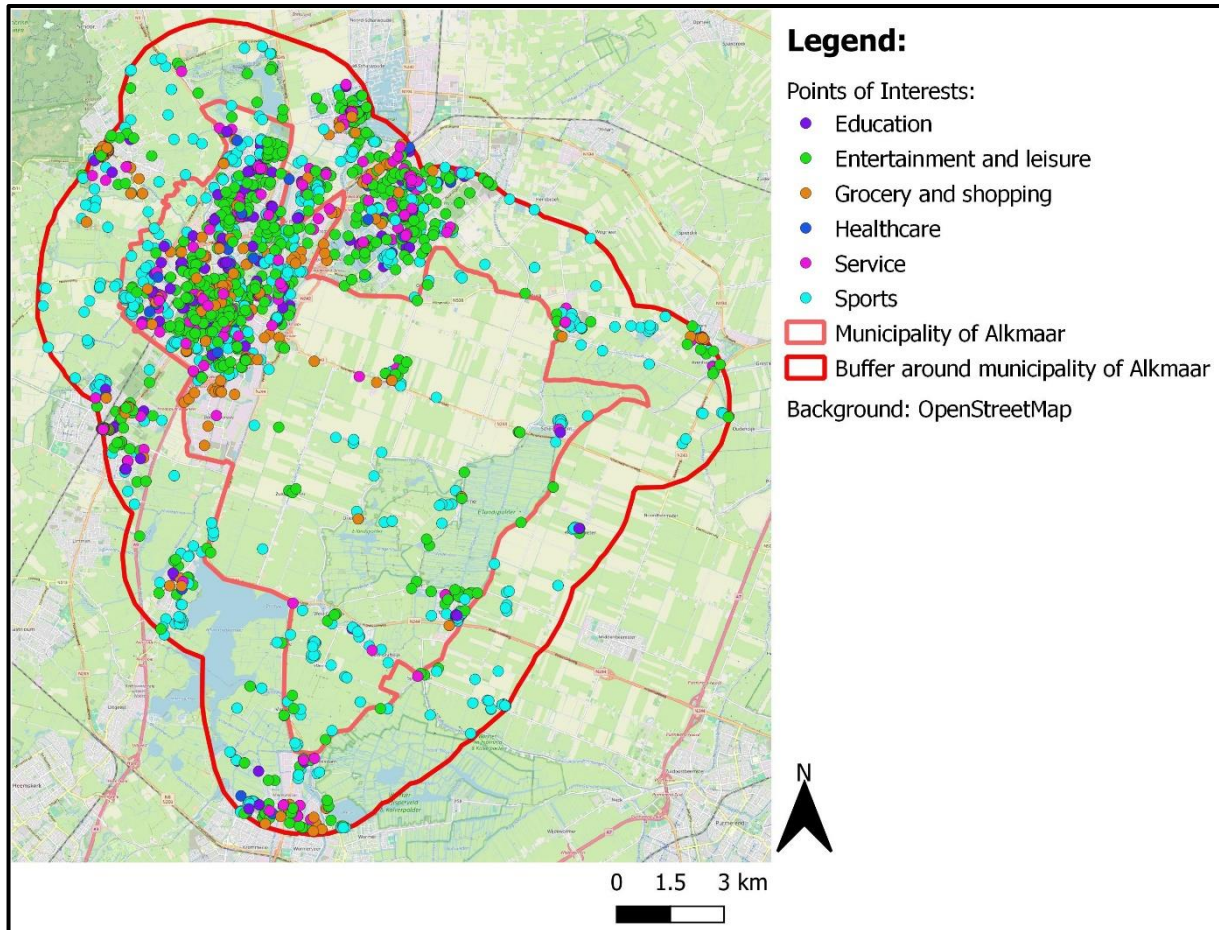


Figure 4 Points of Interests in municipality of Alkmaar and buffer zone

2.4 Catchment Areas

To define the catchment areas used in this study, a two-step spatial analysis approach was used, beginning with a Service Area Network Analysis and followed by the construction of a Convex Hull polygon around the resulting service area. This method was applied to both the cycling and walking networks.

