Creating an interactive map visualising the geographic variations of the burden of diabetes to inform policymaking: An example from a cohort study in Tasmania, Australia

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Abstract

Objectives: To visualise the geographic variations of diabetes burden and identify areas where targeted interventions are needed.

Methods: Using diagnostic criteria supported by hospital codes, 51,324 people with diabetes were identified from a population-based dataset during 2004–2017 in Tasmania, Australia. An interactive map visualising geographic distribution of diabetes prevalence, mortality rates, and healthcare costs in people with diabetes was generated. The cluster and outlier analysis was performed based on statistical area level 2 (SA2) to identify areas with high (hot spot) and low (cold spot) diabetes burden.

Results: There were geographic variations in diabetes burden across Tasmania, with highest age-adjusted prevalence (6.1%), excess cost ($2627), and annual costs per person ($5982) in the West and Northwest. Among 98 SA2 areas, 16 hot spots and 25 cold spots for annual costs, and 10 hot spots and 10 cold spots for diabetes prevalence were identified ($p<0.05$). 15/16 (94%) and 6/10 (60%) hot spots identified were in the West and Northwest.

Conclusions: We have developed a method to graphically display important diabetes outcomes for different geographical areas.

Implications for Public Health: The method presented in our study could be applied to any other diseases, regions, and countries where appropriate data are available to identify areas where interventions are needed to improve diabetes outcomes.

Key words: diabetes, data linkage, geospatial mapping, prevalence, mortality, costs

What is already known about the topic?

- Spatial analyses have been used in a number of studies to investigate geographic variations in diseases affected by geographic factors, especially diabetes.
- Socioeconomic status may be a potential underlying factor for these variations.

What does the paper add to existing knowledge?

- Several geographical areas in Tasmania, Australia were identified with exceptionally high diabetes burden. In Tasmania, there is an important association between socioeconomic status and diabetes burden.
- Interactive maps are effective tools to visualise the geographic variations of the burden of diabetes, especially the economic burden.

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What are the implications?

- An interactive map allows easier comparison between geographical areas by consolidating a wealth of information onto a single platform to provide a comprehensive picture of the burden of diabetes. Mapping and spatial analyses can be used to identify and target areas with high diabetes burden to inform policy and practice, as well as enhance the community's awareness.

Introduction

Diabetes is a major public health challenge worldwide due to its increasing prevalence, high mortality rates and considerable healthcare costs required. In Australia, diabetes prevalence increased from 4.9% in 2017 to 5.3% in 2020.[1,2] It was also ranked as the seventh leading cause of death in Australia in 2020.[3] In terms of healthcare expenditure, $3.0 billion (2.3% total healthcare expenditure) was spent on diabetes in Australia in 2018.[4] As diabetes imposes an increasing burden on the healthcare system, identifying regions with higher burden is crucial to tailor interventions to reduce the burden of diabetes.

Spatial analyses have been used as effective tools in investigating communicable diseases. Recently, these methods have also been applied to non-communicable diseases associated with geographic factors, especially diabetes, and demonstrated their potential to inform policy and practice.[5] A recent systematic review has concluded that limited spatial studies on type 2 diabetes outcomes have been conducted around the world.[5] To the best of our knowledge, few studies utilising spatial analyses to investigate outcomes related to diabetes in Australia have been published. These studies typically focused on small regions,[6–8] used static maps that did not facilitate exploring information of small areas in detail,[6–12] and were not based on the Australian Bureau of Statistics (ABS) geographic main structures that facilitate the comparison with other statistical data published by the ABS.[9–13]

Tasmania is a rural island state in Australia with a population of 558,000 people living within a total area of 68,401 km^2.[2,14] Based on data from the 2016 census, only 4.6% people in Tasmania lived in the most advantaged areas (lowest across Australia) and 37% people lived in the most disadvantaged areas (highest across Australia).[15] In addition, the median age of the Tasmanian population is 42 years, older than the national figure (38 years).[14] As a result, the Tasmanian population experiences a large burden of chronic diseases, particularly diabetes. Using Tasmania as an example, our study aimed to use spatial analyses in combination with statistical analyses to.

