Spatially consistent annual Socio-Economic Indexes for Areas (SEIFA) data for Australian statistical areas, 1996 – 2021

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Abstract

Background: National census data are frequently used as a source of area-level socioeconomic information. However, this data is less suitable for longitudinal analysis. Infrequent data collection may result in failure to capture rapid changes in socioeconomic conditions. Additionally, administrative boundaries of census areas are often revised with each new census, limiting comparisons over time. To accurately observe changes in socioeconomic factors over time, temporally and spatially consistent data are needed. Using the Australian Bureau of Statistics (ABS) Socio-Economic Indexes for Areas (SEIFA) as an example, this paper presents a method to overcome traditional census limitations, providing timely, geographically consistent socioeconomic data.

Results: The dataset includes a final sample of 59,421 Statistical Area 1s (SA1) after excluding those with no SEIFA data for any census year. The methodology resulted in annual, spatially, and temporally consistent SEIFA data from 1996 to 2021 standardised to the 2021 SA1 boundaries.

Conclusion: The proposed method for creating annual SEIFA data at a small geographic scale addresses key challenges associated with tracking area-level socioeconomic factors over time. By aggregating and standardising data across multiple years, this approach maintains consistency in geographic units, to overcome potential limitations of using census data in longitudinal research.

Keywords: socioeconomic indexes, neighbourhood, census, spatial analysis, small areas, longitudinal

Background

Understanding evolving area-level sociodemographic factors is necessary to inform public policy and guide resource allocation (e.g. health services, education and housing) (Ajebon & Norman, 2016; Coffee et al., 2016; Norman, 2010). Researchers and policymakers analyse population changes, age distribution and indicators of area disadvantage to identify trends in health outcomes and spatial inequalities as well as infrastructure needs. Central to this research is spatial and temporal data, which captures both geographic location and timing (Coffee et al., 2016; Reibel, 2007; Stillwell et al., 2013).

National census data have traditionally been used as a source of population and housing information (Bell et al., 2007; Coffee et al., 2016; Fecht et al., 2020; Geronimus & Bound, 1998; Langford, 2013; Stillwell et al., 2013). Although some area-based socioeconomic indexes, such as the New Zealand Index of Multiple Deprivation, incorporate administrative or survey data (Exeter et al., 2017), in many countries, these indexes are often derived solely from census variables and produced for varying administrative boundaries such as census tracts or postcode areas (Ajebon & Norman, 2016; Bell et al., 2007; Bensken et al., 2023; Geronimus & Bound, 1998). Examples include the Socio-Economic Indexes for Areas (SEIFA) in Australia (Australian Bureau of Statistics, 2021a), the NZDep Index in New Zealand (Crampton et al., 2020), and the Canadian Index of Multiple Deprivation (Statistics Canada, 2023). These indexes are created by aggregating various socioeconomic indicators, such as unemployment rates, household income, and education levels, into a single measure or score that reflects the overall socioeconomic conditions of an area (Bell et al., 2007).

Census data provide a valuable snapshot at one time point; however, they are less suitable for examining changes over time for two key reasons: first, census data are typically collected every 5 to 10 years (Fecht et al., 2020; Geronimus & Bound, 1998). The infrequent data collection may result in failure to capture rapid changes in socioeconomic conditions (Weden et al., 2015).

Without timely data, policymakers may overlook critical developments, such as changes in the prevalence of health conditions, leaving them unable to respond effectively (Fecht et al., 2020). Second, the administrative boundaries of census areas are often revised with each new census and are subject to the modifiable areal unit problem (Blake et al., 2000; Coffee et al., 2016; Grubesic & Matisziw, 2006; Norman et al., 2003). The modifiable areal unit problem is where the data patterns vary based on the scale or boundaries of spatial units used (Openshaw, 1984). These boundary changes may mean data from one census are not directly comparable to those from another census. Shifting boundaries create a challenge when conducting longitudinal analysis as it is difficult to determine whether observed changes are genuine or simply due to the changing boundary (Blake et al., 2000; Norman et al., 2003; Schroeder, 2007; Zoraghein & Leyk, 2018). While data custodians provide tools such as geographic conversion tables to assist with this challenge (Simpson, 2002), this does not solve the problem of only having snapshots of data 5 to 10 years apart.

