Sustainable Transport Usage and Medium-Density Housing in the Canberra-Queanbeyan Urban Area

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by

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This thesis contains no material which has been accepted for the award of any other degree or diploma in any university. To the best of the author's knowledge, it contains no material previously published or written by another person, except where due reference is made in the text.

Glenn James

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Abstract

Medium-density housing is known to have many benefits and is becoming further encouraged in cities across the world. One of these benefits is the ability to encourage sustainable transport modes (walking, cycling and public transport), by reducing the distances between where people live and where they want to go. This thesis looks at actual and various potential housing distributions in the Canberra-Queanbeyan urban area across the 2016-2021 5-year time period, and compares the effects of these housing distributions on walking, cycling and public transport usage. Geographic Information Systems (GIS) is used for this analysis, using transport networks for each sustainable transport mode to give a gravity-model estimate of mode usage. The gravity model here utilises distances from Australian Bureau of Statistics Census population data to places established by a household travel survey as areas residents commonly travel to. The results from this analysis back up existing literature that medium-density housing, in combination with mixed land-use, encourages sustainable transport usage, with medium-density scenarios giving ~25-30% increase in each mode share's usage, as compared to ~10-20% in lower-density density scenarios more typical of Australian development. The model was also used to give an estimate of the resulting emissions and economic effects of this sustainable transport mode increase, finding a ~1% decrease in annual ACT emissions and an annual economic benefit of ~$35m under medium-density scenarios. It is suggested that in future research greater timeframes are used to get a better highlight of the effect of medium-density housing, as the population increase across the 5-year time period was not sufficient to reach typically defined medium-density levels.

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Nomenclature

ACT – Australian Capital Territory

ABS – Australian Bureau of Statistics

HTS – Household Travel Survey

GIS – Geographic Information Systems

GDA – Geographic Datum of Australia

GTFS – General Transit Feed Specification

Mesh blocks – the smallest geographic regions where ABS Census data is available

ND – Network Dataset

NSW – New South Wales

SA1/SA2/SA3/SA4 – Other statistical areas defined by the ABS, each with different spatial resolutions, with SA1 being the smallest geography that most data is available for

TOD – Transit-Oriented Development

Chapter 1 – Introduction

Transportation accounts for the largest proportion of greenhouse gas emissions in the ACT at 64%, coming predominantly from private vehicle use [1]. Private vehicles also exhibit a substantial burden on society through impacts such as air pollution, collisions and high infrastructure costs [2-4]. In order to help mitigate these impacts, sustainable transport options, here defined as walking, cycling and public transport, should be encouraged.

Land use and transportation are well known to be linked, with higher density housing being linked to increased rates of sustainable transport usage [5-7]. Walkable, higher density neighbourhoods also come with many other benefits to society [8-10]. Densities above 32 dwellings per hectare (~75 people per hectare), are considered optimal for health, and medium-density housing is considered the most effective way to increase housing affordability, while simultaneously creating highly beneficial social and economic outcomes [11, 12]. Medium-density housing typologies include duplexes, triplexes, townhouses and low-rise apartments [13].

Infill development in the ACT is primarily designated close to town centres, and along transit routes, following a transit-oriented development (TOD) model [14]. While TOD is considered beneficial for achieving sustainable transport outcomes, medium-density housing at the densities required to achieve increased health outcomes and other societal benefits, is currently only allowed on ~7.5% of ACT residential land [15, 16]. Additionally, other research suggests that transit-oriented development may not be needed to encourage sustainable transport with the presence of medium-density housing [5, 17].

Recently, more cities in the western world have been moving to broader medium-density allowances. Minneapolis (in 2018), Portland (in 2019), and all major New Zealand cities (2022) have allowed for medium-density housing to be built in any area of the city [18-20]. Currently, medium-density housing of any form is not allowed to be built on over 80% of ACT residential land [16]. This project aims to look at how broader medium housing strategies, similar to those implemented in these cities, could change sustainable transport in Canberra and Queanbeyan. It aims to add technical recommendations to future policy debate regarding these issues.

This thesis begins with background information in Chapter 2 covering methods for the estimation of transport usage, various models of accessibility and the GIS tools useful in implementing these. Chapter 3 presents the method used in evaluating and comparing the sustainable usage for different housing strategies, covering the population and service data used in the analysis, the network datasets created to calculate trip distances, the creation of the development scenarios for comparison, the implementation of the gravity model used to model accessibility, and finally the process used for estimating mode increases, as well as emissions and economic effects. Next, Chapter 4 presents the results of the analysis, consisting of accessibility maps, mode increase maps and data, and comparisons of the emissions and economic effects of each scenario. Chapter 5 discusses the meaning and implications of these results, and considers the limitations and potential future improvements to it. Finally, the appendices contain more detailed methodology and results, additional accessibility maps and more ideas for future work.

Chapter 2 - Background Information

In modelling sustainable transport usage, a number of components are important to be considered. These include the context around how sustainable transport modes are used and their impacts Section 2.1, models to estimate transport usage Section 2.2, the various methods of modelling accessibility Section 2.3, and the GIS tools that can be used to implement the analysis Section 2.4. In this analysis, research on the context of the urban area is also needed, including population, employment, and service distributions.

2.1 Benefits of Sustainable Transport Modes

Active and public transport exhibit substantial benefit to society, such as through the health-related benefits of physical activity. Walkable cities are also found to have significant benefits to society at large, leading to increased social equitability, better mental health, increased physical activity, reduced emissions, increased air quality, improved sense of community, lower crime rates, increased social skills and connectivity, and increased worker productivity [8, 9]. Walking and cycling are an added benefit to society, at an estimated value of $52 and $27 per 100 kilometres respectively, while the use of automobiles costs society, at an estimated rate of $17-46 per 100 kilometres. Due to the substantial benefits, cities around the world are seeking to promote sustainable transport modes as methods of transport.

2.2 Modelling Sustainable Transport Usage

As outlined in the introduction, land-use and transport are linked, and to analyse the effect of different land-use scenarios, a way of estimating transport usage based on geographic and Census data is needed. These typically take the form of accessibility-based or travel-demand based modelling [21, 22].

Accessibility can be defined as the potential for participating in activities that are distributed over space [23]. Using accessibility as a model for transport usage can be flawed as it this potential may not be realised in an area, with the actual usage dependant on other societal and demographic factors of an area [24]. However, it can provide a good approximation, and increases in accessibility for a particular mode are known to result in increased usage of that mode [25-27]. Accessibility here does not consider the known demand of a particular region, and this is often not available, but uses general demand trends in the creation of models. Accessibility is defined as a measure of whether someone can use a service, not whether they will.

If data around the typical trips people in different areas take is available, travel demand modelling is an alternative way of measuring transport usage [28]. Travel demand models include the 4-step model and the activity-based models [29]. The 4-step travel demand model generates trips following data on the population’s typical travel patterns. Activity-based models are considered more rigorous, as activities are a more fundamental element of analysis, and result in better models, but require more sophisticated analysis and more data, including microdata often not widely available [22, 30]. While the microdata required for use in these models is not available for Canberra and Queanbeyan, it could be generated by the use of synthetic population constructed according to algorithms outlined by the Australian Government Department of Transportation [31]. However, this is considered outside the scope of this project, and the freely available data is seemed insufficient for the use of travel demand models.

Due to the data requirements around travel demand modelling, accessibility will be used in this analysis as an estimate of mode share increases. The incorporation of this demand modelling is an opportunity for future work, and as travel-demand models often use accessibility measures, could directly build upon this work [32]. Accessibility modelling also has the benefit of providing accessibility maps, which highlight areas where transport usage is able to be used, an informative contextual visualisation that can be used in other analyses, such as to guide places for future development and in assessing transport inequality [25]. There are also various kinds of accessibility models, and an appropriate model will need to be chosen for this analysis.

2.3 Accessibility Models

There are a number of different accessibility models discussed in the literature. Throughout these sources, a few key models are commonly represented. These methods are the distance-based, isochrone, gravity, and random utility [23, 27, 33-35]. Within these models, it is important to specify individual modes and service types, and have detailed spatial zones [34]. Other types of models found include the radiation model, (shown to give similar results to the gravity model), and the composite and constraints-based models [21, 35].

The four commonly used and represented models are summarised below, primarily sourced from Miller's 2020 "Measuring Accessibility Methods and Issues" for consistent notation between equations. This source was also chosen due to its reputability being from the International Transport Forum.

2.3.1 Distance Method

The distance method is a simple accessibility model which gives the accessibility as the minimum distance between a point and a particular service. In this model, unlike other models, lower accessibility values are better, as they correspond to travel times or distances.

$$A^{ip} = {}_{j\in L^p}^{MIN} \left(d_{ij}\right) \qquad Eq. 1$$

Here, A^{ip} is the accessibility of location i to a location of type p, L^p is the set of locations of type p and d_{ij} is the distance (or travel time), between location i and location j the location of the service [27].

While limited by not accounting for multiple locations of different types, this may be valuable in special cases, where services of a particular type are identical or close to identical. The model also provides a good starting point from which other models can be built.

2.2.2 Isochrone Method

The isochrone method, or cumulative count method, measures accessibility by considering the number of services as the cumulative number of activity opportunities within a specific radius of time or distance from a home. It is one of the most commonly used accessibility models. This model is defined according to the following equation:

$$A^{ip} = \sum_{j \in L^p_{D|i}} X^p_j \qquad Eq.2$$

Here, $L^p_{D|i}$ is the set of locations of each activity type p, for each region of radius D around the location i to find the accessibility of, and X^p_j is the size or value of the activity p at location j [27]. This method is similar to the nearest distance method, where the distance method only sums the nearest entry in the series. Some papers consider these the same type, [33, 34]. Something not considered in this model, and the models following this, is identical services. For instance, having a second service of the same type, just further away, may not be any more valuable, but would be rated as having twice the accessibility. This is not something discussed in the research around these models. A solution to this could be incorporated through a scaling factor, which further reduces the contribution of additional services when they are similar.

It is noted that this model, due to its summation, and all models following this, will no longer have values in times or distances. Thus, accessibility values may not be able to be intuitively interpreted and instead are only valuable to measure relative accessibility, or accessibility across different scenarios.

2.2.3 Gravity Model

Gravity models are another one of the most commonly used accessibility models, and add a layer of complexity which enables greater accuracy [34]. They measure accessibility through distance and attractiveness (an estimate of the size or value of a location). Distance in the gravity model is weighted by a defined impedance function, in order to reduce the utility of services further away.

$$A^{ip} = \sum_{j \in L^{ip}} X^p_j \, f(d_{ij}) \qquad Eq.3$$

Here, L^{ip} is the set of locations of type p in for location i, X^p_j is the size or value of the activity p at location j, and the presence of the impedance function $f(d_{ij})$, allows for a choice of distribution distances with each mode to be introduced [27]. Typically, the impedance function increases in value with distance, codifying the disutility of being further away from a service. This impedance function can be chosen to reflect the likelihood of travel as distance increases.

A number of impedance functions are commonly chosen for accessibility modelling. These include cumulative (returning the isochrone method), power, exponential and Gaussian functions [36]. This thesis also goes on to describe values which might be used to calibrate such functions for the sustainable transport modes, using a Cumulative-Gaussian distribution that is deemed most appropriate for the analysis [36].

2.2.4 Random Utility Model

Utility based models incorporate individuals' preferences and decision-making from a probabilistic perspective. This theoretical formulation results in the following accessibility equation:

$$A^{ip} = \ln\left(\sum_{j \in L^{ip}} e^{\boldsymbol{\beta} \cdot \boldsymbol{Z}_j}\right) \qquad Eq. 4$$

Where $\boldsymbol{\beta} \cdot \boldsymbol{Z}_j$ is the average population utility of each alternative j, determined by a set of explanatory vectors $\boldsymbol{Z}_j$, and parameter vector $\boldsymbol{\beta}$ [27].

The random utility model and the gravity model have been found to be equivalent, under a particular definition of gravity model impedance function [37]. This gives credence to gravity model as having a good basis in the information theory foundations that the random utility model uses. [27, 37].

2.2.5 Choice of Model

Due to accounting for a number of important factors, and its widely recognised use, the gravity model will be the primary model used for the analysis. It provides a level of complexity which will give a more accurate model, while not having the data requirements of the random utility model, which unavailable for this work. The gravity model can be used with a distribution that can be researched based on the mode or service required, and greater strengthen the model.

2.2.6 Huff Model

The Huff Model is a type of gravity model which considers the probability of interaction based on the set of all available choices [38]. While this a widely used model in spatial analysis, this model does not directly apply in this analysis. It does not apply because the total probability of travel by a single mode is not 1. For instance, modelling walking, if person had a store 10km away and no other stores in their choice set, the Huff Model would estimate a probability of 1, when in reality that person is likely to drive to that location, making the probability of walking much lower.

2.3 Network Analysis Tools

To implement these accessibility models, and conduct the analysis required for this project, geographic information systems (GIS) are required to be used. This analysis will use Esri's ArcGIS Pro software to undertake analysis in this project. Throughout the accessibility models, a distance metric is required to be used, this can be done using straight line (Euclidean) distance, gridded (Manhattan) distance or by the network present in an area [33]. Of this the network method is the most accurate, reflecting barriers and shortcuts which people can use on the ground [34]. Additionally, networks allow for a time metric to be used, a more useful and accurate measure for accessibility, particularly given modes other than walking are likely non-linear with the distance [33]. Utilising networks and time feature is something that can be done using network datasets, a dataset type in ArcGIS Pro.

2.3.1 Network Datasets

Network datasets in ArcGIS Pro encode the geographic information needed to calculate the routes, times and distances between multiple points on the network [39]. They also have some key features which allow for greater robustness of modelling. These include evaluators, the GTFS to Public Transport Network tool, and connectivity. Evaluators enable for the travel times for different modes to be calculated from the distance and other features of a line segment on a network [40]. The GTFS to Public Transport Network tool, which provides a way to take industry standard public transport feeds, known as GTFS (General Transit Feed Specification), to a network dataset which can be used to find the routes and travel times between points [41]. Additionally, network datasets allow for the modification of connectivity, allowing for different input layers to be used together in a network dataset in different ways [42].

Following their construction, network datasets can be used in a number of other Network Analyst tools, including OD Cost Matrix and Location-Allocation tools.

2.3.2 OD Cost Matrix

The OD Cost Matrix network analysis tool finds the lowest cost paths between a given set of origins and destinations on a network [43]. It can be set to find these routes based on the shortest distances or times along a network, and finds routes between every origin and every destination [44]. It provides a well optimised way of calculating times and distances between a set of origins and destinations, making it particularly useful for large sets of data. This tool allows for the effective implementation of the gravity model, providing all the route data between locations needed to find accessibility values.

The OD Cost Matrix tool is a routing tool, and is based on Dijkstra’s algorithm for path planning [45]. It adds to the Dijkstra’s algorithm implementation by also able to implement other constraints set by the network, such as one-way turns or section restrictions. It also incorporates d-heap data structures to help improve processing time and can give paths to locations not on a node (junction) of a network. Compared to other network analysis routing tools, it saves time by not calculating the shape of paths, with the only output for each route being the cost of traversing it [45].

2.3.3 Location-Allocation

The location-allocation tool made by Esri finds the optimum locations for a given number of new services to operate, based on services of the same type already in existence, and distances and other fields such as population [46]. This tool is designed to be used by businesses to decide on the best location for a new store to be set up, but can be used for any service to be located closest to the most people. It will be used in the analysis to model the effect of different population distributions on placements of new services.

Location-allocation solves the Facility Location Problem for the input data [45]. The facility location problem involves the geographic placement of new facilities such that the transport costs from customers to facilities is minimised for overall set of facilities [47]. This problem is a combinatorial problem, where the naïve solution can be described in computer science as having complexity O(n!). This means it cannot be solved directly, but instead is implemented in Esri's location-allocation tool utilising a heuristic process [45].

The location-allocation tool has a number of different problem types, being able additionally locate services based on competitor locations, and based on variable facility amounts [48]. This analysis does not need to consider competitors and will have a set amount of facilities so only the problem types "Minimise Impedance" and "Maximise Attendance" need to be considered. "Minimise Impedance" considers all demand points in the location of facilities, whereas the "Maximise Attendance" only considers the amount of demand points within a given region. This two processes work similarly, but the "Maximise Attendance" has a shorter runtime, due to not having to consider the entire set of demand points [48]. This is particularly important for this tool, due to the complexity of the algorithm meaning it has a high runtime. Therefore, the "Maximise Attendance" tool will be used for this analysis.

Other inputs to the tool include required sites, candidate sites, and demand points. Required sites are sites that will always be chosen in the solution space, typically used in an expansion of an existing service, as will be done in this analysis [46]. Candidate sites are the locations from which the tool will choose new locations from. Demand points reflect the population data, where this algorithm attempts to distribute locations such that they are most useful to the most people [46]. Demand points are typically in the form of Census population centroids, and can be weighted by an amount, (such as the population in each Census group) [46].

2.4 Summary of Background

The research and tools outlined here give the importance of accessibility in sustainable transport usage. It also identifies the gravity model as an appropriate model for accessibility and outline the tools in ArcGIS Pro which can be used to implement the model.

Chapter 3 – Methodology

This section will cover the process used to evaluate the sustainable transport accessibility of various housing strategies for Canberra-Queanbeyan, and their resulting economic and emissions impacts. It will cover the data gathered in this process for where people live and where they travel to, the network datasets used to model travel between places, the development scenarios used, and how accessibility and the resulting emissions and economic effects were calculated. This split into 5 sections, one for each of these main topics, beginning with the population and service data.

3.1 Population and Service Data

The first stage of the analysis was to find data for Canberra and Queanbeyan containing where people live (population data), and what places they commonly travel to (such as workplaces, schools and shops), which will be referred to as "services" going forward in this analysis. These datasets will cover the study area, which will be defined as the ACT, and the 4 SA2's in NSW that cover the Queanbeyan urban area, excluding the Googong and Royalla exurbs, and other small country towns in the nearby NSW area.

3.1.1 Population Data

Population data is integral to the analysis of sustainable transport mode usage. This analysis seeks to show how different distributions of where people live affect the travel modes which they take. The data for current and past population will form the basis for creating these different housing distributions, or development scenarios and give a control group to compare these too.

For population data, Australian Bureau of Statistics Census data is used. This analysis will use population data from the two previous Censuses, 2016 and 2021. The highest spatial resolution data available for population, mesh blocks, is used, to give the best spatial accuracy. While only limited other demographic data is available at the mesh block spatial resolution, other data is not needed for the scope of the analysis, and the higher spatial resolution will increase the accuracy of modelling. Other statistical areas defined by the ABS include SA1, SA2, SA3, and SA4, in increasing order of geographic size, these provide more data, but at a reduced spatial resolution.

Mesh block population tables and digital boundary files (shapefiles), from the ABS Censuses for both 2016 and 2021 are available and used [49-52]. The data for each respective Census is joined to its spatial layer within ArcGIS Pro, to give the spatial distribution of population. This is done for the ACT, and for 4 SA2's in NSW that cover the Queanbeyan urban area, and these two layers are merged.

Additionally, for consistency of the population layer between scenarios, the 2016 population data was then mapped onto the 2021 mesh block layer, the ABS suggests using their "correspondences" product for this process, but due to time constraints on the project, another method was used, and is described in Appendix A1.1 [53]. This mapping was done to allow the analysis to run on only one set of mesh block data, halving the computational time. In addition, this process gives a marginal increase in spatial resolution. It also prevents issues with projections, as the 2016 mesh block data uses the GDA94 projection, while the 2021 mesh blocks use the GDA2020 projection [49, 51]. Regardless, this projection issue is inconsequential, due to the small error between them (~1.8m), the small scale of the ACT compared to the Earth's surface and later of stages of the analysis eliminating the need for the mesh blocks to be aligned. The processes used to create these layers given in Figure 1 with resulting 2021 population layer is shown in Figure 3, with the.

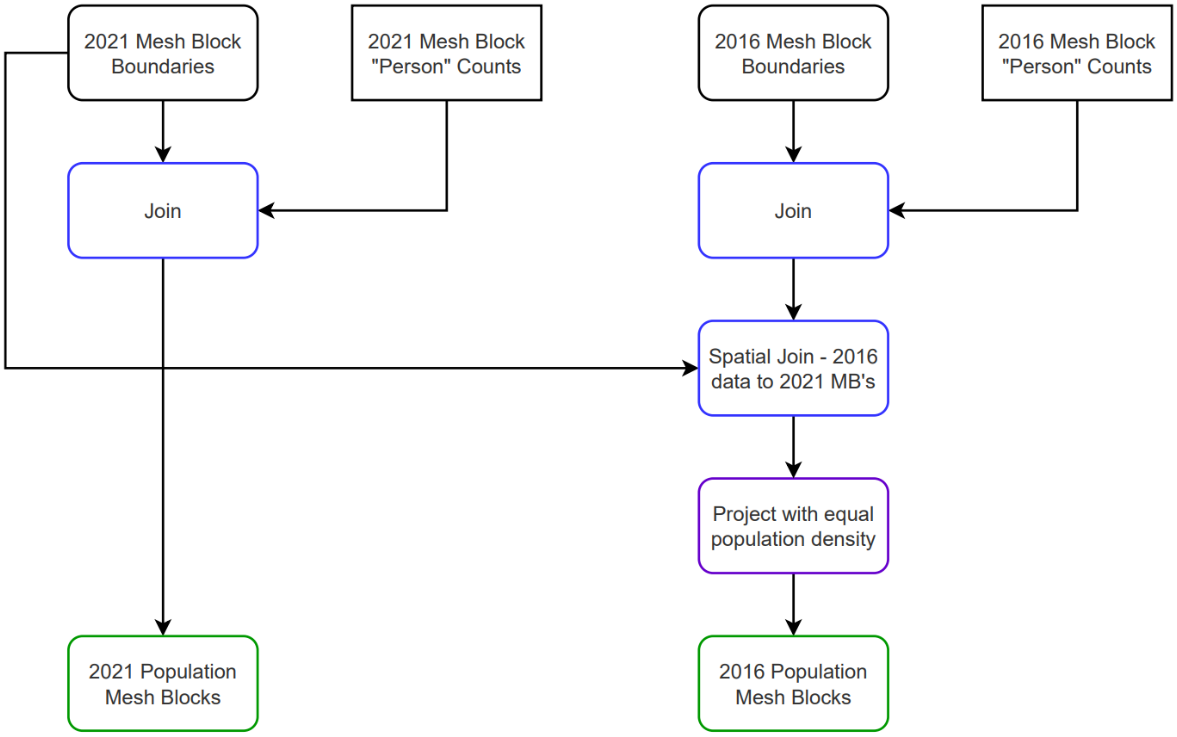

Figure 1: Pre-processing of population data. Here black boxes are spatial (smooth edges) and non-spatial (square edges) input data, blue boxes are ArcGIS Pro commands, purple boxes are processes designed specifically for this analysis, and green boxes are output layers

3.1.2 Service Data

The places people commonly travel to (services), were chosen using the 2017 ACT-QPRC Household Travel Survey [54]. This survey gives a broad outline of how, where, and why ACT and Queanbeyan resident's travel. This survey gives the most common reasons for travel for residents as work-related, social and recreational, to buy something and for education. While this data does not tell of the exact locations which people travel to, we can use it to give an estimation of where people travel by using proxies for each one. The proxies for each data source are outlined in Table 1 below.

Table 1: Equivalent services and their corresponding household travel survey trip purposes and usage

Reason for travel	Percent of total trips (HTS)	Equivalent service for this analysis	Data source
Work related (Employment)	25.9%	Employment data	2016 ABS Census [49, 55]
Social/Recreational	21.8%	Local centres	Google Earth [56] ACT Planning Strategy [57]
To buy something (Shopping)	11.9%	Town centres, group centres	ACT Planning Strategy [57]
Education	10.5%	Schools	ACT Government GeoHub [58]

This gives us a set of locations which we can find data for, and use going forward in our accessibility analysis. The datasets used are derived from the SA2 “Place of Work” field from the 2016 ABS Census for employment, a Google Earth search for typical local shops found across Canberra and Queanbeyan for local centres, and the ACT Government location data on Town Centres, Group Centres and Schools. The processing used to create these initial datasets is outlined in Figure 2, with more detailed explanations contained in Appendix A.1.

A map showing the geographic distributions of these services are given in Figure 4.

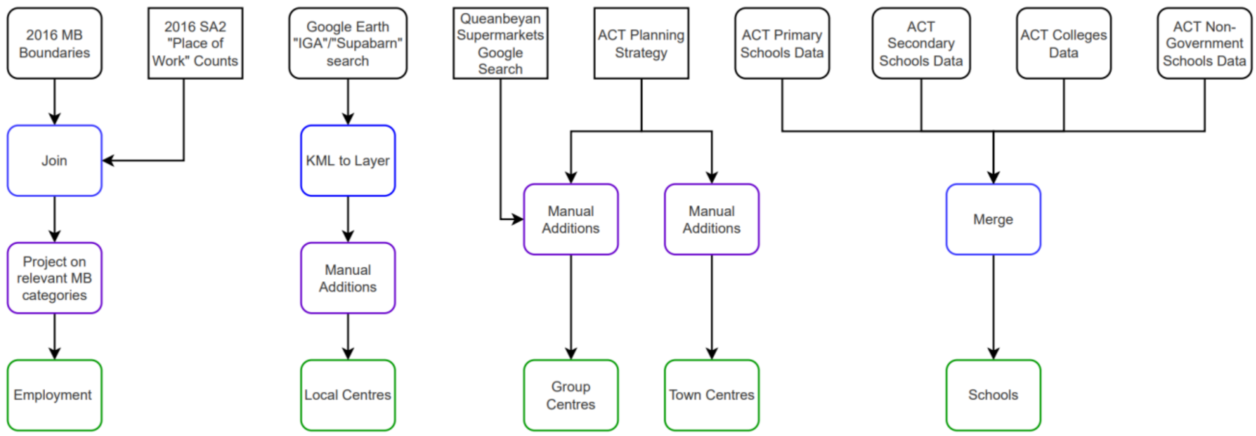

Figure 2: Pre-processing of service data, showing the raw data inputs, and the resulting layers for use in the analysis

3.1.3 Summary of Population and Service Data

These datasets cover the most common use cases for people to travel, and while they require number of assumptions to construct, they cover some of the main travel destinations, and make sense when compared with personal local knowledge of Canberra. Next, the network datasets created to model travel between these areas were created.