1. Create an interactive map based on the ABS structures (statistical area [SA] level) to visualise the geographic variations of diabetes-related outcomes, including diabetes prevalence, total costs, annual costs, excess costs, and mortality rates in people with diabetes; and
2. Identify areas where targeted interventions should be implemented and investigate the association between diabetes burden and socioeconomic status.

Methods

Data sources

This retrospective matched cohort study used a deidentified dataset linked from two pathology and five administrative datasets, namely: Royal Hobart Hospital Pathology (RHHPATH), Hobart Pathology (Diagnostic Services Pty Ltd [DSPL]), Tasmanian Public Hospital Admitted Patient Episodes (AP), Tasmanian Public Hospital Emergency Department Presentations (ED), Tasmanian Death Register and Tasmanian Coded Cause of Death (DEATH), Tasmanian Cancer Registry (TCR) and Australia and New Zealand Dialysis and Transplant Registry (ANZDATA). Being developed to investigate the burden of chronic kidney disease in Tasmania, the dataset included all Tasmanians who had at least one serum creatinine test recoded in RHHPATH/DSPL datasets during the period from 1/1/2004 to 31/12/2017. Information regarding variables extracted from each component dataset has been described in detail elsewhere.[16,17] Based on data from 2013–2017, it was estimated that this dataset included 87% (355,622/409,729) of the Tasmanian adult population.[17]

Data linkage was performed by the Tasmanian Data Linkage Unit. The linkage process has been described in detail previously.[17]

Participants

People with diabetes were identified from the linked dataset based on either diabetes diagnostic criteria[18] or diagnostic codes.[19,20] They were included if they met at least one of the following criteria between 01/01/2004 and 31/12/2017.

1. ≥1 HbA1c test ≥ 48 mmol/mol (6.5%).
2. ≥1 fasting plasma glucose (FPG) tests ≥ 7.0 mmol/l (126 mg/dl).
3. ≥1 random plasma glucose (RPG) test ≥ 11.1 mmol/l (200 mg/dl).
4. International Statistical Classification of Diseases and Related Health problems 10th Revision Australian Modification (ICD-10-AM) diagnosis code (primary or other) in the E10-E14 ranges recorded in either AP or ED.
5. A primary or underlying ICD-10-AM coded cause of death in the E10-E14 ranges recorded in DEATH.

These methods have been used in previously published studies based on the same cohort.[16,21,22]

To calculate the excess costs (or incremental costs)—he difference between mean costs in people with diabetes and those without[16]—each person with diabetes was matched with two non-diabetes counterparts identified from the remaining individuals in the dataset, using propensity score matching. Matching was performed based on age (decile), gender, statistical area level 4 (SA4) of residence, year of first serum creatinine test, and follow-up time (time interval [years] between the last and the first record). Participants were censored at the time of their last record in the dataset. Because of the availability of data from the AP datasets, the final analysis was based on data from 01/01/2007 to 31/12/2017 and included 51,324 people with diabetes and 102,648 people without diabetes (Appendix 1).

Main outcomes

We investigated five outcomes related to diabetes: prevalence, mortality rates, total costs (per year), annual costs, and excess costs per diabetes person.

Diabetes prevalence was calculated from the number of people with diabetes in 2017 divided by the total estimated resident population in each area in 2017.[23] All-cause mortality rates in 2017 were calculated from the number of deaths in people with diabetes (extracted from

the cause of death dataset) divided by the total diabetes population in each area in 2017 (presented as the total amount of time people are at risk [person years-PY]). To enable comparison between areas, prevalence and mortality rates were age-standardised using the Australian population in 2017.[23]

The direct costs in people with and without diabetes were estimated from the healthcare system perspective and took into account three cost components available in our dataset: hospital admission, ED visits, and pathology costs. Information regarding cost calculation has been described in detail elsewhere.[16] In summary, hospital and ED visit costs were estimated by multiplying the price weight assigned for each hospital episode (based on Australian Refined Diagnosis-Related Groups version 6,7) or each ED presentation (based on Urgency-Related Groups version 1.4) by the National Efficient Price (sourced from the Independent Hospital Pricing Authority [IHPA]).[24–29] Pathology costs were estimated by multiplying each pathology test by its unit costs, sourced from the Medicare Benefits Schedule.[16,30] The costs estimated were then inflated to 2020 Australian dollars based on the Government Final Consumption Expenditure on hospitals and nursing homes index.[16,31,32] Total costs per year, annual costs, and the excess cost per diabetes person using data from 2007 to 2017 in each area were calculated.