Australian Context

In Australia, the Australian Bureau of Statistics (ABS) SEIFA are widely used to examine area-level socioeconomic characteristics (Australian Bureau of Statistics, 2021a). Derived from census data collected every five years, SEIFA includes four indexes: The Index of Relative Socio-Economic Disadvantage (IRSD), The Index of Relative Socio-Economic Advantage and Disadvantage (IRSAD), The Index of Education and Occupation (IEO) and The Index of Economic Resources (IER). These indexes use a weighted combination of selected variables related to advantage and disadvantage to produce an area-based aggregate measure (Australian Bureau of Statistics, 2021a). The indexes are derived using principal components analysis, a method that reduces a large set of highly correlated variables into a smaller number of principal components that capture the most important information in the data. Each index summaries a different range of socioeconomic conditions such as income, education, employment and housing (Australian Bureau of Statistics, 2021a).

Australian census data are available for a range of nested area-level boundaries (i.e. smaller geographic units fit within larger ones) through the Australian Standard Geographic Classification (ASGC) and the Australian Statistical Geography Standard (ASGS). From 1986 to 2006, the ASGC was used. Under the ASGC, Census Collection Districts (CD) were the smallest geographic areas used to derive SEIFA, with an average of 220 dwellings in urban areas. (Mesh Blocks, introduced from 2004, are smaller units used to provide a broad classification of land use, such as residential or commercial) (Australian Bureau of Statistics, 2006). CD boundaries were primarily designed to support data collection, traditionally defining an area manageable by a single census collector (Australian Bureau of Statistics, 2001). To accommodate population changes the boundaries of the CDs were not necessarily the same each census. For example, approximately 20% of CDs were adjusted from 1996 to 2001 (Australian Bureau of Statistics, 2002).

In 2011, the ABS introduced the ASGS, a substantial change from the ASGC, with minimal overlap in spatial units (Australian Bureau of Statistics, 2011). CDs were replaced with Statistical Area 1 (SA1) as the smallest geographic areas used to derive SEIFA (limited census data is available for Mesh Blocks). Rather than being defined by number of dwellings, SA1s contain between 200 and 800 people, with an average of approximately 400, and therefore have greater consistency in population size (Australian Bureau of Statistics, 2011). Although the ASGS boundaries are more stable than the previous geography standard (ASGC), they are still subject to changes with each census to reflect shifts in population, especially in rapidly growing areas. Figure 1 illustrates boundary changes across each census year from 1996 to 2021 at a single location. The number of CDs and SA1s for each year are presented in Table 1.

Figure 1: CD and SA1 boundary changes 1996 to 2021.

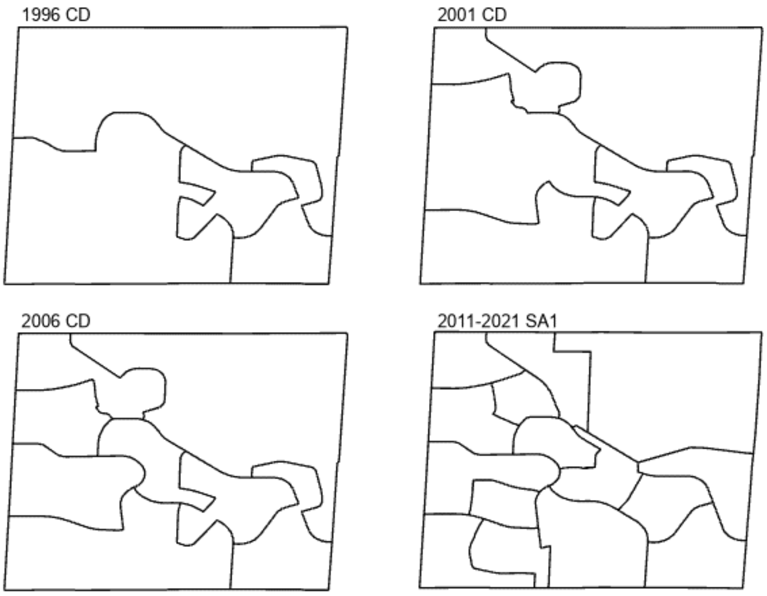


Table 1: Number of CDs or SA1s at each census 1996 to 2021.

