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## Perils of place: identifying hotspots of health inequalities

Methodological supplement

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### 1 How we define hotspots

*Perils of place* analyses geographic variation in potentially preventable hospitalisations across Victoria and Queensland and identifies 63 priority places – small geographic areas in need of special attention. This section explains how we define hotspots and provides an overview of the data our analysis was built on.

We first detail the analysis for Victoria; Chapter 5 details the same analysis for Queensland.

#### **1.1 Introduction to spatial analysis**

"Hotspots" are small areas with relatively high incidence or rates of a variable of interest, in comparison to their surroundings. In *Perils of place* small area rates of potentially preventable hospitalisations are compared within states.

Hotspots are commonly identified using spatial analytical approaches. For example, Local Indicators of Spatial Association (LISA) are statistics for identifying patterns in the spatial arrangement of a variable. LISA statistics identify the local association between each area's rate and its neighbours' rates, up to a specified distance. LISA statistics are used to identify statistically significant clusters of high or low values (e.g. a group of neighbouring areas with high rates) as well as outliers (e.g. an area with a high rate relative to its low rate neighbours).<sup>1</sup>

Point data is ideal for spatial analysis as it identifies the exact location of each incident. Many points enable a more precise

estimation of the density of risk across a broader area (rather than just the total number of incidents within a given area).<sup>2</sup>

However, point data is not available for analysis of disease prevalence or hospitalisations. Point data would breach privacy by effectively identifying the patients concerned. Estimation of the location and probability of potentially preventable hospitalisations occurring across a Primary Health Network or state therefore relies on small-area analysis.

*Perils of place* analyses potentially preventable hospitalisations at postcode and SA2 level. Smaller spatial units exist, but these are the smallest units that are more widely available.

Applying spatial analytical approaches such as LISA to small area data identifies clusters of high rate areas – in urban areas, often 10 suburbs or more, and in rural areas potentially large portions of the state.

LISA statistics point to five regions of Victoria where potentially preventable hospitalisations have tended to cluster. The results of this analysis are presented in Appendix A.

However *Perils of place* introduces a new method for identification of small area hotspots that avoids this aggregation, enabling

<sup>&</sup>lt;sup>2</sup> Kernel density estimation (KDE) is the typical approach for predicting risk across an area from point data. KDE takes a finite sample of data points and makes inferences about the underlying probability density function (risk) everywhere, including where no data are observed.

<sup>&</sup>lt;sup>1</sup> Anselin (1995)

prioritisation of smaller areas for place-based health interventions given the scale of data available.

#### 1.2 What defines a hotspot?

We use five principles in identifying candidate 'hotspot' areas. These principles aim to identify places that have real and actionable health inequalities:

- Preventable or reducible: we focus on health outcomes that we can do something about (potentially preventable hospitalisations, see Section 1.4).
- 'Hot enough' (evidence of substantial disparity): The area must have a sufficiently high rate of one or more potentially preventable conditions, relative to an appropriate benchmark, to warrant intervention. We use the annual state-wide rate as our benchmark. We take a rate multiple of 1.5 times the state rate as the minimum 'heat' threshold of interest (i.e. an area must have a rate at least 50 per cent above the state average to be considered a candidate for intervention).<sup>3</sup>
- Persistently hot: A good candidate area should be persistently hot (rather than intermittently) to be worth allocating resources. High rates can be driven by chance so enduring disparities should be prioritised. We take a minimum persistence threshold of three years.

Areas that meet these first three conditions have a real and potentially actionable problem; however two further conditions make a hotspot more amenable to action:

- Likely to stay hot (predictable): To invest in an intervention today, we need to be reasonably sure the area will still be a hotspot in the future, when that intervention takes effect. Prediction is related to persistence, but it is forward-looking. We can only assess areas with the information we have today, so we need to be able to accurately predict future hotspots based on the characteristics of each area that we know today. We expect it to take at least 3-5 years for an intervention to be developed, rolled-out and begin to take effect.
- High impact: Hotspots must have a big enough health and/or financial impact to warrant action. The potential impact of taking action in a hotspot depends on several factors: absolute numbers of individuals affected, severity of the condition, efficiency gains through targeting high concentrations of individuals at risk, and equity gains through addressing entrenched place-based problems. These must all be balanced against the costs involved before grounds for intervention can be established.