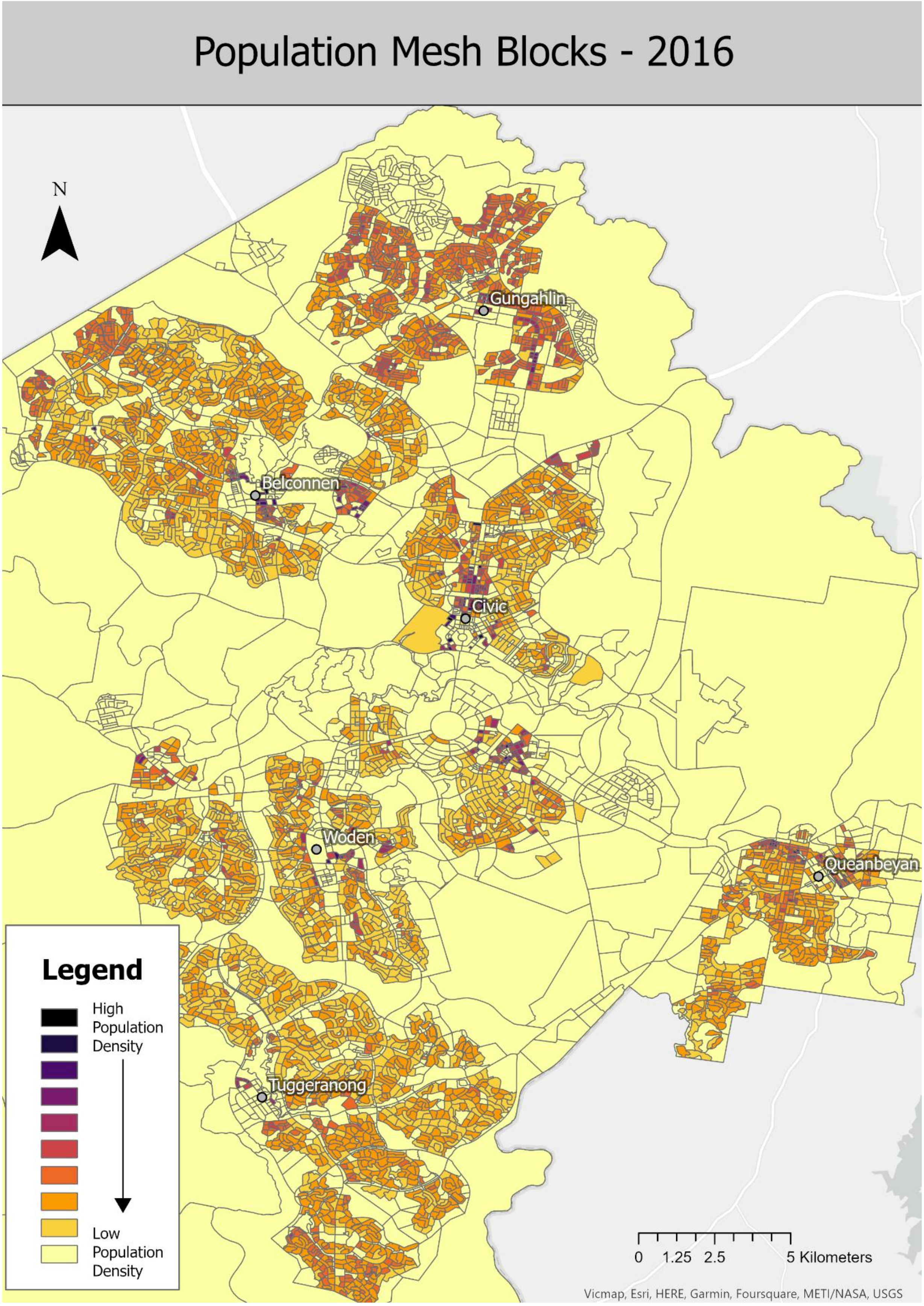

Figure 3: 2016 Population density map of Canberra-Queanbeyan, displayed on 2021 Mesh Blocks. Population data and geographics boundaries are sourced from the ABS 2016 and 2021 Census's respectively.

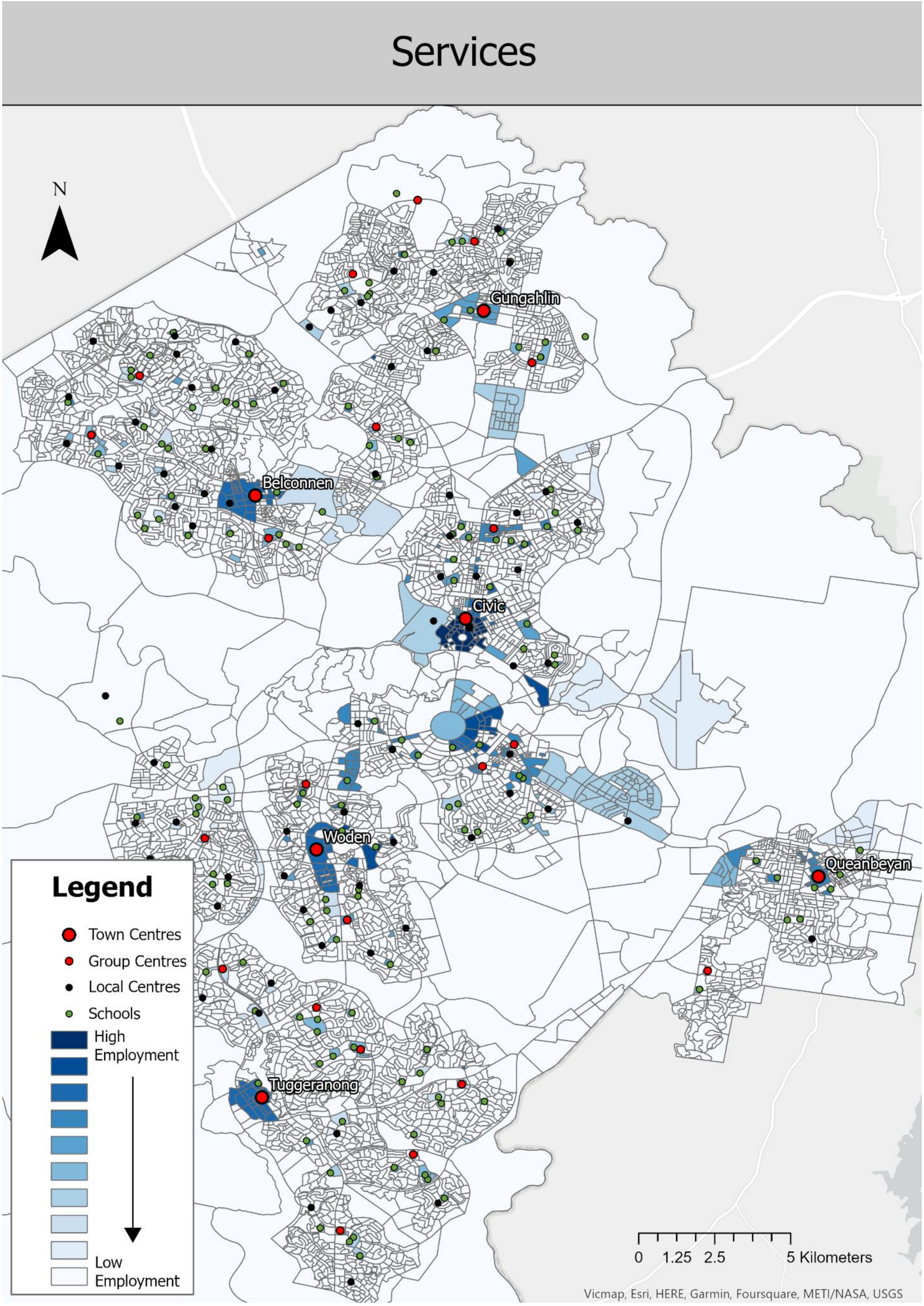

Figure 4: Data for all services used in the analysis, covering the main travel purposes outlined in the HTS. Sources and methods used in the creation of this data are explained in Section 3.1.2

3.2 Network Datasets

Network datasets, as discussed in Section 2.3.1 provide a way to show which transport routes people use when travelling through an urban area. This is much more accurate than using other measures such as Euclidean or Manhattan distance. To model walking, cycling and public transport, two network datasets are required to be made. One of these, the paths network dataset, covers the routes available to walked and cycled on, while the second, the public transport network dataset, will combine this paths network with bus and tram routes and timetables, to give a holistic public transport model.

3.2.1 Paths Network Dataset

The paths network dataset (Paths_ND) is used to model both walking and cycling. It differentiates between these modes using evaluators, which assign different speeds based on different layers of the network datasets. For this network dataset, there are five different layers, each providing a different role in the network dataset. The layers used in this network data are set out in Table 2.

Table 2: The layers used in the Paths_ND network dataset, their roles, and the data sources for them

Layer	Role	Source
Shared paths	Provides the dedicated cycling infrastructure, according to Vancouver and EU cycling standards [59, 60]	OpenStreetMap [61]
Residential streets	Provides secondary dedicated cycling infrastructure	OpenStreetMap [61]
Footpaths	Provides the dedicated walking infrastructure	ACT Government [62]
Roads	Provides a fully connected layer, and walking infrastructure for Queanbeyan	ACT Government [63], OpenStreetMap [61]
Connectivity Layer	Connects the footpaths layer to the roads layer, allowing a fully traversable network	Manually created, details given in Appendix A.2.4

An important attribute of this layer is connectivity, which the ability of any point on the network to be traversed to any other point. The wide range of sources they come from and that they are not produced directly for network analysis, mean the walking and cycling specific datasets do not have connectivity. The roads layer does have connectivity meaning connecting the other layers to this layer will ensure the network is fully traversable. Roads are expected to have footpaths, but not necessarily be suitable for cycling, as such this layer is given the same role as footpaths in the network. The connectivity layer does introduce some unphysical paths, discussed further in Section 5.2.2.1, but these are mitigated through a lower speed, and their rarity makes the impact on the analysis small. Connectivity is a high priority in the function of a network making this small error necessary to introduce. The creation of the Paths_ND network dataset makes use of the Integrate ArcGIS Pro Data Management tool, which aligns the vertices of each layers, meaning physical junctions between layers are represented in the network dataset.

The different layers used in the network are given different walking and cycling speeds to better model these transport modes. Walking speeds are made to be constant (at 5 km/h) between all layers except the connectivity layer (set to 1 km/h), whereas cycling speeds vary with the quality and comfort of the route. Cycling speeds are set to 18 km/h on dedicated cycle paths, reflecting an average commuting cyclist speed [64]. On other infrastructure, a cycling speed of 60% of average is set (10.8km/h), this particular percentage is chosen as it reflects the ACT's e-scooter speed difference, allowing for an e-bike/e-scooter mode to be easily incorporated in later analyses [65]. These speeds are outlined in Table 3.

Table 3: Evaluators used for the different layers in the walking and cycling modes of the Paths_ND network

Layer	Cycling speed	Walking speed
Shared paths	18 km/h	5 km/h
Residential streets	18 km/h	5 km/h
Footpaths	10.8 km/h	5 km/h
Roads	10.8 km/h	5 km/h
Connectivity Layer	1.8 km/h	1 km/h

The processes involved in the creation of this network dataset are given in Figure 1, with more detailed discussion outlined in Appendix A.2.

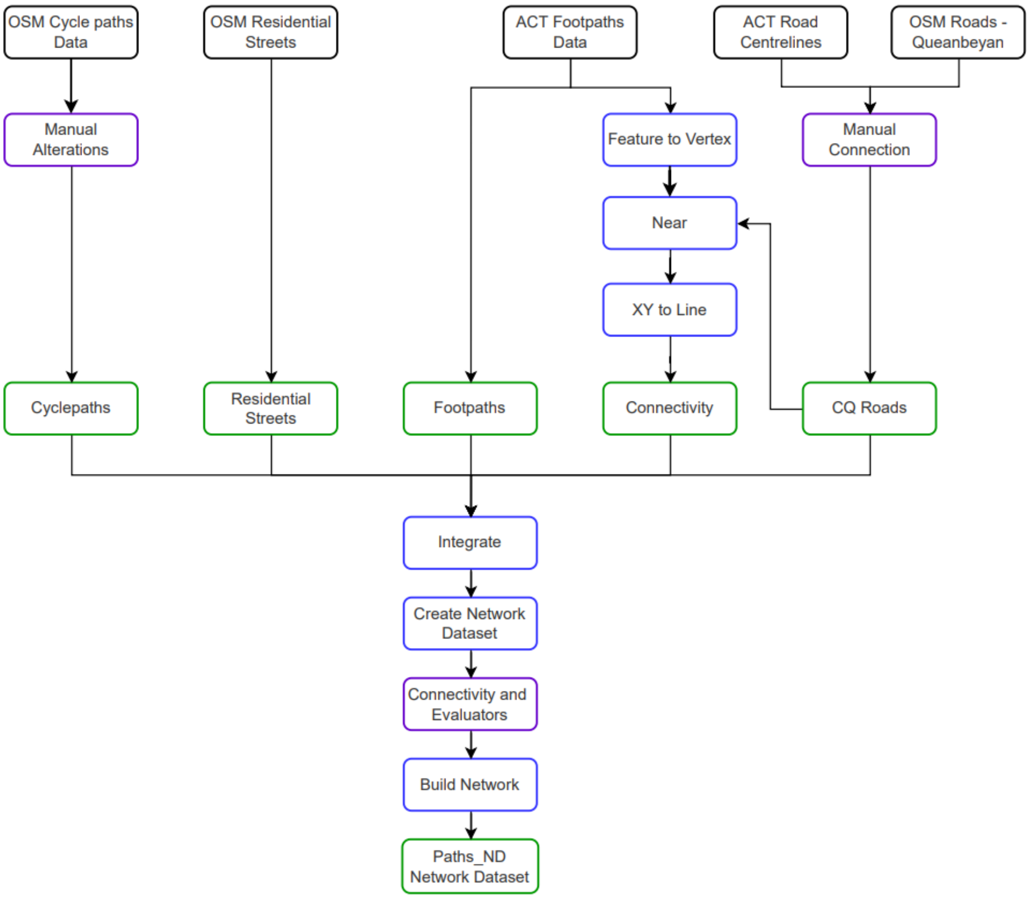

Figure 5: Processes involved in the creation of the Paths_ND network dataset. Here black boxes are input data, blue boxes are ArcGIS Pro commands, purple boxes are processes designed specifically for this analysis, and green boxes are output layers

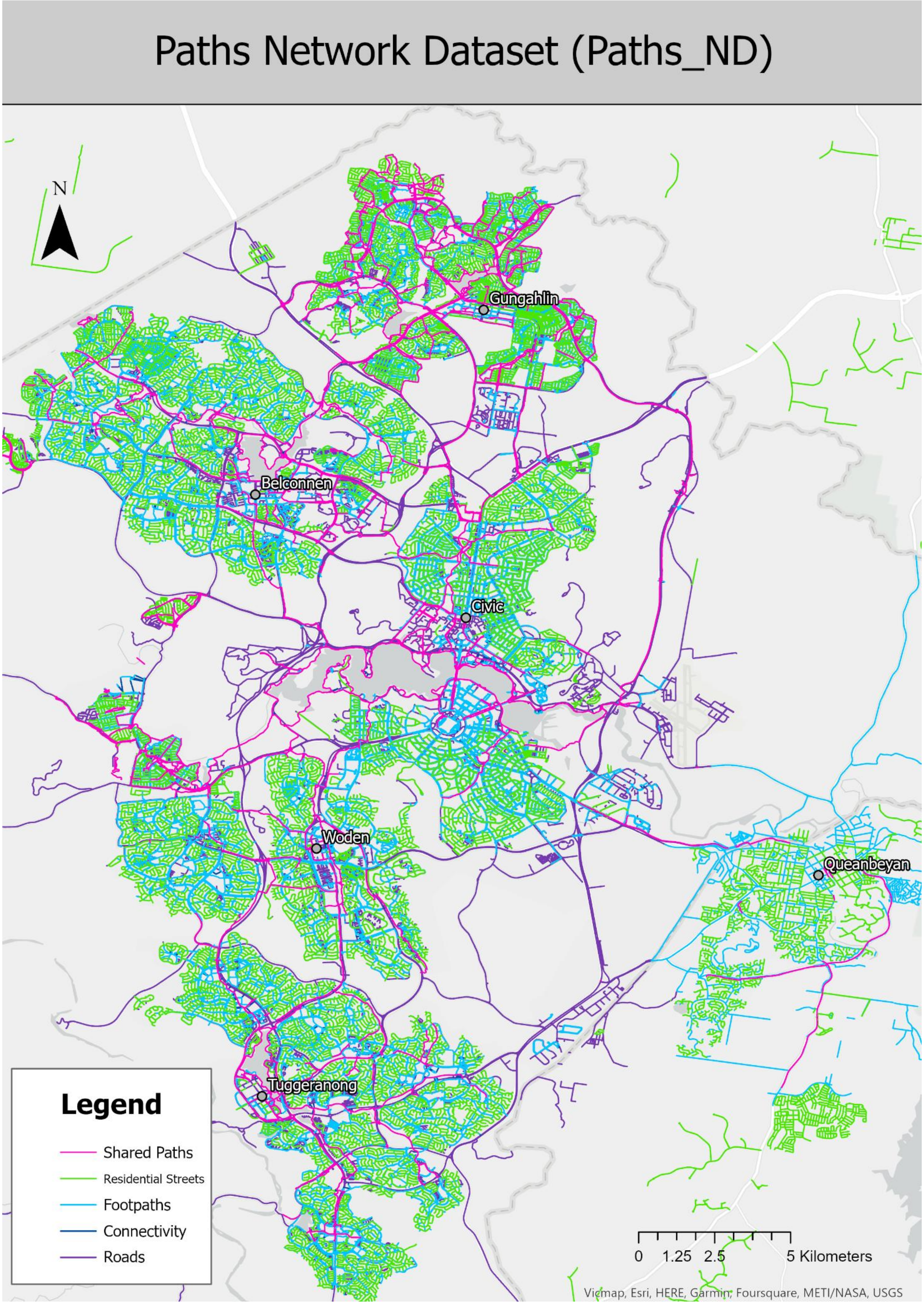

Figure 6: The paths network dataset to be used in the analysis for the generation of both walking and cycling route data. This network dataset covers the infrastructure able to be used by these modes of transport, and gives associated speeds based on the quality of infrastructure. Sources and methods used in the creation of this data are explained in Section 3.2.1

3.2.2 Public Transport Network Dataset

The public transport network dataset was created using General Transit Feed Specifications (GTFS), combined with the roads layer used in the paths network dataset. This network dataset was created following Esri's "Create and use a network dataset with public transit data" guide, commonly used throughout the industry [66]. It utilises the GTFS to Public Transport Network tool, the following data sources Table 4 and the connectivity outlined below.

Table 4: Datasets used in the creation of the public transport network dataset

Data	Role	Source
ACT buses GTFS	Public transport feed for the ACT	Transport Canberra [67]
ACT light rail GTFS	ACT light rail feed	Transport Canberra [67]
NSW GTFS	Public transport feed for Queanbeyan	Transport for NSW [68]
ACT road data, OpenStreetMap roads data	Provides the Streets network to be used for walking to public transport.	ACT Government [63] OpenStreetMap [61]

Multiple feeds can be used as the standard of GTFS feeds allows the multiple different feeds to be combined into a single public transport network dataset. The created public transport network dataset is given in Appendix A.2.8.

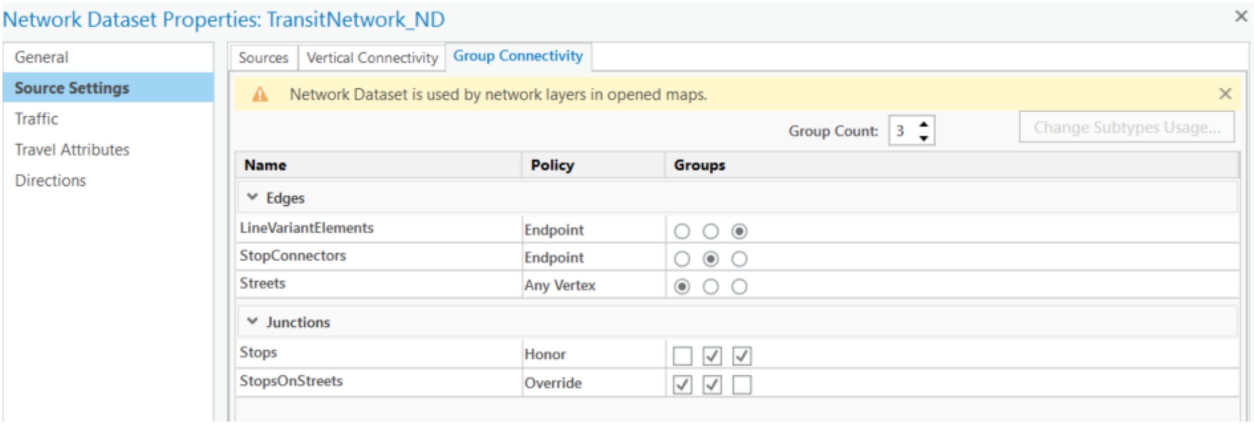

Figure 7: The connectivity settings used in the public transport network dataset. Here each transit route (LineVariantElements), can only be left at an endpoint (a transit stop). These stops each have a 'StopConnectors' point on them, which can be traversed to its endpoint on the nearest street. The street network can be traversed across any vertex, the same as the Paths_ND network dataset.

An important note is the GTFS feed varies with the time of day, following the public transport schedule of a particular date and time. As such the time chosen to run the network dataset affects the results. It is also noted that the NSW GTFS feed has data only on day of the week and time, meaning particular travel dates can't be used here. For the analysis, an arbitrary day and time of Thursday 11am was chosen. This was chosen due to being a weekday, and avoiding peak times which may be unrepresentative for this analysis.

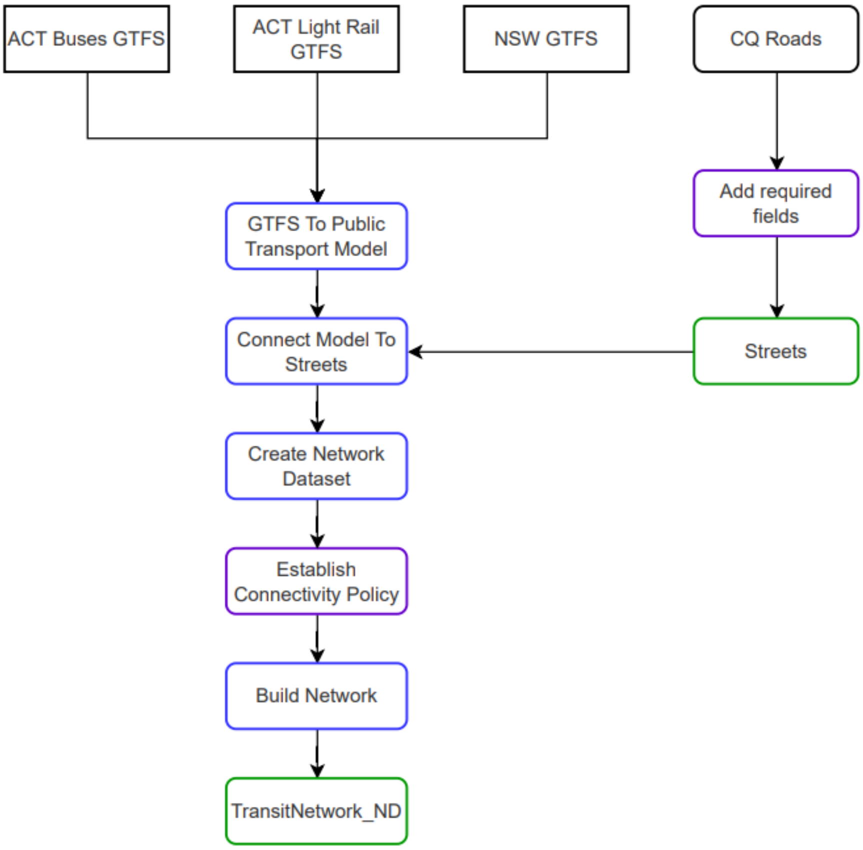

Figure 8: Processes involved in the creation of the TransitNetwork_ND network dataset. Here black boxes are input data, blue boxes are ArcGIS Pro commands, purple boxes are processes designed specifically for this analysis, and green boxes are output layers

3.3 Development Scenarios

The aim of this analysis is to compare how a range of different ways future housing within the study area affect the use of sustainable transport modes. To do this, we need a range of potential development scenarios to compare.

3.3.1 Scenarios to Model

The scenarios to model aim to cover the actual scenario, lower-density (typical suburban-style development), and medium-density development. The choice of timeframe from a base year of 2016 to an analysis year of 2021 allows for an actual scenario to be created as point of reference for the other scenarios and give an accurate measure of population increases over time. The suburban-style low-density scenarios will include greenfield development and equal development across the city, while the medium-density scenarios will include medium-density inner city development and transit-oriented development. These are chosen to reflect common and beneficial ways which cities can be developed. This will involve geographically spreading the known population increase of 58,197 between 2016 and 2021 among residential areas in different ways. The development scenarios are outline in Table 5 below. Processes for there creation are given in Figure 9.

Table 5: Descriptions of the processes used in creating each development scenario, and an explanation of the resulting population distribution

Development Scenario	Process	Effect
Actual	Uses the actual 2021 population mesh blocks	A combination of population increases in inner city areas, and development on the urban fringe.
Equal Development	Apply the overall population density increase to every mesh block in the city.	Every 2016 residential mesh block's population density is increased by 366 people per square kilometre (p/sqkm). Densities are typically 2000-3000 p/sqkm.
Greenfield Development	Apply a standard suburban population density to population free areas outlined in the ACT planning strategy until the population increase is met.	Mesh blocks in the Molonglo valley, north Gungahlin and west Belconnen that were undeveloped in 2016 are increased to a population density of 2719 p/sqkm.
Medium-Density Inner City (mdINIS)	Mesh block population densities in the Inner North and Inner South SA3's are progressively increased, starting with the lowest population density.	Most mesh blocks in the inner north and south are given a population density of 4455 p/sqkm.
Transit-Oriented Development (TODInfill)	Population densities in transit corridors outlined in the 2018 ACT planning strategy are progressively increased, starting with the lowest population density.	Most mesh blocks in the areas outlined in the 2018 ACT Planning Strategy are given a population density of 4444 p/sqkm.

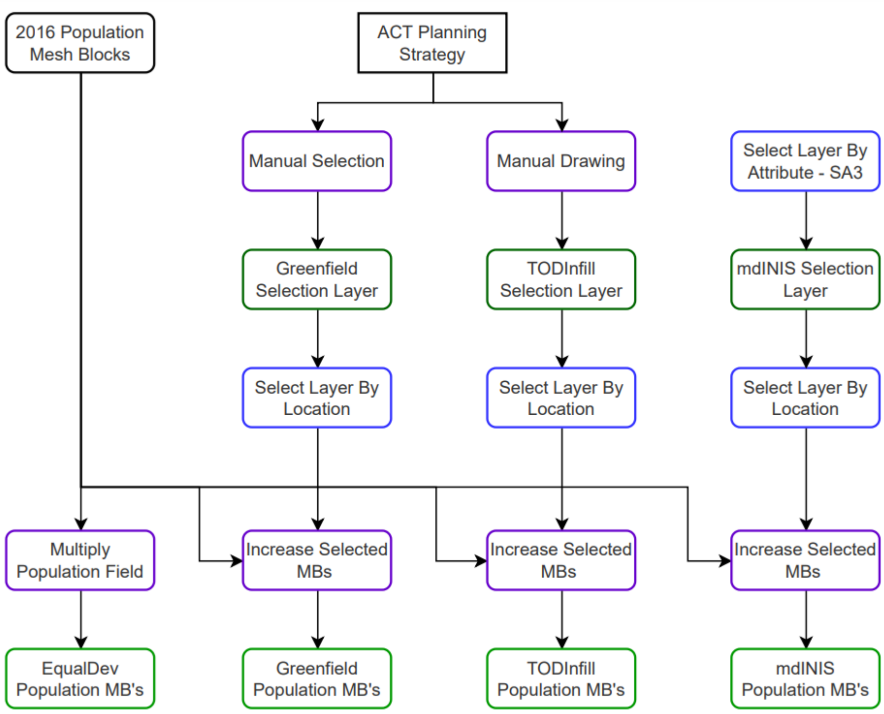

Figure 9: Processes involved in the creation of each of the development scenarios. black boxes are input data, blue boxes are ArcGIS Pro commands, purple boxes are processes designed specifically for this analysis, and green boxes are output layers

3.3.2 Population Equivalents of Services

An important aspect of development is that more people mean more services can be supported within a city [69]. To model the effect of this, a rough measure of the amount of population required to support each service was calculated, and thus the number of extra services a given population increase can support was found. This was done by dividing the number of each service by projected population of that service's source year, and then finding the equivalent number of services in 2016 and 2021. Details of this process are given in Appendix A.4.