For the cycling network, a maximum travel distance of 3750 meters was used, based on an average speed of 15 km/h over a 15-minute period. The Service Area Network Analysis calculates the area that can be reached within this distance from a starting point, taking into account the actual layout and connectivity of the road infrastructure. For walking, a maximum distance of 1250 meters was used, corresponding to an average walking speed of 5 km/h over 15 minutes, which reflects a realistic walking distance in an urban environment.

To ensure that the catchment areas reflect realistic accessibility from locations where people actually reside, the previously computed population-weighted centroids were used as the starting points for the Service Area Network Analysis. This approach ensures a more realistic estimate of reachable facilities from the actual locations where people live.

After generating the service areas, a Convex Hull was constructed around each network-based catchment. The Convex Hull generalizes the boundary of the reachable area, creating a continuous and simplified polygon suitable for overlay and spatial comparison across different locations. The use of a Convex Hull is justified in this context due to the dense and highly connected nature of the transport networks. Unlike simpler methods that use straight-line buffers (e.g., radius buffers), network-based catchment areas provide a more realistic representation of accessibility.

3. Accessibility Score

All POIs falling within each catchment area are identified and categorized by type to enable analysis of accessibility. The number of POIs within each catchment area is then counted.

To relate these scores to spatial units relevant for statistical analysis, each catchment area is linked to neighbourhoods. The locations of the population-weighted centroids (e.g., the origin points of the catchment area) determines which administrative unit it is assigned to. For each unit, the population-weighted average number of accessible facilities is calculated using the following formula:

$$(Inhabitants_{cell1} * POIs_{cell1} + Inhabitants_{cell2} * POIs_{cell2} + ...) / Total\ number\ of\ inhabitants\ in\ the\ unit$$

The population data is derived from the 500-by-500m grid cell dataset. To ensure data quality and prevent distortions in the analysis, grid cells with missing population data were excluded from the calculation. These missing values occur when a cell contains fewer than five inhabitants or five houses, in line with CBS privacy regulations (CBS, 2024). As these cells represent areas with negligible residential presence, they were omitted from the analysis under the assumption that no meaningful number of trips originates from them.

The population-weighted approach is particularly important because catchment areas from multiple centroids within the same administrative unit may overlap, potentially leading to an overcount of POIs. By weighing the accessibility score by population, the method reduces the impact of such overlaps and provides a more balanced representation of actual accessibility for residents within each unit.

The final value represents the accessibility score, meaning that the higher the number of reachable POIs, the better the spatial accessibility of that location. This score provides a clear and quantifiable measure of spatial access to amenities from residential locations. This is showed in Figure 5.

Importantly, the accessibility analyses are performed separately for the cycling and walking networks, ensuring that differences in reachability between transport modes are preserved and can be analysed distinctly.

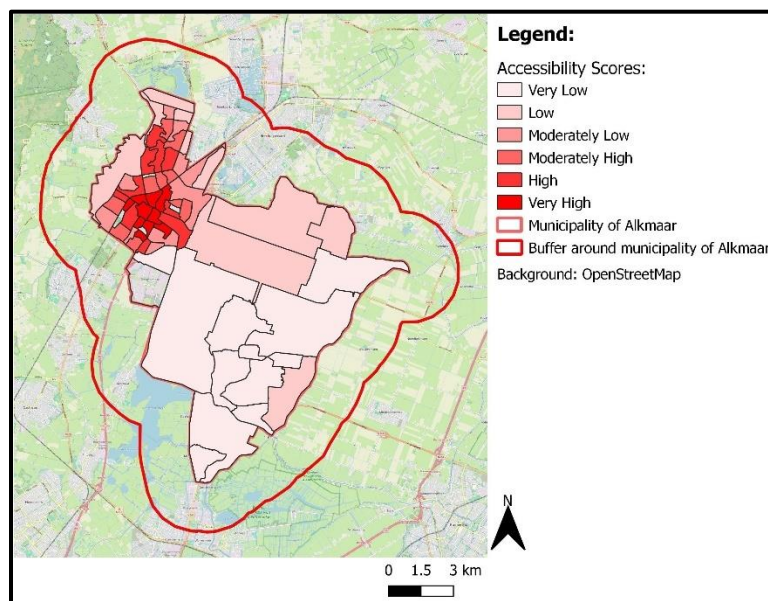


Figure 5 Accessibility score for each neighbourhood

4. Discussion

While the methodology applied in this study offers a practical approach to delineating catchment areas and measuring spatial accessibility, several limitations and methodological considerations should be acknowledged. These concern, among others, the precision of the catchment area boundaries, assumptions about travel behaviour, the quality of the construction of the underlying network data, and the classification of POIs.

