Australian Government
Australian Institute of Health and Welfare

Modelling access to GPs relative to need in Australia:

Geographic variation among First Nations and non-Indigenous populations

AIHW

The AIHW is a Corporate Commonwealth entity producing authoritative and accessible information and statistics to inform and support better policy and service delivery decisions, leading to better health and wellbeing for all Australians.

A complete list of the Institute's publications is available from the Institute's website www.aihw.gov.au.

ISBN 978-1-923272-00-2 (Online)

ISBN 978-1-923272-01-9 (Print)

DOI: 10.25816/397z-m180

Suggested citation

Australian Institute of Health and Welfare (2024) *Modelling access to GPs relative to need in Australia: Geographic variation among First Nations and non-Indigenous populations,* catalogue number IHW 293, AIHW, Australian Government.

Any enquiries about or comments on this publication should be directed to:
Australian Institute of Health and Welfare
GPO Box 570
Canberra ACT 2601
Tel: (02) 6244 1000
Email: info@aihw.gov.au

Published by the Australian Institute of Health and Welfare.

Please note that there is the potential for minor revisions of data in this report. Please check the online version at www.aihw.gov.au for any amendments.

Modelling access to GPs relative to need in Australia

Geographic variation among First Nations and non-Indigenous populations

Australian Institute of Health and Welfare
Canberra
Catalogue number IHW 293

Contents

Summary

First introduced in 2014, the Australian Institute of Health and Welfare's (AIHW) index of Access Relative to Need (the 'ARN index') estimates how local access to General Practitioners (GPs) relative to the need for primary health care varies across Australia for First Nations people and non-Indigenous Australians at the level of the Australian Bureau of Statistics' (ABS) Statistical Areas Level 1 (SA1). The type of access to GPs considered in the ARN model is physical access and does not take other potentially important barriers such as affordability or cultural appropriateness into account. This report presents the recent refinements of the ARN methodology and discusses data and other methodological issues that have the potential to limit the accuracy of estimates of access to services in Australia.

The model used to calculate the estimate of access that is part of the ARN index belongs to a family of models called floating catchment models. Instead of relying on services-to-population ratios within fixed areas or other similar measures, these models assume that access to services also depends on distance or travel time. The ARN index access model is a **3-step floating catchment** model:

1. The **first step** estimates the number of people from each SA1 population who choose each available GP service location based on estimated drive times and GP capacity (full-time equivalent GPs). Services with relatively short drive times and high capacity attract more people than other services. The model assumes that all GP service locations within an hour's drive can be accessed.
2. The **second step** estimates the GPs to need-adjusted population ratio for each service – that is the demand on each service relative to its capacity. The demand put on each service location by a population depends on the willingness to travel from each population to the service, the number of people from each population choosing to use the service and the per capita need of each population. The longer the drive time, the less willing people are to travel to their chosen service location.
3. The **third step** estimates the access of each SA1 population based on the GP to need-adjusted population ratio at each service used by the population as the sum of the ratios of all services within reach of each population adjusted for the drive time cost and the proportion of people attending each service adjusted by the willingness to travel.

Per capita need and drive times are key components of this model. The need estimates are based on socioeconomic and demographic characteristics of the First Nations, non-Indigenous and total SA1 populations. Analysis of the high-level associations between those characteristics and the amount of time that Australians spend with GPs in parts of Australia where access to services is relatively good has allowed us to calibrate the overall differences in per capita need between populations.

Drive times from local populations to service locations were estimated using the centroid (geographic midpoint) of each SA1 or, for SA1s larger than 3,000 km^2, multiple point locations based on where people live within the SA1s as captured by the ABS's population grid.

In addition to estimates of access produced by the 3-step floating catchment model, we also calculate an estimate of access relative to need (the composite ARN index). The rationale behind using a measure of access relative to need, rather than just a measure of access where per capita need is used to estimate demand on services, is that the impact on a population of a change in access will depend on its need. A population with a high per capita need is likely to be affected more severely by low access than a population with a low per

capita need. Whereas calibration of the demand aspect of need can be done using data on the use of GP services, it is much more challenging to calibrate how need interacts with access to shape health outcomes over long periods. Because of this, the access relative to need estimates should always be considered alongside the access estimates.

The ARN modelling shows that the proportion of people living in areas where physical access to GPs is relatively limited increases with increasing remoteness. For example, 3% of First Nations people and 1% of non-Indigenous Australians in *Major cities* live in areas with an access score below 7 (access equivalent to having 7 GPs per 10,000 people of average need if there are no drive time barriers). This increases to 71% and 58% respectively in *Very remote* areas. Whereas a higher proportion of First Nations people live in areas with relatively poor access in both *Major cities* and *Very remote* areas, that is not the case in *Inner regional*, *Outer regional* or *Remote* areas.

A higher proportion of First Nations people than non-Indigenous Australians live in regional and remote areas where residents are more likely to live in areas with poor access than in the major cities. This contributes to the overall difference in the proportion of First Nations people (17%) and non-Indigenous Australians (5.1%) living in areas with access scores below 7.

1 Introduction

How easy it is for Australians to see a General Practitioner (GP) when they need to depends on where they live. This is not surprising given Australia’s mix of cities, regional towns and smaller communities spread out over vast areas. However, how easy it is also varies within cities, between towns and from community to community (AIHW 2014, 2015). The AIHW’s index of Access Relative to Need (the ‘ARN index’) estimates how local access to GPs relative to the need for primary health care varies across Australia for First Nations people and for non-Indigenous Australians. Output from the modelling underlying the ARN index has been used to identify where timely access to appropriate primary health care is likely to be particularly challenging for First Nations people because of poor physical access to First Nations-specific health care services in combination with poor access to GPs in general (AIHW 2015, 2020).

This report presents the recent refinements of the ARN methodology and discusses data and other methodological issues that have the potential to limit the accuracy of estimates of access to services in Australia.

The AIHW introduced the first edition of the ARN index in 2014 (AIHW 2014). Based on data on GP services, population characteristics and estimated drive times between populations and GP services, it is a GPs-to-population ratio that has been adjusted to reflect that access to services declines gradually with travel time and that different populations have different per capita health care needs. The ARN index is calculated separately for the First Nations, non-Indigenous and total Australian populations of each of the Australian Bureau of Statistics’ (ABS) more than 58,000 SA1s but takes into account that different population groups, and people from different SA1s, often use the same services.

Several new sources of information that were not available in 2014 have now been incorporated into the ARN modelling. They include:

- a much more detailed representation of where people live in sparsely populated parts of Australia based on the ABS’s population grid
- a better supported calibration of per capita need based on Medicare Benefits Schedule data on visits to GPs in non-remote areas
- a better supported calibration of how drive time influences choice of GP service to visit based on Medicare Benefits Schedule data on visits to GPs.

The model used to calculate the access to GPs component of the ARN index belongs to a family of models called floating catchment models. A number of these models have been developed to estimate geographic variation in access to health services – including in Australia (for example, Luo & Wang 2003; Luo & Whippo 2012; McGrail & Humphreys 2009, 2015; Wan et al. 2012; AIHW 2014; Chen & Jia 2019; Delamater et al. 2019; Stacherl & Sauzet 2023). Access to services, and/or service catchments, are based on distances or travel times between populations and service locations in these models. This approach has several benefits compared with other approaches such as services-to-provider ratios based on fixed non-overlapping areas. Services-to-provider ratios can be highly misleading when people are able to access services outside the areas they live in or when the areas used are too big for people to be able to access all services within their home area.

The floating catchment model used to calculate the access component of the ARN model has been refined based on how it and other similar models capture variation in access under different scenarios. In particular, by introducing a step that models service selection based on drive time and service capacity (see for example Luo 2014 for a similar approach), the refined model captures the likely improvement in access due to decreased competition that a population experiences as a result of populations at other locations gaining access to new services. This refinement to the model also ensures that large populations of major cities and big towns with access to large numbers of nearby GPs do not have an unrealistically big effect on the access of populations in surrounding regional areas.

Section 2 presents conceptual explanations of the different components of the ARN index followed by a detailed description of how they are used mathematically in the modelling in section 3.

2 Key concepts

Access

The type of access to GPs considered in the ARN model is physical access, which is assumed to be affected by 2 barriers:

1. How easy it is to travel to a GP service.
2. Competition with other patients over the time of the available GPs.

Taken together, these 2 barriers should have a big impact on for how long people have to wait when they decide to see a GP and also on how often they end up actually seeing a GP at all when they need to.

In the analysis underlying the ARN index, the first barrier is modelled using estimates of drive time between populations and GP locations. The longer it takes to drive to a GP service, the less accessible the GPs at that service are to a population. The GPs are not considered accessible at all if the estimated drive time is more than one hour. People do sometimes travel for longer periods to access GPs in Australia but one hour was chosen as the maximum time people should reasonably be expected to travel in line with many international studies on access to health services (for example, Bagheri et al. 2008; Lerner & Moscati 2001; McGrail & Humphreys 2009; Tanser et al. 2006). We have also found that the vast majority of GP visits in Australia happen within a one-hour drive (see also Drive times section). For example, even outside of the major cities, fewer than 1% of MBS claims involving standard GP items and patients with delivery area postcodes in their Medicare addresses are for care provided by services located in postcodes outside a one-hour drive of the patient's Medicare address postcode.

The second barrier is modelled by combining information on population sizes, GP numbers (full-time equivalent GP at each service location), per capita need for primary health care and drive times between populations and GP services. The access of a population depends on the number of accessible GPs relative to the size of the population and the sizes of other populations with access to the same GPs. Population size is adjusted in the model by the estimated per capita need for primary health care of each population. The higher the need, the greater the demand put on the available GPs by a certain population. Population size is also adjusted by drive time. The greater the drive time, the smaller the demand a population puts on a GP service and the less that GP service contributes to the overall access of the population. Finally, the model also reflects that the demand a population puts on a service will decrease with improved access to other services.

There are other potentially important barriers to access to adequate primary health care. Services may vary in the quality of care they provide. There may be differences in the cost associated with visiting different services depending on, for example, their bulk billing practices. Some people may be reluctant to visit certain services because they are not culturally appropriate or because either male or female GPs are not available. None of these potential barriers have been accounted for in the ARN index – primarily because of a lack of data.

It is also important to note that the ARN index reflects access to GPs only. Important primary health care is also delivered by other health care professionals, for example at nurse-led clinics.

Need

The need estimates used in the modelling underlying the ARN index are estimates of per capita need for primary health care based on the characteristics of each SA1 population. This is not the same thing as the current health of a population. Nor is it a measure of how well the local health services are currently meeting the needs of their patients. It is possible for a population to have a very high per capita need that is being met to a high degree by the available health services. It is also possible for a population to have a low per capita need that is not being met by the local services.

It is obvious that populations can vary in their per capita need for primary health care. For example, a population made up of a large proportion of elderly people, many of whom have chronic conditions, will need to use the available primary health care services more frequently than most other populations of a similar size. This concept of need can be thought of in the following way when applied to GPs:

> The per capita need of a local population reflects the level of care provision from GPs that is high enough for any increase in provision of care to not result in an improvement of the health outcomes of that population.

It is not possible to measure the need of any local Australian population directly. However, many measurable demographic and socioeconomic characteristics of populations are known to be associated with variation in the prevalence of health issues that increase the need for primary health care (AIHW 2024; Kalseth & Halvorsen 2020). The ARN model requires estimates of the per capita need of each local First Nations, non-Indigenous and total population to estimate the demand on the local GP services and to calculate the access relative to need of each population group.

The ARN need estimates are not estimates of the level of access required for the need to be fully met. Instead, they are estimates of the per capita need relative to that of other populations. To fully meet their need, a population with a need of 2 would require twice as much time with GPs as a population of the same size with a need of one. The model assumes that the need for physical access to GPs and the per capita demand placed on GPs by the populations they serve are directly proportional. That is, a population with a need of 2 will place twice the per capita demand on their GPs as a population with a need of one if there are no differences in drive times to the GP services. Any other barriers that could create variation in demand, such as the ability to pay for services or cultural preferences, are not accounted for in the ARN model.

The need estimates used in this update of the ARN index are based on socioeconomic and demographic characteristics of the First Nations, non-Indigenous and total SA1 populations. Analysis of the high-level associations between those characteristics and the amount of time that Australians spend with GPs in parts of Australia where access to services is relatively good has allowed us to calibrate the overall differences in per capita need between populations (see Appendix A for detail on how need was estimated).

Access relative to need

The composite ARN index combines each population’s estimate of access and its estimate of need. The rationale behind using a measure of access relative to need, rather than just a measure of access where per capita need is used to estimate demand on services, is that a population with a high per capita need is likely to be affected more severely by low access than a population with a low per capita need. For example, if 2 populations have the same relatively poor access but different per capita needs, the population with the higher need is likely to be affected more severely by the relatively long waiting times or infrequent GP visits than the other population. In statistical terms, there is likely to be an interaction between access and need. The impact on a population of a change in access will depend on its need and vice versa.

As described in section 3's Estimation of per capita need, whereas calibration of the demand aspect of need can be done using data on the use of GP services, it is much more challenging to calibrate how need interacts with access to shape health outcomes over long periods. Because of this, the access relative to need estimates should always be considered alongside the access estimates.

3 Detailed methods

Modelling access to GPs

The model of access used here calculates a score that reflects to what extent the need for primary health care in each SA1 can be met by the capacity of the local GP services. The score is a full-time equivalent (FTE) GPs-to-population ratio that has been adjusted to account for:

- different local populations having a different per capita need for primary healthcare
- demand on the services by other nearby populations
- services being less accessible the longer it takes to reach them.