The change in number of services is then added to services in our original datasets to give the number to use in our development scenario. This is done regardless of the source year of the original dataset, and thus gives an overestimate of the amount of services for a number of datasets (particularly those with source years of 2021 or 2022). However, it is deemed necessary due to the ambiguity associated with attempting to remove locations.

Table 6: Number of services for each service type, for the base year scenario (2016) and the development scenarios (2021)

Service	2016* Amount	Estimated 2021 Amount
Town Centres	6	6
Group Centres	27	30
Local Centres	102	113
Schools	151	169
Employment	224991	255215

**The 2016 amount is taken to be the datasets found in Section 3.1.2, regardless of the source year of the data.*

3.3.3 Location-Allocation

The number of services the new population can support were then added to each of the development scenarios, in a geographic spread that reflects each of the new population distributions. This was done using the Location-Allocation Network Analyst tool discussed in Section 2.3.3, requiring inputs for problem type, demand points, required sites and candidate sites.

Location-Allocation was evaluated using the "Maximise Attendance" problem type, using a cut-off walking distance of 100 min (~7km), reflecting a large distance. This model allowed for similar results to the "Minimise Weighted Impedance" problem type, which has no cut-off, while significantly improving computation time. This choice of model may not be valid for services where long trips might be common, such as employment or town centres, but we do not need to model these in this analysis. The demand points used were the mesh block centroids, weighted by their population field of the development scenario in question. Required sites used are the source year service datasets, reflecting existing services. Candidate sites were chosen as the mesh-blocks for each scenario with a non-zero change in population. This aids computation time, while emphasising the effect of each development scenarios, rather than placing services in currently deficient areas of Canberra, however, this introduces a bias towards the "Equal development" and "Actual" scenarios, discussed further in Section 5.2.3.5.

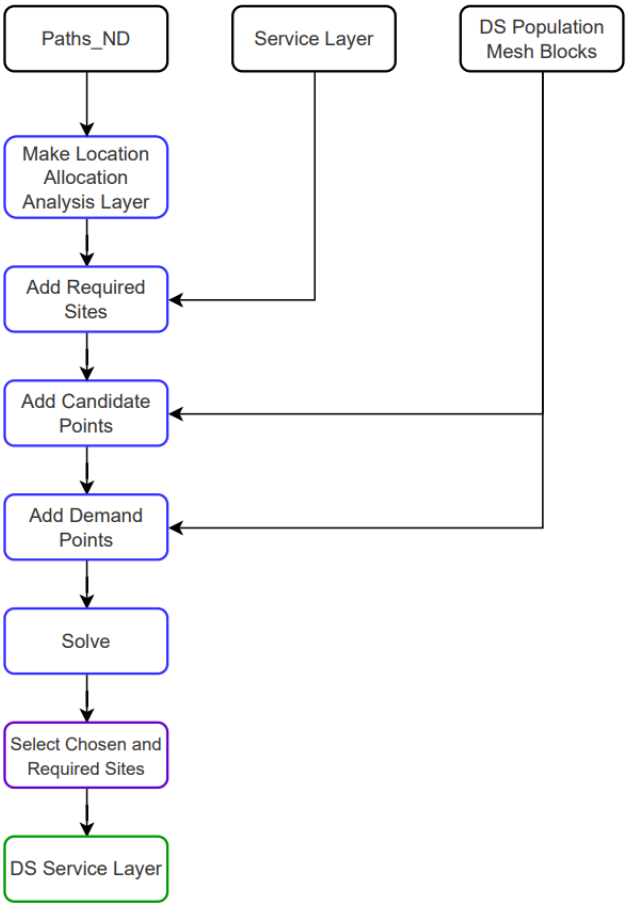

Figure 10: Location-allocation process used for each development scenario to determine the new service locations for each development scenario

3.3.3 Summary of Development Scenarios

The development scenarios created give a range of alternate ways to accommodate a given population growth. This covers examples of both suburban-style development, and medium-density development as well a case for the actual population distribution. These development scenarios include how the distribution of services might change under each scenario, enabling the reinforcing cycle of increasing population in accessible areas to be modelled. The “Greenfield” and “Medium-density inner city” development scenario population distributions are given in Figure 11 and Figure 12 respectively, representing examples of suburban-style and medium-density development respectively. The other development scenarios are given in Appendix A.3. The effect of development scenarios on service distribution is also given in Appendix A.3.

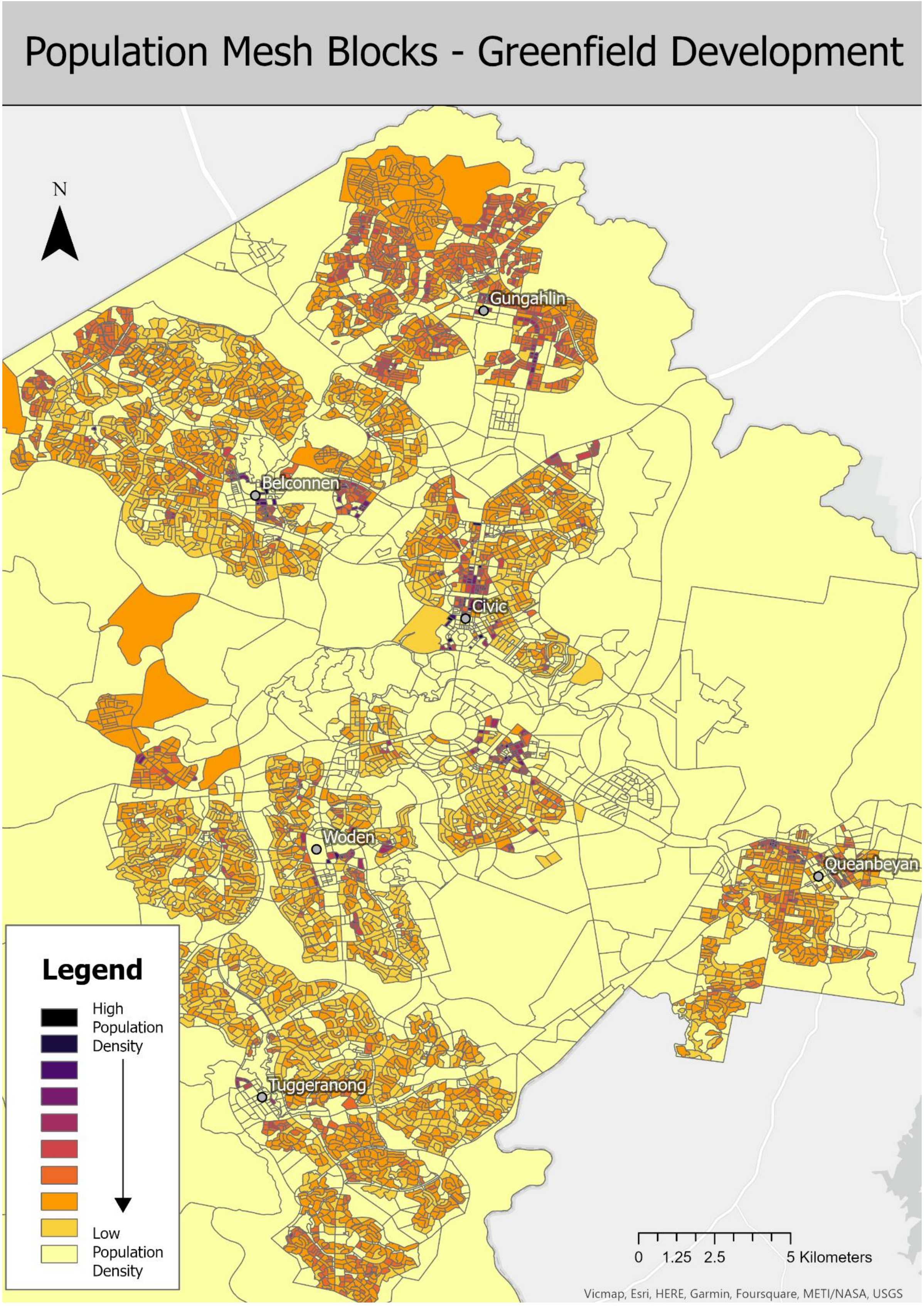

Figure 11: The population distribution used in the "Greenfield" development scenario, representing a suburban-style development scenario. Here the population increase is spread over various greenfield development areas established in the 2018 ACT Planning Strategy, which can be seen as constant population density areas to the west and north of the city.

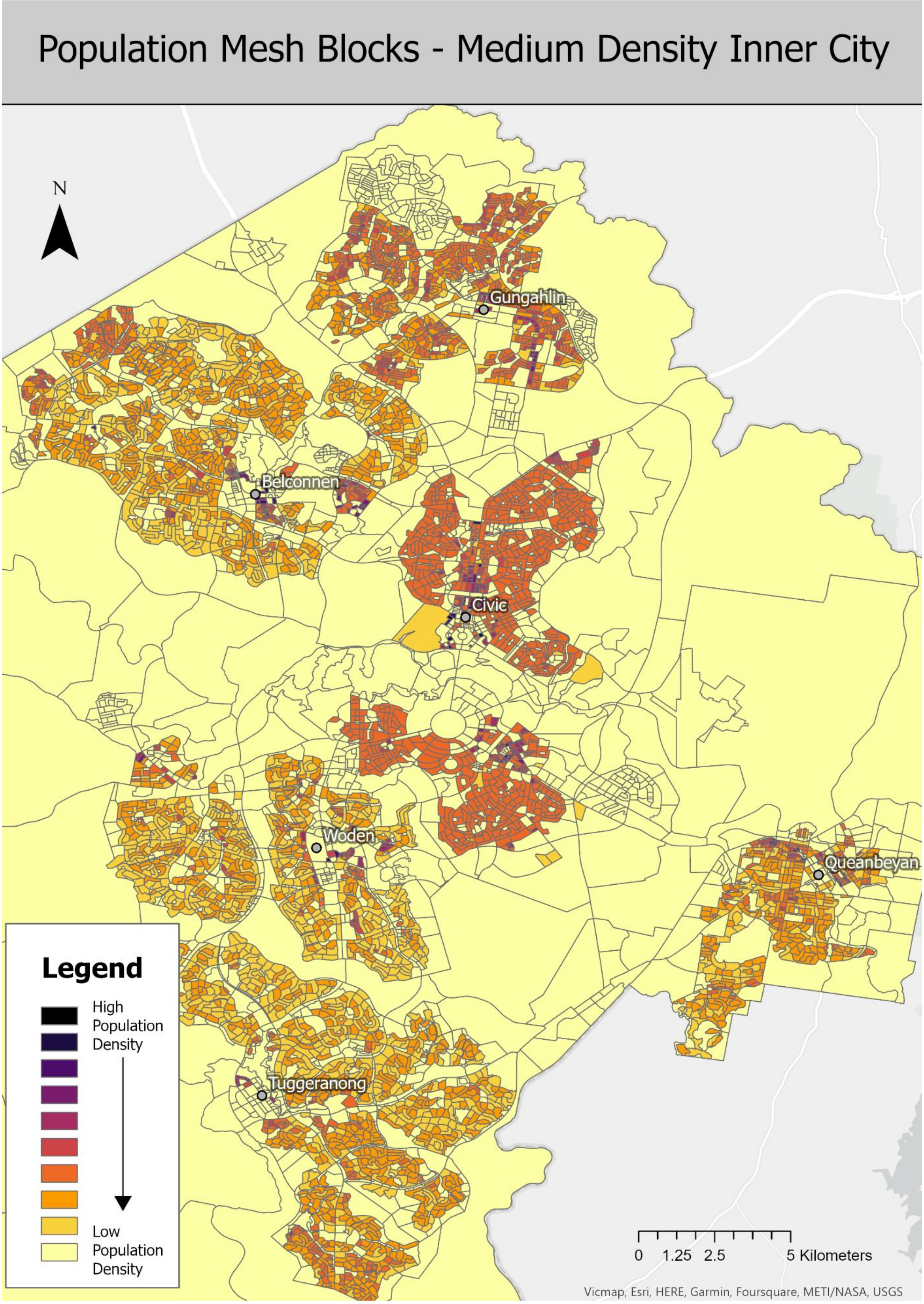

Figure 12: The population distribution used in the "Medium-density Inner City" development scenario, representing a medium-density style development scenario. Here the population increase is confined to the "North Canberra" and "South Canberra" SA3's and can be seen as increased density in the centre of the city.

3.4 Accessibility modelling

The sustainable transport accessibility of different development scenarios will be evaluated using the gravity model outlined in Section 2.2. The gravity model provides a relative level of accessibility between areas and between development scenarios, enabling them to be compared. To implement the gravity model, the components in Eq. 3 need to be found. These are found by generating origin-destination time data (d_{ij}), creating an impedance function for each travel mode (f), and creating an attractiveness measure for each service (X_j^p). Once these components are evaluated, the accessibility of each mesh block for each service and travel mode can be found and compared.

3.4.1 Generating Origin-Destination Time Data

Evaluating the time it takes for a group of people to travel to each service enables the likelihood of them travelling to each of those services to be better calculated, with places that are further away having a lower likelihood of travel. To use this data in the gravity model, the travel times between every mesh block centroid and each service by each mode is needed to be found. This is done using the OD Cost Matrix Network analysis tool discussed in Section 2.3.2.

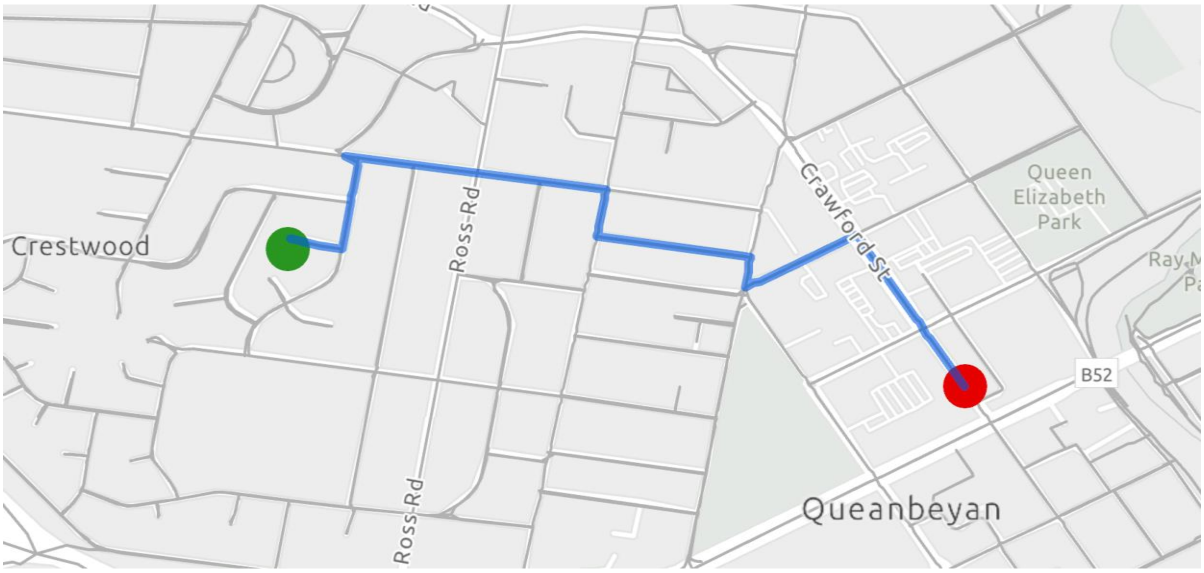

Figure 13: Example of a route from a mesh block centroid (green) to a service (red), in this case the service is Queanbeyan town centre. The time taken to travel along the shown route will be the d_{ij} variable in the gravity model.

In this data generation process, employment public transport data dominates the computation time due to the complexity of the public transport network, and the high amount of employment locations. For employment data, all mesh blocks with non-zero employment values were used, giving a total of around 700 destinations. Combined with the ~7000 mesh blocks centroid, this generates a significant amount of data. However, due to the employment locations being kept constant with each development scenario, and only the employment values being changed, this process only has to be run once. All other services are run for each development scenario to generate all of the origin-destination data.

3.4.2 Impedance Function

The impedance function used in the gravity model should give the relative probability of taking each travel mode at a particular distance. This will give a lower proportion of people taking each sustainable transport mode as the distance from a service increases. Vale and Pereira undertake a detailed discussion of different formulations of the gravity model and come up with an impedance function for pedestrian accessibility [36]. The gravity model will be implemented using their Cumulative-Gaussian Distribution, and parameters set according to found data.

The distribution to fit uses the following equation:

$$f(d_{ij}) = \begin{cases} 1, & d_{ij} < a \\ e^{-\frac{(d_{ij}-a)^2}{b^2}}, & d_{ij} \geq a \end{cases} \qquad Eq.5$$

Where a and b are our parameters to be set. Data on proportions of trip by distance was converted to proportions by time and fit to the curve using least squares linear regression. These parameters define our impedance function to be used in the gravity model.

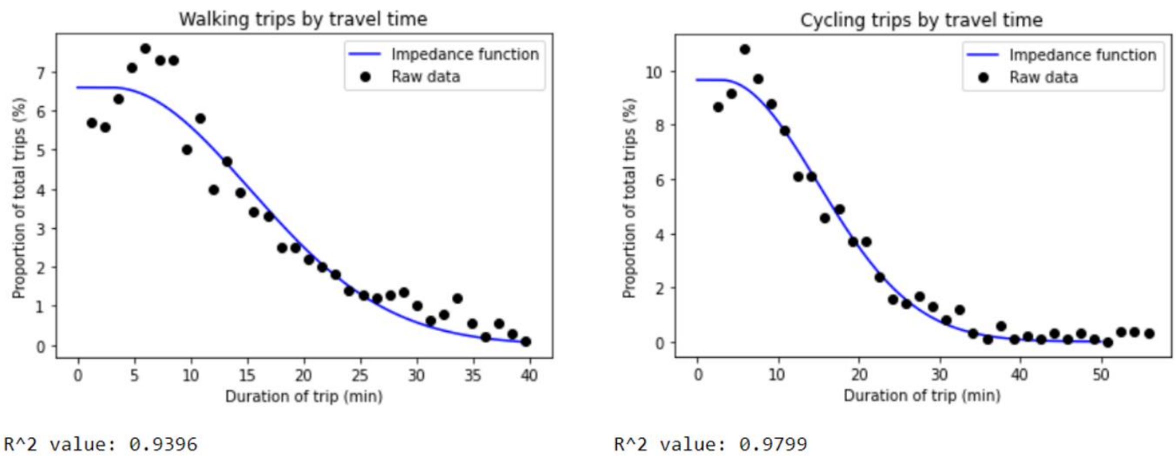

Figure 14: Walking (left) and cycling (right) curve fitting for the impedance function.

The choice of the Cumulative-Gaussian Distribution here achieved a high R^2 value, with a better result than others using the same data with an inverse square model [70].

The data found to determine these parameters is proportions of trips taken by distance [70]. The source comes from Montreal and covers travel to a variety of different locations. This data was used, despite not being from Canberra or Australia, as it provides a level of precision not available from other sources, enabling a curve to be fit to the data specified. However, it may be limited due to the differences in city from Montreal to Canberra. While Montreal is a developed western city, it is much larger, has higher population density and has a different culture, which may affect the validity of this data.

Additionally, a main limitation of this data is the use of proportions of trips for fitting, which does not consider population distributions, and is therefore likely inaccurate, this is discussed further in Section 5.2.4.2. Despite these limitations, the curves are reasonably close to expected results, dropping off after a typical 10-15 minute travel time, and thus used in the overall model [71]. The curves identified here are also used for public transport, while this is flawed, with no other data found, this is deemed necessary.

3.4.3 Attractiveness Parameter

Finally, the attractiveness parameter was needed for the model. The attractiveness parameter gives the relative value of each service to a particular demand point (mesh-block). For example, a second store of a similar kind, at an equal distance will be less valuable than the first. Here, different methods are used between services.

3.4.3.1 Employment attractiveness parameter

For the employment service, the employment count will be the attractiveness parameter. This reflects that areas with higher levels of employment are more valuable than those with less.

3.4.3.2 Other services attractiveness parameters

Throughout Canberra and Queanbeyan, local, group and town centres are expected to provide similar services for their respective service types. To account for this, a diminishing returns curve is used to reduce the value of extra services. This diminishing return is also expected to occur for schools, albeit with a reduced drop-off, reflecting the many variables in deciding a school other than location. These values are estimated based on personal expectations and are not rigorous, with potential improvements discussed in Section 5.2.4.3. Details of the calculations involved are given in Appendix A.4, with the resulting values given in Figure 15.

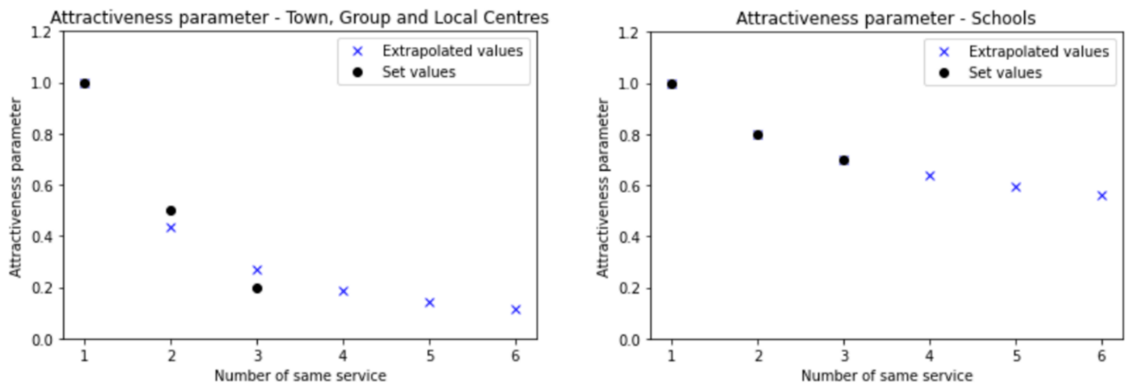

Figure 15: Diminishing returns curves for various services' attractiveness parameters, set values are chosen for the expected value of the 2nd and 3rd services, and are extrapolated for higher service numbers by fitting these values to an inverse relation

3.4.2 Summary of Accessibility modelling

Using the gravity model with the origin-destination time data, the impedance function and the attractiveness parameter, an accessibility measure for the analysis is able to be found. The accessibility data created gives a measure of the relative likelihood of taking a particular mode compared to another area in that dataset. This accessibility data is then able to be mapped for a variety of cases. This accessibility data is produced for each of the 6 Development scenarios, 3 modes of transport, and 5 services, for a total of 90 different datasets. These datasets can then be compared to give an estimate of mode share differences between scenarios, hence allowing for the evaluation of a number of wider societal impacts.

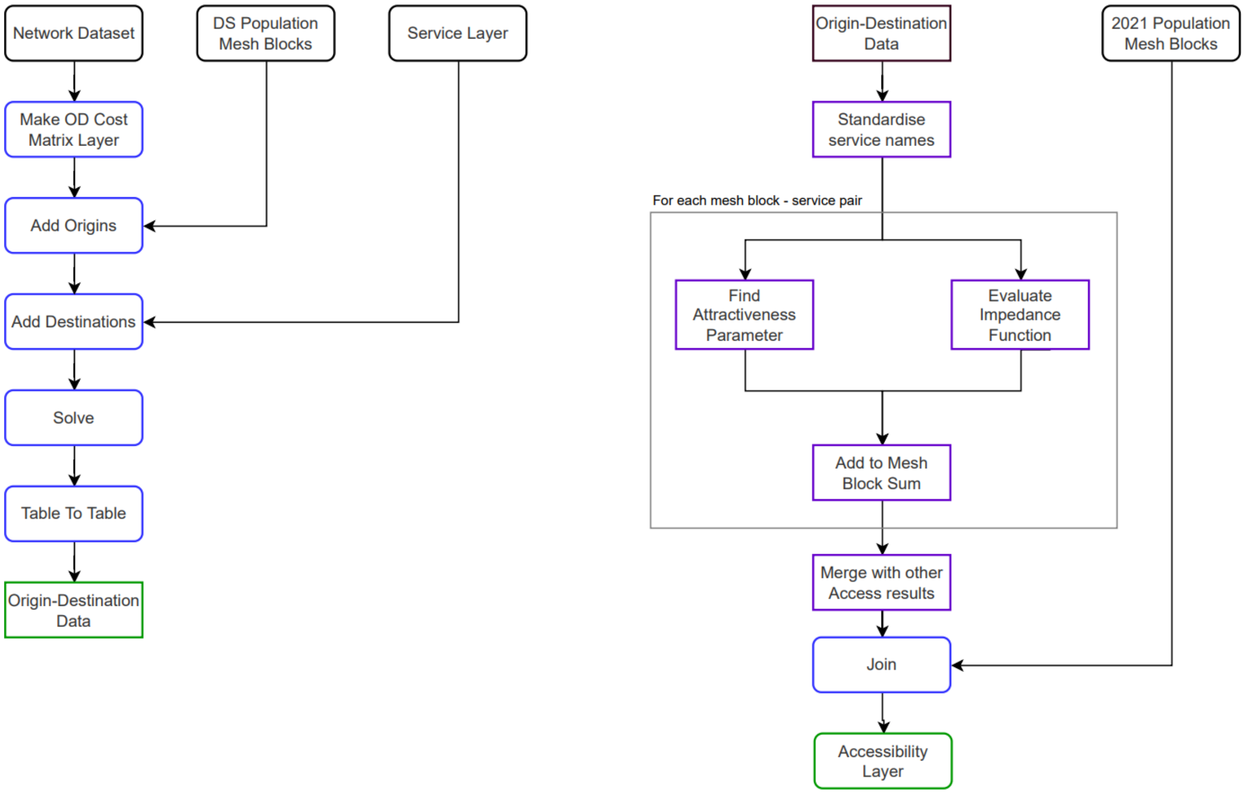

Figure 16: Process for evaluating the accessibility layers for the various development scenarios, services, and modes of transport. Here black boxes are spatial (smooth edges) and non-spatial (square edges) input data, blue boxes are ArcGIS Pro commands, purple boxes are processes designed specifically for this analysis, and green boxes are output layers.

3.5 Estimation of Mode Usage, Emissions and Economic Effects

The accessibility measures found allow for a relative estimate of how likely people in a given area are to take a particular transport mode, thus, enabling different development scenarios' impacts on sustainable transport usage to be compared. This will involve finding an estimate of the amount of people changing mode under each scenario, and how far each of them travelled. The different services can then be combined using HTS data, allowing an overall sustainable transport distance travelled to be found. Using estimates for the emissions and economic effect of each transport mode, an overall emissions and economic effect can be found.

3.5.1 Estimation of Mode Usage Change

This estimation will act under the assumption that the accessibility value of an area is proportional to the probability that a person in that area will take a particular transport mode to a particular service. There are two ways in which the usage of a mode could increase under this assumption:

- The accessibility of the area increases
- The population of an accessible area increases

To model both of these factors, and using the above assumption, a new measure can give the mode share change: population-accessibility, the population of an area multiplied by its accessibility. The proportion mode change under a development scenario (ΔM) is then modelled by:

$$\Delta M^p = \frac{km_2^p}{km_1^p} = \frac{\sum_i P_2^i A_2^{ip}}{\sum_i P_1^i A_1^{ip}} \qquad Eq.6$$

Where P is the population of the mesh block, A is the accessibility of that mesh block, and km is the total kilometres travelled by that mode to service p. This also assumes that all trips are directly to and from home.