Year	Number of CD/SA1
Census Collection Districts (Australia Standard Geographical Classification)	
1996	34,500
2001	37,209
2006	38,704
Statistical Area Level 1 (Australia Statistical Geographical Standard)	
2011	54,805
2016	57,523
2021	61,845

(Australian Bureau of Statistics, 1999, 2001, 2006, 2011, 2016, 2021b).

Due to the introduction of the new geographic standard and ongoing boundary changes, as well as potential changes the to the variables used to construct the indexes, the ABS do not recommend using SEIFA for longitudinal analysis. These changes may affect an area's index score or ranking, reducing the comparability across time. If SEIFA are used for longitudinal analysis, the ABS advises using deciles instead of ranks or scores, as this approach is less sensitive to minor changes. This approach is commonly used in Australian studies.

Nevertheless, the results should be interpreted with caution as changes within deciles may still reflect socioeconomic shifts that are not fully captured by this approach (Australian Bureau of Statistics, 2008).

Researcher responses to changing census boundaries

To overcome the limitations of varying census boundaries Blake et al. (2000) proposed four approaches for generating spatially consistent data using Geographic Information Systems (GIS). They include (1) maintaining a fixed set of geographic boundaries over time and adjusting future data to fit those boundaries; (2) updating historic spatial data to align with a set of contemporary boundaries; (3) constructing custom boundaries from smaller building blocks; and (4) geo-referencing household data to assign precise geographic coordinates to individual addresses then aggregating on custom boundaries (Blake et al., 2000).

The potential strengths and limitations of these approaches have been discussed in several studies. For example, the first approach to maintaining a fixed set of geographic boundaries over time can provide consistency, however, it can become increasingly outdated as time progresses (Blake et al., 2000; Norman et al., 2003).

Wilson et al. (2015), following the second approach, aligned Australian historical population and census data to align with the 2011 ABS geography. By updating data from 1986, 1991, and 1996 to the contemporary boundaries, the study ensured temporal consistency, enabling comparisons over time on a single, consistent set of boundaries. Similarly, a recent study in New Zealand, analysing changes in deprivation, addressed the historical gap in area-level socioeconomic data by converting older geographic data to match more recent boundaries (Deng et al., 2024). The researchers developed a time-series deprivation index for 1981, 1986 and 1991 by aligning census data from the earlier years to the 1991 census boundaries using a population-weighted conversion method. This method accounted for population variability within intersection zones between geographic boundaries and enhanced the accuracy and comparability of the data over time. Norman et al. (2016) aligned the 2001 census data to the 2011 Statistical Area 2 (SA2) boundaries, to examine the link between small area population changes and deprivation. By using the most current geography, the data is more relevant for planning, policymaking, and resource allocation. However, while this approach has demonstrated a good level of accuracy, it still has the potential for error (Blake et al., 2000; Norman et al., 2003).

Jione and Norman (2023) constructed custom boundaries (third approach) in Tonga to resolve inconsistencies such as overlapping census blocks and areas without defined boundaries. This facilitated analysis of non-communicable diseases in relation to area deprivation. While constructing new boundaries harmonised incompatible datasets there were limitations such as data quality issues and manually creating new geographies is time intensive.

While geo-referencing household data offers the most granular and flexible solution, the substantial investment required and the challenges of maintaining data confidentiality are key limitations (Blake et al., 2000; Coffee et al., 2016).

Despite the availability of methods to improve the use of census data in longitudinal studies, researchers frequently rely on data from a single census year to represent multiple years. For example, several Australian longitudinal studies examining neighbourhood socioeconomic factors in relation to range of health outcomes (e.g. body mass index, brain development, cardiometabolic risk) have used SEIFA data from one census year across their entire study period (Carroll et al., 2020; Keramat et al., 2021; Menigoz et al., 2018; Tanamas et al., 2014; Whittle et al., 2017). Longitudinal data is a valuable source of information in causal inference epidemiology (Frees, 2004). By monitoring changes in both socioeconomic exposures, such as neighbourhood disadvantage, and health and behavioural outcomes, longitudinal studies provide a stronger foundation for inferring causation (Diez Roux, 2001). However, relying on data captured at a single point in time assumes that the exposure remains static over the analysed period and may overlook evolving socioeconomic conditions over time. For instance, substantial population changes in Australia in recent decades, particularly in major cities, have led to growth in outer suburban areas and the transformation of inner and middle-city neighbourhoods through processes like gentrification, altering their social and economic composition (Atkinson et al., 2011; Coffee et al., 2016; Pegler et al., 2020; Randolph & Tice, 2014). These changes may be unaccounted for if using data from a single census year.