Statistical methods

Using packages Leaflet and Shiny in R version 4.2.1, we created a web-based interactive map visualising diabetes burden across Tasmania. The map was based on SA levels (the main ABS geographic structures) designed for the consistency in geography to facilitate data comparing in different periods. They were designed using a list of criteria but in general, SA2 represents a suburb (or a group of suburbs), SA3 is built from SA2s with similar regional characteristics, and SA4 is the largest sub-state regions built from SA3s.[33] Based on the Australian Statistical Geography Standard [ASGS] 2011,[34] Tasmania comprised four SA4, namely: Hobart, Launceston and North East, South East, and West and Northwest. These SA4 were further subdivided into 15 SA3. Additionally, these SA3 were subsequently categorised into 98 SA2. The average population size was 130,538 people for SA4; 34,810 people for SA3 and 5,328 people for SA2, respectively.

Because our interactive map targeted both policymakers and the community, crude prevalence and mortality rates were presented with clear explanations of how we calculated these outcomes, supported by specific numerators/denominators in each area. Healthcare costs were presented as aggregated costs and separate costs (hospital, ED visit and pathology). We estimated the arithmetic mean of costs (the average of sum of all values) because it is the relevant measure required for accurately obtaining the total expenditure, rather than the geometric mean (the average of product of all values, e.g., mean costs calculated by log transform).[35,36]

To identify areas with high (hot spot) and low (cold spot) diabetes burden, as well as identify spatial outliers, the cluster and outlier analysis (Anselin Local Moran's I) was performed based on SA2 for all diabetes outcomes. This method calculates a local Moran's I value, a z-score, and a pseudo p-value for each area in the dataset while considering each area in relation to its neighbours.[37,38] A significant and positive z-score determines that the targeted area and its neighbours have similar values of interest (either high–high [hot spot] or low–low [cold spot]). Whereas in contrast, a significant and negative z-score determines that either the targeted area has higher or lower values than its neighbours (spatial outliers: high-low or low-high).[37] The pseudo p-value was calculated by comparing the observed local Moran's I value to a distribution of local Moran's I values generated by randomly rearranging the neighbourhood values around each targeted area (permutation). Results with 95% confidence intervals or higher from a two-tailed distribution were considered statistically significant.

Because this method (like many other spatial cluster analyses) is based on neighbourhood relationships, choosing a conceptualisation that properly reflects the spatial relationship between areas is crucial for accurate results. Due to the sophisticated geographic characteristics of Tasmania with some isolated islands, an optimised cluster and outlier analysis was conducted for annual costs and excess costs per diabetes person. This tool uses a set of analyses to select the scales of analysis (the distance for considering neighbourhood relationship) to ensure optimal results.[39] To deal with the non-normal distribution of age-standardised diabetes prevalence, mortality rates, and total costs per area, cluster and outlier analysis using "K nearest neighbours" conceptualisation with the default value (8) for number of neighbours was chosen. Although choosing the "K nearest neighbours" conceptualisation might cause a significant change in the scale of analysis when the polygon sizes vary greatly,[39] we decided to choose this method for these outcomes because this method was recommended for skewed data by ensuring that each targeted SA2 area has at least eight neighbours.[40] In circumstances where determining the scale of analysis is less important than fixing the number of neighbours, using the K nearest neighbours method would be suitable.[40] SA2 areas without population (Mount Wellington, Wilderness-East, and Wilderness West) were not considered in the spatial analyses. All spatial analyses were performed using ArcGIS Pro version 3.0 (ESRI).