In a hypothetical scenario where everyone in a local population lives close to all available GPs and no other populations have access to those GPs, the access score will simply be the number of GP FTEs per 10,000 people if the population has an average per capita need for primary healthcare. This aspect of the model reflects that:

- each GP FTE represents a finite capacity to provide care, which results in access worsening with decreasing numbers of GP FTEs per 10,000 people
- local populations vary in their per capita need for primary health care in ways that influence demand on GPs and that can be estimated using available information about local populations and data on how people use GPs in areas with different population characteristics.

The adjustments made to the GP FTE-to-population ratio under scenarios that are more complex than the hypothetical scenario outlined above makes the access scores produced by the model comparable across populations by reflecting that:

- people are more likely to choose GP services the less time it takes to reach them and the greater their capacity to provide care (GP FTEs)
- people visit GP services less frequently the longer it takes to reach them
- the benefit derived from having access to a GP service decreases with travel time
- for the purposes of the modelling presented in this report, GP services located more than 60 minutes away are not considered accessible at all.

A 3-step floating catchment model was used to estimate local access to GPs in each SA1. In a 2-step model like the model used for the first version of the ARN index (AIHW 2014), the demand placed on services within reach of a population only depends on drive time without taking what other services are available into account. The new 3-step model allows people to be allocated mostly to the closest services instead of influencing the FTE-to-population ratios at each service within reach. This creates a more realistic scenario under which adding services that are accessible for one population also improves access for nearby populations through reduced competition even when they do not have access to the new services. For example, this ensures that city populations with access to large numbers of nearby services do not have an unrealistically big impact on services in surrounding rural areas. It also enables a more realistic estimation of drive time statistics, which can be an interesting complement to the access scores. For example, with the new model, the average drive time to services in an area will no longer be biased by people living on the fringes of cities having access to a large number of services in the cities that they are unlikely to visit because they also have access to a smaller number of services nearby.

Model steps

The 3 steps used to calculate the access component of the ARN index are described below.

Step 1

The first step estimates the number of people from each SA1 population who choose each available GP service location based on drive times and GP capacity (FTE). Services with relatively short drive times and high capacity attract more people than other services.

If all available services are located close to the maximum one-hour away, all people will choose these services as no other services are available (but attend less frequently than they would have had the services been closer – see step 2).

Step 1 is modelled by the following equation:

$$\boldsymbol{P_{ij}} = \frac{\boldsymbol{f_a(d_{ij}) \times S_j}}{\boldsymbol{\sum_j f_a(d_{ij}) \times S_j}} \times \boldsymbol{P_i}$$

- $\boldsymbol{P_{ij}}$ is the number of people from population i choosing service location j.
- $\boldsymbol{f_a(d_{ij})}$ is the "attractiveness" function that defines how drive time $(\boldsymbol{d_{ij}})$ affects the relative attractiveness of service locations to each population (see figure 2).
- $\boldsymbol{d_{ij}}$ is the drive time between population i and service location j.
- $\boldsymbol{S_j}$ is the capacity of service j (GP FTE) – very small (FTE < 1) services are made proportionally less attractive by using the cube of the FTE to reflect the non-permanent availability of many of these services.
- $\boldsymbol{P_i}$ is the size of population i.

In other words, each service location can be said to exert a "pull" on the populations within reach depending on drive time and service capacity. The numerator in the step 1 equation calculates the pull of service location j on population i. The denominator is the sum of the pull of all service locations within one hour. The numerator divided by the denominator is the proportion of the total pull coming from service location j and therefore the proportion of people from population i choosing service location j. Multiplying this proportion by the number of people in population i is the number of people from population i who choose service location j.

Step 2

The second step estimates the GPs to need-adjusted population ratio for each service – that is the demand on each service relative to its capacity. The demand put on each service location by a population depends on the willingness to travel from each population to the service, the number of people from each population choosing to use the service and the per capita need of each population. This is modelled by the following equation:

$$\boldsymbol{R_j} = \frac{\boldsymbol{S_j}}{\boldsymbol{\sum_i f_w(d_{ij}) \times P_{ij} \times N_i}}$$

- $\boldsymbol{R_j}$ is the provider to population ratio at service location j.
- $\boldsymbol{S_j}$ is the capacity of service j (GP FTE).

- $f_w(d_{ij})$ is the "willingness" function that defines how drive time (d_{ij}) affects the willingness of people from population i to travel to service location j (see figure 2).
- P_{ij} is the number of people from population i choosing service location j as calculated in step 1.
- N_i is the per capita need for primary health care in population i (see Estimation of per capita need).

In other words, the step 2 equation is the capacity of service j divided by the total demand on that service from all populations within reach.

Estimation of per capita need

Step 2 of the model includes an estimate of per capita need (N). Separate estimates of the per capita need of the First Nations, non-Indigenous and total populations of each SA1 were produced based on demographic and socioeconomic data from the ABS's 2016 Census of Population and Housing. The estimates were calibrated using data on GP visits in non-remote areas with different demographic and socioeconomic compositions using data from the Multi Agency Data Integration Project (MADIP) (see Appendix A for a detailed description of how per capita need was estimated).

The need component was calibrated to reflect per capita demand on the available GP services when the access component is calculated. Step 2 uses the total population need estimate for each SA1. The estimates for the First Nations, non-Indigenous and total populations of each SA1 are all used in the calculation of the composite access relative to need index. Ideally, a separate need component that had been calibrated to reflect how each level of access translates into health outcomes for each level of need would be used for this purpose. More studies of the links between local access to GPs and health outcomes are needed for that type of calibration to be possible.

Step 3

Step 3 estimates the access of each SA1 population based on the GP to need-adjusted population ratio at each service used by the population as the sum of the ratios of all services within reach of each population adjusted for the drive time benefit and the proportion of people attending each service adjusted by the willingness to travel. The adjustment by the drive time benefit in addition to the adjustment by the willingness to travel is necessary because otherwise the decline in access with increasing drive time is cancelled out by the improvement in the GPs to population ratio resulting from fewer people travelling. Step 3 is modelled by the following equation:

$$A_i = \sum_j f_b(d_{ij}) \times R_j \times \frac{f_w(d_{ij}) \times P_{ij}}{P_i} \times 10,000$$

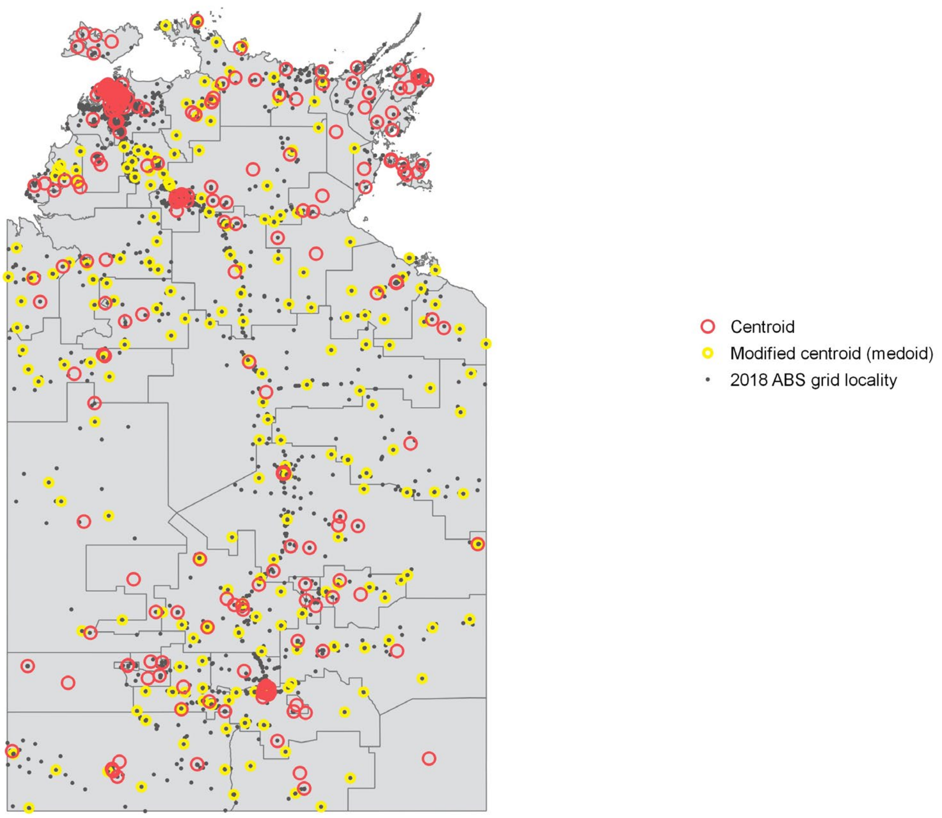
- A_i is the access of population i.
- $f_b(d_{ij})$ is the "benefit" function that adjusts the access benefit a population derives from a service location based on the drive time (d_{ij}).
- R_j is the provider to population ratio at service location j as calculated in step 2.
- $f_w(d_{ij})$ is the "willingness" function that defines how drive time (d_{ij}) affects the willingness of people from population i to travel to service location j (see figure 2).
- P_{ij} is the number of people from population i choosing service location j as calculated in step 1.
- P_i is the size of population i.

The multiplication with 10,000 means that the access component is basically an adjusted ratio of GP FTEs per 10,000 people.

Drive times

Drive times between SA1 populations and GP services were estimated using the MapInfo Professional GIS package with the Routefinder software and Pitney Bowes' 2018 road network (later Precisely's road network) data. SA1 populations were represented by the centroid (geographic midpoint) of each SA1 or, for SA1s larger than 3,000 km^2, by multiple point locations, or medoids, based on the ABS's population grid. The medoids of each SA1 were defined through hierarchical clustering using R (see Appendix B for a detailed description of how the medoids were defined). Figure 1 shows an example of how the medoids improve the representation of where people actually live, which is indicated by the populated ABS Grid localities, compared with single centroids in the large SA1s of the Northern Territory.

Figure 1. Point locations used to represent where people live in large SA1s in the Northern Territory



The estimated drive times influence the 3 steps of the floating catchment access model through 3 functions:

Step 1 – Attractiveness (which service people choose to attend)

For drive times up to 15 minutes, attractiveness is:

$$\underset{0 \le d_{ij} \le 15}{f_a(d_{ij})} = 0.65^{d_{ij}}$$

For longer drive times up to 60 minutes, attractiveness is:

$$\underset{15<d_{ij}\leq 60}{f_a(d_{ij})} = 0.9^{d_{ij}} \times \left(\frac{0.65^{15}}{0.9^{15}}\right)$$

$(\boldsymbol{d_{ij}})$ is the drive time between population i and service location j

Step 2 – Willingness (how often people attend their chosen service when they need to)

Willingness is 1 for drive times up to 10 minutes:

$$\underset{0\leq d_{ij}\leq 10}{f_w(d_{ij})} = 1$$

For longer drive times up to 60 minutes, willingness is:

$$\underset{10<d_{ij}\leq 60}{f_w(d_{ij})} = 0.3 \times cos\left(\frac{2\pi}{100} \times (d_{ij} - 10)\right) + 0.7$$

Step 3 – Benefit (how travel time affects the positive impact of the service on the health outcomes of the population)

Benefit is 1 for drive times up to 10 minutes:

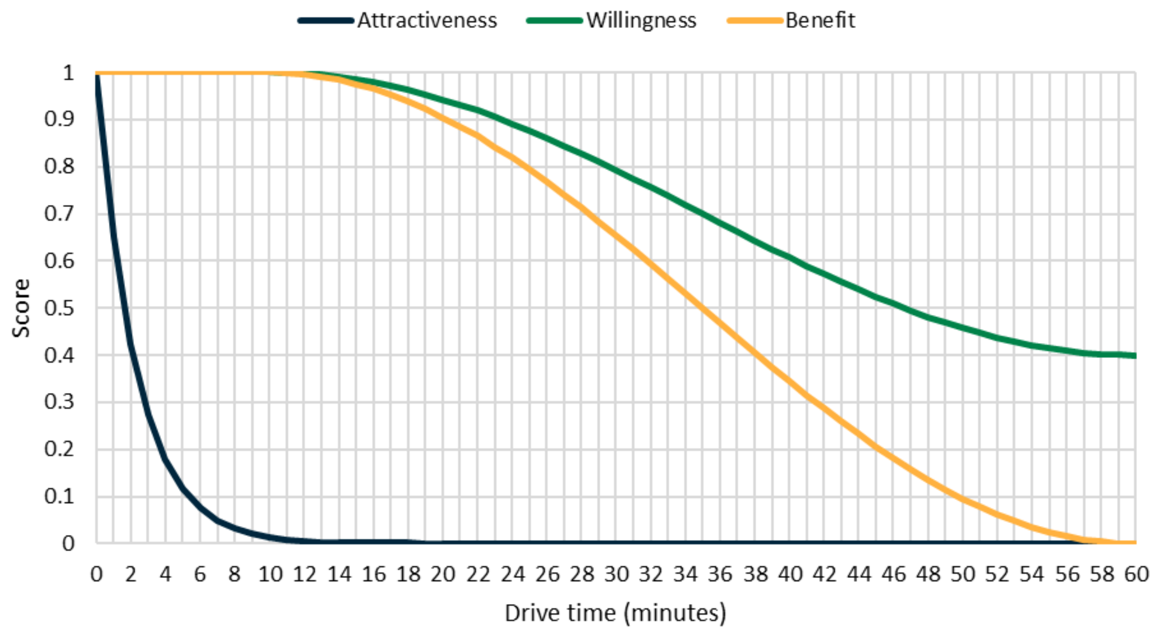
$$\underset{0\leq d_{ij}\leq 10}{f_b(d_{ij})} = 1$$

For longer drive times up to 60 minutes, benefit is:

$$\underset{10\leq d_{ij}\leq 60}{f_b(d_{ij})} = 0.5 \times cos\left(\frac{2\pi}{100} \times (d_{ij} - 10)\right) + 0.5$$

Figure 2 shows the 3 functions.