To accurately observe changes in socioeconomic factors over time, fine grained temporally and spatially consistent data are needed. The aim of this paper is to present a method that addresses the constraints of traditional census-based approaches to creating socioeconomic indexes by producing more frequent, geographically consistent data, facilitating longitudinal analysis of socioeconomic conditions at a small geographic scale. We illustrate the approach using the Australian SEIFA and share the resulting dataset of annual SEIFA data from 1996 to 2021 standardised to the 2021 SA1 boundaries available in the Figshare repository, https://doi.org/10.6084/m9.figshare.27936471.v1

Method

We aimed to create a time-series of annual SEIFA data from 1996 to 2021 standardised to the 2021 SA1 level. We chose to standardise to the 2021 SA1 boundaries for two reasons: it is the most recent census year, and 2021 SA1s are smaller than 1996 CDs therefore providing more refined data for analysis (61,845 SA1s in 2021 compared to 34,500 CDs in 1996) (Australian Bureau of Statistics, 1999, 2021b).

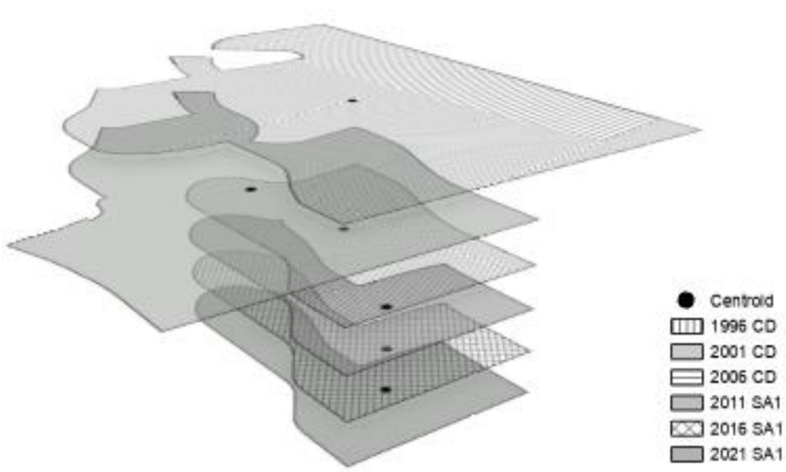
Digital boundaries and SEIFA data from census years 1996, 2001, 2006, 2011, 2016 and 2021 were downloaded from https://data.gov.au/home on 15 May 2024. This included CD boundaries for the years 1996, 2001 and 2006 and SA1 boundaries for the years 2011, 2016 and 2021.

The digital boundaries were imported to GIS software ArcGIS Pro 3.1 (Esri, 2024). The Geocentric Datum of Australia 1994 (GDA94) coordinate reference system was used for all files to ensure that spatial data aligned accurately across different census years.

In ArcGIS we first represented each CD or SA1 polygon as a centroid. The centroid represents the geographical centre of each area, creating a reference point for subsequent spatial analysis. To do this we used the ArcGIS 'Feature to Point' tool to generate geometric centroids for every CD/SA1 polygon, selecting the 'inside' option to ensure that each centroid was located within its corresponding polygon.

Next, we identified the closest CD/SA1 from previous census years (1996, 2001, 2006, 2011, and 2016) to the corresponding 2021 SA1 using the 'Spatial Join' function and 'closest' option.

Figure 2: Example of a selected CD/SA1 with centroids from each census year, illustrating the spatial join process across multiple census years.

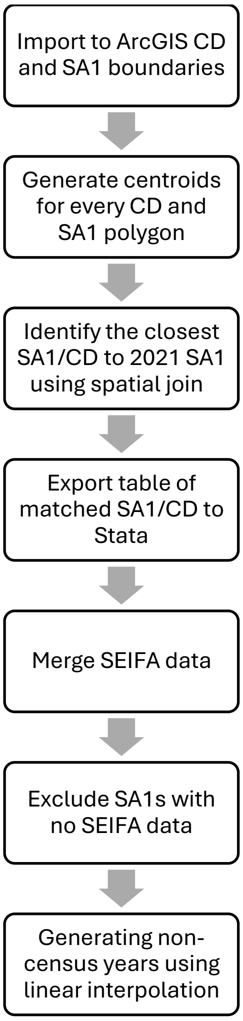


The resulting table of matched CDs/SA1s across multiple census years was exported into Stata MP version 18 (StataCorp, 2023).