3.5.2 Combination of Different Services

Eq. 6 above results in mode increase data for each different type of service. These can be combined to a single dataset according to how many trips are taken to each kind of service. The information on trip purposes percentages and our proxies of them is outlined in Section 3.1.2, and gives us the following weighted sum:

$$\Delta M^{all\ services} = \sum_p w^p \, \Delta M^p \qquad Eq.7$$

Where p denotes the different service types, w_p is the weight of each services, and ΔM is the proportion mode change under a development scenario.

Table 7: Service weightings used to calculate the overall mode increase factor for each scenario

Service	Weighting
Employment	0.344
Local Centres	0.290
Schools	0.206
Group Centres	0.119
Town Centres	0.0396

These weightings are based off Section 2.1.2, but as the services used in this model only cover the most commonly used services, these do not add to 100%, and so are appropriately scaled (divided by 0.751). Additionally, both group and town centres are considered shopping, so the total shopping weighting is split between them. This is weighted 3:1 to group centres, as it is expected most shopping is done there, and group centres include the town centre locations. Another difference from these measures is education. In the HTS there is a field “Pick up/drop off”, which is likely to be a significant part of school pick-ups and drop-offs. As such a further 5% is added to the original education purpose share (to give a total of 15.5%).

This mode increase factor is also useful in comparing development scenarios, as it provides a combined measure for each development scenario, something that is not able to be done using accessibility data, due to accessibility values having different scales.

3.5.3 Estimating Emissions and Economic effects

Initial research undertaken outlined an emissions and economic impact of each different mode by kilometre of travel. A difference in kilometres travelled by each mode for each service will allow each development scenario's environmental and economic effects to be modelled. This kilometre value will be found using the HTS overall kilometres travelled by each mode, and the mode share established in Section 3.4.3. Any mode share increases and decreases will be assumed to be taken from driving, with conservative estimate of societal cost as \$0.17/km and carbon emissions of 0.181 kg/km [72]. Public transport is assumed to be buses, with a carbon emissions per km at 0.017 kg/km, and is assumed to have an estimated net societal cost of \$0/km [73]. These establish the following relations for this comparison to take place:

Table 8: The change in emissions in emissions and economic effects from each kilometre of travel switched from driving to each of the sustainable transport modes.

Mode	Change in emissions per kilometre (Δe) [kg CO_2 /km]	Change in economics (societal income) per kilometre ($\Delta \mathrm{i}$) [\$/km]
Walking	-0.181	0.69
Cycling	-0.181	0.44
Public Transport	-0.164	0.17

Using these values, the following equations can be used to compare different scenarios:

$$\Delta E = \%\Delta M\ km_1\ \Delta \mathrm{e} \qquad Eq.8$$

$$\Delta I = \%\Delta M\ km_1\ \Delta \mathrm{i} \qquad Eq.9$$

These equations give the overall estimate for the emissions and economics effects of the scenarios, useful in the results.

3.5.4 Summary of Emissions and Economic Estimations

Using the population changes and the accessibility measures created for each mode and service, an estimate for the emissions and economic impact of various development scenarios for Canberra-Queanbeyan are able to be found. This is done be assuming an increase in accessibility or population results in a proportionate increase in kilometres travelled by mode, giving a mode increase factor. Utilising researched values for the emissions and economic impact of sustainable transport modes by kilometre, this mode increase factor estimates these external effects. The mode increase factor can also be used to compare the accessibility values of different scenarios.

3.6 Summary of Method

This analysis consists of implementing a gravity model to determine accessibility data for the Canberra-Queanbeyan under various development scenarios. In implementing this, a large focus is on preparing the data to be used, this included population and service distributions (Section 3.1), network datasets (Section 3.2) and the development scenarios (Section 3.3). Accessibility data found from the gravity model and the use of the created datasets (Section 3.4), and is used to estimate a mode increase factor, allowing different development scenarios to be compared. It also allows for estimates for emissions and economic effects to be calculated.

Chapter 4 – Results

The results for this analysis can be split into three components, accessibility maps, mode increase factor maps, and the emissions and economic effects. Firstly, maps showing the accessibility values found using the gravity model give information on what areas people might be likely to walk and cycle. This accessibility maps are for each development scenario, service and transport mode, Section 4.1 covers the accessibility results. Secondly, mode increase factor maps give an estimate for what proportion more people are likely to take the particular mode, under the given development scenario. These are able to be combined for all services using HTS data as discussed in Section 3.5.2, and these results are given in Section 4.2. Finally, the emissions and economic effects for each scenarios can be calculated and compared between each scenario (Section 4.3). Due to the large amount of data generated, the maps for accessibility and mode increases will focus on comparing the "Greenfield" and "Medium-density inner city" development scenarios, giving an example of the effect of suburban-style development and of medium-density housing.

4.1 Accessibility Results

These highlight which areas are currently accessible, and where population increases might see the greatest sustainable transport usage. Due to the large amount of accessibility maps generated (6 development scenarios, 5 services, and 3 modes for a total of 90 maps), only a few example maps will be given in this section, with more examples given in Appendix B.1. Accessibility is not able to be combined using a weighted sum, due to having no defined reference values to scale the data to, so each accessibility map is only for one service. For example, the maximum probability of walking to employment may be different to the maximum probability of walking to shops.

The example maps here are walking accessibility to employment (Figure 17), and walking accessibility to group centres under the 2016 and "Medium-Density Inner City" development scenarios (Figure 18 and Figure 19). These represent some of the most significant sustainable transport usage maps and highlight how accessibility changes with development. In Appendix B.1, maps showing the effect of different modes on accessibility are given. Those accessibility results show cycling as having a considerably higher accessible area than the other sustainable transport modes.

4.2 Mode Increase Factor results

The mode increase factor shows how each development scenario might change the sustainable transport usage, calculated according to Eq. 6 and Eq. 7 in Section 3.5.2. We have the following results for the mode increase factor Table 9.

Table 9: Mode increase factor for all scenarios, where 1 is the total distance travelled in the base scenario (2016). Here the mode increase factors for each service are combined into a single measure for each mode. Detailed results with mode increase factors for each service type are given in Appendix B.2.

		Development Scenarios				
Mode	**2016**	**Actual**	**EqualDev**	**Greenfield**	**mdINIS**	**TODInfill**
Public Transport	1	1.234	1.166	1.115	1.260	1.264
Cycle	1	1.194	1.171	1.118	1.266	1.226
Walk	1	1.252	1.188	1.121	1.270	1.302

Here, we can see that the medium-density scenarios: “Medium-Density Inner City” and “TOD”, give the best sustainable transport usage across all three modes. The “Medium-Density Inner City” scenario did particularly well on cycling, while the “TOD” scenario did best on walking. Both suburban-style development scenarios performed the worst, with the “Greenfield” scenario giving the worst sustainable transport outcomes, with mode increases less than the overall population increase of 13.1%. The “Actual” scenario, consisting of both suburban-style and higher-density development, is fits in between these scenarios.

4.3 Emissions and Economic Effects

Applying the mode increase factors to the per kilometre emissions and economic effects, as outlined in Section 3.5.3, Table 10 and Table 11 were calculated.

From these results, we can see a decrease in overall emissions by ~1.1% for the medium-density scenarios, and by 0.5-0.7% for more suburban style development. These results show the effect of medium-density housing is higher, but still a small impact on overall emissions compared to the overall annual ACT emissions of 1685 kilotons of CO_2 [74].

Table 10: Change in emissions (kilotons per year) by development scenario, and comparison to the ACT's 2020-21 yearly emissions of 1685 kt CO_2-e

		Development Scenarios				
Mode	**2016**	**Actual**	**Equal Development**	**Greenfield**	**mdINIS**	**TODInfill**
Public Transport	0	-9.93	-7.06	-4.89	-11.05	-11.22
Cycle	0	-2.41	-2.11	-1.45	-3.29	-2.80
Walk	0	-3.77	-2.80	-1.81	-4.03	-4.51
Total	0	-16.11	-11.97	-8.15	-18.37	-18.52
% of Total ACT Emissions	*0 %*	*-0.96 %*	*-0.71 %*	*-0.48 %*	*-1.09 %*	*-1.10 %*

Table 11: The change in annual societal economic benefit from sustainable transport, for reference the total annual ACT budget is $7.5b and the total ACT active travel budget is $24m

			Development Scenarios			
Mode	**2016**	**Actual**	**Equal Development**	**Greenfield**	**mdINIS**	**TODInfill**
Public Transport	0	$10.3m	$7.32m	$5.07m	$11.46m	$11.6m
Cycle	0	$5.86m	$5.14m	$3.54m	$7.99m	$6.81m
Walk	0	$14.4m	$10.7m	$6.91m	$15.4m	$17.18m
Total	0	$30.5m	$23.14m	$15.5m	$34.8m	$35.6m
Active Travel Total	*0*	*$20.2m*	*$15.8m*	*$10.4m*	*$23.4m*	*$24.0m*

These results show a small impact compared to the overall ACT budget of $7.5b. However, compared to the ACT transport expenditure of $291m, and public transport expenditure of $150m+, these values are not insignificant [75] [76]. Additionally, the benefit from active travel just from the change in usage under the medium-density scenarios pays for the active travel expenditure of $24m [77]. This gives the total active travel contribution from these scenarios to society being 4-5x the current expenditure on them. Other estimates of the return on investment (ROI) for active travel, align with this found value, with cycling infrastructure typically having an approximately 5:1 ROI [78, 79].

Maps for mode usage under the “Actual”, “Greenfield”, and “Medium-Density Inner City” scenarios are given in Figure 20, Figure 21 and Figure 22 respectively. Here, darker colours here represent a greater mode usage and white areas are those with no people living in them, or with a very low population density.

4.4 Summary of results and maps

The results highlight the inner areas of Canberra as the most accessible, with other town centres also having high accessibility. These accessibilities are also reflected in the resulting mode increases, with scenarios increasing populations in these areas (the medium-density scenarios) giving the greatest mode increase factors. Translating these mode increases to emissions and economics effect, the resulting emissions and economic effects appear small, with the exception of active travel, where the additional economic benefits from the medium-density scenarios are enough to offset the current active travel expenditure.

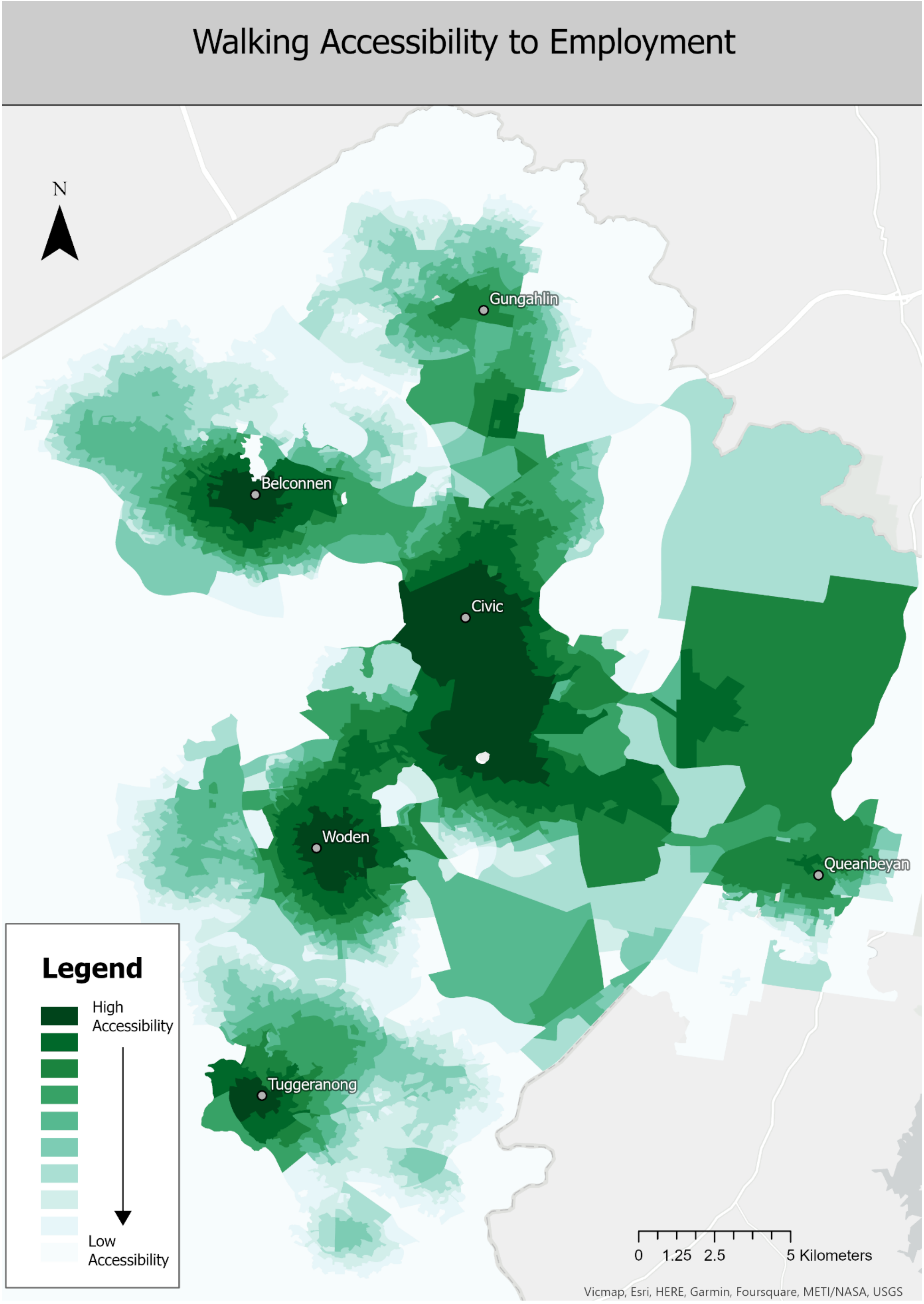

Figure 17: Accessibility values for walking to the employment service. This map is for the 2016 development scenario, but is the same as for the other development scenarios, as the employment location do not change between scenarios (Section 3.3.3). This shows the inner city as highly accessible, as well as the town centres of Belconnen, Woden and Tuggeranong, which each have large amounts of employment in them.

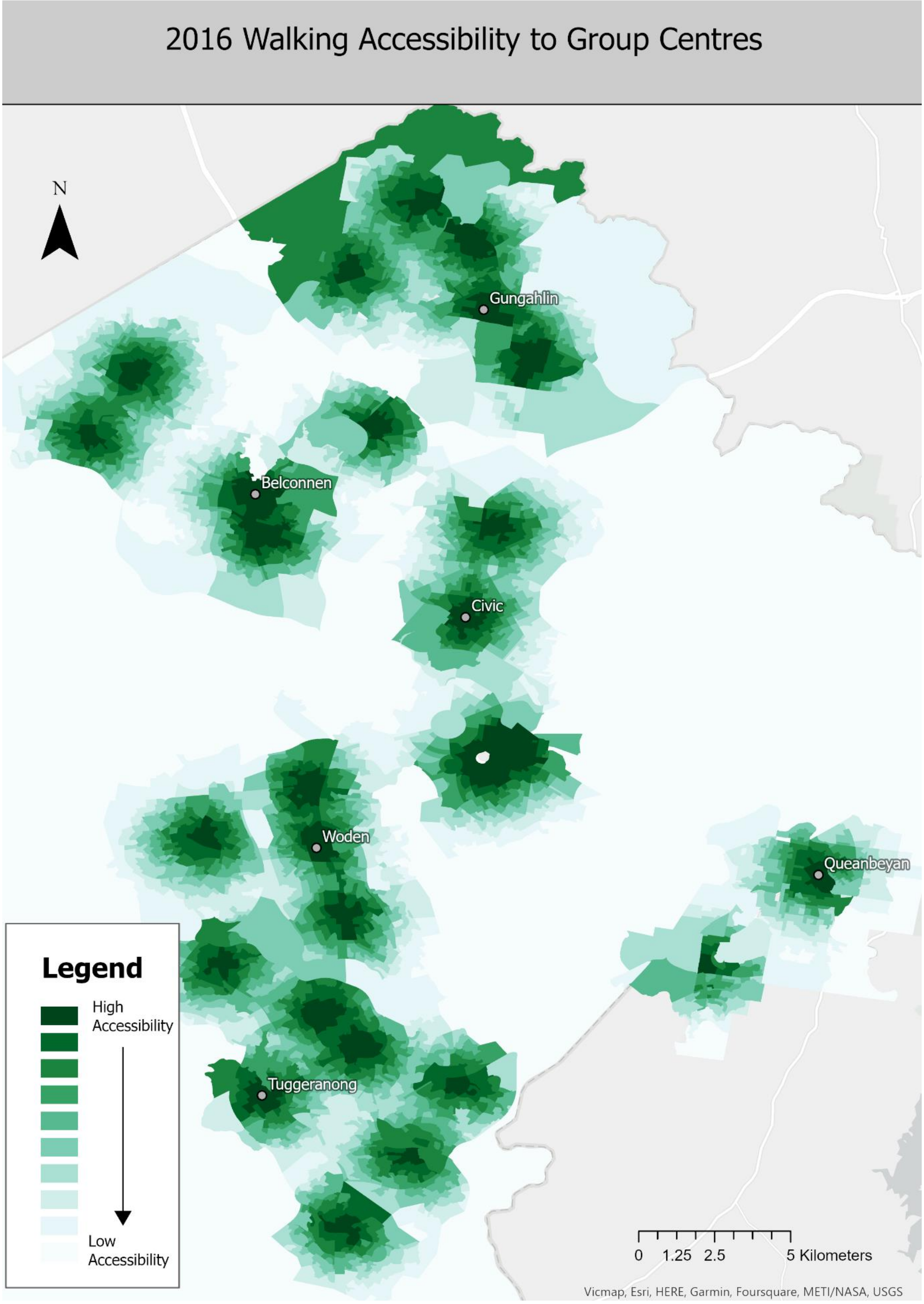

Figure 18: Accessibility results for walking to Group Centres for 2016, highlighting the initial distribution of group centres

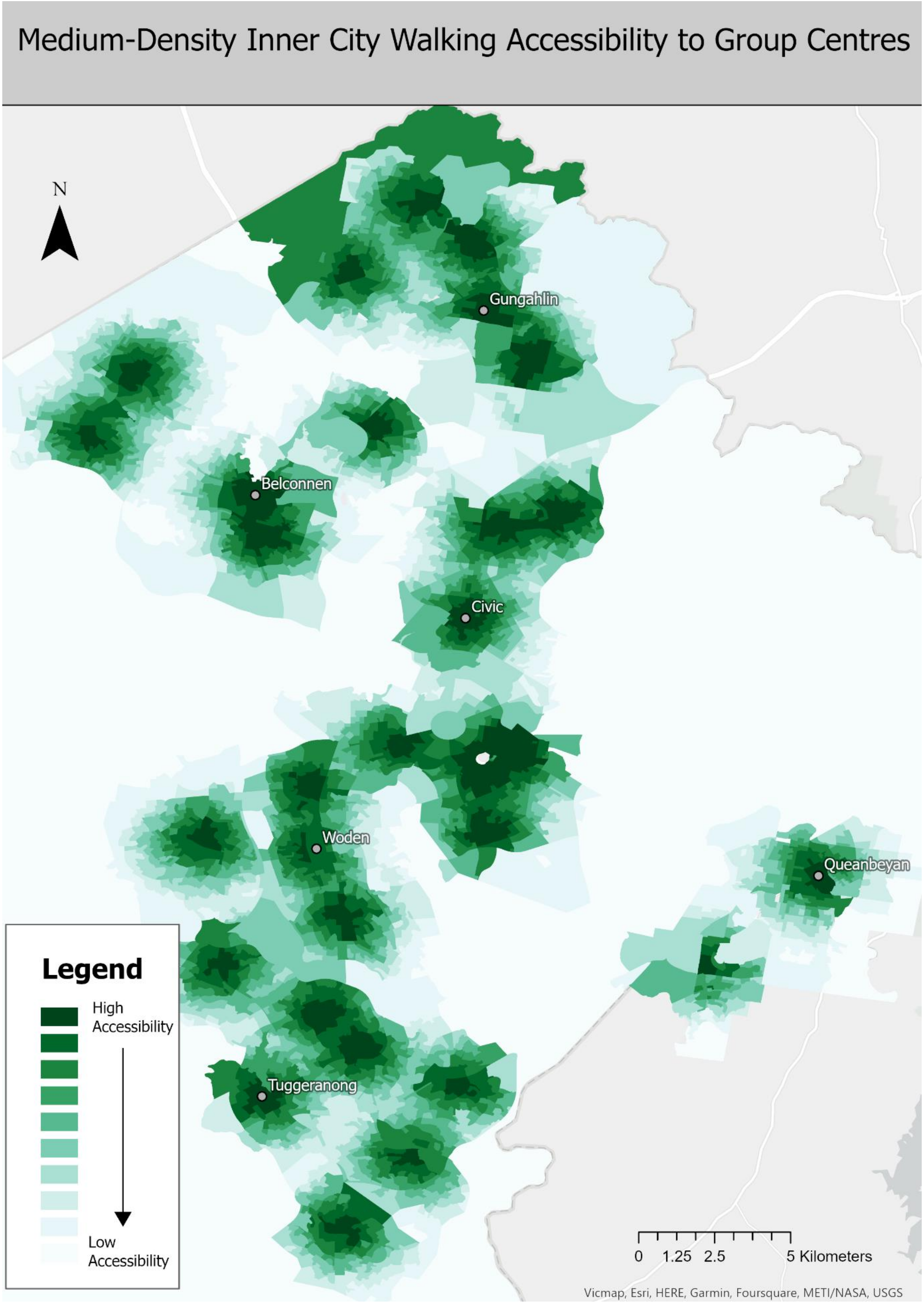

Figure 19: Accessibility for walking to Group Centres under the "Medium-Density Inner City" devlopment scenario. Here, some areas near the inner city now have increased accessibility values, showing how the increased population can support extra group centres in these areas.

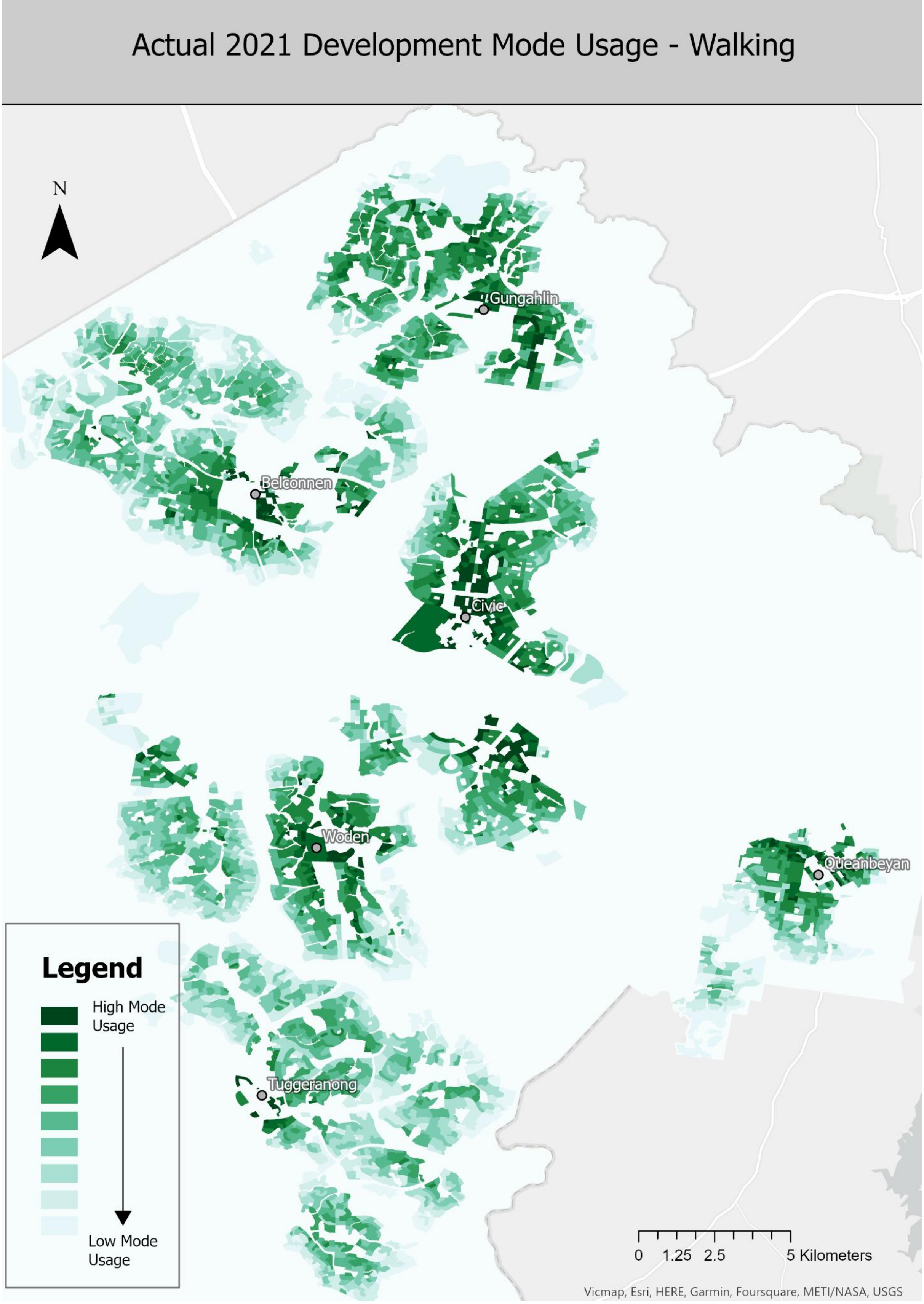

Figure 20: Estimation of the contribution of different areas to the overall walking mode usage amount. This data is for the "Actual" development scenario, and shows higher walking transport close to town centres, and in highly populated areas.