Figure 2. The functions that describe how drive time affects the relative attractiveness[(a)] of each service, the willingness[(b)] of people to travel to each service location and the benefit[(c)] derived from each service



(a.) Attractiveness: A 2-step exponential function, whereby: from 0 to 15 minutes, with each extra minute, attractiveness decreases by 35%; and from 15 to 60 minutes, with each extra minute, attractiveness decreases by 10%. This score is multiplied by the FTE at a given service location, except at services with less than 1 FTE, for which the score is multiplied by the cube of the FTE.

(b.) Willingness: Equal to 1 from 0 to 10 minutes, then decays to 0.4 via a cosine curve.

(c.) Benefit: Equal to 1 from 0 to 10 minutes, then decays to 0 via a cosine curve.

The attractiveness and willingness functions were informed by AIHW analysis of actual travel between postcodes to access GPs as reflected by Medicare Benefits Schedule (MBS) data. They were also informed by a survey of travel to access services in regional towns and communities conducted by McGrail et al. (2015). The benefit function conforms to the willingness function but takes into account that people should not have to travel for more than 60 minutes to access services. This is reflected by the access benefit derived from a service reaching 0 after 60 minutes.

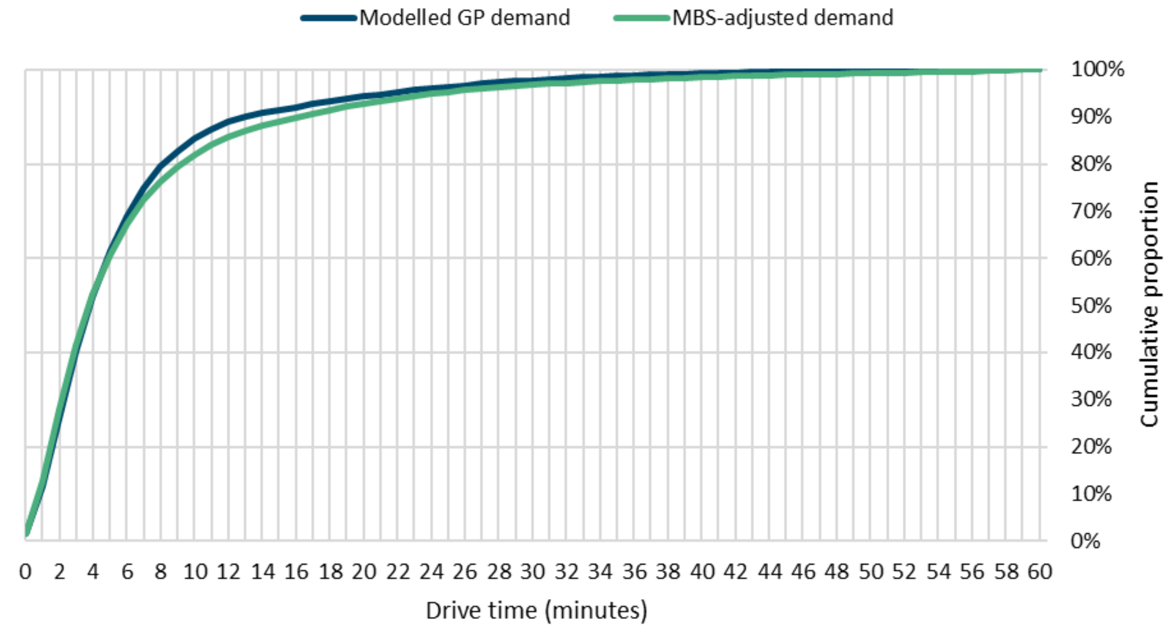
As a result of the calibration against the MBS data, the distribution of drive times at the national level predicted by the ARN access model matches the distribution of approximated actual drive times closely. Figure 3 shows how the cumulative proportion of trips to the GP increases with increasing drive time (for example, the proportion of drives lasting up to 10 minutes) as predicted by the first 2 steps of the ARN access model. For comparison, figure 3 also shows an adjusted version, scaled to match the recorded MBS activity from July 2017 to June 2019, based on certain GP consultation items. This adjustment factors in the Postal Areas[1] (POA) associated with the MBS activity on both the GP and patient side. For example, if the first 2 steps of the ARN access model predicted that 55% of the modelled demand for residents from a particular POA was linked to GPs in the same POA, but only 50% of the MBS services for the POA's residents were linked to GPs in that POA, then the modelled demand on GPs in that POA would be down-scaled relative to other POAs that

[1] Postal Areas are an ABS Mesh Block approximation of a general definition of postcodes. In 2016, there were 2,668 Postal Areas covering the whole of Australia without gaps or overlaps.

residents were modelled to visit. The fit of the 2 distributions is very close, which was the aim of the calibration of the attractiveness and willingness functions – noting that this comparison has some limitations:

- only including drive times of up to one hour
- not including postcodes without a corresponding POA
- with many POAs being large in area, the results after adjustment remain somewhat dependent on the initial predictions.

Figure 3. The cumulative proportion of trips to the GP increases with drive time in very similar ways when predicted by the first 2 steps of the access model[(a)] and when estimated based on the Postal Areas of services and patients in the MBS services data[(b)] (for drive times up to one hour)



Sources: AIHW analysis of access to GPs by SA1 (2018) and MBS data.

(a) Drive times for modelled GP demand calculated from SA1 centroids/medoids to service locations, as predicted in the first 2 steps of the access model. Drive times were floored to one-minute increments for graphical representation.

(b) Drive times for modelled GP demand, after adjusting the amount of demand from each Postal Area (POA) linked to POAs within one-hour's drive, in accordance with MBS services data. The MBS services data used were the numbers of non-referred GP attendances at consulting rooms (MBS items: 3, 23, 36, 44, 5000, 5020, 5040, 5060), delivered from July 2017 to June 2019, by patient enrolment postcode and service provider postcode (excluding postcodes missing from the ABS's 2016 Postal Areas (POA) geography). Drive times were floored to one-minute increments for graphical representation.

The composite index of Access Relative to Need

The composite Access Relative to Need index is intended to capture how the interaction between access and need is likely to shape health outcomes. For example, out of 2 populations with equally poor access, the one with the highest need is likely to suffer more and be in the most urgent need of improved access to prevent negative health effects. This is not something that is generally included in floating catchment models of access to services.

The estimated access from our 3-step floating catchment model is combined with the need component to calculate the composite ARN index for each population group in an area in the following way:

$$\boldsymbol{ARN_{pi} = A_i / N_{pi}}$$

- $\boldsymbol{ARN_{pi}}$ is the access relative to need of people belonging to population group p (First Nations, non-Indigenous or total population) in population i
- $\boldsymbol{A_i}$ is the access of people of population i (step 3 in the floating catchment model)
- $\boldsymbol{N_{pi}}$ is the per capita need of people belonging to population group p (Indigenous, non-Indigenous or total population) in population i

As discussed above, the need component has been calibrated to reflect how often people generally need to visit the GP. Using its population-group specific version also in the calculation of the composite ARN index relies on the assumption that the difference in access relative to need between 2 populations with the same access is linearly proportional to the difference in per capita need. Exactly what the interaction between access and need looks like is challenging to test with the available data and may well vary depending on what health outcome is being considered. The composite ARN index should always be considered alongside the more easily calibratable access component.

Data sources and limitations

Combining the available information about GP services and activities in Australia makes it possible to conduct modelling of geographic variation in access to these services in a more meaningful and accurate way than what is possible for many other service types. However, it is important to note a few key limitations associated with the data sources used in the ARN modelling:

- Data on GP FTEs from the Online Services Report (OSR) have been used to estimate GP FTEs at service sites operated by OSR-reporting organisations. Where multiple sites are operated by the same organisation, the FTE distribution across sites has been assumed to reflect the First Nations population distribution in SA1s near the sites. This is likely to result in an overestimation of FTEs at some sites and an underestimation of FTEs at other sites.
- Data on GP FTEs at Royal Flying Doctor Service of Australia (RFDS) clinics have been estimated based on typical frequencies of clinics. More detailed information would likely change some estimates.
- Data on GPs have been obtained from the Australasian Medical Publishing Company (AMPCo) and complemented by data from the Australian Health Practitioner Regulation Agency (AHPRA). FTEs or information on part-time work arrangements are not included in the AHPRA data. GPs only sourced from the AHPRA data have been assumed to work full time, which will lead to overestimation of GP FTEs in some locations.
- Data on GP activity from the Department of Health and Aged Care’s MBS-based HeaDS UPP tool (SA1 level, made available by the Department) and GP FTE estimates from the National Health Workforce Data Set (NHWDS) (SA3 level) have also informed the FTE estimates used in the modelling. There are important discrepancies between these data sources – especially in remote areas – that reflect a significant uncertainty associated with the FTE estimates in some areas based on the data that are currently available. Several factors may contribute to these discrepancies including that the nature of the

MBS data may make any MBS-based estimate mostly reflective of GP activity rather than GP capacity. Furthermore, the NHWDS was not designed to capture geographic variation in GP FTEs accurately at a low level. The NHWDS collects information about GP activity over one fortnight, which of course can vary significantly from fortnight to fortnight – especially in remote areas with small numbers of GPs.

An important issue affecting the quality of the GP FTE estimates is how to handle discrepancies between the different data sources and the information they are capturing. For example, the best source of information about actual local GP activity in Australia available to the AIHW is the HeaDS UPP data, which are based on claims submitted to the MBS by GPs. However, whereas a measure of capacity is the input needed for the ARN modelling and what is estimated in other data sources, activity may not always be a perfect reflection of capacity as the number of MBS claims submitted per GP FTE could vary due to variation in demand on each GP and the routines of each service.

The uncertainty in some of the local GP FTE information can have a big impact on local estimates of access and access relative to need. Consequently, how the information about GP FTEs from the different data sources is used, and which source is relied on more heavily, does have a big impact on the access and access relative to need scores of some individual SA1s. A key challenge for future work is to understand the discrepancies between the data sources and to keep improving the accuracy of the FTE estimates.

4 Output from the model

The output from the ARN model includes the following for each SA1:

- separate per capita needs estimates for the First Nations and non-Indigenous populations
- an access score for the total population (because the First Nations and non-Indigenous populations of each SA1 are represented by the same centroid, or modoids, and therefore have identical drive times to the same services with the same capacity relative to demand)
- separate access relative to need scores for the First Nations and non-Indigenous populations (because the 2 populations have identical access scores but different per capita need estimates).

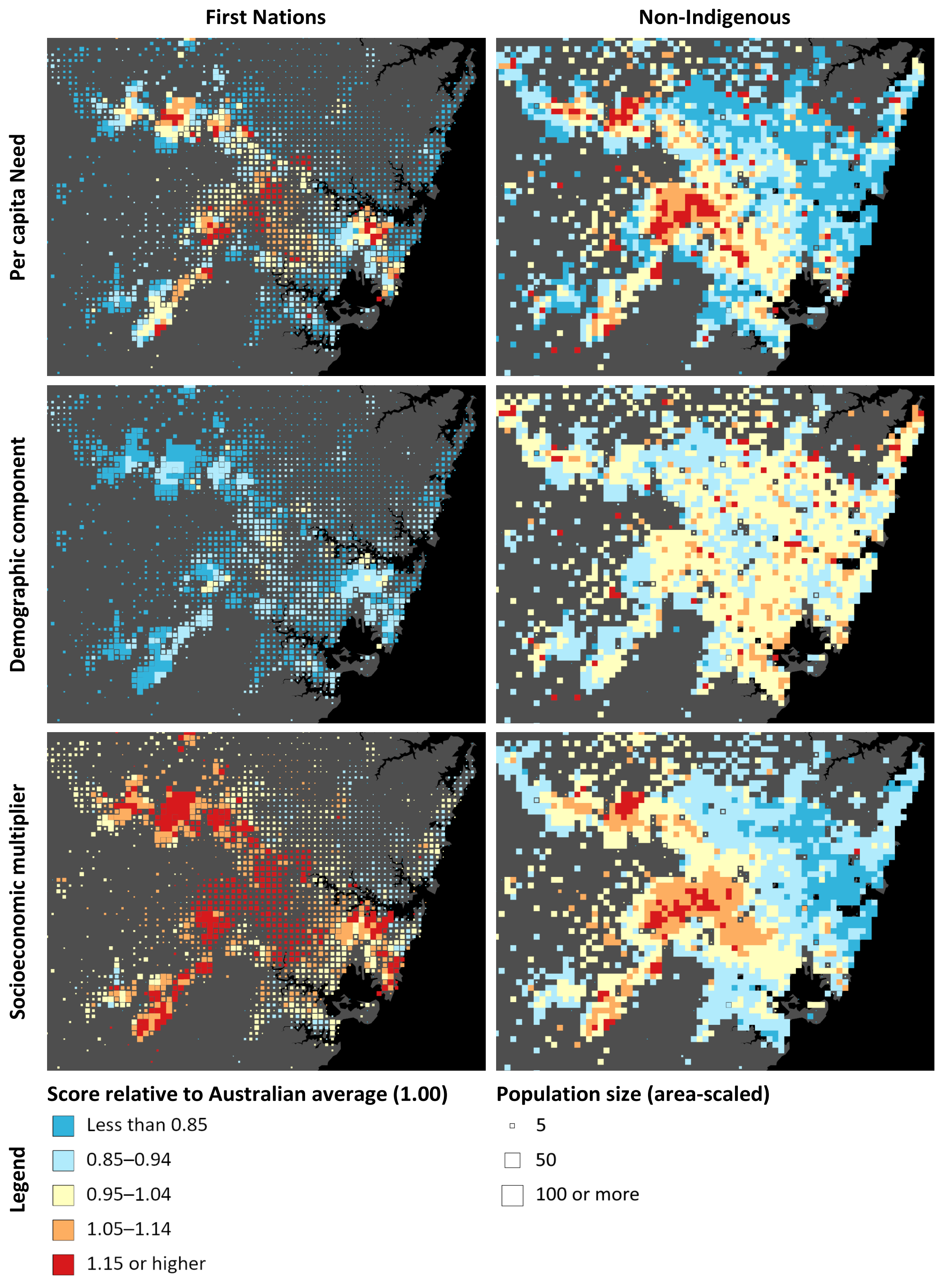
Figure 4 shows what the geographic variation in First Nations and non-Indigenous SA1-level per capita needs estimates can look like using the Sydney region as an example. The size of the population in each SA1 is indicated by the size of each coloured square.