First, the accuracy of the catchment area delineation is limited by the tools that could be implemented during this study. Ideally, more advanced methods such as QNEAT3 or Concave Hull would have been applied to generate catchment polygons that precisely follow the transport network, capturing the true shape of accessible space including cutouts. However, due to technical limitations encountered during the analysis these more precise methods could not be implemented successfully. As a result, the study resorts to generating simplified polygons using Convex Hulls around service area points. This simplification may lead to slight overestimations of accessible areas, particularly near the edges of the catchment.

Secondly, the calculation of the catchment areas is based on a fixed average speed (5km/h for walking and 15 km/h for cycling), without accounting for real-world variations in travel behaviour. Factors such as traffic lights, intersection delays, terrain, and individual differences in pace are not included in the model. As a result, the actual area a person can reach in 15 minutes may differ from the modelled catchment. While this assumption allows for a standardized comparison, it does introduce a degree of uncertainty in the representativeness of the results.

A further source of potential error lies in the construction of the walking and cycling networks. These networks were constructed manually, which, while offering a high level of control, also introduces potential sources of error. Some segments remain disconnected or were manually joined, which may have affected the network's continuity and consequently, the outcomes of the Service Area Network Analysis. For future studies, more severe and automated cleaning of the network data is recommended to ensure full connectivity and accuracy.

Another notable limitation is the classification of POIs. There is no universally standardised system for categorising POIs, and many facilities provide multiple services or fulfil several functions simultaneously. For example, a community centre may offer both educational programs and sports activities. IN this study, each POI was assigned to a single amenity category based on its primary function as interpreted from its OSM tag (*fclass*). While this method supports consistency in classification, it can lead to a simplification of real-world usage patterns. The ambiguity in some POI's function mean that some detail is inevitably lost.

These reflections demonstrate the importance of transparent assumptions and methodological choices when working with spatial models. Despite the described improvement points involved, the methodology used here remains consistent and reproducible and offers meaningful insights into spatial accessibility patterns.

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Appendix

A1. Walkway and Cycleway Networks

The python script that was used to clean the transport networks is given below.

```
def merge_links(mergelist):
    #print('merge',mergelist)
    mls={'mergelist': list(mergelist)}

    testcur.execute('select          st_geometrytype(st_linemerge(st_union(geom)))          as
    linetype,st_issimple(st_linemerge(st_union(geom))) as simple from wegen_osm where id = any
    (%(mergelist)s)',mls)

    t=testcur.fetchone()

    linetype=t['linetype']

    simple=t['simple']

    testcur.execute('select  w2.id    from    wegen_osm    w1,wegen_osm    w2    where
    st_intersects(w1.geom,w2.geom) and st_intersects(st_points(w1.geom),st_points(w2.geom))
    and w1.id = any (%(mergelist)s) and w2.id <> all (%(mergelist)s)',mls)

    island=(testcur.rowcount==0)

    closed=False

    if not(linetype=='ST_MultiLineString'):

        testcur.execute('select st_isclosed(st_linemerge(st_union(geom))) as closed from wegen_osm
        where id = any (%(mergelist)s)',mls)

        closed=testcur.fetchone()['closed']

        #print('merge linetype',linetype,'simple',simple,'island',island,'closed',closed)

        if island:

            delcur.execute('delete from wegen_osm where id = any (%(mergelist)s)',mls)

            elif simple and not(closed) and not(linetype=='ST_MultiLineString'):

                inscur.execute('insert into wegen_osm(geom) select st_linemerge(st_union(geom)) from
                wegen_osm where id = any (%(mergelist)s)',mls)

            delcur.execute('delete from wegen_osm where id = any (%(mergelist)s)',mls)

            conn.commit()

            selcur.execute('select osm_id,geom,st_issimple(geom) as simple,st_isclosed(geom) as closed
            from wegen_osm_input order by osm_id')

            state={}