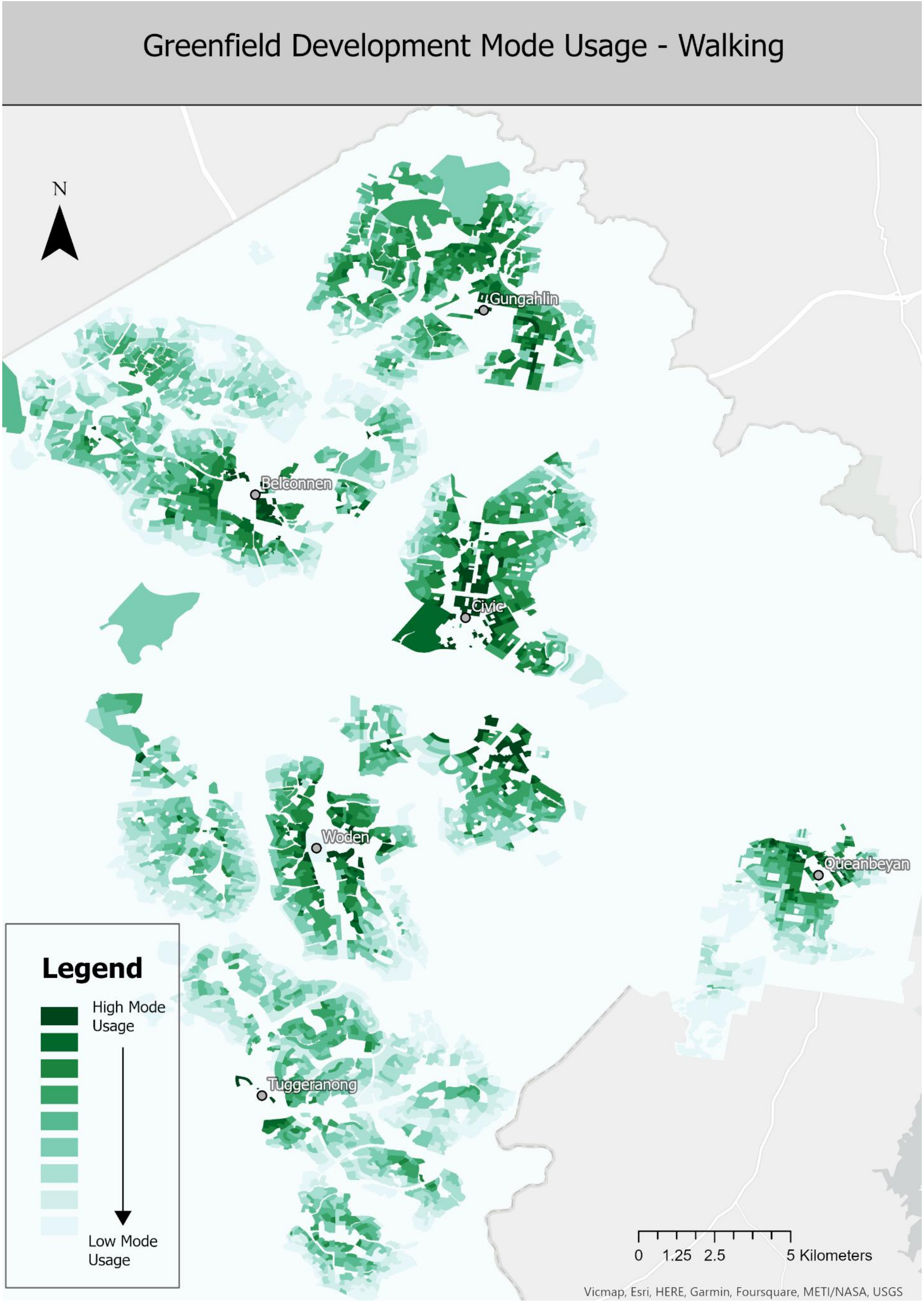

Figure 21: Estimation of the contribution of different areas to the overall walking mode usage amount. This data is for the "Greenfield" development scenario and shows some changes in the new greenfield areas to the west and north of the city, but overall minimal changes to walking usage.

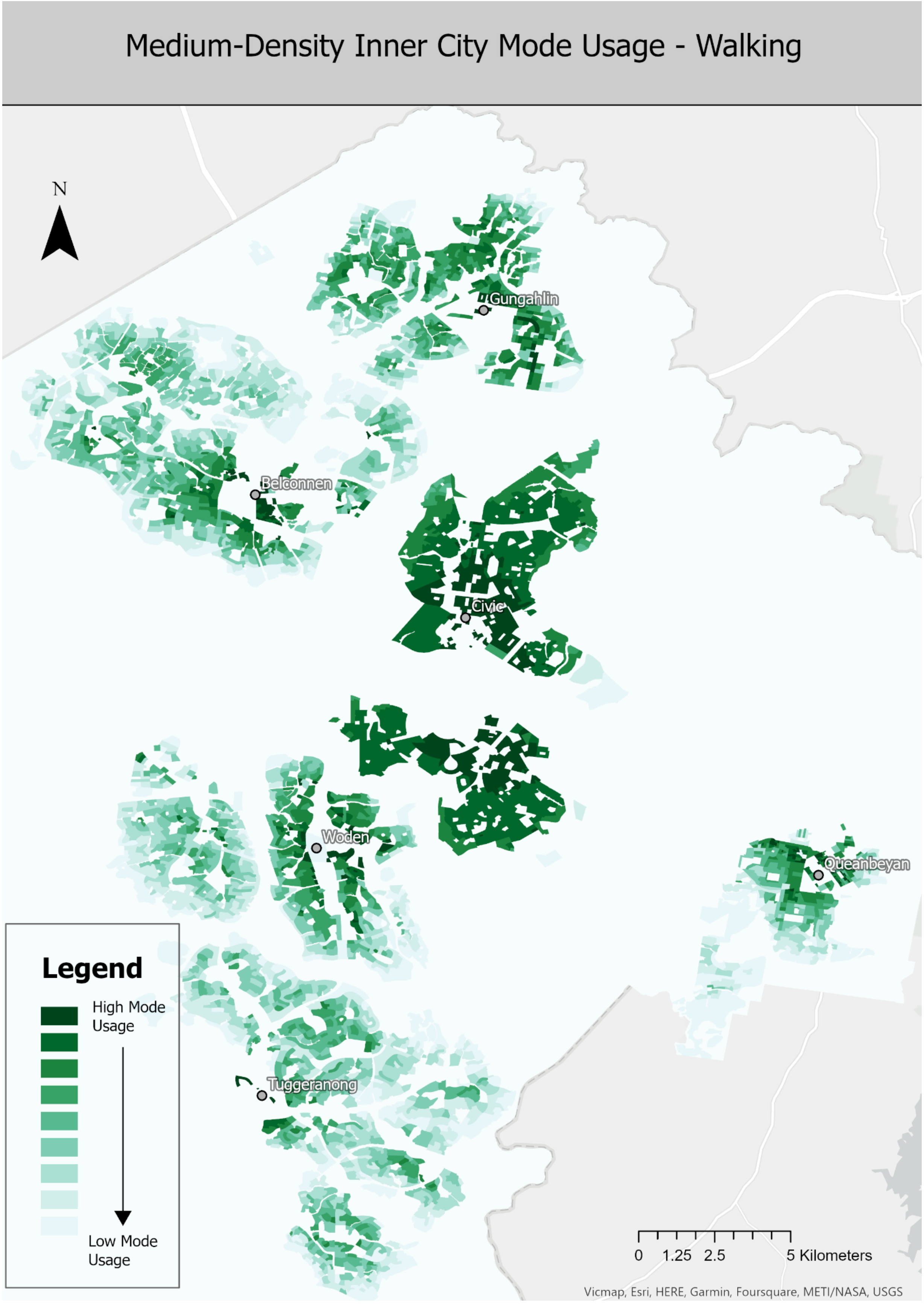

Figure 22: Estimation of the contribution of different areas to the overall walking mode usage amount. This data is for the "Medium-density Inner City" development scenario, and shows higher walking transport in the medium-density areas created.

Chapter 5 – Discussion

The analysis was able to identify accessibility values for various development scenarios and compare and evaluate the effect of different land-use strategies on sustainable transport, this is discussed in Section 5.1. However, there were a number of limitations in the model (outlined in Section 5.2), and there are many ways which the model could be improved upon in future (Section 5.3). This particularly identified a longer timescale, finer granularity of data, and further research on trip purposes as key areas the analysis could be improved.

5.1 Implications of Results

The results identified the two development scenarios which allow for greater medium-density housing, the medium-density inner city and the transit-oriented development scenarios, as encouraging the most sustainable transport. This was considerably more than the suburban-style “Equal Development” and “Greenfield” scenarios (25-30% vs 10-20%), but not much more than the “Actual” scenario. The overall emissions and economic effects were found to be small contributing to a maximum reduction of ~1% in emissions, and ~0.5% of ACT government expenditure.

Explaining the small resulting changes, the low initial mode of sustainable transport in the ACT and Queanbeyan, means that even with good mode share increase factors, the resulting carbon emissions and economic effects are not large compared to overall emissions and budgets.

5.1.1 The Effect of Medium-Density Housing on Sustainable Transport

The results identified the medium-density scenarios as having the greatest impact on the sustainable transport usage, reinforcing theoretical background [5-7]. The “Medium-Density Inner City” scenario performed particularly well on cycling, likely owing to a population distribution contained within an ~5km radius of major employment and shopping centres. Similarly, the “TOD” scenario’s high performance on walking is expected as TOD concentrates development on areas within walking distance of key locations.

The suburban-style scenarios performed the worst. This is to be expected as development is located away from existing services, and must be built from scratch with the development, naturally resulting less services. The “Equal Development” scenario did better, but fails to meet the densities needed to support sustainable transport to a greater extent. The model is also biased towards the “Equal Development” (and “Actual”) scenarios, as the location-allocation can access the entire map for these scenarios (discussed further in Section 5.2.3.5). This means the medium-density scenarios likely perform even better than suggested here.

The “Actual” development scenario also had accessibility values close to the medium-density results. This could be due to much of the “Actual” development scenario consisting of high- or medium-density housing, with 63% of development between 2012 and 2018 being infill development (predominately high- or medium-density), and a goal of 70% infill development going forward [80]. Recent ACT development has been of higher densities in the past, and additionally, the “medium-density” scenarios did not yet reach typical medium-density development levels.

Despite showing an increased sustainable transport accessibility, the medium-density scenarios created were only able to achieve minimal density increases across there given areas, at around 4500 p/sqkm. This does not reach the greater 7500 people per square kilometre stated to increase health benefits, nor does it reached generally accepted medium-density housing definitions of around 5000-15000 p/sqkm. Modelling housing in this range would likely give a better measure of the effect of medium-density. These densities could be achieved by considering a longer timeframe or increasing population across a smaller area. Of these, a longer timeframe is likely more realistic of development trends, and could be done in future work. Cities change across long time periods, and thus a longer timeframe would not be out of context for this kind of analysis.

The results suggests that any incorporation of medium-density housing helps to improve sustainable transport usage, even at the small density increases here. Further research could look at increasing densities further to better assess the effect of medium-density housing, such as through an increased analysis timeframe (discussed in Section 5.3.2).

5.1.2 Explanation for Low Impact Results

The small emissions and economic effects as a result of the mode share changes can primarily explained as a result of a low initial mode share. Increasing the small initial mode share sustainable development modes by 20 or 30% still has only a small impact on overall. Additionally, our initial mode shares were considered for the overall city, but in fact vary considerably between regions. Particularly, the inner-city areas with some of the greatest accessibility increases are also the ones with the highest initial mode shares, meaning accounting for this could have a large impact on the results.

Another major factor is the minimal density increases in our medium-density scenarios. As discussed in section 5.1.1, the medium-density scenarios were not able to reach density levels associated with increased health benefits (due to increased sustainable transport mode usage), or typical medium-density definitions. This means the densities modelled were still in a suburban-style range, and thus may not be able to see the effects of medium-density housing.

Other factors which the medium-density housing strategies may encourage, but were not modelled in this analysis, may also have contributed to the small results. These include the absence of emerging modes such as e-bikes and e-scooters (Section 5.3.3), no modelling of social effects (Section 5.2.6), and no modelling of transport infrastructure changes over time with increasing population. Some social factors may be able to be calibrated by using a higher spatial resolution mode share data: total mode travel distances are available in the HTS by SA3, and this could be used to calibrate the assumption of accessibility as a measure of mode share, this was not implemented in this analysis due to time constraints.

The low impact results on land use change alone indicate that while land use can give the potential for sustainable transport modes to be used more through accessibility increases, other factors are needed for sustainable transport to be encouraged in broader society. Transport usage is a complex issue, and even incorporating improvements to the model, it is likely land-use is only one component of many necessary in encouraging sustainable transport.

5.1.3 Other Observations

Despite a low economic effect overall throughout the modes, the active travel modes (walking and cycling) economic changes were comparable to the active travel budget. This excluded the current mode shares, and suggests that current walking and cycling levels pay for the money spent on them ~4 times over ("Actual" development scenario walking and cycling contribution of $100m). These benefits take the form of health effects, reducing expenditure on private vehicle infrastructure and reduced traffic congestion (outlined in Section 2.1).

Another observation that came out of this analysis was the high accessibility values of cycling. Cycling accessibility maps covered large areas compared to the other two modes, but actual cycling mode share is the lowest across the modes. This suggests other factors play a large role in people's decisions to cycle, these could include safety and physical exertion concerns. The results suggest improving cycling infrastructure and encourage its use, as well as supporting the proliferation of e-bikes and e-scooters, could have a large impact on sustainable transport usage.

5.2 Limitations and Assumptions

This section will discuss the limitations of the analysis, going over each section of the method and highlighting any limitations and assumptions uses, whether they have a significant impact on the results, and ways in which future work might be able to improve upon them.

5.2.1 Data Limitations and Assumptions

Within the input data used for this analysis (excluding network data discussed next), some of the key limitations include the spatial resolution of the available data, and the choice of which services to use in the analysis.

5.2.1.1 Spatial resolution of population data

Mesh block data represents the finest spatial resolution data available from the ABS but is still not perfectly accurate. Additionally, in our analysis process, the centroid of each mesh block is taken, where the population of an area is represented by a single point. This has the potential to provide misleading information, as the population is unlikely to be uniformly distributed throughout the mesh block as this method assumes. However, on the scale of a city, these population mesh blocks are very small, and are thus a minimal source of error in the analysis. Additionally, in projecting 2016 mesh blocks to their 2021 equivalents, a slightly higher resolution than initially available was able to be achieved.

Another issue in the mesh blocks came from converting polygon mesh block data to points. This is a process required for the use of network analysis, but sometimes results in areas of population that are inaccessible to the network. Many of these issues were fixed in construction of the network, and only a few mesh blocks remain inaccessible to the network, with minimal effects on the overall results (some of the inaccessible mesh blocks include

Manuka Oval, and remote regions of Namadgi National Park, were there happens to be no roads or paths).

5.2.1.2 Spatial resolution of employment data

As discussed in the method Section 3.1.2, the employment data used comes from projecting SA2 ABS data to a mesh block level, providing an increased spatial resolution, but potential introducing inaccuracies. This process required assuming no employment in areas with the "Residential" mesh block category, this could mean local businesses, with potentially very high accessibility values are moved to less accessible areas. As such, the methods used here likely gives an underestimate of the overall employment accessibility. Still, values are often with 20% of their actual values (Appendix A1.2), and in cases of error, misplaced employment will be within the same SA2, giving minimal error. Additionally, the projection provides a substantial improvement over using the raw SA2 data, so its use in the analysis is deemed justified.

5.2.1.3 Choice of services from HTS

The services chosen for this analysis were taken from the ACT-QPRC HTS, but only the largest travel purposes were taken, and proxies were assumed for these. The trip purposes used in this analysis collectively only account for ~75% of the overall trip purposes, leaving a significant component of people's travel unaccounted for in this analysis. These purposes were "Pick-up/Drop-off someone", "Personal business" and "Other/Not Stated", with proxies for these purposes being more difficult to model. This is a significant limitation in the model, as these purposes are likely to less typical to others seen and resulting in the analysis giving an overestimate for accessibility. Future work could involve investigating what kinds of trips these refer to and developing a suitable service proxy for them.

The choice of proxies is also a significant source of error in the analysis, particularly for fields such as "Social / Recreation" as the amount of possible geographic locations this could refer is large and very difficult to model. Likewise, "Education" and "Work related" purposes, while having more fixed sets of locations they could refer, have a large amount of possible factors in which school or workplace someone travels to. This makes it difficult to model travel to these locations and introduces error (this is estimated in this analysis using the attractiveness parameter, but does still give error). Another important limitation for this analysis is that schools are not scaled by their enrolments, and universities have not been included, potentially largely misrepresenting the education trip purpose.

5.2.2 Network Dataset Limitations

While providing significantly more accurate transport modelling than other methods, the network datasets created and used for this analysis still have several limitations.

5.2.2.1 Paths_ND – Remaining connectivity issues

The Paths_ND network was created with features to improve connectivity, but this introduced a potential some barriers (such as lakes, walls and houses) to be traversed. This issue is likely minor, as low speeds were incorporated to make this unlikely, but it still has the potential to create unrealistic routes. Manual alteration of any impossible connections could be done to fix this for future analysis.

Figure 23: Example of misplaced connectors issue, where the connectivity layer (dark blue), allows for paths through houses to be traversed. This is mitigated through a low speed, so the path around becomes.

5.2.2.2 Paths_ND – Unconsidered factors

Some factors which affect people's ability to walk and cycle to different locations were excluded from this network. These include traffic lights, hills, low-quality footpaths, and accessibility to people with limited mobility. Adding these factors to the network would help to improve the accuracy of this network in modelling routes.

5.2.2.3 Paths_ND – Queanbeyan data footpath availability

Footpath data was unavailable for the Queanbeyan area, and instead roads data for this region was used. This means that many laneways and paths that provide safer and faster routes to many places are excluded from this region, increasing the walking and cycling times for this area.

5.2.2.4 Paths_ND – Walking and cycling speeds assumptions

Walking and cycling speeds were taken at 5 km/h and 18 km/h respectively, found from researched averages. However, many people could have different walking and cycling speeds depending on demographics and trip purposes which are not reflected here.

5.2.2.5 TransitNetwork_ND – Choice of time of day

A significant limitation of the public transport network is that public transport travel times vary substantially based on time of the day and day of the week. An arbitrary day and time was chosen in attempt to reflect an average point, but may not be representative of overall public transport and will favour particular routes which having public transport leaving close to the chosen time. A better way to model public transport would be to use the "Calculate Travel Time Statistics" tool, which runs the analysis over a given number of different days and times and gives the average of the results [81]. This avoids biases towards particular routes, and gives a better representation of public transport usage. This tool was not implemented in this analysis due to the high computation times associated with running this tool on a dataset of this size. A single run of public transport accessibility takes ~24 hours, and running this many times was not feasible.

5.2.2.5 TransitNetwork_ND – Snapping of stops to the Paths_ND network

A minor limitation of this network occurs in the snapping of public transport stops to the Paths_ND network. These stops may not snap to the correct point on the network, or if sufficiently far away, not snap at all, creating different travel times than what might actually occur. This issue is minor and only effects a few cases where roads and paths appear far from stops.

5.2.3 Development Scenarios Limitations

The development scenarios represent potential future scenarios, so there is necessarily a large amount of estimation and uncertainty involved. The limitations primarily revolve on how to model future scenarios in a realistic way with the data available.

5.2.3.1 Uniform distribution of population throughout scenario

In many of the development scenarios, population increase is modelled to give a constant population density across large areas, with abrupt boundaries to lower population density areas. This was done for ease of modelling, and is likely a minor limitation, given situations like this do occur, and any other distributions would also introduce uncertainty, but is unlikely to be entirely realistic.

5.2.3.2 Date incompatibility of service data

In collecting data on services from various sources, each service has a different source date, and they do not all begin at the base year of 2016. The estimation process for all services increases for the 5-year development period act under the assumption the raw service data was sourced at 2016. This is inaccurate, particular as some sources are as recent as 2021 or 2022 and are likely quite different from the values in 2016. This results in an overestimate of the services in each development scenario, as services with later sources are still increased by a 5-year equivalent time period but was deemed a better option than attempting to remove services from data with later source dates. This issue is however mitigated by being consistent between all development scenarios, and as this analysis looks at proportional increases and not absolute values, the effect of development distributions on sustainable transport will still be seen. Still, this could be improved in future analysis by seeking out more contemporary data for initial services.

5.2.3.3 No consideration of zoning rules

This analysis is done to consider alternatives to current zoning rules, so inherently does not consider this as a factor.

5.2.3.4 Location-allocation not used on employment data

Due to employment values varying greatly with location, and employment tending to be concentrated in town centres, it was deemed more accurate to not use location-allocation on employment data, and instead proportionally increase employment values. This means the geographic distribution of employment does not consider any location changes of job centres over time. Employment data could be improved here by considering the actual areas in which employment increased, and when available, 2021 Census data could be used here.

5.2.3.5 Choice of candidate sites for location-allocation

In the location-allocation process, the set of all places new services can be placed (the candidate sites) was chosen as the mesh-blocks for each scenario with a non-zero change in population. This aided computation time, while emphasising the effect of each development scenarios, rather than placing services in currently deficient areas of Canberra. Under the assumption that there is currently a good service distribution by population in Canberra, this would be an accurate model. However, this perfect service distribution is unlikely, and so this method introduces a bias towards more spread-out development scenarios' accessibilities, here biasing towards the "Equal Development" and "Actual" development scenarios. These have candidate sites in currently service-deficient areas of Canberra, with greater potential for accessibility increases. Future analyses should use the full set of mesh-blocks as candidate sites, this will see the effect on areas where there is population increase reduced, but an overall accessibility increase and a better point of comparison. This was not done to give differences in development scenarios, but these differences would likely arise over a longer analysis timeframe, where accommodating service-deficient areas would represent a smaller proportion.

5.2.3.6 Incorporation of different school types in location-allocation

The location-allocation could be improved by incorporating all different levels of schools, as these were not split into primary, secondary and college levels. The data is available for this to be done, but was not implemented due to time constraints on the project

5.2.4 Accessibility Modelling Limitations

A number of limitations are present in the use of accessibility modelling, and the gravity modelling, particularly due to it being an attempt to model human behaviour, which is highly complex.

5.2.4.1 Accessibility does not consider actual demand

While the data used in the accessibility model does use general behavioural trends to emulate people's behaviour (through use of the impedance function and attractiveness parameter), the accessibility model is still a measure of potential, and does not consider any data regarding the known trips which people take in the study area. As defined earlier, the accessibility models measure whether people can travel somewhere, not whether they will. Incorporating sources such as the household travel survey or the "Journey to Work" field from ABS SA2 Census data could give insights on the distances travelled for services currently. This data could then be used to calibrate a simulated set of trips people take, enabling a travel demand model to be used.

5.2.4.2 Impedance Function Data Issues

A limitation of this data is that it gives the percentage of total trips taken at a particular distance, rather than the percentage of people that would take a trip, given that particular distance. The impedance function should use the latter. The set of people at each particular distance is not the same size, so this percent of total trips does not reflect the proportion of people using this mode at this distance. For instance, there may be a larger number of people living a range of 16-18 minutes from work compared to 10-12 minutes, so an equal percentage of total trips for these two distances would in reality mean that there is a higher proportion for the 10-12 minute range. For walking is it expected that there will be larger population sets as distances increases, and so should have lower parameters than estimated, and the reverse for cycling.

With further disaggregated data, this would be able to be improved, however this was not available. It is also an area when in future a survey might be able to be undertaken, to get this data. It is expected that the walking distribution would have lower parameters than calculated, and the cycling should have higher.

5.2.4.3 Choice of attractiveness parameter values

The attractiveness parameter values chosen for local, group and town centres and for schools are not based on any data, but instead chosen based on assumed similarities and differences between services. The estimation here is a potential place for improvement, and more data on this could improve these values.

5.2.5 Emissions and Economic Differences Models

Estimating the emissions and economic effects of the different development scenarios requires a large number of assumptions and provides only a ballpark estimate. This error is primarily in equating the accessibility values, a potential measure (as discussed in Section 2.2), to a mode increase factor. Other associated errors are in the emissions and economic contribution by kilometre values used, and the assumption that all mode shifts are from an equal distance trip vehicle usage as a driver.

5.2.5.1 Equating accessibility values to a mode increase factor

The mode increase factor is a rough approximation based on the accessibility and population values. It assumes an increase population or accessibility will result in a proportional increase in mode usage. The measure of accessibility as a proportion of total trips is limited (discussed in Section 2.2), is not intended to be representative of a mode usage in an area. The population is based on more rigorous data, but it is still an approximation that an increase in population will result in a proportional increase in sustainable transport mode usage for that area. This is likely also largely dependent on the demographics of the people moving into the area compared to the existing population and considering these could help improve the model. Still, this model is likely a suitable approximation for our services, with limitations here primarily resulting from errors in accessibility data.

5.2.5.2 Economic and emissions values per kilometre

The equivalent values used for the per kilometre emissions and economic impact (Section 3.5.3) are taken from a European study, and thus may not be applicable in the Australian context. Additionally, the process of encapsulating all economic effects into a single per kilometre value oversimplifies the issue, and some parts of this figure may not be relevant for this analysis, and likewise other factors may not be considered.

5.2.5.3 Assumption of mode share switch from private vehicle usage of equal distance

As private vehicles are the dominant form of travel in Canberra-Queanbeyan, it is assumed that all mode share changes are from private vehicle usage. However, this might not always be accurate, a mode share change could involve switching between sustainable transport modes, resulting in a different effect. Also, the mode change assumes the route is of equal distance, but this is likely incorrect as driving distances will typically have been higher. Under a mode switch from an accessibility increase, a service has been established closer to the person's location, so the distance travelled under the new mode is shorter than the original driving distance. This may result in an underestimate of the overall emissions and economic effects.

This model also does not consider changes in trip distances within the private vehicle mode, which could have a substantial impact on emissions and economic results, given the high initial mode share of private vehicles. For example, development in lower accessibility areas likely mean higher emissions due to the longer distance travelled than if the same development took place in a higher accessibility area. Additionally, increases in accessibility within a given area could reduce driving distances travelled. However, this analysis only considers the change directly related to sustainable transport modes, and not different distributions of driving trips. This could be incorporated in future work through the use of a network dataset considering private vehicle use.

Incorporating these factors would likely dramatically change the emissions and economic effects, due to the high initial mode share of driving, and potentially give a more holistic result from transport change in the different development scenarios, as opposed to the current analysis only considering the direct impacts of sustainable transport modes.

5.2.6 Other Relevant Limitations and Assumptions

There are other factors which are not taken account in this model. As we are attempting to model human behaviour, despite best efforts here, there is necessarily a large amount of uncertainty associated.

5.2.6.1 No wider social effects considered

Transportation choice is affected by many more factors than accounted for in this model, including safety, pleasantness, and a wide array of human and societal factors. One of these is the reinforcing social effects of transport choice. For example, more people walking and cycling results in increased safety for pedestrians and cycling, according to Jacobsen's growth rule, which in turn encourages usage of these modes [82, 83].

Modelling these societal effects was considered outside the scope of the analysis, but they are likely a substantial impact on sustainable transport and can be related to land-use. These could be incorporated in future models through a more detailed mode increase factor calculation.

5.2.6.2 Infrastructure not taken into account

A benefit of medium-density housing is that it allows for more people in a given area than suburban areas, this means not only more services, as has been modelled, but likely means more infrastructure can be built and maintained. Increased amounts of infrastructure may mean more frequent bus services, and more cycling routes, increasing overall travel times, and this increasing accessibility. Quality infrastructure plays a big role in mode share choice, affecting large factors in mode share choice such as safety [84, 85].

5.2.6.3 No modelling of multi-purpose trips

Many trips which people take in real life join together different purposes, meaning the starting and ending location of a trip is not at someone's home. This is not something that has been modelled here, with the analysis only considers the accessibility of population locations to services.

5.2.7 Overview of Significant Limitations and Assumptions

Some of the most significant assumptions in this model come from the estimation of emissions and economic effects (particularly resulting from the use of accessibility as an equivalent for trips taken), the equivalence of service locations to trip purposes, and the data used in the calculation of the impedance function. While there are a number of rough approximations in this model, these are likely dominated by the assumptions listed here due to them each affecting the entire analysis process in a meaningful way.

5.2 Future Work

Future work for this analysis is suggested to improve how the model relates to the context, and improve some of the key limitations of the model.