SEIFA score, rank, percentile and decile for each of the four indexes (IRSAD, IRSD, IEO, IER) from 1996, 2001, 2006, 2011, 2016 and 2021 censuses were assigned to each point according to the CD/SA1 in which it occurred using the 'Merge' function in Stata. Note that 1996 did not have an IRSAD index (it included the Urban Index of Relative Socio-Economic Advantage and Rural Index of Relative Socio-Economic Advantage instead) so only IRSD, IEO IER values were included for 1996 (Australian Bureau of Statistics, 1998).

Data for each index for the non-census years was generated using linear interpolation. Deciles and percentiles were rounded to the nearest whole number to maintain consistency with how SEIFA is typically reported.

Figure 3: Workflow for Deriving Spatially Consistent Annual SEIFA Data using ArcGIS and Stata.



Validation Method

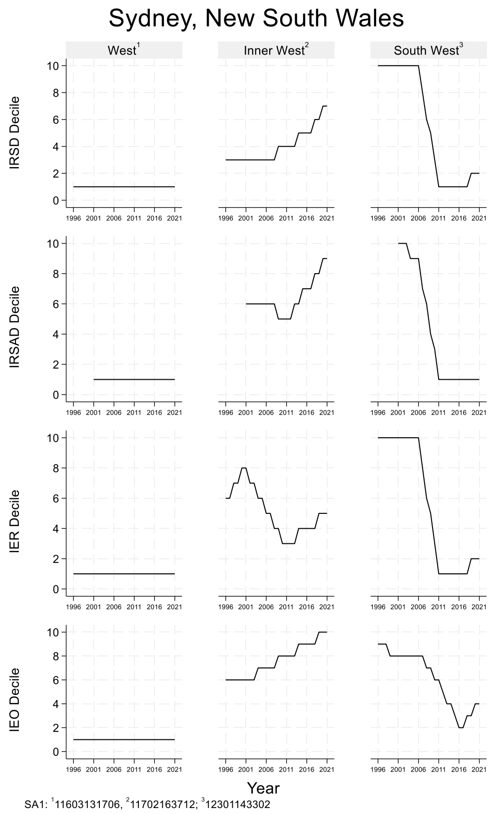
To validate the matching process of SA1s and CDs across census years, manual spot checks were conducted on five 2021 SA1s from each state, including at least one SA1 from a capital city, outer, and regional area. In all cases, the SA1s and CDs from previous years were found to be in the same geographic location, further confirming the validity and reliability of the matching process. To verify that the SEIFA data merged in Stata aligned with the original ABS data, the process was reversed on a sample of index scores for each census year and compared. No differences were found between the merged data and the original ABS data, confirming accuracy and consistency in the merging process.