The Index of Relative Socio-economic Advantage and Disadvantage (IRSAD) was used to reflect participants' socioeconomic status. Based on a list of variables describing both socioeconomic advantage and disadvantage measures, this index returns a score and ranking across Australia for each area of the ABS main structures.[41] To investigate the association of hot/cold spots and the IRSAD quintile, Fisher's exact test was conducted using Stata version 17.0 (StataCorp LLC). The adjusted Pearson residuals were also calculated to guide the identification of sub-groups that contributed the most to the difference, if applicable. As the generally accepted rule, the adjusted Pearson residuals smaller to -2 or greater to 2 indicate sub-groups that significantly contribute to the results.[42]

Results

Characteristics of the study cohort are presented in Appendix 2. Matched variables including age, sex, and follow-up time were comparable between people with and without diabetes. In terms of IRSAD quintile, compared to people without diabetes, there was a higher proportion of people with diabetes living in the most disadvantaged areas (52% versus (vs) 45%) and a lower proportion of people with diabetes living in the most advantaged areas (2.8% vs 4.0%). There was also a higher proportion of people with diabetes who died during the study period (20% vs 13%).

The interactive map (link) showed three options of statistical area levels (SA4, SA3, SA2) and five options of diabetes-related outcomes

(crude prevalence, total costs per year, annual costs per diabetes person, excess costs per diabetes person, and crude mortality rates in people with diabetes) and results of the cluster and outlier analysis (for SA2 only). Based on the options that the user selects, the map will present data accordingly. The detailed information related to each area can be obtained by hovering the pointer over it.

In people with diabetes in Tasmania, the age-standardised all-cause mortality rate was 23.6/1,000 PY. The age-standardised diabetes prevalence and healthcare costs estimated for Tasmania (without estimates for smaller geographical areas) have been published previously are as follows: age-standardised diabetes prevalence 5.7%; annual costs per diabetes person $5,209 (95% CI 5,112-5,317); total costs for Tasmania per year $267 million; excess costs per diabetes person $2,427 (2,322-2,543).[16]

Our maps demonstrated the geographic variations in diabetes burden across Tasmania (**Figure 1**, Appendix 3-7). Based on SA2, the age-standardised diabetes prevalence ranged from 3.2% to 10.1% (>threefold) (Appendix 8); annual costs ranged from $3088 to $7487 (>twofold); total costs ranged from $0.8 million to $12.4 million (>15-fold); excess costs ranged from $280 to $3717 (>13-fold); and age-standardised mortality rates ranged from 0 to 86.3/1,000 PY (Appendix 9). Based on SA4, the burden of diabetes in Tasmania was largest in the West and Northwest and lowest in the Southeast and Hobart, except for total costs (largest in the Hobart region because it is the most densely populated SA4 region) and mortality rates (largest in the city of Launceston and the North-East).

The cluster and outlier analysis identified 16 hot spots (high-high), 25 cold spots (low-low), 16 high-low, and six low-high outliers for annual costs per diabetes person (**Figure 2**). Additionally, 10 hot spots, 10 cold spots, and two low-high outliers for age-standardised diabetes prevalence were identified (**Figure 3**). However, there were no significant clusters as well as outliers for the remaining outcomes. Interestingly, there was overlap between age-standardised diabetes prevalence and annual costs per diabetes person's hot spots.

Compared to the map of IRSAD quintile in Australia, our maps of diabetes burden indicated similar distribution of hot spots and IRSAD level 1 areas (most disadvantaged) as well as cold spots and IRSAD level 5 areas (most advantaged) (Appendix 10).

The results of Fisher's exact test demonstrated an association between hot/cold spots of annual costs/age-standardised diabetes prevalence and IRSAD quintile (p=0.001 and p<0.001, respectively). The adjusted Pearson residuals suggested that there were more hot spots of annual costs/age-standardised diabetes prevalence in the IRSAD quintile 1 (most disadvantaged-adjusted Pearson residuals=2.523 and 2.258, respectively); more cold spots of annual costs in the IRSAD quintile 4 and 5 (most advantaged-adjusted Pearson residuals=3.317 and 2.945, respectively); more cold spots of age-standardised diabetes prevalence in the IRSAD quintile 5 (adjusted Pearson residuals=5.131) than would be expected by chance.

Discussion

Our interactive map was based on the ABS geographical areas, which aligns with other statistics published by the ABS (e.g., Socio-Economic Indexes for Areas [SEIFA], number of Indigenous people by Indigenous geographical structure) to ensure a more comprehensive understanding and thorough interpretation of the findings. Moreover, the use of an interactive map allows easier comparison between areas, by consolidating a wealth of information onto a single platform to provide a comprehensive picture of the burden of diabetes. Within our interactive map, five diabetes outcomes and two cluster and outlier analyses were presented, along with data regarding methodology for outcome calculation.