5.3.1 Considering mode increase factors by SA3

In this analysis, the mode increase factor is found by summing population-accessibility of the entire study area for each development scenario. A change which could make this model more effective is by using the data available for mode share by SA3 and calculating mode increase factors and the associated kilometre values by each SA3, before combining for the overall area. This gives a better spatial resolution, and hence accuracy, by translating accessibility increases in significant sustainable transport regions to greater overall increases, and vice versa for low sustainable transport usage areas.

5.3.2 Increasing timeframe of analysis time period

A key limitation which affected the results of the project was that the scenarios attempted to model medium-density development, but were not able to be increased to meet typically defined medium-density levels. Increasing the time-period, and hence the population increase, is a way in which the densities typically associated with medium densities could be achieved, and the effect of these analysed. Cities change across long time periods, and thus a longer timeframe would not be out of context for this kind of analysis.

5.3.3 Consideration of new technology

In recent times, electric bikes and scooters have been becoming more mainstream. These modes of transport provide quick ways for people to get around without the use of a car, while providing an ease of use that often presents a barrier to entry for cycling. E-bikes present an interesting mode to consider, as the distances people are willing to travel on them are much greater than normal bikes. E-scooters have also been recently introduced to Canberra, and so would be relevant for this kind of analysis. These modes of transport have very little emissions, and do not require the large infrastructure that cars do. Their high potential range and ease of use could allow these to have a large impact on overall emissions and to wider society. The Paths_ND network was designed for the associated speeds of e-bikes and e-scooters to be easily incorporated, and the potential willingness for people to ride e-bikes for longer times could be further accounted for in an e-bike impedance function.

5.3.4 Transport network changes with population density increases

With increased population densities, unlike road networks, sustainable transport modes increase in utility. Increased bus service frequencies could give a better idea of how increasing density could also improve sustainable transport. This was taken out of the scope of the project and could potentially be implemented by adjusting a “waiting time” with population density. Additionally, improved cycling networks are likely to able to be present with higher densities, and future paths could be included. Walking and cycling represent areas which these infrastructure impacts could make a big difference, as factors such as safety represent

5.3.5 Demand modelling

A discussed issue with this analysis was the use of accessibility to estimate travel usage, which only gives a measure of potential travel rather than demand. Using a travel demand model would help address multiple of the main issues around the model, improving issues around the equivalence of mode usage and accessibility, and how trips taken are related to service locations.

5.3 Summary of Discussion

Interpreting the results, it is suggested that the small emissions and economic effects result from a small initial mode increase, as even high mode share increases have limited effects. It is also noted that the medium-density scenarios did reach typically defined medium-density levels, and an increased timeframe may be helpful to better model the effect of medium-density housing. In addition to this context-based limitation, accessibility as an estimate for transport usage, the equivalence of service locations to trip purposes, and the data used in the gravity model impedance function are identified as key limitations. Future work could improve on these limitations through calibrating with further data, or by the use of travel demand modelling. Other suggestions for further work include changes to the transport network with development scenarios, and the consideration of e-bike and e-scooter modes. Other potential improvements to the model are detailed in Appendix C.

Chapter 6 – Conclusion

This analysis aimed to determine the effect of broader medium-density housing strategies on the sustainable transport accessibility of the Canberra-Queanbeyan urban area. It adds to existing research on the links between housing density and sustainable transport and could help contribute to future policy debate in the ACT regarding housing allowances.

This study measured the effect of multiple medium-density housing development scenarios on sustainable usage compared to typical lower-density suburban-style developments using a gravity-model based accessibility measure.

Using these methods, medium-density scenarios across the 5-year analysis period were found to increase sustainable transport usage (by between 20-30%), compared to the suburban-style scenarios 10-20%, and the actual population distribution with ~20%. Within these, the medium-density scenario gave the best cycling mode increase, the transit-oriented development scenario gave the best walking increase, with both resulting in similar public transport increases. These results are in line with existing research showing medium-density areas giving greater sustainable transport usage and shows that this applies to the Canberra-Queanbeyan urban area. It also contributes to existing research by providing a model showing how the underlying mechanism of micro-scale decisions lead to this relationship between housing and transport.

Accessibility results highlighted the areas of Canberra and Queanbeyan which are most conducive to sustainable transport usage. It also served to highlight the potential of cycling as a sustainable transport mode, with areas accessible to cycling covering a much wider range of areas than walking or public transport. This suggests investing in cycling infrastructure and social changes could have a large impact on sustainable transport usage. E-bikes and e-scooters are likely to result in even higher accessibilities and have a large potential for increasing sustainable transport usage.

The emissions and economic results show a small effect on overall ACT annual emissions and budget. For emissions, this is a surprising result, as transport is such a large contributor to ACT emissions, but can be explained by the low initial mode share of sustainable transport. Another interesting result is the economic impact of active travel despite this small initial mode share, with modelled economic effects under the base scenario of ~4x the current ACT active travel budget of $24m, with the medium-density scenarios reaching up to 5x. These benefits come from health benefits, reduced road wear and traffic congestion.

While achieving these results, there are a number of ways this work could be built upon going forward. A longer timeframe could be considered in this analysis, as the population increase 5-year period used still left the medium-density scenarios at lower densities than is expected to achieve many other benefits of these housing typologies. With more data, the accessibility modelling could also be replaced with a demand model, reflecting actual trips taken. Other ways this analysis could be improved would be modelling infrastructure changes with population increases, and considering the usage of emerging technologies such as e-bikes.

Overall, this analysis was able to show that medium-density housing strategies contribute to sustainable transport usage more suburban-style ones.

Bibliography

1. Point-Advisory, *ACT GREENHOUSE GAS INVENTORY FOR 2020-21*, P.a.S.D.D. ACT Government Environment, Editor. 2021.
2. Gössling, S., et al., *The Social Cost of Automobility, Cycling and Walking in the European Union.* Ecological Economics, 2019. **158**.
3. Gössling, S., J. Kees, and T. Litman, *The lifetime cost of driving a car.* Ecological Economics, 2022. **194**.
4. Dresden, T. *The True Costs of Automobility: External Costs of Cars Overview on existing estimates in EU-27*. 2012 [cited 2022 March 12]; Available from: https://tud.qucosa.de/api/qucosa%3A30084/attachment/ATT-0/.
5. Chatman, D.G., *Does TOD Need the T?* Journal of the American Planning Association, 2013. **79**(1): p. 17-31.
6. Mooney, S.J., et al., *Residential neighborhood features associated with objectively measured walking near home: Revisiting walkability using the Automatic Context Measurement Tool (ACMT).* Health & Place, 2020. **63**: p. 102332.
7. Haarhoff, E., L. Beattie, and A. Dupuis, *Does higher density housing enhance liveability? Case studies of housing intensification in Auckland.* Cogent Social Sciences, 2016. **2**(1): p. 1243289.
8. Baobeid, A., M. Koç, and S.G. Al-Ghamdi, *Walkability and Its Relationships With Health, Sustainability, and Livability: Elements of Physical Environment and Evaluation Frameworks.* Frontiers in Built Environment, 2021. **7**.
9. Zannat, K.E., D.R. Raja, and M.S.G. Adnan, *Pedestrian Facilities and Perceived Pedestrian Level of Service (PLOS): A Case Study of Chittagong Metropolitan Area, Bangladesh.* Transportation in Developing Economies, 2019. **5**(2): p. 9.
10. Haigh, F.N.C., H; Harris, P. *Housing density and health: A review of the literature and Health Impact Assessments*. 2011; Available from: http://hiaconnect.edu.au/wp-content/uploads/2013/04/housing_density_HIA_review1.pdf.
11. Sarkar, C.W., Chris; Gallacher, John, *Association between adiposity outcomes and residential density: a full-data, cross-sectional analysis of 419 562 UK Biobank adult participants.* The Lancet Planetary Health, 2017. **1**(7): p. E277-E288.
12. Daley, J.C., Brendan, *Housing Affordability: Reimagining the Australian Dream*. 2018, Grattan Institute.
13. Bryson, K. and N. Allen, *Defining medium-density housing.* 2021.
14. ACT-Government, *ACT PLANNING STRATEGY 2018*, A. Government, Editor. 2018.
15. Curtis, C., *Handbook of Sustainable Transport*. 2020, Cheltenham, UK: Edward Elgar Publishing.
16. ACT-Government, *Housing Choices Discussion Paper*, P.a.S.D.D. Environment, Editor. 2017.
17. Talbot, J.L.-S., M; Speakman, A; Streb, M; Nuttall, S; Carlino, D; Johansson, P; Sheehan, N; Groot, N; Lovelace, R, *Active Travel Oriented Development: Assessing the suitability of sites for new homes.* OSF Preprints, 2021.
18. Schamisso, B., *Minneapolis Aims To Fix Its Housing Shortage Through Zoning Changes*. 2022, NEWSY.
19. Shumway, J., *White House: Oregon single-family zoning law could be model for nation*. 2021, Oregon Capital Chronicle.
20. Woods, M.P., David, *Red tape cut to boost housing supply*. 2021, Beehive.govt.nz.
21. Piovani, D.A., E; Uchoa, G; Wilson, A; Batty, M;, *Measuring accessibility using gravity and radiation models.* Royal Society Open Science, 2018. **5**(9).
22. Bhat, C. and F. Koppelman, *Activity-Based Modeling of Travel Demand*. Vol. 56. 2003. 39-65.
23. Miller, E.J., *Accessibility: measurement and application in transportation planning.* Transport Reviews, 2018. **38**(5): p. 551-555.
24. *Concepts of Travel Behaviour - Accessibility*. 2022 [cited 2022 10/11/2022]; Available from: https://tfresource.org/topics/Accessibility.html.

25. Cui, B., et al., *Accessibility matters: Exploring the determinants of public transport mode share across income groups in Canadian cities.* Transportation Research Part D: Transport and Environment, 2020. **80**: p. 102276.

26. El-Geneidy, A. and D. Levinson, *Making accessibility work in practice.* Transport Reviews, 2021. **42**: p. 1-5.

27. Miller, E.J. *Measuring Accessibility Methods and Issues* 2020; Available from: https://www.itf-oecd.org/sites/default/files/docs/measuring-accessibility-methods-issues_1.pdf.

28. Kaidi, W., Z. Wenwen, and M.S.S. Henning, *Improved Travel Demand Modeling with Synthetic Populations*, in *Multi-Agent-Based Simulation XXI*, S. Swarup and B.T.R. Savarimuthu, Editors. 2021, Springer International Publishing. p. 94--105.

29. Australian Transport Assessment and Planning. *Travel Demand Modelling*. 2016; Available from: https://www.atap.gov.au/tools-techniques/travel-demand-modelling/4-data.

30. Acheampong, R.A. and E. Silva, *Land use–transport interaction modeling: A review of the literature and future research directions.* Journal of Transport and Land Use, 2015. **8**(3).

31. Ping Lim, P. *POPULATION SYNTHESIS FOR TRAVEL DEMAND MODELLING IN*

AUSTRALIAN CAPITAL CITIES. 2020 [cited 2022 11/11/2022]; Available from: https://www.bitre.gov.au/sites/default/files/documents/bitre-staff-paper-for-pop-syn-may-2020.pdf.

32. Baraklianos, I., et al., *Does the accessibility measure influence the results of residential location choice modelling?* Transportation, 2020. **47**(3): p. 1147-1176.

33. Long, J., *Modelling Accessibility.* Geographic Information Science & Technology Body of Knowledge, 2017. **2017**.

34. LaMondia, J.B., C; Bhat, C *Comparing Transit Accessibility Measures:*

A Case Study of Access to Healthcare Facilities Texas ScholarWorks, 2010.

35. Baradaran, S. and F. Ramjerdi, *Performance of Accessibility Measures in Europe.* Journal of Transportation and Statistics, 2002. **4**.

36. Vale, D.S. and M. Pereira, *The influence of the impedance function on gravity-based pedestrian accessibility measures: A comparative analysis.* Environment and Planning B: Urban Analytics and City Science, 2017. **44**(4): p. 740-763.

37. Anas, A., *Discrete choice theory, information theory and the multinomial logit and gravity models.* Transportation Research Part B: Methodological, 1983. **17**(1): p. 13-23.

38. David, H. *Parameter Estimation in the Huff Model*. 2003.

39. Esri. *What is a network dataset?* ; Available from: https://pro.arcgis.com/en/pro-app/2.8/help/analysis/networks/what-is-network-dataset-.htm.

40. Esri. *Types of evaluators used by a network*. Available from: https://pro.arcgis.com/en/pro-app/2.8/help/analysis/networks/types-of-evaluators-used-by-a-network.htm.

41. Esri. *Create and use a network dataset with public transit data*. Available from: https://pro.arcgis.com/en/pro-app/2.8/help/analysis/networks/create-and-use-a-network-dataset-with-public-transit-data.htm.

42. Esri. *Understand connectivity*. Available from: https://pro.arcgis.com/en/pro-app/2.8/help/analysis/networks/understanding-connectivity.htm.

43. Esri. *Calculate the travel time between origins and destinations with OD Cost Matrix*. [cited 2022 12/11/2022]; Available from: https://pro.arcgis.com/en/pro-app/latest/help/analysis/networks/od-cost-matrix-tutorial.htm.

44. Esri. *OD cost matrix analysis layer*. [cited 2022 04/08/2022]; Available from: https://pro.arcgis.com/en/pro-app/latest/help/analysis/networks/od-cost-matrix-analysis-layer.htm.

45. Esri. *Algorithms used by Network Analyst*. [cited 2022 11/12/2022]; Available from: https://pro.arcgis.com/en/pro-app/latest/help/analysis/networks/algorithms-used-by-network-analyst.htm.

46. Esri. *Location-allocation analysis layer*. Available from: https://pro.arcgis.com/en/pro-app/2.8/help/analysis/networks/location-allocation-analysis-layer.htm.
47. Liu, B., *Facility Location Problem*, in *Theory and Practice of Uncertain Programming*, B. Liu, Editor. 2009, Springer Berlin Heidelberg: Berlin, Heidelberg. p. 157-165.
48. Schietzelt, T.H. and P.J. Densham. *Location-allocation in GIS*. 2003 [cited 2022 11/12/2022]; Available from: https://web.pdx.edu/~jduh/courses/geog492w11/Week8a.pdf.
49. Australian Bureau of Statistics. *1270.0.55.001 - Australian Statistical Geography Standard (ASGS): Volume 1 - Main Structure and Greater Capital City Statistical Areas, July 2016* 2016 [cited 2022 04/04/2022]; Available from: https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/1270.0.55.001July%202016?OpenDocument.
50. Australian Bureau of Statistics. *2074.0 - Census of Population and Housing: Mesh Block Counts, Australia, 2016* 2017 [cited 2022 04/04/2022]; Available from: https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/2074.02016?OpenDocument.
51. Australian Bureau of Statistics. *Digital boundary files*. 2022 [cited 2022 28/06/2022]; Available from: https://www.abs.gov.au/statistics/standards/australian-statistical-geography-standard-asgs-edition-3/jul2021-jun2026/access-and-downloads/digital-boundary-files.
52. Australian Bureau of Statistics. *Census mesh block counts*. 2022 [cited 2022 28/06/2022]; Available from: https://www.abs.gov.au/census/guide-census-data/mesh-block-counts/latest-release#:~:text=In%202021%2C%20there%20were%20368%2C286,for%20accurate%20small%20area%20statistics.
53. Australian Bureau of Statistics. *Correspondences*. 2022 [cited 2022 13/11/2022]; Available from: https://www.abs.gov.au/statistics/standards/australian-statistical-geography-standard-asgs-edition-3/jul2021-jun2026/access-and-downloads/correspondences.
54. ACT-Government, *Household Travel Survey*, T.C.a.C.S.D.Q.-P.R. Council, Editor. 2017, Transport Canberra.
55. Australian Bureau of Statistics. *Census GeoPackages*. 2022 [cited 2022 04/04/2022]; Available from: https://www.abs.gov.au/census/find-census-data/geopackages?release=2016&geography=AUST&topic=ATSIP&type=ATSIP.
56. Google. *Canberra region IGA's, Supabarn's and SupaExpresses*. 2022 [cited 2022 04/04/2022]; Available from: https://earth.google.com/web/search/IGA/@-35.27843244,149.16409297,656.65602547a,53808.55692789d,35y,0h,0t,0r/data=CigiJgokCYtxEdW6ikHAEfcA3qhawkHAGeJEJCvxtmJAIS59A5sWlWJA.
57. ACT Government *ACT PLANNING STRATEGY 2018*. 2018. **2022**, 40.
58. ACT Government GeoHub. *ACT Government GeoHub - Education*. 2022 [cited 2022 22/04/2022]; Available from: https://actmapi-actgov.opendata.arcgis.com/search?tags=education.
59. Interreg-Europe, *INTEGRATED CYCLING PLANNING GUIDE*, E.U.E.R.D. Fund, Editor. 2021.
60. City-of-Vancouver, *Transportation Design Guidelines: All Ages and Abilities Cycling Routes*. 2017.
61. OpenStreetMap. *OpenStreetMap*. 2022 [cited 2022 01/05/2022]; Available from: https://www.openstreetmap.org/#map=13/-35.2649/149.1375.
62. ACT Government. *Footpaths in the ACT 2019*. 2019 [cited 2022 14/04/2022]; Available from: https://www.data.act.gov.au/Transport/Footpaths-in-the-ACT-2019/ee7d-h7nm.
63. ACT Government. *Road Centrelines*. 2022 [cited 2022 14/04/22]; Available from: https://www.data.act.gov.au/dataset/Road-Centrelines/r8wk-ud5i.
64. Bike Commuter Hero. *What's the average cycling speed of a bike commuter?* 2022 [cited 2022 14/05/2022]; Available from: https://bikecommuterhero.com/whats-the-average-cycling-speed-of-a-bike-commuter/#:~:text=Your%20average%20commuting%20speed%20is,25%2D45%20minutes%20each%20way.

65. ACT Government. *E-scooter rules*. 2022 [cited 2022 12/11/2022]; Available from: https://www.transport.act.gov.au/travel-options/e-scooters/e-scooter-rules.
66. Esri. *Create and use a network dataset with public transit data*. [cited 2022 01/05/2022]; Available from: https://pro.arcgis.com/en/pro-app/latest/help/analysis/networks/create-and-use-a-network-dataset-with-public-transit-data.htm.
67. Transport Canberra. *Information for developers*. 2022 [cited 2022 01/05/2022]; Available from: https://www.transport.act.gov.au/contact-us/information-for-developers.
68. Transport for NSW, *Timetables Complete GTFS*. 2022, NSW Open Data Hub.
69. Fang, C. and D. Yu, *Urban agglomeration: An evolving concept of an emerging phenomenon.* Landscape and Urban Planning, 2017. **162**: p. 126-136.
70. Larsen, J., et al., *Beyond the Quarter Mile: Examining Travel Distances by Walking and Cycling, Montréal, Canada.* 2010.
71. Yang, Y. and A.V. Diez-Roux, *Walking distance by trip purpose and population subgroups.* Am J Prev Med, 2012. **43**(1): p. 11-9.
72. National Transport Commission. *Carbon Dioxide Emissions*

Intensity for New Australian

Light Vehicles 2019. 2020 [cited 2022 16/08/2022]; Available from: https://www.ntc.gov.au/sites/default/files/assets/files/Carbon-dioxide-emissions-intensity-for-new-Australian-light-vehicles-2019.pdf.
73. Transport, I.f.S. *Transport and Climate Change*. 2018 [cited 2022 16/08/2022]; Available from: https://sensibletransport.org.au/project/transport-and-climate-change/.
74. ACT Government. *Measuring ACT greenhouse gas emissions*. 2021 [cited 2022 23/09/2022]; Available from: https://www.climatechoices.act.gov.au/policy-programs/act-greenhouse-gas-emissions-inventory-reports.
75. ACT Government, *ACT Government Budget at a Glance 2022-23*, T.a.E.D. Directorate, Editor. 2022.
76. ACT Government, *ACT Budget 2018-19. Factsheet - Transport*. 2018.
77. ACT Government. *ACT Budget to deliver more road safety upgrades*. 2022 [cited 2022 30/10/2022]; Available from: https://www.act.gov.au/our-canberra/latest-news/2022/july/act-budget-to-deliver-more-road-safety-upgrades#:~:text=Roads%20and%20active%20travel%20infrastructure,travel%20and%20support%20local%20jobs.
78. UK Government, *Investing in Cycling and Walking*

The Economic Case for Actio, D.f. Transport, Editor. 2015.
79. QLD Government. *Cycling investment in Queensland*. 2022 [cited 2022 12/11/2022]; Available from: https://www.tmr.qld.gov.au/Travel-and-transport/Cycling/Cycling-investment-in-Queensland.
80. ACT Government. *ACT Planning Strategy FAQs*. 2018 [cited 2022 13/09/2022]; Available from: https://www.planning.act.gov.au/act-planning-strategy/faqs.
81. Morang, M. *CalculateTravelTimeStats.py*. 2022 [cited 2022 11/11/2022]; Available from: https://github.com/Esri/public-transit-tools/blob/master/transit-network-analysis-tools/CalculateTravelTimeStats.py.
82. Robinson, D., *Safety in numbers in Australia: more walkers and bicyclists, safer walking and bicycling.* Health promotion journal of Australia : official journal of Australian Association of Health Promotion Professionals, 2005. **16**: p. 47-51.
83. Jacobsen, P., *Safety in numbers: More walkers and bicyclists, safer walking and bicycling.* Injury prevention : journal of the International Society for Child and Adolescent Injury Prevention, 2003. **9**: p. 205-9.
84. Dill, J., *Bicycling for Transportation and Health: The Role of Infrastructure.* Journal of Public Health Policy, 2009. **30**(1): p. S95-S110.

85. Garrard, J., G. Rose, and S.K. Lo, *Promoting transportation cycling for women: The role of bicycle infrastructure.* Preventive Medicine, 2008. **46**(1): p. 55-59.

Appendix A – Data

A.1 Detailed Processing of Population and Service Data

This section goes over the detailed analysis process around the processing of the population and service data.

A.1.1 2016 population on 2021 mesh blocks

To project the 2016 data onto 2021 mesh blocks, the population of each 2016 mesh block was spread amongst the new 2021 mesh blocks. This can be done due to the ABS maintaining boundaries between Census, only splitting mesh blocks when needed. This means each 2016 mesh block, will have 1 or more mesh blocks contained within it.

Figure 24: 2016 population on 2016 mesh blocks (left) and on 2021 mesh blocks (right). This is visualised using population density, highlighting how this method maintains population density across the two layers. Here darker colours represent higher population density.

To get an estimate of the 2016 population on the 2021 mesh blocks, the distribution of the 2021 population on their respective 2016 mesh blocks are used, with the same distribution applied to the 2016 population. This assumes constant growth in each area of a mesh block, maintaining population density, as can be seen in Figure 24. This is unlikely to be completely accurate but is at least as accurate as 2016 mesh blocks with lower spatial resolutions. To implement this, the percentage increase from 2016 to 2021 is applied inversely to the 2021 population layer. This is done using Eq. A1 below:

$$^{21}P_{16} = {}^{21}P_{21} \frac{100}{\%\Delta^{21}P_{16\rightarrow 21} + 100} \qquad Eq.A1$$

The resulting layer gives the 2016 population data on the 2021 mesh block layer Figure 3, able to be used as the base population layer in the analysis.

A.1.2 Employment

The employment data uses the ABS 2016 Census field "Place of Work". The finest resolution data available for this field is Statistical Area 2 (SA2) level, giving data for approximately each suburb in the ACT.

To improve the precision of this data, areas within each suburb which is unlikely to contain employment can be excluded. This is done by projecting the total SA2 employment count among the relevant mesh blocks it is made up of. This utilises the category field of mesh block data, which gives the dominant land-use for that area. Here the employment of an SA2 is spread out across mesh blocks which are not in one of the “Parkland”, “Water” or “Residential” mesh block categories. While these categories act as only proxies, it serves as a more accurate measure than the original SA2 data. The accuracy was verified to be within 30% for most mesh blocks tested, a good accuracy for such a high spatial resolution. This method breaks down for a few cases, such as Canberra Airport, which has a very large mesh-block with only the runway in it, and this takes most of the employment figures. Despite this, this method provides an improved employment dataset compared to the original SA2 data.

Table 12: Quality check of employment mesh block projection using mesh blocks with a workplaces taking up an entire mesh-block, where staff statistics were able to be found. Highlights how despite a dramatic increase in spatial resolution, the data remains mostly accurate.

Workplace	No. of staff	Mesh block Estimate	Percentage difference
The Canberra Hospital	6025 [86]	4083	**-32%**
The Canberra Hospital (including neighbouring mesh block)	6025 [86]	4778	**-20%**
Canberra Grammar School	683 [87]	554	**23%**
St. Mary MacKillop College	199 [88]	249	**-20%**

A.1.3 Social/Recreational

Canberra is designed around a number of different community centres, where services such as shops, restaurants and employment are located [14]. These centres, known as town, group and local centres, each have an approximately similar number of services according to their category. This can be used as a proxy for other services where other data could be hard to find, for instance, supermarkets are likely to be found at town and group centres, but not likely to be found at local centres.

Local centres are the local shops commonly seen through the ACT, which Canberra was traditionally planned around having in each suburb. These often consist of local shops, cafes, restaurants and small-scale retail. As such these provide a good proxy for the social/recreational travel purpose. However, local centres are often quite close to where people live, and many people likely do not go to their closest local centre for social/recreational purpose and may not go to a local centre at all. As such there is a large degree of error in this data source. In attempt to account for this, local centres will be weighted less in the model.

Data for local centres is found from Google Earth. Here, local centres are assumed to contain either a IGA, Supabarn or SupaExpress, the local stores common in Canberra-Queanbeyan. The locations found on Google Earth are exported to a KML file, which is then converted to a feature class within ArcGIS Pro, using the KML to Layer tool. Some additional local centres are added where known, and the Bungendore and Googong IGA’s are removed, being outside the scope of this analysis. Town and group centres from the ACT Planning

Strategy will also be included as local centres, as they are assumed to include a variety of social and recreational uses.

To improve this component of the analysis, further research into where people go for the social/recreational trip purpose could be done, as well as more data on these locations, such as where cafes, restaurants and bars are.

A.1.4 Education

For education, schools data is available from the ACT Government GeoHub [58]. This provides data for government primary, secondary and college schools, as well as for non-government schools at any level. Each of these schools layers are merged together, and given a binary attribute for each of "Primary", "Secondary" and "College", depending on their source. This binary approach allows for each school to have more than one type, common in non-government schools. Non-government schools are not initially split by their type, so they are manually assigned based on information in the ACT Non-Government Schools 2016 Map [89]. Additionally, data for Queanbeyan is added manually, due to the small of number of schools there.

The schools data is treated as combined for this analysis, but could be split into primary, secondary and college to add further refinement to the model.

A significant limitation of this schools dataset as an education proxy is that it does not include university, which are likely a large component of the education travel statistic in the household travel survey. These could also be found and added to the analysis to further refine it.

A.1.5 Shopping

As discussed in Section 2.1.2.2, Canberra is designed around town, group and local centres. Town and group centres typically contain supermarkets and a wide range of shopping services, and as such will be used as a proxy for the shopping travel statistic.