```

```

for sel in selcur:

state['osm_id']=sel['osm_id']

wegcur.execute('select w2.osm_id from wegen_osm_input w1,wegen_osm_input w2 where
st_intersects(st_points(w1.geom),st_points(w2.geom)) and w2.osm_id<>%(osm_id)s and
w1.osm_id=%(osm_id)s',state)

if wegcur.rowcount==0:

continue

if sel['simple'] and not(sel['closed']):

wegcur.execute('select
w1.osm_id,(st_dump(st_split(w1.geom,st_union(st_intersection(st_points(w1.geom),st_points(
w2.geom)))))).geom as geom from wegen_osm_input w1,wegen_osm_input w2 where
st_intersects(st_points(w1.geom),st_points(w2.geom)) and w2.osm_id<>%(osm_id)s and
w1.osm_id=%(osm_id)s group by w1.osm_id',state)

else:

wegcur.execute('select w1.osm_id,(st_dump(st_split(w1.geom,st_points(w1.geom))))).geom as
geom from wegen_osm_input w1 where w1.osm_id=%(osm_id)s',state)

for weg in wegcur:

state['geom']=weg['geom']

insert_weg(state)

conn.commit()

state['id']=0

while True:

selcur.execute('select id,st_startpoint(geom) as sp,st_endpoint(geom) as ep from wegen_osm
where id > %(id)s order by id limit 1',state)

if selcur.rowcount==0:

break

for sel in selcur:

state['mergelist']={sel['id']}

state['id']=sel['id']

state['geom']=sel['sp']

wegcur.execute('select id from wegen_osm where st_intersects(%(geom)s,geom) and %(geom)s
in (st_endpoint(geom),st_startpoint(geom)) and id<>%(id)s',state)

island=(wegcur.rowcount==0)

if wegcur.rowcount==1:

```

```

for weg in wegcur:

state['mergelist'].add(weg['id'])

state['geom']=sel['ep']

wegcur.execute('select id from wegen_osm where st_intersects(%(geom)s,geom) and %(geom)s
in (st_endpoint(geom),st_startpoint(geom)) and id<>%(id)s',state)

island&=(wegcur.rowcount==0)

if wegcur.rowcount==1:

for weg in wegcur:

state['mergelist'].add(weg['id'])

if len(state['mergelist'])>1:

merge_links(state['mergelist'])

elif island:

#print('delete island',state['id'])

delcur.execute("delete from wegen_osm where id=%(id)s",state)

conn.commit()

```

A2. Population-Weighted Centroids

To enhance transparency and reproducibility, the following flowchart provides a visual overview of the key geoprocessing steps used to generate population-weighted centroids.