Additionally, our study set a pioneering example of displaying healthcare cost data through an interactive map. Healthcare cost data can be investigated using different approaches, resulting in different metrics such as total costs, annual costs, and excess costs, which reflect different aspects of diabetes burden. Furthermore, healthcare

Figure 1: The web-based interactive map of the burden of diabetes in Tasmania. (link: https://ngandinh.shinyapps.io/DM_Map/?_ga=2.256464910.42312771.1654066291-1555120292.1653892286).

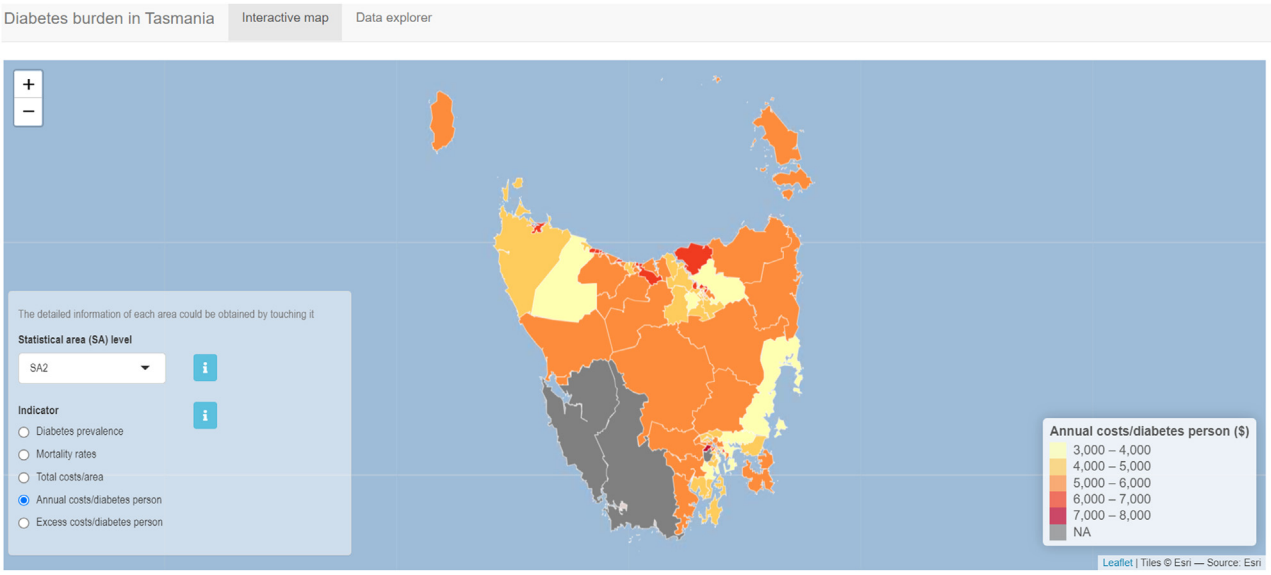
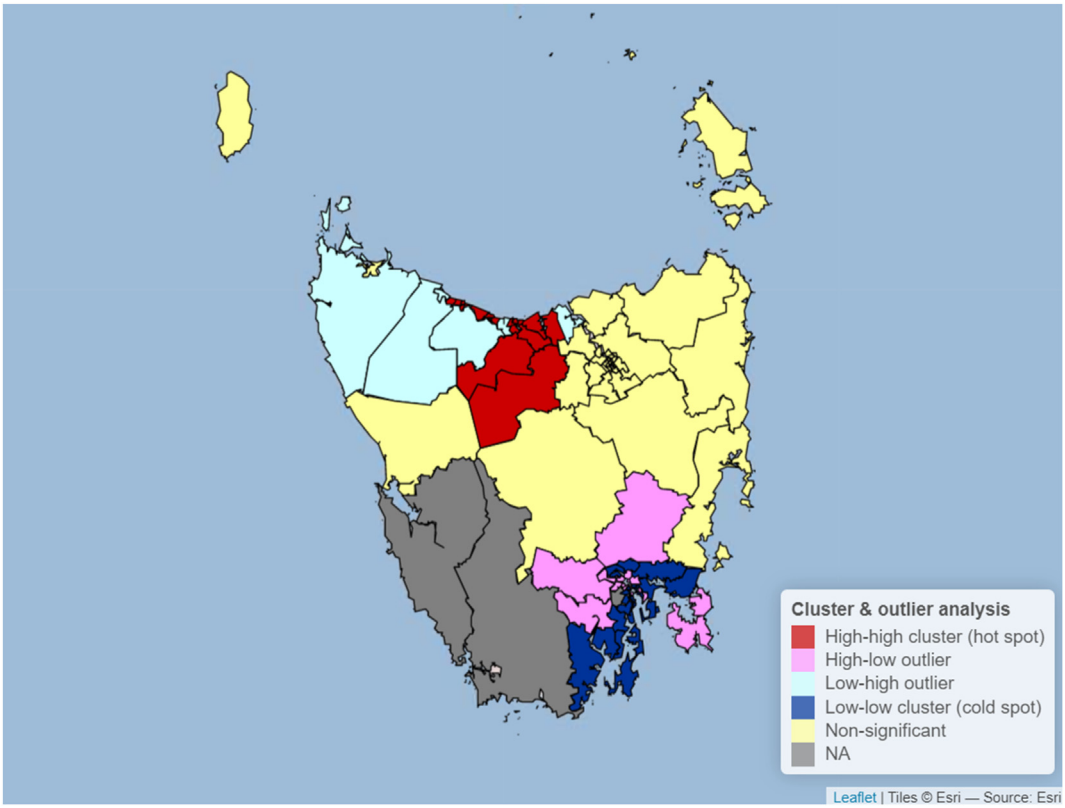