Figure 4 also shows the demographic component and the socioeconomic multiplier that combine to make up the per capita need estimate. The Sydney example illustrates a general difference between the population groups. Whereas the First Nations population is younger with more people in the low needs age groups than the non-Indigenous population, it is also more socioeconomically disadvantaged overall resulting in relatively high scores for the socioeconomic multiplier. Taken together, this results in per capita need estimates that are higher for the First Nations than the non-Indigenous population in most areas, but the differences are not as great as they would have been if the 2 populations had more similar age structures.

Figure 5 shows the access scores (total population) and access relative to need scores (First Nations and non-Indigenous) of each SA1 – again using the Sydney region as an example.

Details about the data sources used to produce the set of output presented in this report can be found in Appendix C.

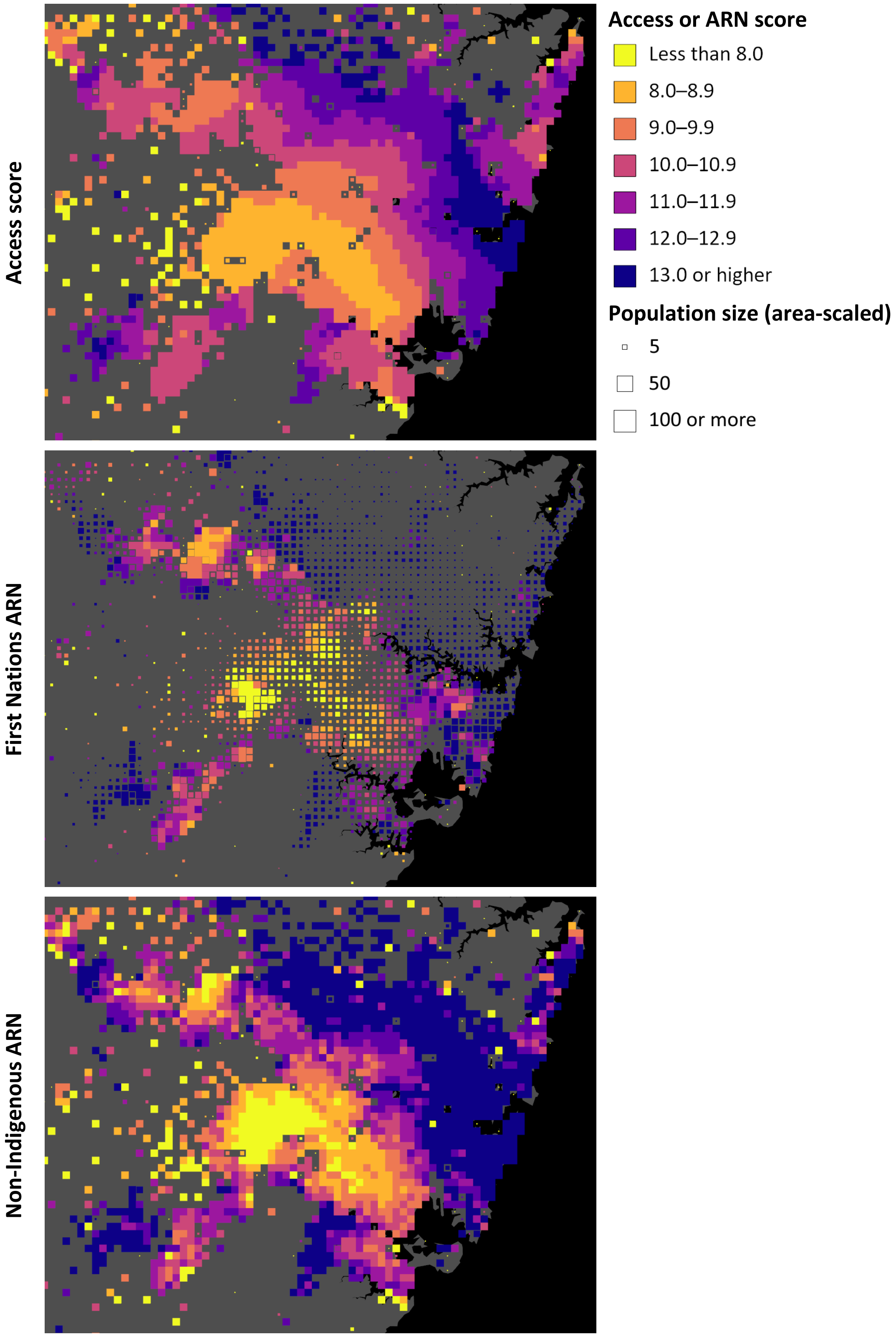
Figure 4. Per capita need and its demographic and socioeconomic components by SA1 for the First Nations and non-Indigenous populations of the Sydney region



Sources: AIHW analysis of access to GPs by SA1 (2018).

Note: SA1 data are aggregated from centroids to 1 km^2 bins to allow easier visual comparisons.

Figure 5. Access for the total population and access relative to need for the First Nations and non-Indigenous populations by SA1 in the Sydney region



Sources: AIHW analysis of access to GPs by SA1 (2018).

Note: SA1 data are aggregated from centroids to 1 km^2 bins to allow easier visual comparisons.

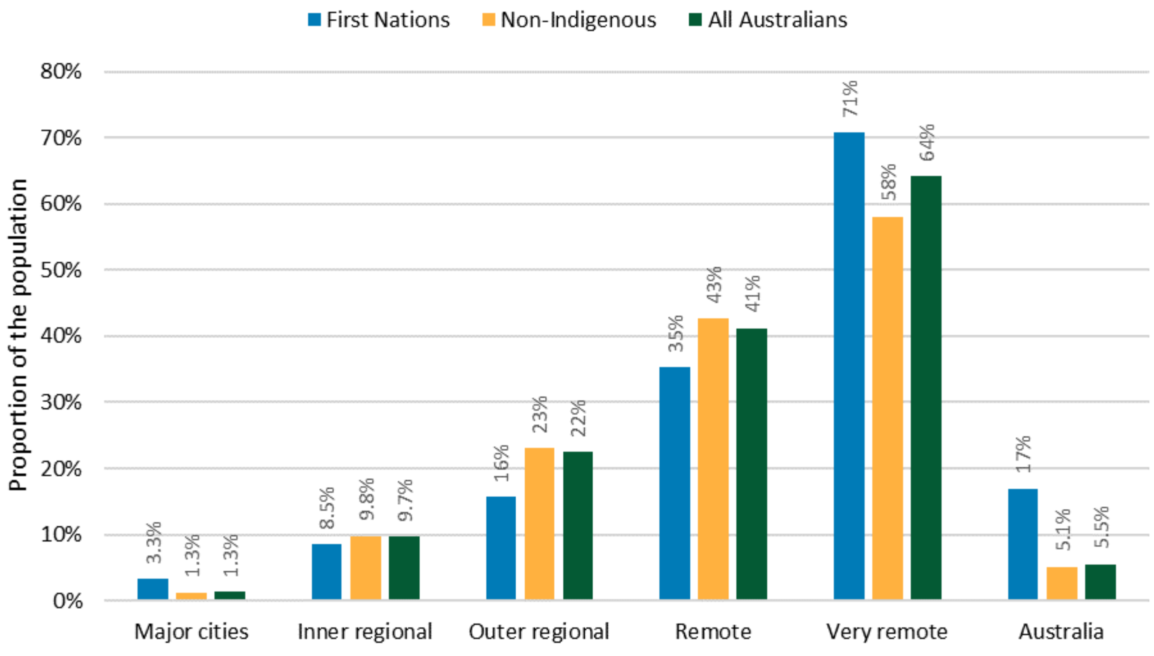
Output by higher geographic levels

The SA1-level output and model components can easily be used to calculate population-weighted averages and other statistics at higher geographic levels. For example, figure 6 shows the proportion of the First Nations, non-Indigenous and total populations who live in SA1s with a relatively low access score. Access scores below 7 were considered as relatively low access in this context. A score of 7 is equivalent to having 7 GPs per 10,000 people of average need if there are no drive time barriers or competition from other populations.

The proportion of people living in areas where physical access to GPs is relatively limited increases with increasing remoteness from 3% of First Nations people and 1% of non-Indigenous Australians in *Major cities* to 71% and 58% respectively in *Very remote* areas. Whereas a higher proportion of First Nations people live in areas with relatively poor access in both *Major cities* and *Very remote* areas, that is not the case in *Inner regional*, *Outer regional* or *Remote* areas.

A higher proportion of First Nations people than non-Indigenous Australians live in regional and remote areas where residents are more likely to live in areas with poor access than in the major cities. This contributes to the overall difference in the proportion of First Nations people (17%) and non-Indigenous Australians (5.1%) living in areas with relatively poor access.

Figure 6. Proportion of First Nations, non-Indigenous and all people living in SA1s with relatively poor access by remoteness area

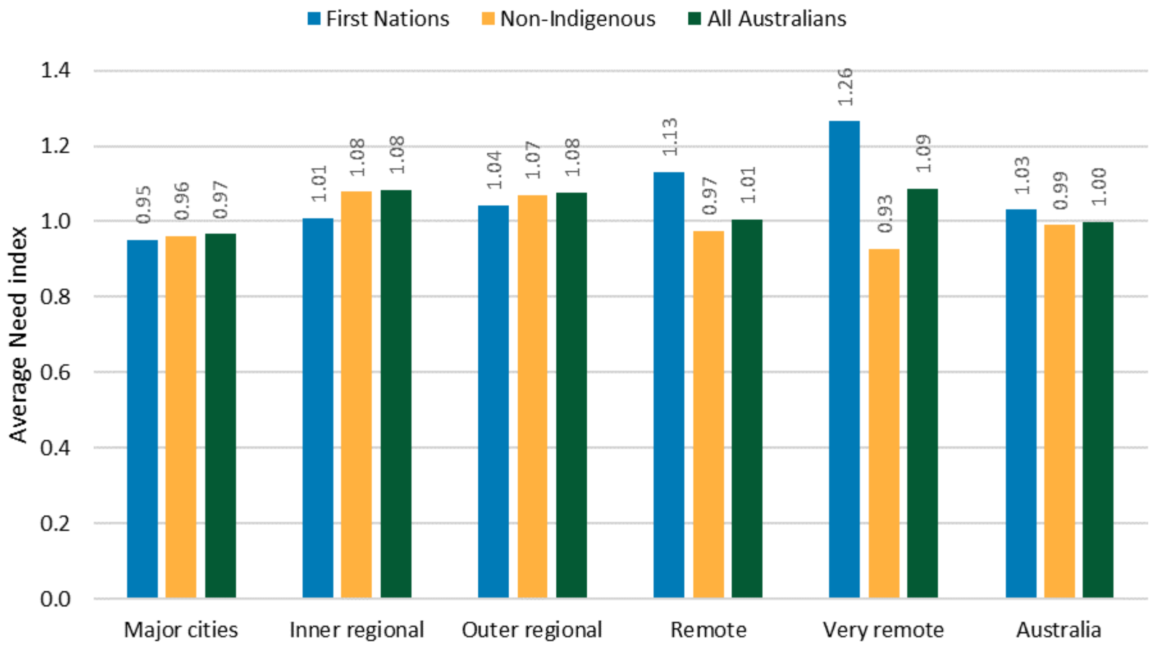


Sources: AIHW analysis of access to GPs by SA1 (2018).

Note: Results weighted with 2018 population estimates.

Figure 7 shows the average per capita need for the First Nations, non-Indigenous and total populations across the different remoteness areas. Whereas the per capita need increases with increasing remoteness in the First Nations population, this is not the case among non-Indigenous Australians who have the highest per capita need in *Inner regional* and *Outer* *regional* areas. The First Nations population has a much younger age structure than the non-Indigenous population. This makes the overall difference in per capita need much smaller than the difference in per capita need within any specific age group (see also figure A3 in Appendix A).