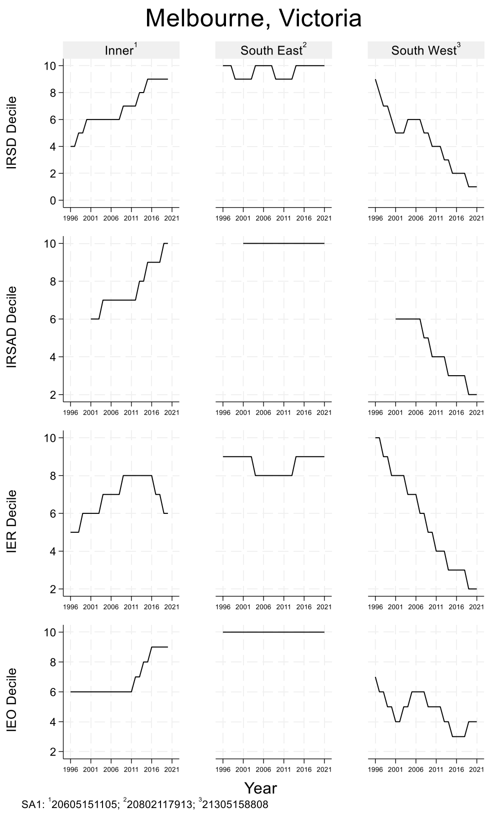
Results

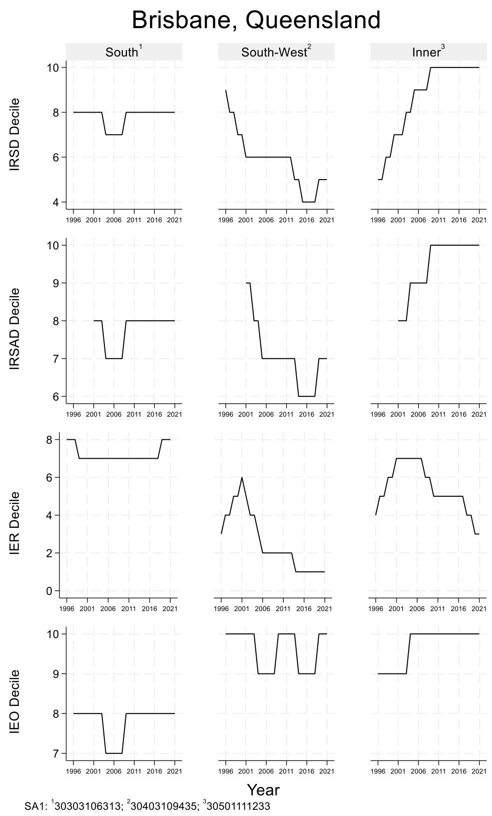
Our data includes a final sample of 59,421 SA1s with data for at least one SEIFA index. SA1s with no SEIFA data for any census year were excluded. The ABS does not generate SEIFA data for a small portion of CDs/SA1s based on 'exclusion rules' (Australian Bureau of Statistics, 2021a). Further information on the exclusion process and the number of excluded CDs and SA1s can be found in the accompanying dataset.

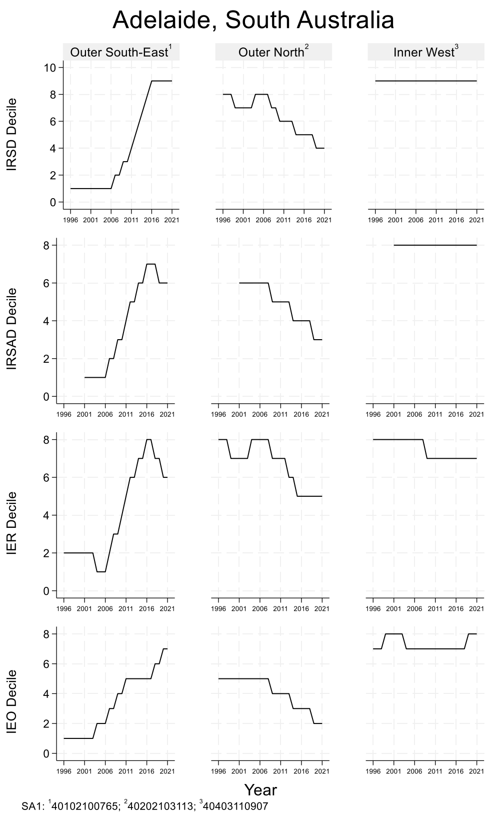
The following graphs demonstrate changes in socioeconomic conditions across a sample of SA1s in each state from 1996 to 2021. These graphs display areas that have experienced stability, increases, or decreases in the four indexes over this period.

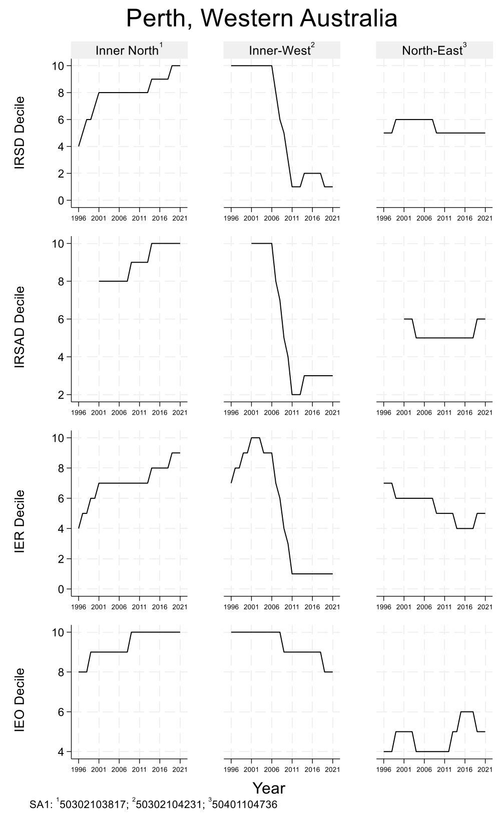
Figure 4: Changes in SEIFA Indexes 1996 to 2021 by Australian state.