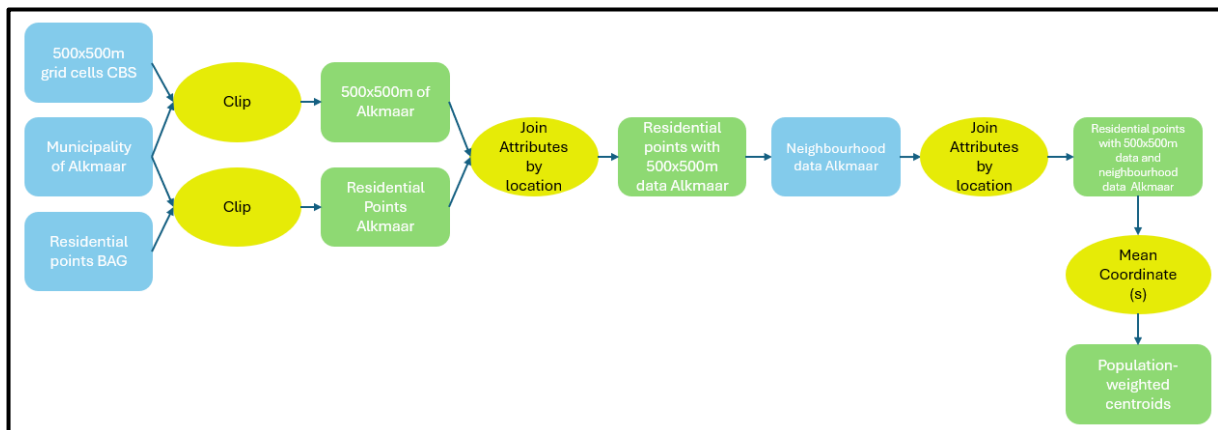


Figure 6 Flowchart with geoprocessing steps taken to generate the Population-Weighted Centroids

A3. Points of Interest

The flowchart below shows the steps taken to process the Points of Interests (POIs) dataset extracted from OSM. The full mapping between *fclass* values and categories is presented in Table A1.

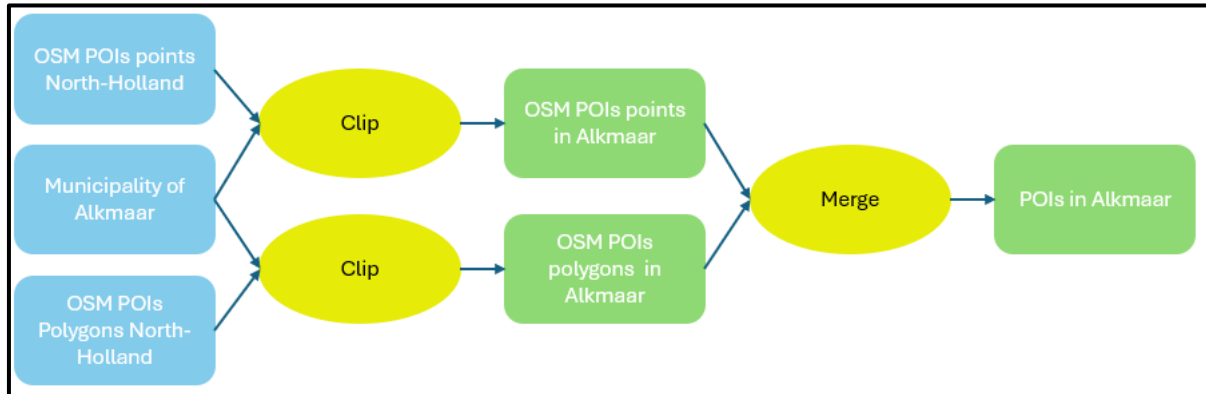


Figure 7 Flowchart with geoprocessing steps taken to generate the POIs dataset

Table A1 The OSM *fclass* values divided into the amenity categories (Ramm, 2022)

| Amenity category | OSM <i>fclass</i> values |
|---------------------------|--|
| Education | library, university, school, kindergarten, college |
| Entertainment and leisure | theatre, nightclub, cinema, park, playground, dog_park, restaurant, fast_food, cafe, pub, bar, food_court, biergarten, attraction, museum, monument, memorial, art, castle, ruins, archaeological, wayside_cross, wayside_shrine, battlefield, fort, picnic_site, viewpoint, zoo, theme_park, fountain, arts_centre, forest, park, nature_reserve, recreation_ground |
| Grocery and shopping | Supermarket, bakery, kiosk, mall, department_store, general, convenience, clothes, florist, chemist, bookshop, butcher, shoe_shop, beverages, optician, jeweller, gift_shop, sports_shop, stationary, outdoor_shop, mobile_phone_shop, toy_shop, newsagent, greengrocer, beauty_shop, video_shop, car_dealership, bicycle_shop, doityourself, furniture_shop, computer_shop, garden_centre, car_rental, bicycle_rental |
| Healthcare | pharmacy, clinic, doctors, dentist |
| Service | veterinary, hairdresser, car_repair, car_wash, car_sharing, travel_agent, laundry, bank, atm, post_box, post_office, community_centre |
| Sports | sports_centre, pitch, swimming_pool, tennis_court, golf_course, stadium, ice_rink |

A4. Catchment Areas

The following flowchart outlines the geoprocessing steps for creating catchment areas based on travel distances for walking and cycling.