Figure 7. Average Need index for First Nations, non-Indigenous and all people by remoteness area



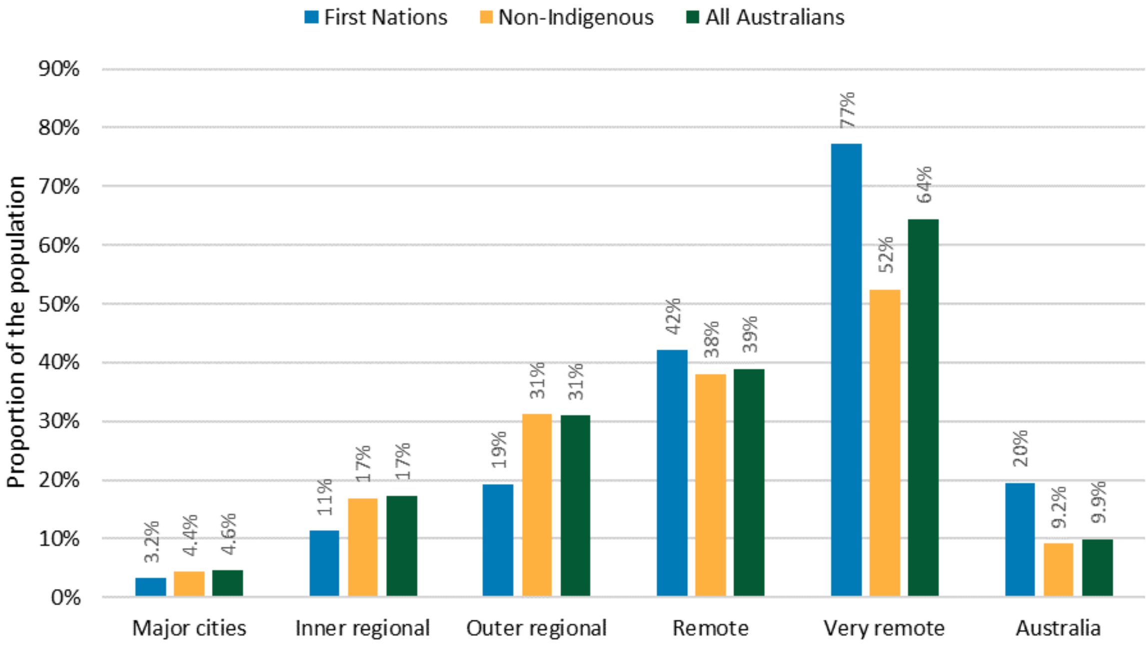
Sources: AIHW analysis of access to GPs by SA1 (2018).

Note: Results weighted with 2018 population estimates.

Figure 8 shows the proportion of the First Nations, non-Indigenous and total populations who live in SA1s with relatively low scores on the composite access relative to need (ARN) index (access divided by need). As for access (figure 6), a cut-off of 7 has been used. This level of access relative to need is the equivalent of a local population of average need having access to 7 GPs per 10,000 people with no drive time barriers or competition from other populations.

The increase in the proportion of First Nations people living in areas with relatively low access relative to need with increasing remoteness is somewhat more pronounced than for access because of the higher per capita need in more remote areas. For non-Indigenous Australians, the relatively high need in *Inner regional* and *Outer regional* areas, combined with the relatively low need in *Remote* and *Very remote* areas, make the increase in the proportion of people living in areas with relatively low access relative to need with increasing remoteness somewhat less pronounced.

Figure 8. Proportion of First Nations, non-Indigenous and all people living in SA1s with relatively poor ARN score by remoteness area



Sources: AIHW analysis of access to GPs by SA1 (2018).

Note: Results weighted with 2018 population estimates.

Future work

The AIHW will continue to develop the methods underlying the ARN index and publish output from the modelling. Our priorities for the immediate future include to:

- improve the accuracy of GP FTE estimates throughout Australia using a combination of the available data sources issues
- incorporate Census 2021 data and 2021-based population projections into the modelling
- conduct separate modelling of how First Nations people’s access to Aboriginal Community Controlled Health Services varies geographically
- investigate whether the interaction between access and need can be calibrated in a meaningful way with respect to its effect on health outcomes.

Appendix A: Estimating per capita need

What has been used in the past?

Previous Need index

- % Persons in high needs age groups (all children aged 0–4, all women of the child-bearing age 15–44, First Nations people aged 55 and over and all people aged 65 and over) *{standardised}*
- % Persons who need assistance with core activities (that is, activities related to self-care, mobility and communication) *{standardised}*
- % Labour force unemployed *{standardised}*
- % Households without a motor vehicle at home *{standardised}*
- % Persons who have not attained Year 12 or equivalent school qualification (ages 15 and above) *{standardised}*

$$Untransformed\ Need = High\ needs + Needs\ assistance + \frac{Unemployed + Motor\ vehicle + Year\ 12}{3}$$

Other Australian Need indexes

For comparison, 2 other need indexes have been developed (both by McGrail and Humphries) for use in floating-catchment modelling of access to GPs in Australia.

McGrail & Humphreys (2009)

- Scope: 2006 Census Collection Districts in rural Victoria; total population
- Variables:
  - % Persons aged 15 years or over having an advanced diploma or diploma qualification *{standardised}*
  - % Persons aged 15 years and over at university or other tertiary institution *{standardised}*
  - % Employed males classified as ‘Intermediate Production and Transport Workers’ *{standardised}*
  - % Males (in labour force) unemployed *{standardised}*
  - % One parent families with dependent offspring only *{standardised}*
  - % Persons First Nations *{standardised}*

$$Untransformed\ Need = 2 \times First\ principal\ component + 1 \times Second\ principal\ component$$

McGrail & Humphreys (2015)

- Scope: 2011 SA1s in Regional and Remote Australia, SA2s in Major Cities; total population
- Variables:
  - Index of Relative Socio-economic Disadvantage (IRSD) scores, if below 1000 *{transformed}*
  - % Persons First Nations, if above average *{standardised}*

– % Persons either very young (0–4) or old (65+), if above average *{standardised}*

$$Untransformed\ Need = 2 \times IRSD + 1 \times Indigenous + 1 \times Very\ young\ or\ old$$

New approach

$$Per\ capita\ Need = Demographic\ component \times Socioeconomic\ multiplier$$

Demographic component

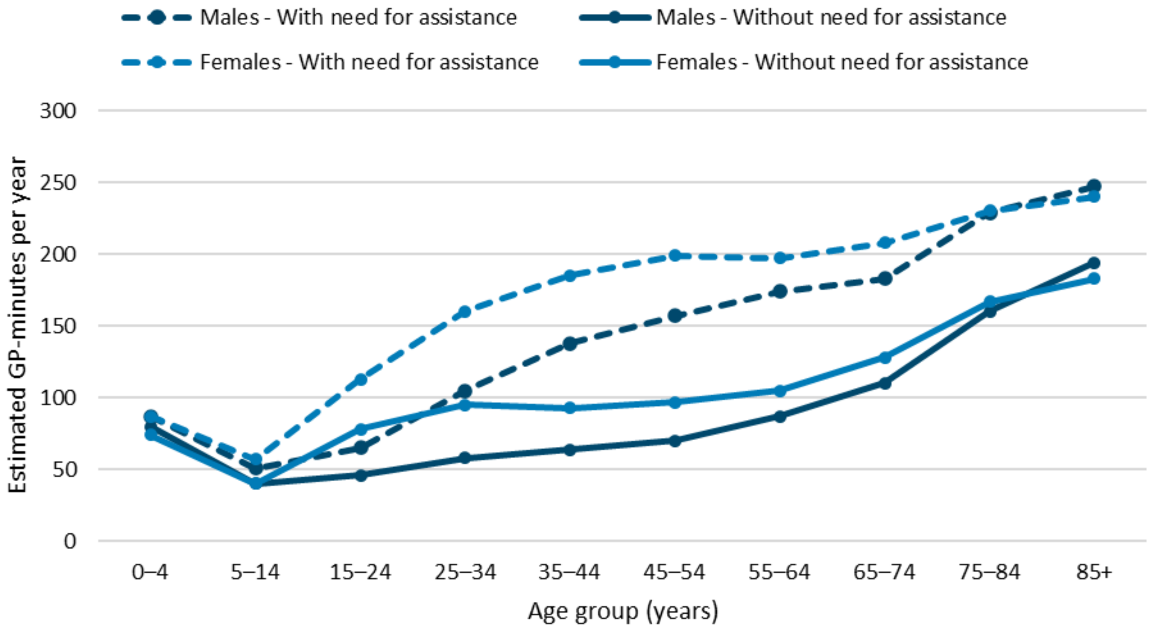
Use of GPs varies widely by age, sex and disability status, so these characteristics were used to form the spine of the new need estimates.

Residents of private dwellings and non-private dwellings were analysed separately, since many socioeconomic characteristics (the secondary component) are not applicable to residents of non-private dwellings.

Private dwellings

To calibrate the relative health care needs of different demographics: utilisation of GPs was estimated by age group (0–4, 5–14, 15–24, 25–34, 35–44, 45–54, 55–64, 65–74, 75–84, 85 and over), sex and disability status ('Core activity need for assistance'). This was primarily achieved by analysing numbers of non-referred GP attendances (MBS data) in 2016 linked to demographic characteristics from the 2016 Census of Population and Housing in the MADIP. Only GP attendances among non-Indigenous Australians living in non-remote areas were analysed, to reduce the extent to which unmet need might be lowering attendance (more important for the socioeconomic multiplier, discussed later). Additionally, average GP consultation length by age and sex from Harrison and Britt's (2011) analysis of the Bettering the Evaluation and Care of Health (BEACH) program (2005–2006 data) were used to convert attendance numbers to average GP-minutes per year for different demographics (see figure A1).

Figure A1: Estimated GP-minutes per year by age group, sex and disability status ('Core activity need for assistance'), 2016



Sources: AIHW analysis of MBS non-referred GP attendances (2016), ABS Census of Population and Housing (2016) and Harrison and Britt's (2011) analysis of GP consultation length from BEACH data (2005–2006).

To estimate the relative health care needs (linked to demographic factors) of different SA1 populations by Indigenous status: counts of people living in private dwellings were extracted from the 2016 Census by the same demographic breakdowns mentioned earlier, as well as Indigenous status ('First Nations, 'Non-Indigenous', 'All Australians'), by place of usual residence for several geographic levels (SA1, SA2, SA3-by-Remoteness Area, ILOC, IARE, IREG, SSC, UCL, SOSR, SOSR-by-Remoteness Area, State/Territory, Remoteness Area). For each SA1 and population by Indigenous status, Census data were retained for whichever fully overlapping geographic area contained the smallest sum of counts ≥75 (or an average of those areas, in the event of a tie), in effort to balance local specificity with reliability. Average GP-minutes per year were then combined with the Census data, to derive crude average GP-minutes per year for each SA1 (linked to demographic factors).

Non-private dwellings

To estimate the relative health care needs (linked to demographic factors) of different SA1 populations by Indigenous status: counts of people living in non-private dwellings (establishments which provide a communal type of accommodation) and at home on Census night were extracted from the 2016 Census by the same demographic breakdowns mentioned earlier, by Indigenous status, by type of non-private dwelling. Those data were combined with estimates of average GP-minutes per year (from the private dwellings analysis), to derive average GP-minutes per year by Indigenous status and type of non-private dwelling. Those estimates were then combined with 2016 Census counts of people living in non-private dwellings, at home on Census night, by Indigenous status, by type of non-private dwelling, by SA1, to derive a crude average for each SA1.

All residents pooled

To estimate each SA1's total average GP-minutes per year by Indigenous status: weighted means of the private and non-private estimates were calculated, following the 2016 Census counts of usual residents in private and non-private dwellings by Indigenous status, by SA1. The weighted mean for Australia, once SA1 population estimates were factored in, was 87.08 GP-minutes in 2016, becoming the benchmark (1.00) against which all SA1s were indexed. The overall demographic component for the First Nations population was 0.83 and for the non-Indigenous population was 1.00 (using estimated SA1 populations, at 30 June 2016, by Indigenous status).

Socioeconomic multiplier

Use of GPs tends to be higher among more socioeconomically disadvantaged populations compared with more advantaged populations, though the strength of that association varies by age group. For this reason, socioeconomic characteristics coupled with age were used to inform the new need estimates.

Residents of private dwellings and non-private dwellings were analysed separately, since many socioeconomic characteristics are not applicable to residents of non-private dwellings.

Private households

Twelve variables were derived from 2016 Census data, with the aim to detect many of the same socioeconomic differences that the ABS's SEIFA IRSAD and CAEPR's IRSEO measure in the private households population (Table A1):

Table A1: List of socioeconomic variables included in Principal Component Analysis

Variable description	Scope
Unemployment rate (%)	Persons in the labour force, aged 15 and over
Not engaged in work or study (%)	Persons aged 15–64
Level of highest educational attainment: Less than Year 12 (%)	Persons aged 15 and over
Level of highest educational attainment: Bachelor degree or higher (%)	Persons aged 15 and over
Occupation skill: Level 1 (%)	Employed persons aged 15 years and over
Occupation skill: Level 5 (%)	Employed persons aged 15 years and over
Annual household equivalised income: $78,000 or more (%)	Persons at home on Census night
Annual household equivalised income: $1–$25,999 (%)	Persons at home on Census night
No motor vehicle at home (%)	Persons at home on Census night
Social housing tenants (%)	Persons at home on Census night
Owner-occupiers (%)	Persons at home on Census night
Severely overcrowded dwelling (%)	Persons at home on Census night

Performing Principal Component Analysis (PCA) on the above variables (standardised using Australia's total population as the mean) for the First Nations population (by Indigenous Locations) and Non-Indigenous population (by SA1) gave two similar first principal components, each associated with around 50% of the variation in their respective populations. By averaging the coefficients across the separate first principal components, this resulted in a pooled socioeconomic score (Table A2), correlated strongly with both the

ABS's SEIFA IRSAD scores for total populations (R^2: 93% by SA1) and CAEPR's IRSEO rankings for First Nations populations (R^2: 95% by Indigenous Areas).