Figure 2: Optimised cluster and outlier analysis for annual costs per diabetes person (by statistical area level 2). High-high cluster: Area with high value of interest surrounded by neighbours with high values (hot spot). High-low outlier: Area with high value of interest surrounded by neighbours with low values. Low-high outlier: Area with low value of interest surrounded by neighbours with high values. Low-low cluster: Area with low value of interest surrounded by neighbours with low values (cold spot). NA: Non-applicable, areas without population.



costs include multiple components, which reflect different healthcare services required to ensure the total health and wellbeing of patients, especially in the case of diabetes. Therefore, presenting healthcare cost data in an interactive map allows the visualisation of these data and facilitates the comparison and interpretation of results.

Our results indicated the heterogeneity in diabetes burden in Tasmania. The findings were meaningful specifically for future planning and resource allocation in Tasmania. However, we acknowledge the potential of "victim blaming", when presenting healthcare costs at the SA2 level allows the identification of communities that are causing the larger economic burden. Our map also illustrated the similar distribution of hot spots and the most disadvantaged areas, as well as cold spots and the most advantaged areas. These findings were further supported by results from statistical analyses that showed a significant association between socioeconomic status and diabetes burden.

We suggest that the inequalities in diabetes health outcomes in different areas might be explained by the disparities in socioeconomic status, as well as the differences in geographical and environmental factors. However, further research is needed to accurately identify the factors influencing the health inequalities for designing proper intervention programs.