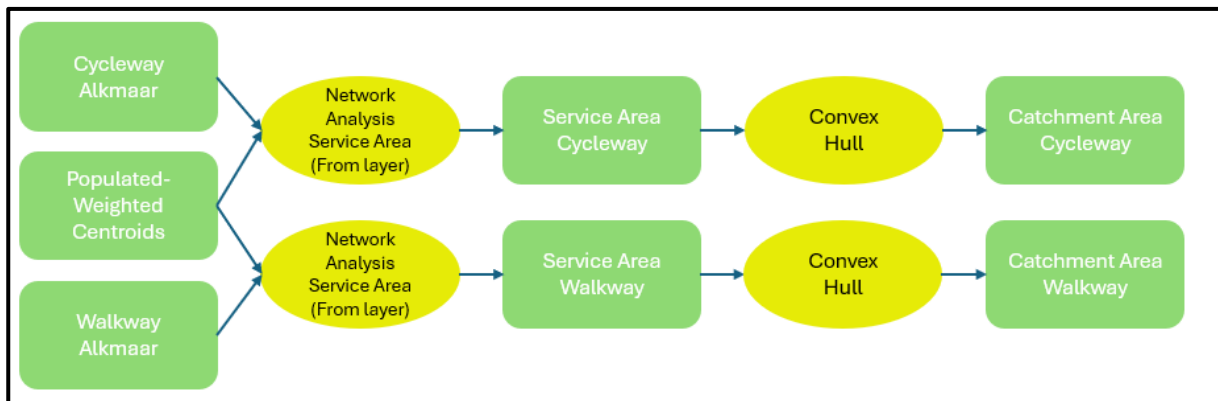


Figure 8 Flowchart with geoprocessing steps taken to generate the catchment areas

A5. Accessibility Score

This flowchart presents the final steps in calculating accessibility scores for each residential location. The python script that was used to perform a calculation is also given below.

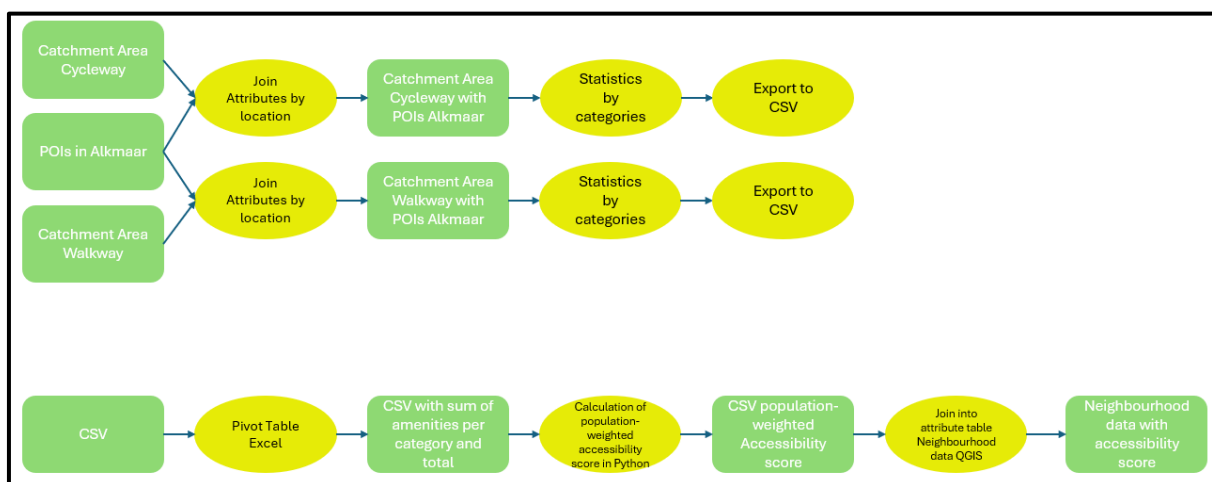


Figure 9 Flowchart with geoprocessing steps taken to generate the accessibility scores