Table A2: List of socioeconomic variables in order of their final PCA coefficients

Variable description	Coefficient
Annual household equivalised income: $78,000 or more (%)	-0.319081
Level of highest educational attainment: Bachelor degree or higher (%)	-0.305863
Owner-occupiers (%)	-0.214001
Occupation skill: Level 1 (%)	-0.154550
Severely overcrowded dwelling (%)	0.153199
No motor vehicle at home (%)	0.194090
Occupation skill: Level 5 (%)	0.200706
Social housing tenants (%)	0.265422
Unemployment rate (%)	0.282246
Level of highest educational attainment: Less than Year 12 (%)	0.342966
Not engaged in work or study (%)	0.355187
Annual household equivalised income: $1–$25,999 (%)	0.363626

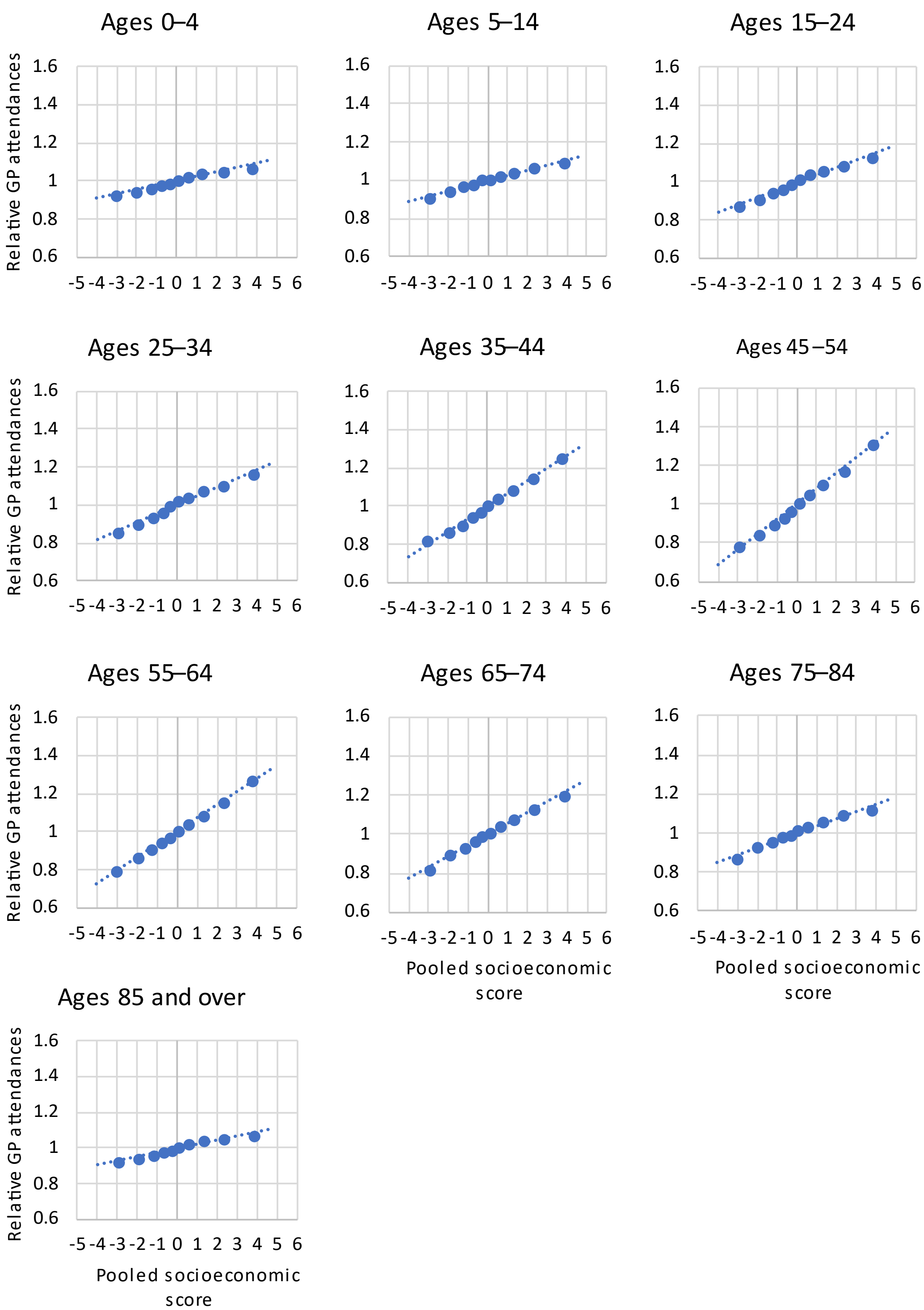
To estimate the pooled socioeconomic score of different SA1 populations by Indigenous status: counts of people living in private dwellings were extracted from the 2016 Census for each of the socioeconomic variables in Table A1, by Indigenous status ('First Nations, 'Non-Indigenous', 'All Australians'), by place of usual residence for several geographic levels (SA1, SA2, SA3-by-Remoteness Area, ILOC, IARE, IREG, SSC, UCL, SOSR, SOSR-by-Remoteness Area, State/Territory, Remoteness Area). For each separate socioeconomic variable, SA1 and population by Indigenous status, Census data were retained for whichever fully overlapping geographic area contained the smallest sum of counts ≥75 (or an average of those areas, in the event of a tie), in effort to balance local specificity with reliability. Coefficients from Table A2 were then combined with the Census data, to derive a preliminary pooled socioeconomic score for each SA1.

To enhance the resolution of First Nations estimates in cities, the preliminary outputs for 'All Australians' were used to create a custom geographic level corresponding to aggregations of 'Major Urban' SA1s (from the ABS's Section of State geographic classification), specific to each state/territory. Custom areas were demarcated based on the preliminary pooled socioeconomic score of SA1s, containing at least 75 First Nations Census counts with a valid occupation skill-level. Census data for those custom areas (collapsed in TableBuilder) were then included as an additional geographic level in the final output of the pooled socioeconomic score for each SA1, with the added distinction that the smallest sum of counts sought was lowered to ≥50, in effort to better detect pockets of social housing with small numbers of First Nations people.

To convert the pooled socioeconomic score into a socioeconomic multiplier, the weighted average of the pooled socioeconomic score was calculated by SEIFA IRSAD decile (2016, SA1-level), specifically for non-Indigenous Australians in non-remote SA1s. This was combined with corresponding (non-Indigenous, non-remote) data from the MADIP, relating to how the average number of GP attendances in 2016 varied by SEIFA IRSAD decile, within each age group (0–4, 5–14, 15–24, 25–34, 35–44, 45–54, 55–64, 65–74, 75–84, 85 and over). For example, the SEIFA IRSAD decile had a stronger association with GP attendances among 45–54-year-olds than among people aged 85 and over. Only GP attendances among non-Indigenous Australians living in non-remote areas were analysed, to reduce the extent to which unmet need might be lowering attendance.

The average number of GP attendances (relative to the overall mean) increased in near-linear fashion with increasing disadvantage when SEIFA IRSAD deciles were plotted by their pooled socioeconomic score, therefore the relationship between the pooled socioeconomic score and relative GP attendances could be approximated from simple linear regression (see figure A2). The youngest age group, 0–4-year-olds, showed an inconsistent trend of GP attendances across IRSAD deciles – but instead of assuming, therefore, that socioeconomic status has no bearing on the underlying health needs of young children, relative attendances were made to increase by uniform increments between deciles, resulting in the lowest IRSAD decile having a 15% higher loading compared with the highest decile. A 15% higher loading was considered conservative, given other age groups differed by 15–68% with respect to the same comparison. By combining the Census counts of people by Indigenous status and age group in each SA1 (drawn from whichever fully overlapping geographic area among SA1, SA2, SA3-by-Remoteness Area, ILOC, IARE, IREG, SSC, UCL, SOSR, SOSR-by-Remoteness Area, State/Territory or Remoteness Area contained the smallest sum of counts ≥50) with the age-specific regression parameters, the pooled socioeconomic scores could be converted to final socioeconomic multipliers.

Figure A2: Age-specific linear regression lines drawn from the number of GP attendances (relative to the age-specific average) by SEIFA IRSAD decile. The populations from each SEIFA IRSAD decile include only non-Indigenous non-remote SA1s and are plotted by their average pooled socioeconomic score (from AIHW analysis of Census data).



Sources: AIHW analysis of MBS non-referred GP attendances (2016) and ABS Census of Population and Housing (2016).

Non-private dwellings

To take account of the needs of residents of non-private dwellings (such as aged care facilities or prisons), the pooled socioeconomic scores for the 20 different types of dwelling (coded as variable NPDD in the 2016 Census) were estimated using multiple linear regression based on the association between highest educational attainment variables ('less than Year 12' and 'Bachelor degree or higher') and pooled socioeconomic scores among the population living in private dwellings (as other socioeconomic variables were not generally applicable to residents of non-private dwellings). Pooled socioeconomic scores were estimated separately by Indigenous status, and only for those residents at home on Census night. The pooled socioeconomic scores were converted to socioeconomic multipliers, based on the age structure in each type of dwelling, by Indigenous status. Those estimates were then combined with 2016 Census counts of people living in non-private dwellings, at home on Census night, by Indigenous status, by type of non-private dwelling, by SA1, to derive a crude average for each SA1.

All residents pooled

To estimate each SA1's socioeconomic multiplier by Indigenous status: weighted means of the private and non-private estimates were calculated, following the 2016 Census counts of usual residents in private and non-private dwellings by Indigenous status, by SA1. The weighted mean for Australia, by definition, was 1.00 in 2016. The weighted mean socioeconomic multiplier for the First Nations population was 1.24 and for the non-Indigenous population was 0.99 (using estimated SA1 populations, at 30 June 2016, by Indigenous status).