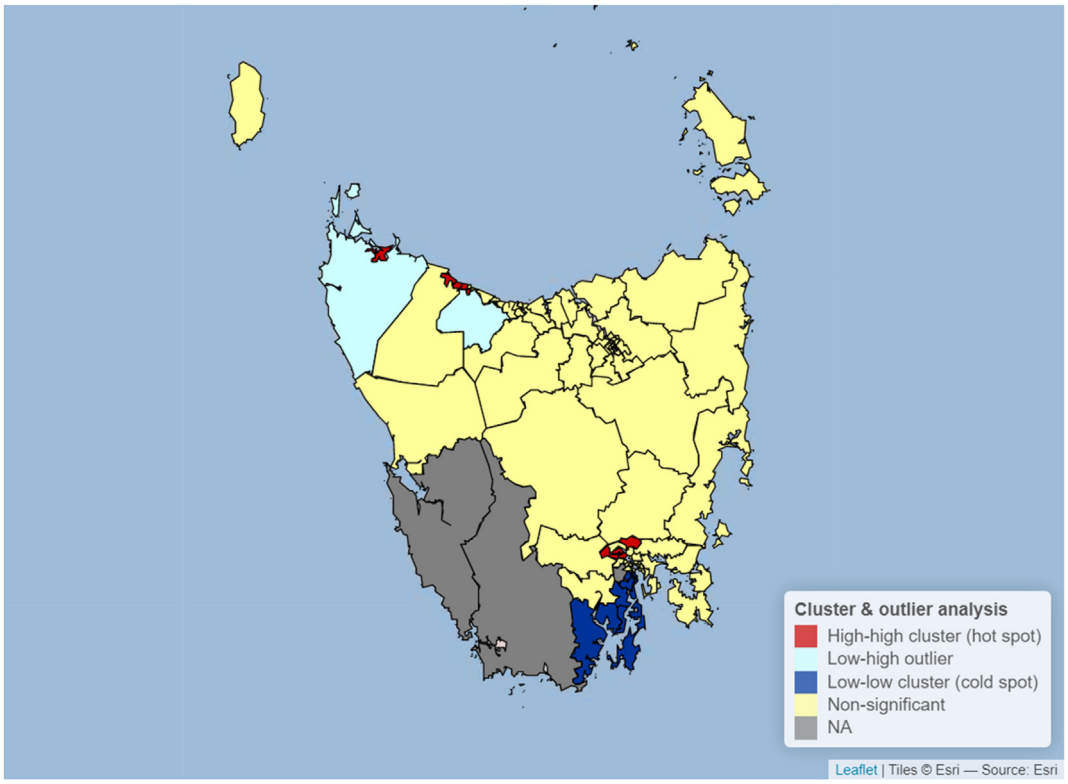
The fact that we found greatest diabetes burden in areas with lowest socioeconomic status raises some important concerns, as it may have revealed some inequities in healthcare provision that should be addressed. In addition, it has been suggested that an area might be affected by the social, economic, and cultural circumstances of the surrounding areas.[43] As a result, it is very likely that the concentration of hot spots with low socioeconomic status may worsen poor health behaviours as well as limit access to resources in areas within the clusters, leading to even higher diabetes burden in the future.[43,44]

Our maps that showed some overlap between significant hot spots of diabetes prevalence and hot spots of annual costs per diabetes person may have highlighted deficiencies with diabetes management in these areas. That could be again due to socioeconomic status and geographical factors. However, other concerns regarding how to allocate resources more efficiently and how to implement interventions more effectively are also worth considering.

Diabetes prevalence in Tasmania estimated from our study (5.7%) was similar to results from the Australian health survey 2017 (5.4%).[1,16] However, the age-standardised all-cause mortality rate in Tasmania estimated in our study (23.6/1,000 PY) was higher than the national figures (type 1: 16.2/1,000 PY; type 2: 8.6/1,000 PY).[45] This might reflect the worse prognosis of diabetes in the Tasmanian population.

Other Australian studies that have focused on different jurisdictions have also reported geographic variations in diabetes-related outcomes and highlighted the association between socioeconomic status and these outcomes through both visualisation and statistical

Figure 3: Cluster and outlier analysis for age-standardised diabetes prevalence in 2017 in Tasmania (by statistical area level 2). High-high cluster: Area with high value of interest surrounded by neighbours with high values (hot spot). Low-high outlier: Area with low value of interest surrounded by neighbours with high values. Low-low cluster: Area with low value of interest surrounded by neighbours with low values (cold spot). NA: Non-applicable, areas without population.



analyses. Based on SA1 level, two studies performed in 2017 and 2020 found the heterogeneity in type 2 diabetes risk score and diabetes prevalence in different areas in West Adelaide, South Australia.[6,7] They also reported an inverse relationship between diabetes risk score/diabetes prevalence and socioeconomic status.[6,7] In addition, one study conducted in 2014 in Sydney, Australia, found geographic variations of the odds of having diabetes, with socioeconomic status explaining 26% of the variations.[10] Despite using different geographic structures, our prevalence results were similar to the Diabetes Australia map based on local government areas, with high-prevalence areas in the West and Northwest of Tasmania and low-prevalence areas in Southern Tasmania.[13]