Python Script

```

df_walkway = df.groupby('buurtcode').apply(
    lambda g: (g['aantal_inw'] * g['Walkway_Total Amenities']).sum() / g['aantal_inw'].sum()
).reset_index(name='Walkway_Accessibility_Score')

df_cycleway = df.groupby('buurtcode').apply(
    lambda g: (g['aantal_inw'] * g['Cycleway_Total Amenities']).sum() / g['aantal_inw'].sum()
).reset_index(name='Cycleway_Accessibility_Score')

df_accessibility_score = df_walkway.merge(df_cycleway, on='buurtcode')
  
```

Table A2 Accessibility scores per neighbourhood

| Buurtcode | Walkway Accessibility Score | Cycleway Accessibility Score |
|------------|-----------------------------|------------------------------|
| BU03610100 | 111,00 | 1150,00 |
| BU03610101 | 533,00 | 1210,00 |
| BU03610102 | 666,00 | 1217,00 |
| BU03610104 | 732,00 | 1240,00 |
| BU03610105 | 239,00 | 1210,00 |
| BU03610106 | 99,33 | 1188,34 |
| BU03610108 | 386,00 | 1295,00 |
| BU03610109 | 70,00 | 1179,00 |
| BU03610200 | 596,00 | 1354,00 |
| BU03610201 | 98,86 | 1200,84 |
| BU03610202 | 103,93 | 1210,67 |
| BU03610203 | 127,06 | 1188,80 |
| BU03610204 | 248,00 | 1299,00 |
| BU03610206 | 123,79 | 1285,92 |
| BU03610208 | 69,88 | 1105,16 |
| BU03610209 | 20,29 | 717,12 |
| BU03610300 | 374,36 | 1164,52 |
| BU03610301 | 78,00 | 1045,00 |
| BU03610302 | 95,06 | 1081,00 |
| BU03610303 | 143,65 | 1144,49 |
| BU03610309 | 15,00 | 984,00 |
| BU03610400 | 71,36 | 1093,81 |
| BU03610401 | 107,34 | 1151,23 |
| BU03610402 | 164,00 | 1278,00 |
| BU03610403 | 146,24 | 1291,65 |
| BU03610404 | 81,76 | 1220,49 |
| BU03610409 | 32,24 | 1065,28 |
| BU03610500 | 116,87 | 1366,95 |
| BU03610502 | 103,02 | 1368,03 |
| BU03610503 | 100,00 | 1345,00 |
| BU03610600 | 130,15 | 1283,16 |
| BU03610601 | 129,01 | 743,33 |
| BU03610602 | 122,98 | 504,33 |
| BU03610603 | 148,86 | 1070,64 |
| BU03610604 | 152,52 | 957,59 |
| BU03610700 | 83,00 | 461,00 |
| BU03610701 | 107,68 | 426,05 |
| BU03610702 | 38,98 | 347,78 |
| BU03610703 | 70,53 | 421,24 |
| BU03610704 | 59,51 | 449,14 |
| BU03610709 | 28,00 | 430,00 |

| | | |
|------------|--------|---------|
| BU03610800 | 740,45 | 1343,66 |
| BU03610801 | 727,01 | 1298,39 |
| BU03610802 | 661,00 | 1352,00 |
| BU03610803 | 736,00 | 1378,00 |
| BU03610900 | 21,19 | 247,11 |
| BU03610901 | 15,78 | 52,02 |
| BU03610902 | 16,84 | 79,63 |
| BU03610903 | 10,20 | 25,16 |
| BU03610904 | 3,57 | 86,10 |
| BU03610905 | 3,36 | 19,84 |
| BU03610906 | 7,87 | 24,09 |
| BU03611000 | 4,00 | 58,13 |
| BU03611001 | 8,50 | 46,40 |
| BU03611002 | 15,02 | 72,16 |
| BU03611003 | 38,64 | 64,66 |
| BU03611004 | 9,00 | 61,33 |
| BU03611005 | 9,12 | 58,22 |
| BU03611006 | 8,21 | 73,07 |
| BU03611100 | 73,28 | 1042,48 |
| BU03611101 | 58,74 | 552,03 |