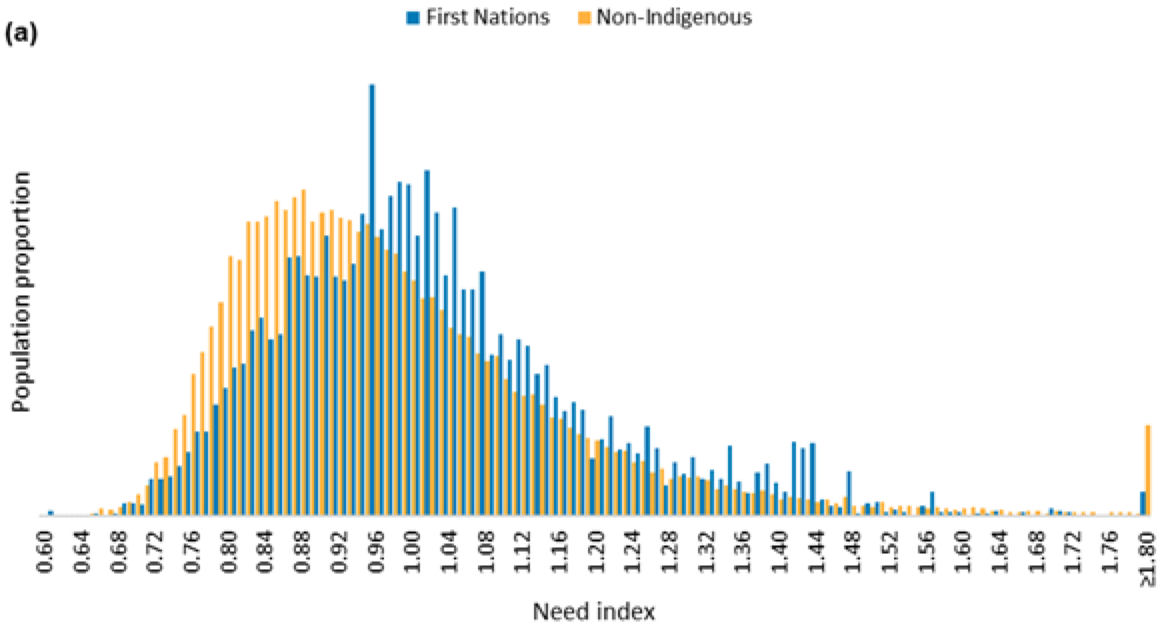
Combined into a single Need index

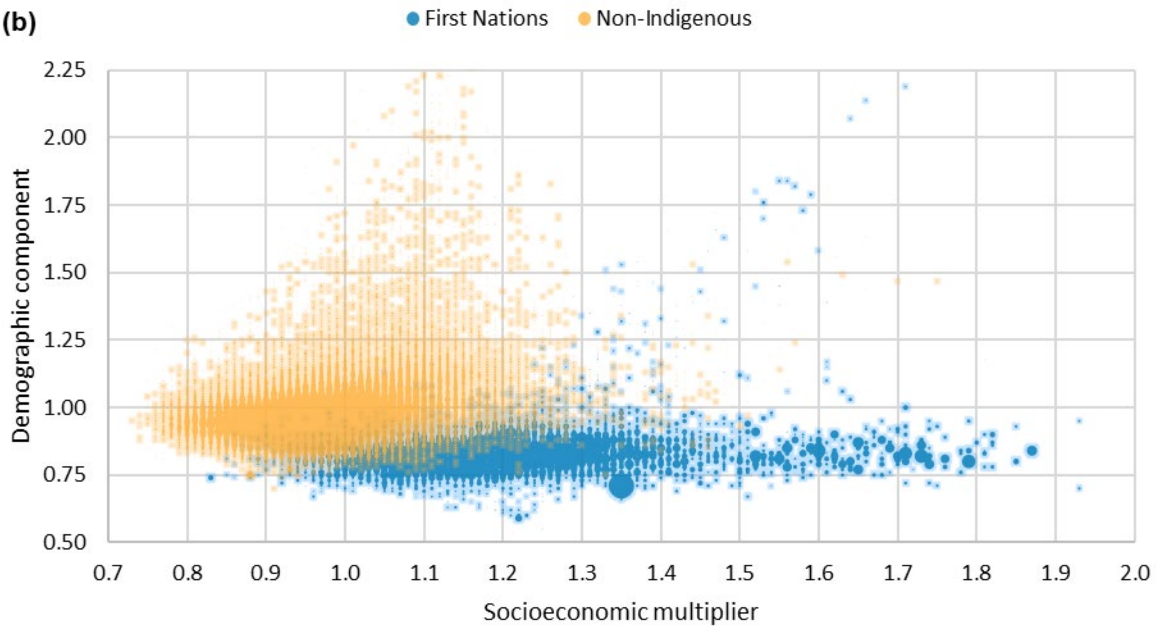
To predict the per capita need for primary health care (Need index) in each SA1, the demographic component and socioeconomic multiplier were multiplied together, specific to Indigenous status. Overall, the weighted mean Need index for 'All Australians' was 1.00, for the First Nations population was 1.03 and for the non-Indigenous population was 0.99 (using estimated SA1 populations, at 30 June 2016, by Indigenous status).

The differences can be examined by looking at the distribution of the First Nations and non-Indigenous populations by their Need indexes and sub-components (figure A3).

Applying the Need model to individual age groups demonstrates how the non-age-related differences (predominantly socioeconomic) result in much higher age-specific Need estimates among First Nations people than non-Indigenous Australians, particularly for those in middle age (figure A4).

Figure A3: (a) The distribution of the First Nations and non-Indigenous population by Need index (summed from SA1-level). (b) The distribution of the First Nations and non-Indigenous population by demographic component and socioeconomic multiplier (summed from SA1-level).

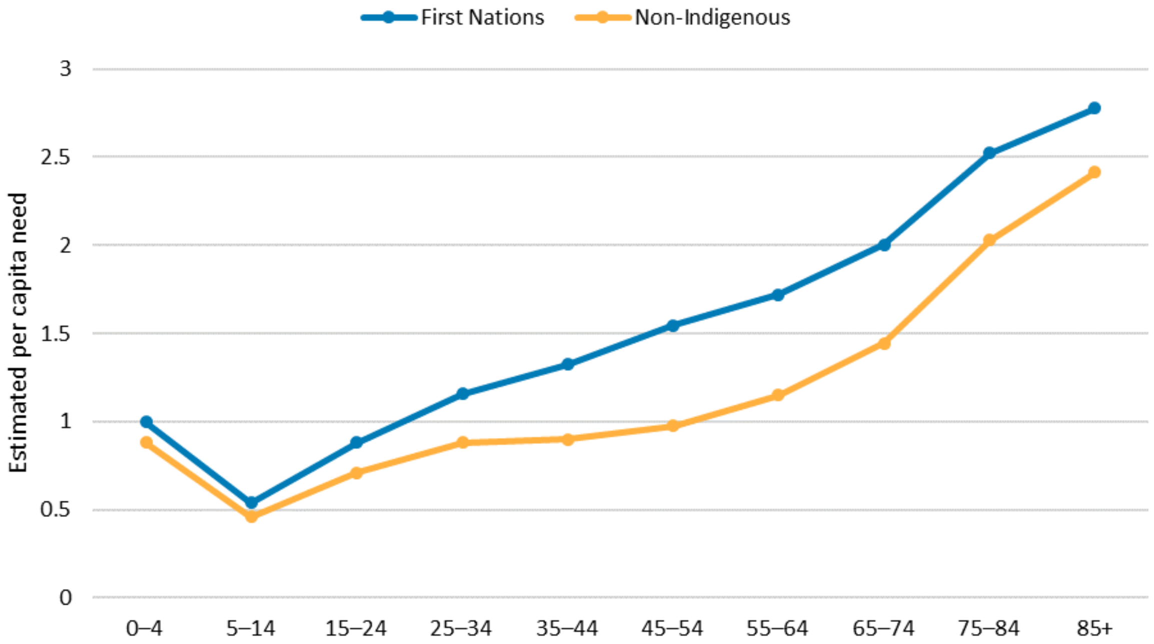




Sources: AIHW analysis of MBS non-referred GP attendances (2016), ABS Census of Population and Housing (2016), ABS population estimates (2016), and Harrison and Britt's (2011) analysis of GP consultation length from BEACH data (2005–2006).

Note: The weighted mean Need index for 'All Australians' was 1.00, for the First Nations population was 1.03 and for the non-Indigenous population was 0.99

Figure A4: Approximate Need index by Indigenous status and age group among residents of private dwellings, 2016



Sources: AIHW analysis of MBS non-referred GP attendances (2016), ABS Census of Population and Housing (2016), ABS population estimates (2016), and Harrison and Britt's (2011) analysis of GP consultation length from BEACH data (2005–2006).

Note: Need model applied to ILOC Census counts for First Nations population and SA1 Census counts for non-Indigenous population.

Notes and limitations

- Census data are subject to perturbation and suppression, which particularly affects the quality of estimates based on smaller counts.
- Census responses from self-identified First Nations people were assumed to be representative of the total First Nations population in each area.
- Residents of non-private dwellings were assumed to utilise GPs in the community in the same way as residents of private dwellings. In reality, populations living in some types of non-private dwelling are likely to utilise GPs in the community to a different extent, if at all.
- Potential differences in average GP consultation length by disability status were not accounted for.
- The method used to draw Census data from larger areas where needed does not necessarily provide a more accurate estimate, but it should provide estimates that are less sensitive to small changes.
- Persons who did not state their disability status or Indigenous status were still included in the calculation of GP-minutes. For each geographic area, the local data was used to calculate weighted means of GP-minutes for males and females in each age group that did not state their disability status, separately by Indigenous status.
- Socioeconomic characteristics were drawn from the populations in-scope, then the associations between area-level socioeconomic characteristics and GP attendances by age were applied to each age group. A more precise method might have involved looking at important socioeconomic characteristics in each age group and their associations with GP attendances.

- Certain socioeconomic variables, such as severe overcrowding, have a long-tailed distribution. Variables with long tails may have an oversized influence on the pooled socioeconomic score in areas with extremely uncommon characteristics.
- While there appears to be a linear relationship between the pooled socioeconomic scores and relative GP attendances among the non-remote, non-Indigenous population across the 10 SEIFA IRSAD deciles, it is not certain that this relationship holds true for scores outside the IRSAD range. Extrapolating that linear relationship to the more extreme socioeconomic scores among the First Nations population in remote areas assumes that underlying need for GPs does not diverge from that trend.
- MADIP data were accessed via the ABS's Protari web interface (since discontinued). The interface did not permit unit record level interrogation.

Appendix B: Computing population locations for large Statistical Areas Level 1

The error introduced into the drive time estimates by using a single centroid to represent where everyone lives in a Statistical Areas Level 1 (SA1) is negligible in the small SA1s most people live in. However, many SA1s in less densely populated parts of Australia can be very large – sometimes hundreds of kilometres across – and have residents that are spread out over large areas, often in small, isolated communities. Using a single centroid to represent the population in these areas can lead to drive time estimates that are not representative of for how long most people in an SA1 must travel to reach a certain GP service.

The accuracy of the drive time estimates could be maximised by using a point for each residential address to represent the distribution of each local population – or a point per populated location or area based on the most detailed available information about where people live. However, there is a trade-off between accurately representing where people live (by increasing the number of points used to represent the population distribution within each SA1) and the burden on computing resources. While having many points in each area improves the accuracy of the drive time estimates, it comes at the cost of greatly increasing calculation times as it is necessary to estimate the drive time to each GP service within an hour's drive for the model used here.

When considering the above, the decision was made to develop a methodology to more accurately represent where people live while still ensuring that computational requirements could be met. This was done by determining population clusters within each SA1 with the support of the 2018 ABS population grid, which is a graphic representation depicting the geographic spread of the Australian population to a resolution of 1 km^2.

A data driven approach was followed – that is, one in which the data themself determine not only the number of population clusters for each SA1 but also the constituent parts of each cluster (the number of points per cluster and which clusters points belong to). Using a machine learning technique known as hierarchical clustering, the geographic makeup of the population was partitioned into meaningful units that assist with determining population access more accurately. Instead of representing an entire SA1 population with a single point, a series of points were now developed with each of them representing a distinct geographic portion of the entire SA1 population.

As the ABS population grid depicts the whole country, and the ARN model requires values at the SA1 level, each SA1 was sliced from the others and treated as a distinct geographic unit taking its portion of the ABS population grid with it. All clustering calculations were then carried out on the grid in isolation. This helped to ensure that clusters stayed local and were not influenced by either their SA1 neighbours or a national context.

Multiple population locations were calculated for SA1s with an area of over 10,000 km^2 as this is where they are most effective in increasing spatial accuracy while minimising computational load.

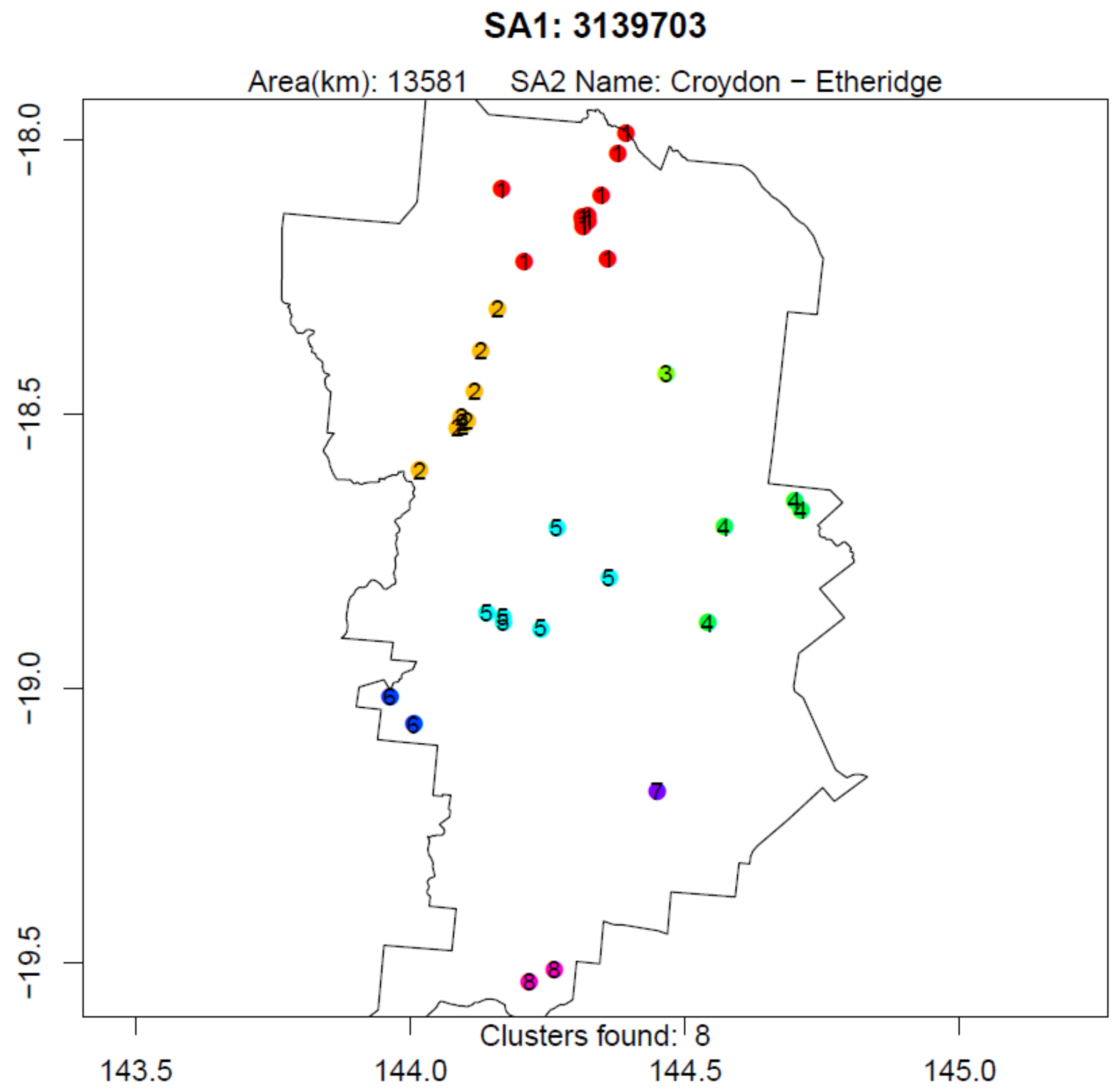
In R 3.5, for each SA1 over 10,000 km^2, the following procedure was carried out:

1. In order to localise the clusters, and thereby prevent clusters from crossing boundaries (or growing too large), each SA1 of interest was treated as a geographically separate entity. In each case the 2018 ABS population grid was sliced by each SA1's geography and clusters were determined for those sections of the grid that became members of that SA1.