To create the town and group centre locations, point data from 2018 ACT Planning Strategy was manually geocoded [57]. This map also includes group centres in areas yet to be developed, and these will be excluded, as we want to find the amount of people which support these services, and there will not be any population around these yet to be developed areas (e.g. the Molonglo group centre). This was done by using a point data template from using Feature to Point on the MB population data, and adding point features to a new layer for town, then group then local centres. Areas in Queanbeyan are not defined by the ACT planning strategy as group centres, and places such as Jerrabomberra and Karabar fit somewhere between these two. For simplicity, the prevalence of a major shopping centre (Woolworths/Coles/Aldi) is taken to imply a group centre in these cases.
This dataset is limited by the assumption that people travel to one of these centres for the "to buy something" purpose, as there are other potential locations, e.g. local centres, or industrial areas, which people could also travel to. However, it should provide a good estimate, due to the prevalence of group and town centres throughout Canberra.

A.2 Detailed Processing of Network Analysis Data

Detailed descriptions of each of the layers involved in the paths network datasets. It also covers shows the public transport network.

A.2.1 Cyclepaths Layer

This layer contains the dedicated cycling infrastructure in Canberra and Queanbeyan, classified as such according to a standard derived from EU and Vancouver cycling standards, and Canberra's construction standards [59, 60]. It contains separated bike lanes, Canberra's shared path network, and footpaths wider than 2.5 metres. It does not include on-road cycling lanes, as these are not considered safe. This data was obtained from OpenStreetMap's "cycleway" layer, and manually altered to ensure these paths met these standards [61].

As dedicated cycling infrastructure, this layer's cycling speed will be set to 18 km/h, reflecting an average commuting cyclist speed [64].

A.2.2 Residential Streets Layer

Low-traffic, low-speed streets are likely to be acceptable for much of the population to be comfortable to cycle on. While no streets in Canberra meet the Vancouver or EU standards for safe cycling streets, due to high-speed limits, it was decided that some acknowledgement of the preference for cycling on lower traffic streets should be included [90]. To do this a residential streets layer is included, where residential streets are used as a proxy for low-traffic streets. To create this layer, OpenStreetMap's "residential streets" layer is used, and upon manual inspection of the layer, appears to be mostly accurate with local knowledge [61]. Some high-capacity traffic streets are mis-included, and some low-traffic streets in non-residential areas are excluded. Still, this provides a good measure. The speed of cycling for this layer will be set at 18 km/h, to reflect the ease of cycling on these.

A.2.3 Footpaths Layer

The footpaths layer provides the main layer for walking, giving the largest coverage of the study area. ACT footpath data is available from the ACT Government, and is highly detailed. There is no footpath data available for Queanbeyan, so instead it is assumed every road has a footpath here, and Queanbeyan road data for this area is used (also from OSM). The Queanbeyan data is then merged with the footpath layer, this misses some key connections, but overall provides a good proxy.

Cyclists are also able to use footpaths, but are unlikely to be able to go at the same speed for them. Instead, a speed of 60% of average is set for these (10.8km/h). This particular percentage is chosen as it reflects the ACT's e-scooter speed difference (25km/h and 15km/h), and so allows for an ebike/escooter mode to be easily incorporated later in future analyses [65].

A.2.4 Roads Layer

While the first three layers provide good coverage of the study area and give accurate walking and cycling routes, the wide range of sources they come from and that they are not produced directly for network analysis, mean the datasets do not have connectivity. This means a point on a network cannot necessarily travel to all other points in the network, resulting in routes being unable to be calculated during the analysis. ACT roads data provides this connectivity, as does OpenStreetMap roads for Queanbeyan [61, 63]. These layers were manually connected and provide a complete network where people can travel from any point to any other point.

In order, to reflect the role of the roads layer as primarily providing connectivity, the roads layer is not given a high priority on their own. Roads are assumed to have footpaths for walking and cycling, and hence are given the same role and speeds as this layer (10.8 km/h for cycling).

A.2.5 Connectivity Layer

To make use of the road layer's connectivity, each layer must also be connected to the roads layer. A connection between the footpaths layer and the roads layer allows this to be done, as the other layers all either cross footpaths or roads, and so will be connected in a later stage. This connectivity layer is created by drawing a line from every footpath endpoint to its nearest road, ensuring it will be connected. This is done using the following process:

- Used Feature Vertices To Points on the endpoints of the footpaths.
- Found the coordinates of these points and the nearest points on the road network (*CQ_Roads*) using Generate Near Table.
- Converted the coordinates of this table to a polyline feature using XY To Line.

A limitation of this is that all footpaths are connected to roads, regardless of if there are obstacles in the way, as can be seen in Figure 25. The issue mainly occurs in parklands and across lakes and is not a common occurrence. Its effect on the network will be mitigated by a low speed along these connectors (1.8 km/h for cycling and 1 km/h for walking). This limits their use for long distances, and makes a physical route the more viable option. Additionally, the low speed provides an approximation for crossing roads, which has not otherwise been modelled in this network dataset.

Figure 25: Example of misplaced connectors issue – here the network gives a possible path to exit these cul-de-sacs when this is not possible on the ground. This is mitigated by a low speed on connectors, so the time to use the unphysical connector path is increased to be similar to going around. Here the connectivity layer (dark blue) gives a possible path between the roads (purple) within the cul-de-sacs and the footpaths (light blue) in the park,

Another option in creating this would have been to limit the search radius for the connectivity. This would help resolve the barriers problem but may result in areas which aren't connected to the network. Connectivity is considered a higher priority, and so this method was not used.

A.2.6 Integration

As someone walking or cycling can in actuality switch between any of these layers at any crossing point between them, this also needs to be modelled in the network dataset. This is done using the Integrate ArcGIS Pro Data Management Tool, and the network dataset connectivity policy. The connectivity policy can be set such that each layer is connected to all others at a vertex, and the Integrate tool aligns the vertices of each layer and creates a vertex where any layer crosses any other. The Integrate tool was run with a tolerance of 0.1 metres, meaning any layer can be moved a maximum of 0.1 metre to give a common vertex with another layer. One limitation of this connection of layers is that it does not consider bridges, tunnels, or any other places layer cross at different heights, but this is assumed to be a small overall issue. Overall, the use of Integrate and the vertex connectivity policy give an overall paths network that makes sense for walking and cycling.

Combining these layers, with both walking and cycling modes, creates a walking and cycling network that is representative of how people would move between different areas, a map of the layers used in this dataset is given in Figure 6. The resulting network dataset was compared to a few example routes on Google Maps and provided very similar (and sometimes more accurate) results. This network dataset is named *Paths_ND* and is used throughout the analysis going forward.

A.2.7 Paths Network Dataset Extract

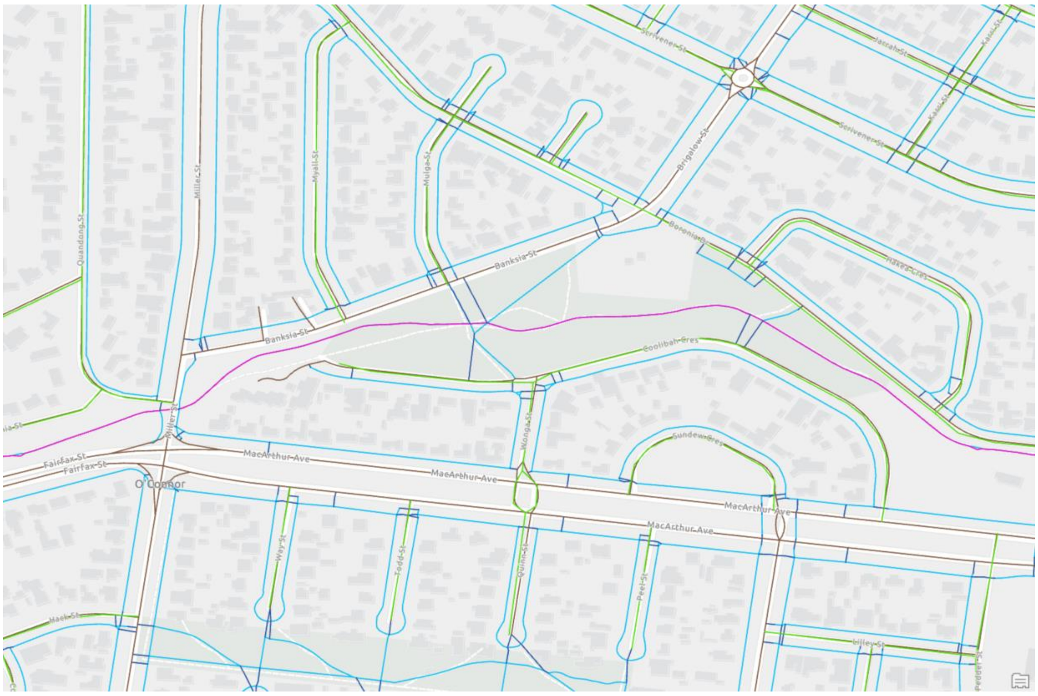

Figure 26: Zoomed in section of the paths network dataset, showing the interconnection of the various components of the dataset. Here pink are shared paths, green is residential streets, light blue shows footpaths, brown shows roads, and dark blue shows connectivity

A.2.8 Public Transport Network Dataset

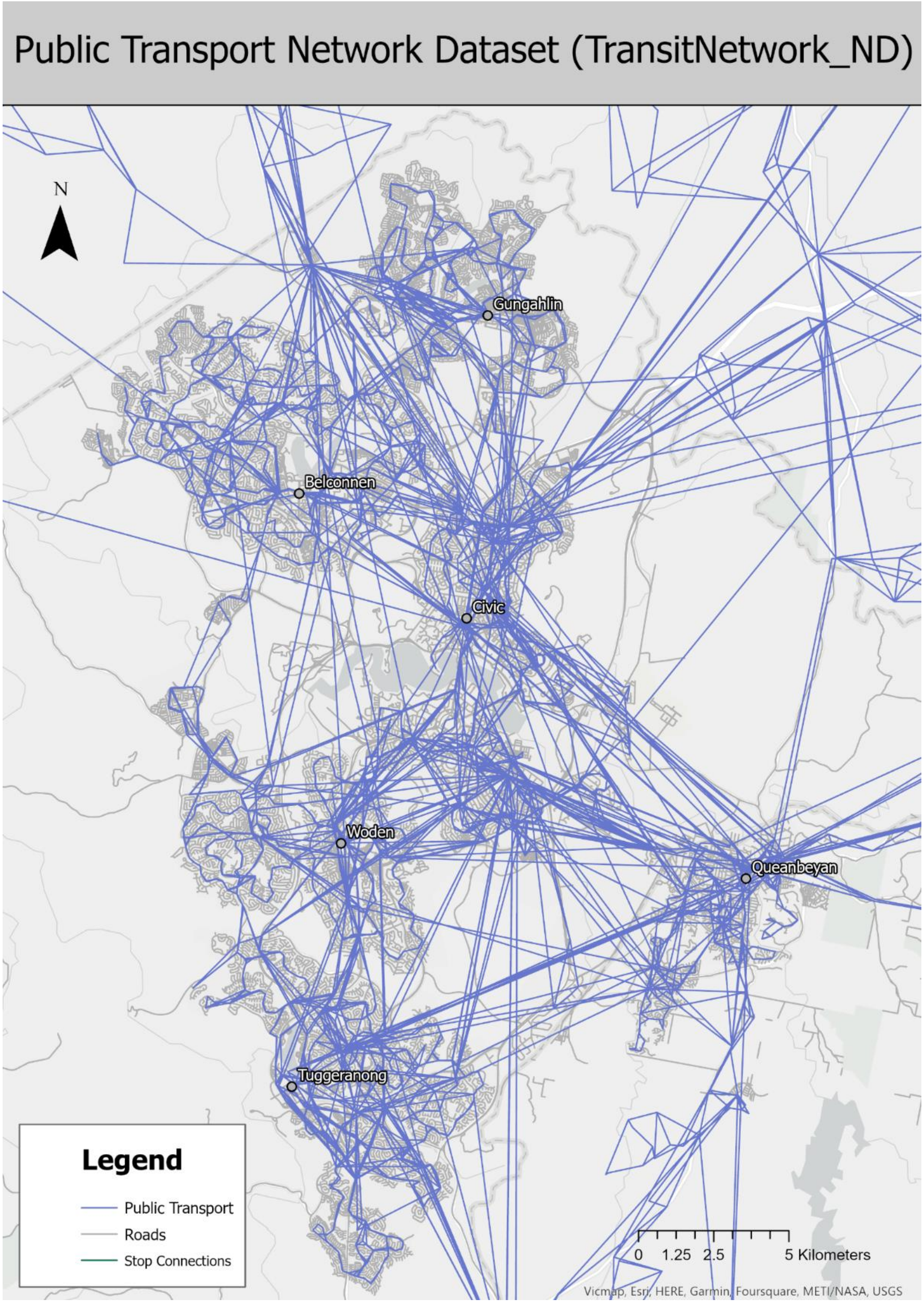

Figure 27: The public transport network dataset to be used in the analysis for the generation of public transport route data. This network dataset includes a roads network to model walking to public transport stops, and a GTFS public transport feed, which uses scheduled public transport data to give accurate travel times for any given start time

A.2 Development Scenarios Details

A2.1 Calculations of changes in number of services under the 5-year study time period

Table 13: Number of services in the base year (2016) and the analysis year (2021)

Service Type	Data source year	Total Number of services	Source year estimated population	Population per service	2016 No. Services	2021 No. Services	Change in No. Services
Town Centres	2018	6	455635	75939	6	6	**0**
Group Centres	2018	27	455635	16875	26	29	**3**
Local Centres	2022	102	503977	4941	88	99	**11**
Schools	2021	151	491429	3251	133	151	**18**
- **Primary**		107	491429	4588	94	107	**13**
- **Secondary**		40	491429	12274	35	40	**5**
- **College**		25	491429	19640	22	25	**3**
Employment	2016	224991	433232	1.925	224991	255215	**30223**

A.3 Other Development Scenarios

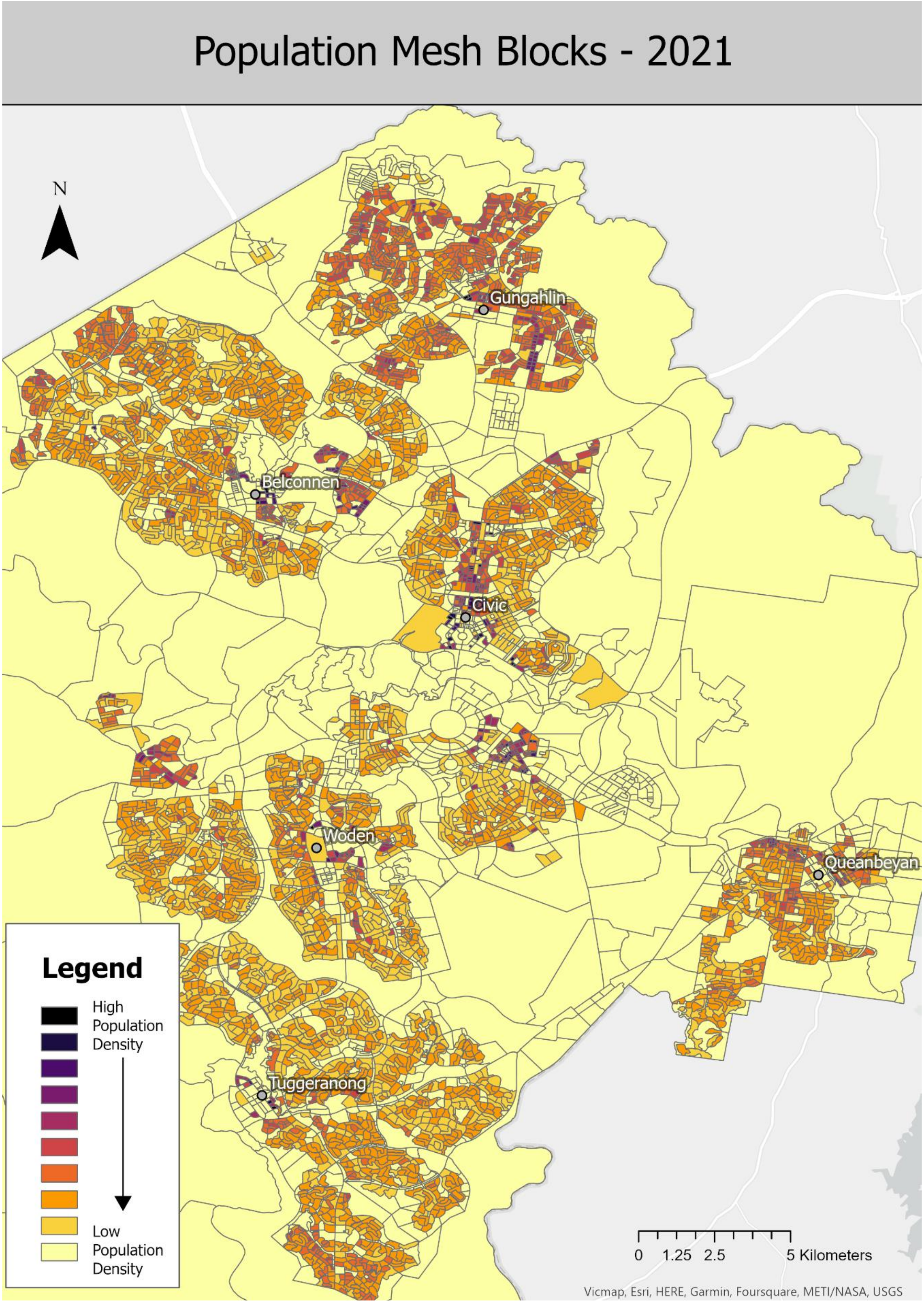

Figure 28: The population distribution used in the "Actual" development scenario, this uses data from the 2021 ABS Census, and show some suburban-style and some medium-density style development. Here population increases can be seen in new greenfield suburbs to the north and west of the city, as well as along the light rail corridor from Civic to Gungahlin.

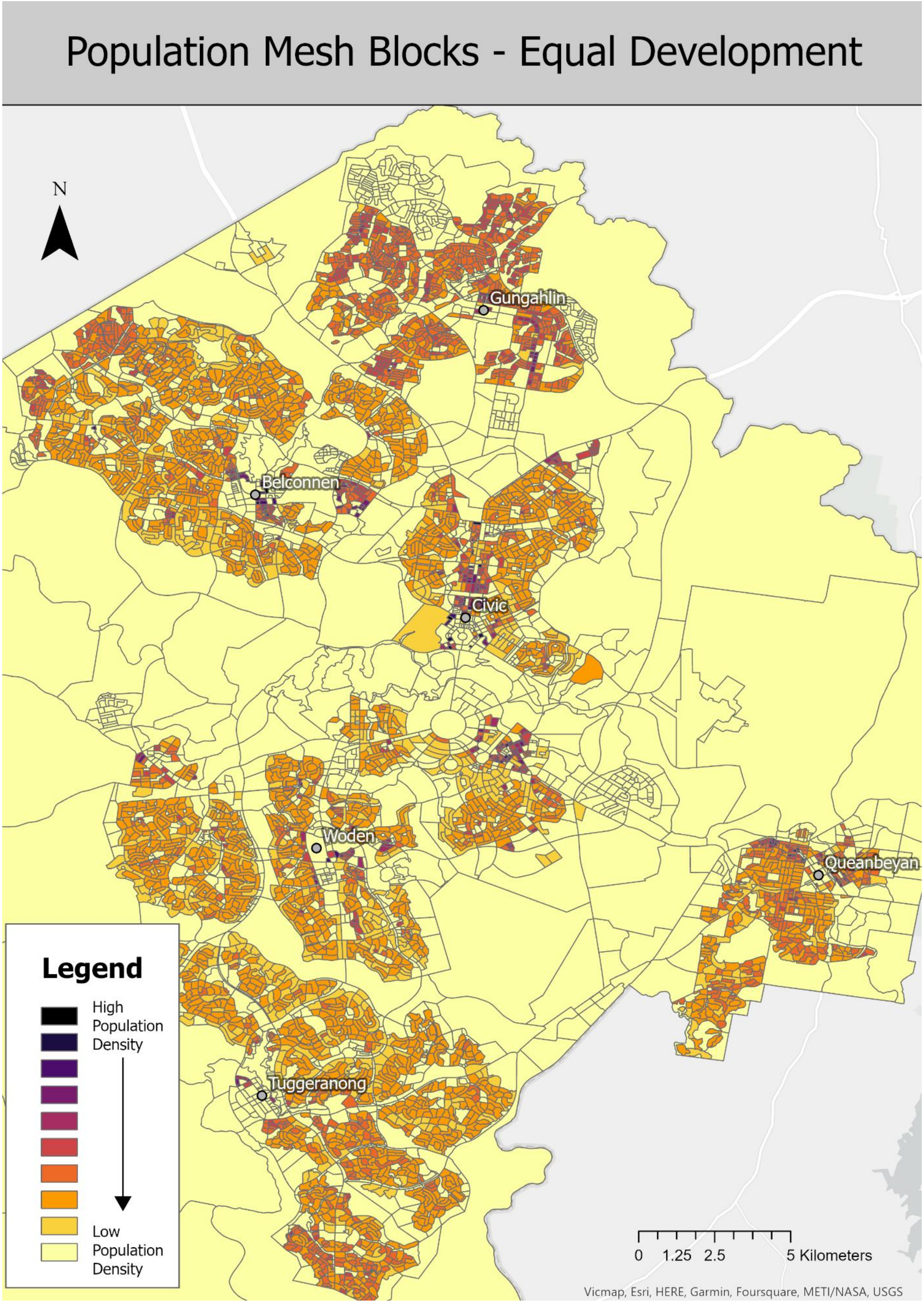

Figure 29: The population distribution used in the "Equal Development" development scenario, representing a suburban-style development scenario. Here each mesh block's population is increased by the same percentage, the overall percentage increase for the time period of 13.1%.

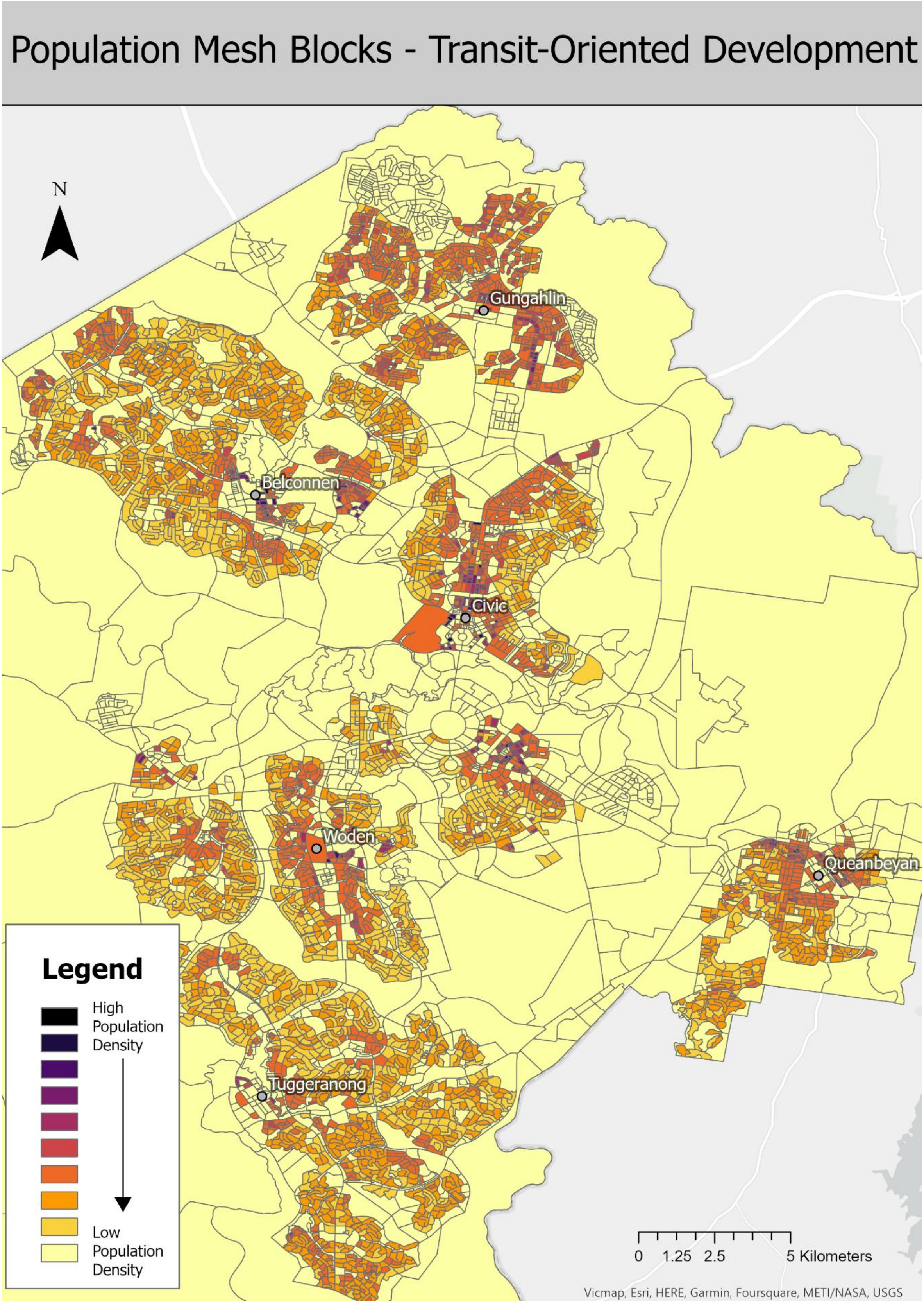

Figure 30: The population distribution used in the "Transit-Oriented Development" development scenario, representing a medium-density style development scenario. Here the population increase is confined to public transport corridors and near town and group centres, according to infill development in the 2018 ACT Planning Strategy.

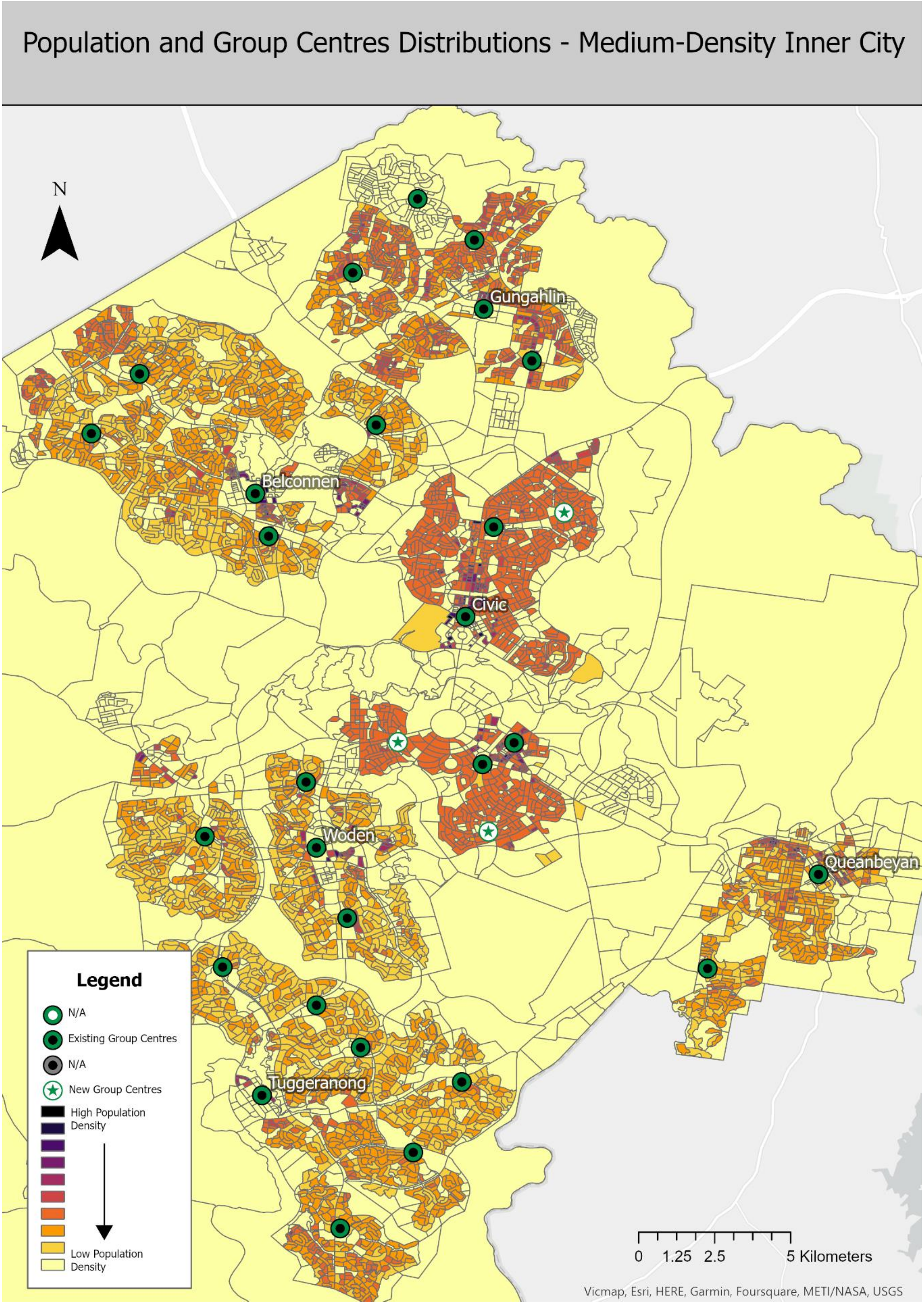

Figure 31: The population distribution and the new group centre location used in the "Medium-density Inner City" development scenarios. This shows how the increased population allows more services to be supported, resulting in further increases in accessibility.