Discussion

The approach outlined in this paper provides annual, spatially, and temporally consistent SEIFA data from 1996 to 2021. To our knowledge, this is the first time SEIFA have been produced annually at a small area level for a period spanning 25 years. Following the methodology proposed by Blake et al. (2000), and used in similar studies (Deng et al., 2024; Norman et al., 2016; Wilson et al., 2015), we have developed spatially consistent boundaries that ensure comparability over time by updating historic census boundaries to align with 2021 boundaries. To address data gaps in non-census years, we applied linear interpolation, a technique commonly used in similar studies, to estimate annual values (Weden et al., 2015). By generating consistent annual estimates, the interpolation may mitigate the limitations of relying solely on census years, as the lack of timely data can fail to capture short-term changes within the socioeconomic conditions.

National census data has long served as a primary source for area-level research on population demographics such as neighbourhood inequality and socioeconomic disadvantage. Although the census is a valuable tool, the presented graphs highlight potential limitations when using census data for longitudinal analysis. Relying on data captured at a single point in time assumes that the exposure does not change over the analysed period. While some areas have remained stable over time, others have had substantial increases or decreases in their SEIFA deciles.

These trends are supported by literature detailing the shifts in socioeconomic conditions in Australia over the past three decades. Inner and middle city suburbs have experienced gentrification and there has been a notable shift in disadvantage to outer suburbs (Atkinson et al., 2011; Pawson & Herath, 2015; Randolph & Tice, 2014). For example, Randolph and Tice (2014), found in Sydney, while the number of suburbs containing at least one highly disadvantaged area slightly declined, the number of suburbs with a high concentration of disadvantaged areas (where over 80% of CDs are highly disadvantaged) saw a substantial increase (Randolph & Tice, 2014). Therefore, using SEIFA indexes from a single census year as the primary exposure may not accurately reflect changes in socioeconomic factors over a multi-year period.

The strengths of this approach include the extensive timeframe which allows for the analysis of trends over a long period as well as the inclusion of four indexes that provide a comprehensive view of various socioeconomic factors, in small geographic areas. Furthermore, the method used to create the dataset follows validated methods outlined in other studies (Blake et al., 2000; Deng et al., 2024; Norman et al., 2016; Norman et al., 2003; Wilson et al., 2015). The method can be applied to generate data at various levels of ABS geography as well as census data from other countries.

However, it is important to note there may be limitations. Using SA1s, the smallest geographic area, may reduce accuracy. A study by Weden et al. (2015) found that while linear interpolation performed well at the county level, smaller geographic areas tended to produce larger errors. To account for this potential limitation, additional steps were taken to validate the matching process across census years and ensure validity and reliability (manual spot checks). Although we did not use a more complex approach (e.g. areal interpolation or weighting), spatially joining CD/SA1 centroids provides a straightforward and efficient alternative.

Conclusion

The method presented in this paper for creating annual SEIFA data at the 2021 SA1 level addresses key challenges associated with tracking area-level socioeconomic factors over time. By aggregating and standardising data across multiple years, this approach maintains consistency in geographic units, allowing for more accurate analysis of changing socioeconomic conditions. The proposed methodology reduces the potential limitations that often arise from changes in area-level boundaries over time. Consequently, this increases data quality in longitudinal analysis, improving the ability to monitor and understand temporal trends in socioeconomic factors and their impacts on populations.

Abbreviations

ABS	Australian Bureau of Statistics
ASGC	Australian Standard Geographical Classification
ASGS	Australian Statistical Geography Standard
CD	Census Collection District
GIS	Geographic Information Systems
IEO	Index of Education and Occupation
IER	Index of Economic Resources
IRSAD	Index of Relative Socio-Economic Advantage and Disadvantage
IRSD	Index of Relative Socioeconomic Disadvantage
SA1	Statistical Area 1
SA2	Statistical Area 2
SEIFA	Socio-Economic Indexes for Areas

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