2. An important consideration in determining clusters is calculating an appropriate bandwidth (that is, distance or cut-off point) that can be used to determine similar and dissimilar groups. If the bandwidth is too large then all points are considered to be one cluster – if too small, all points are treated as separate entities. A constant bandwidth may work for one SA1 but overgeneralise another. Consequently, the bandwidth needs to vary for each SA1. To achieve this, a distance matrix was calculated for each SA1 with the standard deviation of the distances being used to determine an optimal cut-off point for clustering.
3. Using the data for each SA1 (step 1) and the cut-off point determined in step 2, the grid data were then clustered using the hierarchical clustering algorithm. In this case the clustering is based solely on the geographic relationship between all points and not any other attributes or weights. This machine learning algorithm analyses a set by first finding the most similar items based on distance and assigning them their own cluster. It then proceeds iteratively, finding clusters that are similar to other clusters until a single overall umbrella cluster is formed. The result is a series of levels showing how similar and dissimilar each SA1's series of points are to each other in the form of a branching tree. This tree is then "cut" at the cut-off point determined in step 2 with the result being a series of clusters with members whose points are more similar to each other than other points in the same SA1.
4. Finally, each new cluster of points is assigned its own location point. In this case, this is a particular type of point known as a geographic medoid. A geographic medoid is a location that represents the point that is most likely to be in the geographic centre of all its immediate neighbours – that is, the most central value. But it is also one that remains a location where people actually live, rather than the geographic centre of the population, where there may be no population.

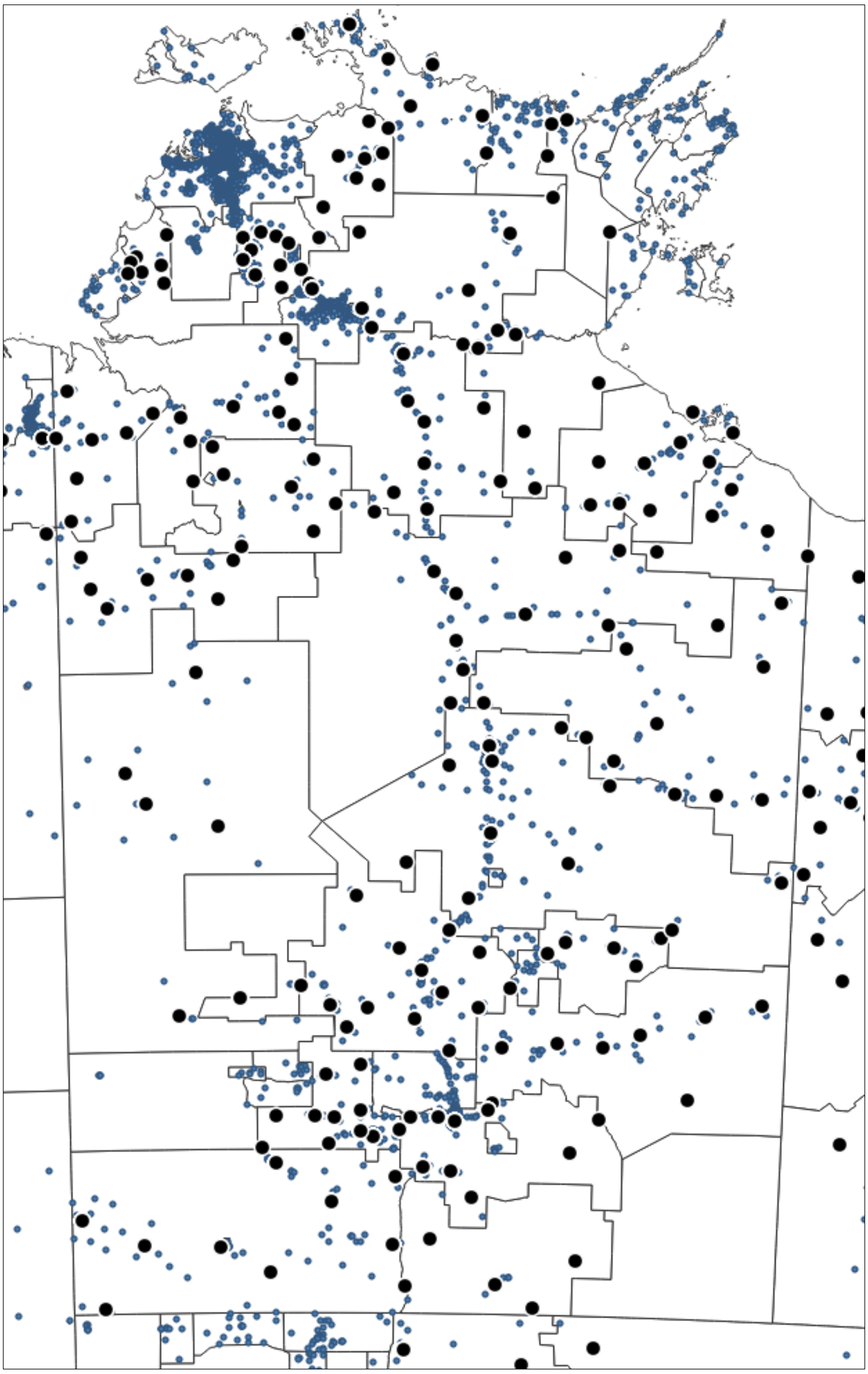
Figure B1 best illustrates the results of this methodology.

Figure B1: R 3.5 output depicting SA1 3139703 in the Croydon-Etheridge Region (QLD) with the distribution of the ABS 2018 population grid represented as differing coloured and numbered circles representing membership of distinct clusters as determined using a hierarchical cluster machine learning technique



Note: Although not represented here, these results are pruned further by taking the medoid (the most central member value) of each cluster and using it to represent the entire cluster.

Figure B2: R 3.5 output showing the results of the algorithm for the Northern Territory for 2016 SA1s over 10,000 km²



Note: Blue dots represent the 2018 ABS population grid. Black circles depict computed population locations (the results of the algorithm, known as medoids). These computed medoids become the starting points for calculating drive-times to service provider distances. In the case of SA1s smaller than 10,000 km² the starting point remains the geographic centroid (which are not plotted in this output).

Appendix C: Data sources used for output in this report

Table C1: Data sources used for output in this report.

Key data	Inputs
Population data, by Indigenous status, SA1	30 June 2018 estimates, approximated by the AIHW using Iterative Proportional Fitting, supported by 2016 Census counts. This technique produces estimates that match the ABS's published outputs when summed back up to larger areas.
GP data (service locations and preliminary FTE)	AMPCo, 2017 • AIHW excluded suspected specialist services and OSR services. Assumed FTE (1 or 0.5) are spread uniformly across practice locations, which is another source of uncertainty. • AIHW geocoded from address information.
	AHPRA, 2019 • AIHW geocoded from geographic information.
	OSR, 2017–18 • GP FTE • AIHW geocoded from address information and additional research.
	RFDS, 2018–19 • 'Regular' clinics run in 2018–19. All assumed to have 0.1 FTE, which may be higher than typical. • Geocodes provided by RFDS.
GP data (FTE benchmarking)	NHWDS FTE, 2018 • Clinical FTE (hours providing clinical services, as reported in Medical Workforce Survey) among Medical Practitioners with 'Job Area: General practitioner (GP)' • Used to benchmark preliminary FTE in SA3s with populations living predominantly in Major Cities SA1s
	HeaDS UPP GPFTE, 2018 • Total FTE (includes non-clinical hours, modelled) • Used to benchmark preliminary FTE in SA2s, outside of those SA3s identified as predominantly Major Cities
Per capita Need, by Indigenous status, SA1	ABS Census of Population and Housing, 2016 (TableBuilder) • Counts of persons and households, by Indigenous status, by various demographic and socioeconomic variables
	MADIP • Number of MBS non-referred GP attendances in 2016, among non-Indigenous population, by various demographic variables, by SEIFA IRSAD area-deciles
	BEACH • Average GP consultation length by age and sex • Harrison & Britt (2011)

Acknowledgements

The authors of this report were Martin Edvardsson, Hayden Stevens and Mark Walker of the First Nations Health and Welfare Group's Spatial Analysis Unit at the AIHW. Other past and present members of the Spatial Analysis Unit have also made significant contributions to the work presented in this report including Brett Nebe, Natalia Eiré Sommer, Maxine Montaigne and Amelia Cook.

Fadwa Al-Yaman and members of the Department of Health and Aged Care's First Nations Health Division provided valuable comments on the work and earlier versions of this report.

References

AIHW (Australian Institute of Health and Welfare) (2014) *Access to primary health care relative to need for Indigenous Australians*, AIHW, Australian Government, accessed 31 July 2023. https://www.aihw.gov.au/reports/indigenous-australians/access-to-primary-health-care-relative-to-need/summary

AIHW (2015) *Spatial variation in Aboriginal and Torres Strait Islander people's access to primary health care*, AIHW, Australian Government, accessed 31 July 2023. https://www.aihw.gov.au/reports/indigenous-australians/spatial-variation-to-access-primary-health-care/summary-1

AIHW (2020) *Aboriginal and Torres Strait Islander Health Performance Framework 2020 summary report 2020*, AIHW, Australian Government, accessed 31 July 2023. https://www.indigenoushpf.gov.au/publications/hpf-summary-2020

AIHW (2024) *Social determinants of health*, AIHW, Australian Government, accessed 22 July 2024. https://www.aihw.gov.au/reports/australias-health/social-determinants-of-health

Bagheri N, Benwell GL & Holt A (2008) 'Modelling accessibility to primary health care using a spatial accessibility index and a need index', *Hawai'i Journal of Public Health*, 1(1):14–27.

Chen X & Jia P (2019) 'A comparative analysis of accessibility measures by the two-step floating catchment area (2SFCA) method', *International Journal of Geographical Information Science*, 33(9):1739–1758.

Delamater PL, Shortridge AM & Kilcoyne RC (2019) 'Using floating catchment area (FCA) metrics to predict health care utilization patterns', *BMC Health Services Research*, 19:144.

Harrison C & Britt H (2011) 'General practice - workforce gaps now and in 2020', *Australian Family Physician*, 40(1–2):12–15.

Kalseth J & Halvorsen T (2020), 'Health and care service utilisation and cost of the life-span: a descriptive analysis of population data', *BMC Health Services Research*, 20(1):435.

Lerner EB & Moscati RM (2001) 'The golden hour: scientific fact or medical "urban legend"?', *Academic Emergency Medicine*, 8(7):758–760.

Luo J (2014) 'Integrating the Huff model and floating catchment area methods to analyze spatial access to healthcare services', *Transactions in GIS*, 18(3):436–448.

Luo W & Wang F (2003) 'Measures of spatial accessibility to health care in a GIS environment: synthesis and a case study in the Chicago region', *Environment and Planning B: Planning and Design*, 30:865–884.

Luo W & Whippo T (2012) 'Variable catchment sizes for the two-step floating catchment area (2SFCA) method', *Health & Place*, 18(4):789–795.

McGrail MR & Humphreys JS (2009) 'The index of rural access: an innovative integrated approach for measuring primary care access', *BMC Health Services Research*, 9:124.

McGrail MR & Humphreys JS (2015) 'Spatial access disparities to primary health care in rural and remote Australia', *Geospatial Health*, 10(2):358.

McGrail MR, Humphreys JS & Ward B (2015) 'Accessing doctors at times of need–measuring the distance tolerance of rural residents for health-related travel', *BMC Health Services Research*, 15:212.

Stacherl B & Sauzet O (2023) ‘Gravity models for potential spatial healthcare access measurement: a systematic methodological review’, *International Journal of Health Geographics*, 22:34.

Tanser F, Gijsbertsen B & Herbst K (2006) ‘Modelling and understanding primary health care accessibility and utilization in rural South Africa: an exploration using a geographical information system’, *Social Science & Medicine*, 63(3):691–705.

Wan N, Zou B & Sternberg T (2012) ‘A three-step floating catchment area method for analyzing spatial access to health services’, *International Journal of Geographical Information Science*, 26(6):1073–1089.

How easy it is for Australians to see a General Practitioner when they need to depends on where they live. This is not surprising given Australia's mix of cities, regional towns and smaller communities spread out over vast areas. However, how easy it is also varies within cities, between towns and from community to community (AIHW 2014, 2015). The AIHW's index of Access Relative to Need (the 'ARN index') estimates how local access to General Practitioners (GPs) relative to the need for primary health care varies across Australia for First Nations people and for non-Indigenous Australians. Output from the modelling underlying the ARN index has been used to identify where timely access to appropriate primary health care is likely to be particularly challenging for First Nations people because of poor physical access to First Nations-specific health care services in combination with poor access to GPs in general (AIHW 2015, 2020).

This report presents the recent refinements of the ARN methodology and discusses data and other methodological issues that have the potential to limit the accuracy of estimates of access to services in Australia.

aihw.gov.au

AIHW

Stronger evidence,
better decisions,
improved health and welfare