A.4 Accessibility Modelling Details

A.4.1 Attractiveness Parameter Calculations

In implementing the attractiveness parameter for non-employment services, marginal value is expected to decrease with additional services, following diminishing returns. These values are set based on personal expectations and are not rigorous. For local, group and town centres, the second services set to be worth 50% of the first, and the third to be 20% of the first. For schools, an 80% and 70% value are chosen for the second and third schools respectively, this reflects the many variables in deciding a school other than location.

Creating a model for diminishing returns, a typical diminishing returns equation is:

$$f(x) = \frac{1}{x^n} \qquad Eq.8$$

Here we set n based on the values we want for the 2nd and 3rd services, using the least squares method of linear regression. The first service is always given a value of 1. The results of this analysis are given in TABLE.

Table 14: Parameters and resulting n value used in the diminishing returns curves for various services' attractiveness parameters

Service	2nd Value	3rd value	n
Local, Group, Town Centres	0.5	0.2	**1.2**
Schools	0.8	0.7	**0.33**

Appendix B – Further Results

B.1 Accessibility Results – Mode comparison

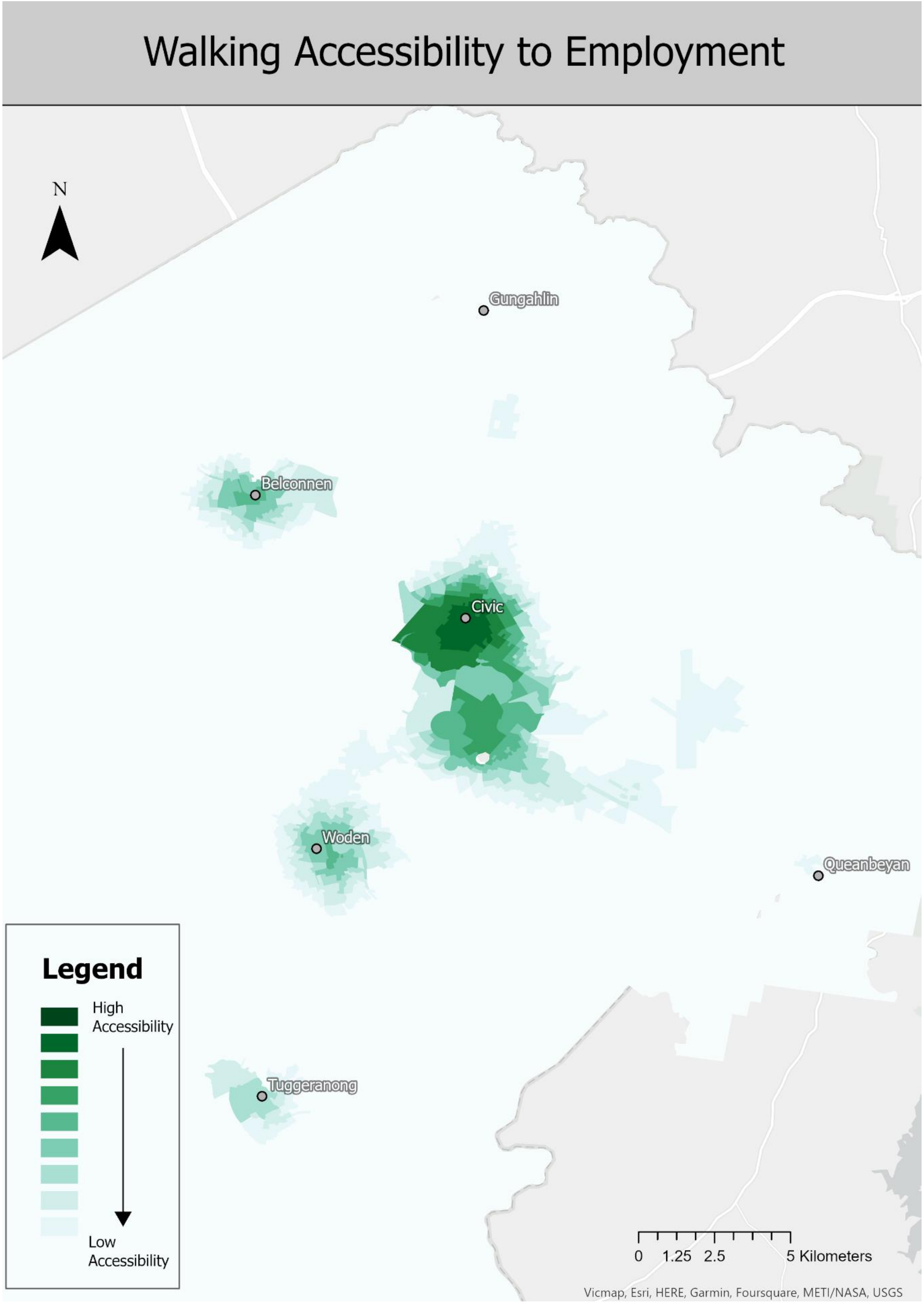

Figure 32: Accessibility results for walking to employment (common for all development scenarios), here a common accessibility scale is used with the other modes, in order to compare them.

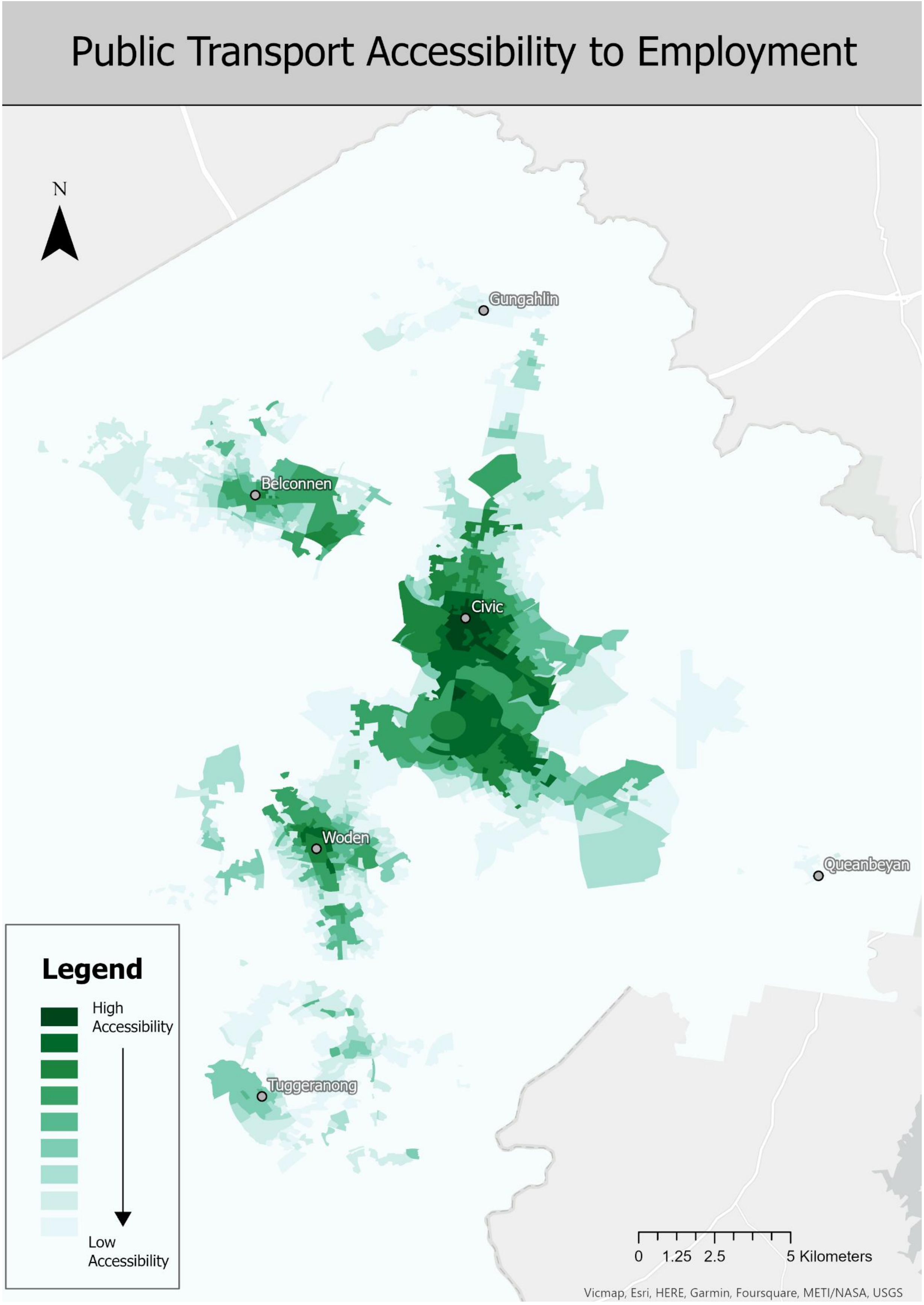

Figure 33: Accessibility results for public transport to employment (common for all development scenarios), here a common accessibility scale is used with the other modes, in order to compare them. This highlights how public transport expands the accessible areas when compared to walking.

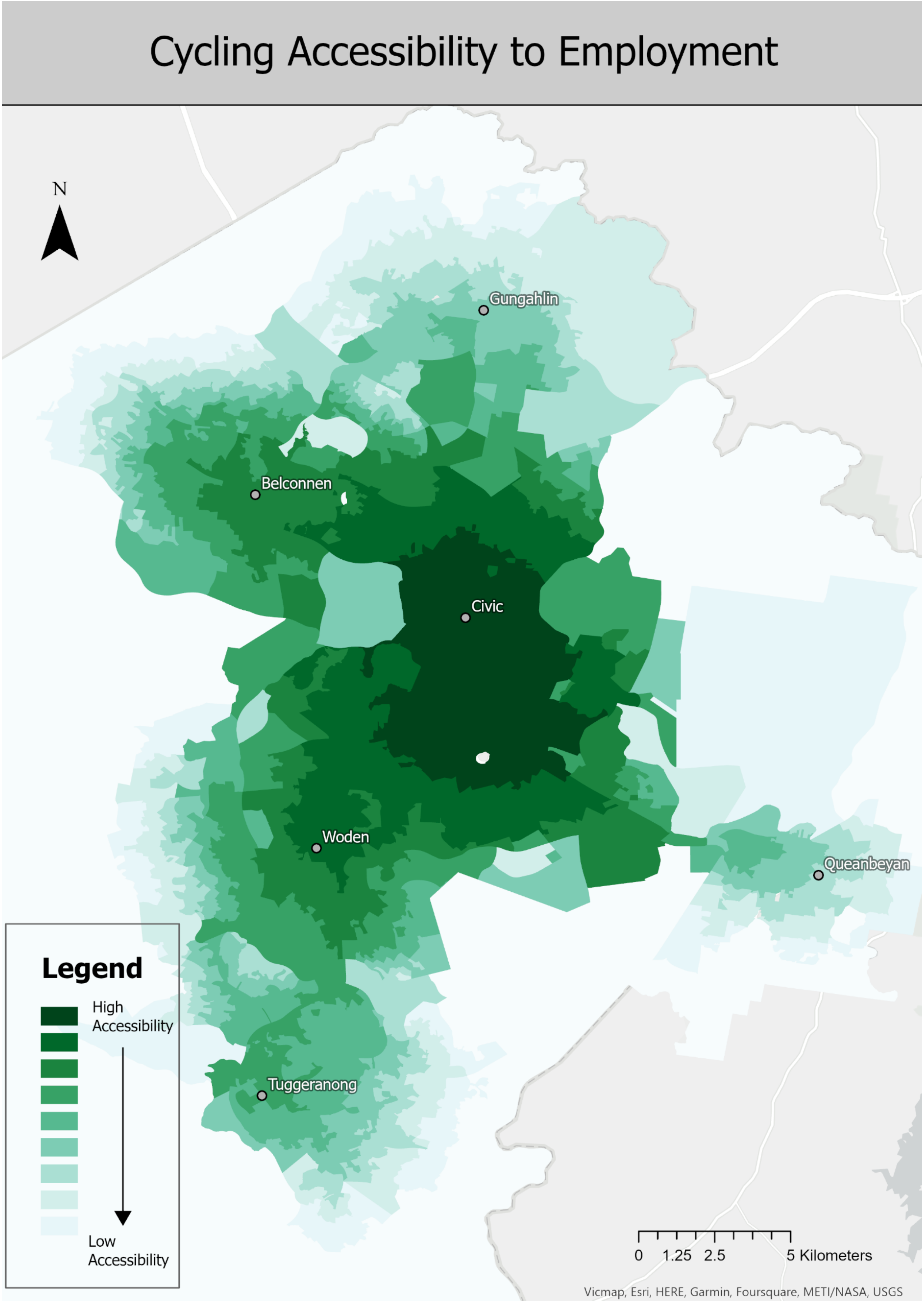

Figure 34: Accessibility results for cycling to employment (common for all development scenarios), here a common accessibility scale is used with the other modes, in order to compare them. This highlights the dramatic increase in accessible area that cycling provides over other transport modes, and shows the potential for usage if cycling is further encouraged.

B.2 Detailed Mode Increase Results

Table 15: Detailed data on the mode increase factors for the various development scenarios, split by the increases to each service

Mode-Service	Service	2016	Actual	EqualDev	Greenfield	mdINIS	TODInfill
Public Transport	Schools	1	1.257122	1.219063	1.178557	1.315114	1.28351
	Local Centres	1	1.222725	1.194311	1.166935	1.230599	1.22659
	Group Centres	1	1.256126	1.203745	1.177976	1.234009	1.262183
	Town Centres	1	1.198131	1.108111	1.038812	1.10921	1.251056
	Employment	1	1.229838	1.108152	1.023727	1.282922	1.29031
Cycling	Schools	1	1.233045	1.217008	1.19041	1.282787	1.264674
	Local Centres	1	1.196716	1.186466	1.156135	1.191017	1.196754
	Group Centres	1	1.205703	1.199108	1.160144	1.209208	1.214536
	Town Centres	1	1.152424	1.126284	1.074406	1.125113	1.191255
	Employment	1	1.174444	1.128246	1.034752	1.357388	1.239602
Walking	Schools	1	1.26131	1.247158	1.195955	1.335259	1.292022
	Local Centres	1	1.252237	1.230493	1.18031	1.247638	1.251144
	Group Centres	1	1.310075	1.259981	1.214304	1.282325	1.330714
	Town Centres	1	1.258096	1.091557	1.004961	1.083412	1.369459
	Employment	1	1.230905	1.105213	1.011462	1.270365	1.33631

A.3 Mode Increase Maps for Other Development Scenarios

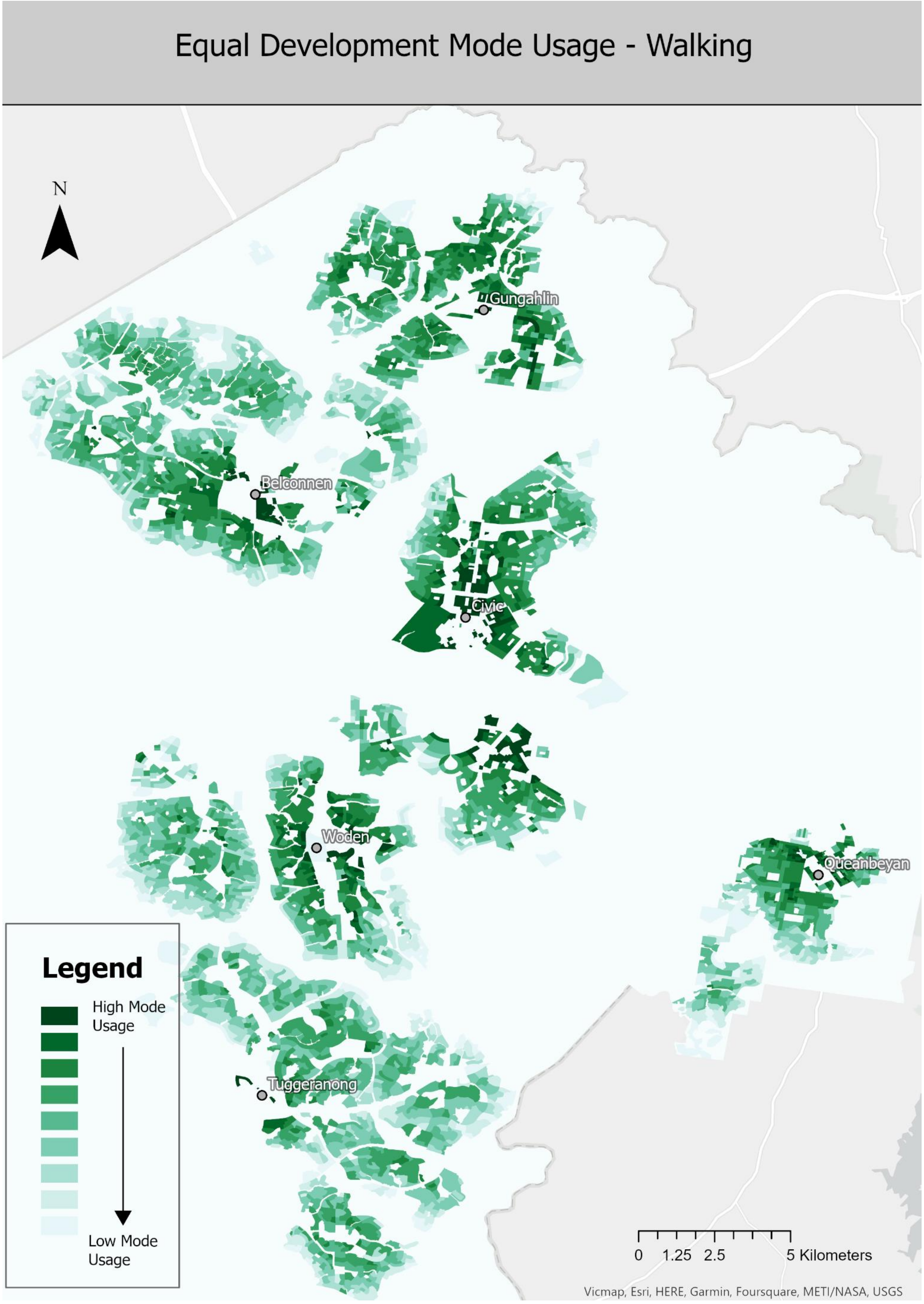

Figure 35: Estimation of the contribution of different areas to the overall walking mode usage amount. This data is for the "Equal Development" development scenario and shows small changes across broad areas of outer Belconnen and Tuggeranong. These currently contain much of Canberra's population, and are likely under-serviced compared to the city average, and so new service locations are placed in these regions.

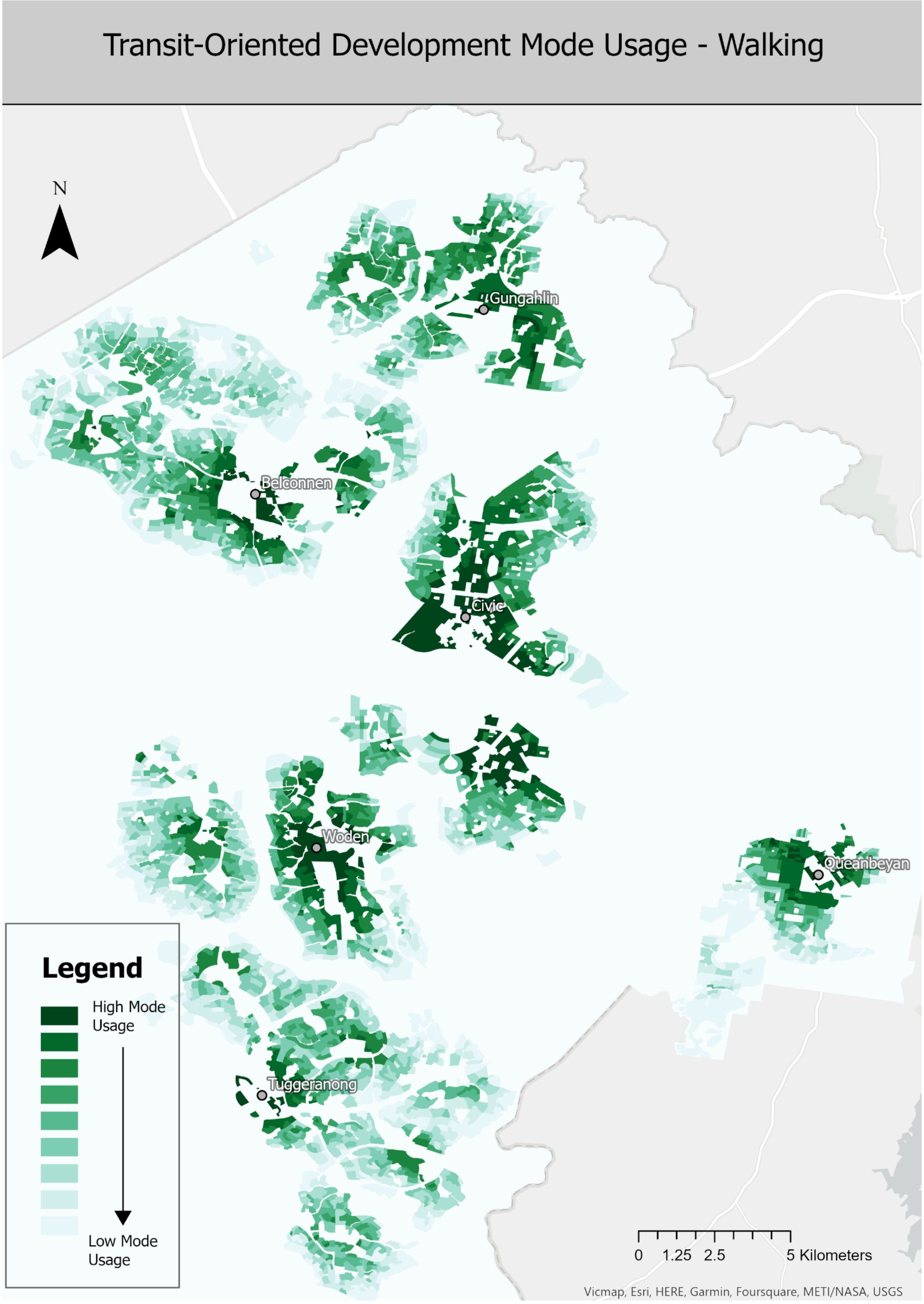

Figure 36: Estimation of the contribution of different areas to the overall walking mode usage amount. This data is for the "Transit-Oriented Development" development scenario and shows substantial increases in mode usage in the regions around town centres and transit corridors where development is placed.

Appendix C – More Potential Further Work

Key areas for future work are outlined in the main body, and this section contains a few other suggestions for improving the model and research going forward.

C.1 Incorporation of Employment Data Changes

An area where this analysis could be improved is the employment distribution of later development scenarios. The location-allocation tool is difficult to use on employment, where there is such a large amount of data, commercial constraints on location, and is less dependent on population distributions. In light of this difficulty, a proportional increase was used in this analysis. However, employment areas do change over time, and incorporating this into the model could improve this. One way to do this would be to use employment count figures for recently released 2021 ABS Census employment data, giving a distribution of how employment locations are changing in Canberra.

C.2 Combined Cycling and Public Transport Network Dataset

A problem well discussed in transport planning literature is the last mile problem. This is that the last mile from a public transport station or home is the most difficult to serve. This occurs due to public transport trading off between coverage and travel times – a bus travelling a route to that goes closer to more people will be less direct and slower – and the typical efficiency trade-off is being a mile from transit stations. A solution to this problem is to combine cycling (or e-bikes/e-scooters) with public transport, mapping this combined mode of transport could show what encouraging this form of transport could have on sustainable transport accessibility.

C.3 Driving Network Dataset

To provide a better estimate of the impact on carbon emissions and cost, a driving dataset could be included, enabling better calculations of emissions and economic impacts of population density on sustainable transport mode shift. And on the broader effects of development scenarios of emissions and economic effects.

C.4 Optimise Sustainable Transport Development Model

The project is looking at considering scenarios of development and comparing their effect on development. This could be extended to look at the optimum development model for sustainable development. This could look at a number of constraints and use an algorithm to continuously alter the scenario until the optimum development is achieved.

Appendix D – Code

The coding used in analysis throughout this thesis was done using python, particularly making use of the arcpy library. The python scripts are contained in an online repository https://github.com/glennj258/Accessability-Scripts.

Appendix E – References Used in Appendices

86. ACT Government, *Canberra Health Services Annual Report 2019-20*, C.H. Services, Editor. 2020.
87. Wikipedia. *Canberra Grammar School*. 2022 [cited 2022 13/04/2022]; Available from: https://en.wikipedia.org/wiki/Canberra_Grammar_School.
88. Wikipedia. *St Mary MacKillop College, Canberra*. 2022 [cited 2022 12/11/2022]; Available from: https://en.wikipedia.org/wiki/St_Mary_MacKillop_College,_Canberra#:~:text=St%20Mary%20MacKillop%20College%2C%20formerly,Peter's%20College%20in%201997.
89. ACT Government. *ACT Non-Government Schools Map 2016*. 2016 [cited 2022 26/04/2022]; Available from: https://www.education.act.gov.au/__data/assets/pdf_file/0007/608263/160210-ACT-Non-GovernmentSchools-Map-2016.pdf.
90. ACT Policing. *Speeding*. [cited 2022 10/11/2022]; Available from: https://www.police.act.gov.au/road-safety/safe-driving/speeding#:~:text=Speed%20limits%20in%20the%20ACT,-The%20maximum%20speed&text=The%20default%20speed%20limit%20in,to%20be%2050%20km%2Fh.