Our study used a population-based dataset that is representative of the Tasmanian population, and indeed captures 87% of the Tasmanian adult population. In addition, the linked dataset with seven components covering different information allowed us to not only accurately identify people with diabetes for estimating diabetes prevalence (using both hospital diagnostic codes and blood glucose tests results) but also investigate a wide range of other diabetes related outcomes. Furthermore, the availability of information related to the ABS main structures enabled us to visualise our results by several geographical levels to provide both an overall and detailed description of the outcomes. However, our study has some limitations that should be acknowledged. First, due to confidentiality concerns, smaller geographical structures (SA1 and mesh block) were not available in our dataset. Second, because of the data provision method for our pathology datasets, only pathology tests performed on the same day with the serum creatinine test were released. As a result, pathology costs may be underestimated in our study. Other direct costs that are relevant to diabetes, including medication costs and general practitioner visit costs were not included due to a lack of Medicare Benefits Schedule and Pharmaceutical Benefits Scheme data. However, hospital costs are the main costs driver in diabetes,[46,47] and our dataset has captured these costs thoroughly. Another limitation was related to migration data (i.e. whether the participant moved to another jurisdiction), as these data were also not available in our dataset. This may have led to inappropriately censoring participants when they did not used health services for a long period of time, but still resided in Tasmania. However, as we included pathology datasets, we believe that the risk is low. Because we largely used administrative datasets, we were not able to identify when exactly participants were first diagnosed with diabetes. As a result, we may have included some participants with prediabetes during some duration of the study. Finally, we were also not able to report outcomes separately for type 1 and type 2 diabetes due to this not being well reported in the datasets.

Compelling evidence is needed to support proper resource allocation and effective policy making. With Tasmania, a state of Australia as an example, our study used spatial epidemiology in combination with statistical analyses to visualise the geographic variations of diabetes burden and identify areas where targeted interventions are needed. Our map could help to establish as well as consolidate hypotheses of diabetes risk factors. Based on the spots with high and low diabetes burden identified, further investigations are needed to determine

potential geographical and environmental risk factors that led to the different distribution in diabetes outcomes, in order to tailor effective interventions to reduce the burden of diabetes.

According to the 2016 census data, a substantial population of Aboriginal and Torres Strait Islander individuals lived in Tasmania-West Coast (3,932 people) and Central Coast-Devonport (3,079 people).[48] These Indigenous areas overlapped the SA4 West and Northwest which had the largest diabetes prevalence, annual costs, and excess costs per diabetes person. Although this study focused on the entire Tasmanian community, rather than exclusively on the Indigenous population, these findings might reflect the health inequities among Indigenous people. Therefore, future studies specifically focus on Indigenous people are needed to understand the situation in Tasmania for timely actions, to contribute to reducing Indigenous health inequities.

In this study, we have created a web-based interactive map visualising the inequalities associated to diabetes outcomes in Tasmania. We have identified areas with high and low diabetes burden, and also demonstrated the association between socioeconomic status and diabetes burden, using visual aid as well as statistical analyses. This study provides clear evidence for policy makers with regard to the level of need for services in different locations. The method described in our study may be applied to any other diseases, regions, and countries where appropriate data are available to identify areas where interventions are urgently needed to inform policy and practice regarding prioritising resource allocation, as well as enhance community' and politician awareness of the burden of diabetes in their area.

Author Contributions

Concept and design: Dinh, de Graaff, Campbell, Palmer.

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Analysis and interpretation of data: Dinh, Saunder, Kitsos.

Drafting of the manuscript: Dinh, de Graaff, Campbell, Jose, Burgess, Saunder, Kitsos, Wells, Palmer.

Statistical analysis: Dinh, Saunder, Kitsos.

Provision of study materials or patients: Jose.

Obtaining funding: Dinh, de Graaff, Campbell, Jose, Palmer.

Administrative, technical, or logistic support: Jose, Burgess, Saunder, Kitsos, Wells.

Supervision: de Graaff, Campbell, Burgess, Wells, Palmer.

Data availability statement

Due to ethical and privacy concerns, the data from which the findings of this study were generated cannot be made openly available.

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Ethical statement

Ethical approval with waiver of consent was granted by the Tasmanian Health and Medical Human Research Ethics Committee (reference number H0018548).

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Conflicts of interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: MJ is a member of the Australia and New Zealand Dialysis and Transplant Registry (ANZDATA).

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Appendix A Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.anzjph.2023.100109.