#### 1.3 The Victorian data set

Our Victorian analysis is built on the Victorian Admitted Episodes Dataset, a data collection comprising all patient admissions at all Victorian public and private hospitals, compiled by the Department of Health & Human Services (DHHS).

Ten years of admissions data (2004-05 to 2013-14) was provided

<sup>&</sup>lt;sup>3</sup> Note the 'rate multiple' we calculate for each area is effectively a 'location quotient', signifying how concentrated a particular potentially preventable condition is for a specific area compared to the state as a whole.

by DHHS Victorian Data Linkages with information on patient diagnosis, postcode of residence, age-group (15 years) and sex.

The dataset included a linkage identifier to enable identification of readmissions. Very small postcodes (less than 300 people) were suppressed in the data and therefore unavailable to us.

#### 1.4 Potentially preventable hospitalisations

Our definition of 'potentially preventable' hospitalisations is drawn from the Council of Australian Governments' National Healthcare Agreement<sup>4</sup>. The National Healthcare Agreement identifies 22 categories of Ambulatory Care Sensitive Conditions (ACSCs).

Importantly, we would not expect 100 per cent of ACSC hospitalisations to be preventable. These categories instead represent a classification of conditions that can be (and generally are) managed in an ambulatory care setting (i.e. outside of hospital).

The risk of hospitalisation for ACSCs may be reduced if the condition is treated and/or managed appropriately in the community (through self-management and/or primary care).

We extracted all ACSC hospitalisations based on the ICD-10-AM 7th edition codes that define these conditions.<sup>5</sup> We generated admission counts by postcode, year, age-group and sex for each ACSC condition (separately) as well as a combined measure of

<sup>4</sup> Council of Australian Governments (COAG) (2015) <sup>5</sup> Ibid. any chronic ACSC.<sup>6</sup> These counts were then used in the calculation of age-sex adjusted rates.

#### 1.5 Calculating rates

We calculated rates of potentially preventable hospitalisations by postcode and year. We adjusted all rates to account for the agesex profile of the postcode, using ABS Estimated Resident Population data purchased for Postal Areas.

Crude rates were calculated as the count of ACSC hospitalisations (by age-group and sex for each postcode, for a particular ACSC and year) divided by the estimated resident population in that age-group and sex, in each postcode, for a particular year.

Expected hospitalisations (by age-group and sex for each postcode, for a particular ACSC and year) were calculated as the crude rate multiplied by the standard population (the Victorian population by age-sex category, by year). Expected counts were then summed (by postcode for each ACSC and year), divided by the total Victorian population in each year, and multiplied by 100,000 to give the age-sex adjusted rate per 100,000 population (by postcode, year and ACSC).

To understand the relative severity of postcodes' ACSC rates and to enable comparison between diseases, we express age-sex adjusted rates as 'rate multiples': the age-sex adjusted rate divided by the state average ACSC rate. An area with a rate

<sup>&</sup>lt;sup>6</sup> The chronic ACSC measure combined all ACSC admissions for angina, asthma, CCF, COPD, diabetes and hypertension.

multiple of 1 has the same ACSC rate as state average while an area with a rate multiple of 2 has an ACSC rate twice the state average.

Across all postcodes, ACSCs and years, rate multiples ranged between zero and over 10x the state average. Figure 1 shows the distribution of rate multiples across postcodes. Many ACSCs are rare, so there are a large number of postcodes with zero hospitalisations for those conditions in any given year. For rare ACSCs a rate multiple of 1 (the state average for that ACSC) will actually represent very few hospitalisations. Given this, we exclude rare ACSCs in later analyses (see the following section detailing exclusions).

When rate multiples are averaged over a decade, 70 per cent of places have a rate multiple between 0.5x and 1.5x the state average.

There is substantial variation in rates year-to-year within some postcodes too. Figure 2 shows that this variation is largely driven by small population size and/or a low disease count (few hospitalisations). Figure 1: Postcode rates distributed around the state average, for a single year (top) and as a 10-year average (bottom)

Frequency count of postcodes (all diseases, all years) by rate multiple 50000



Notes: There are a large number of postcodes with zero hospitalisations for rare ACSCs. Given this we chose to exclude some of the rarer ACSCs from later analyses (see Section 1.6 on Exclusions).

Source: Grattan Institute analysis of VAED

Figure 2: Rate variability year-to-year is particularly high in small postcodes and those with a low number of hospitalisations Interquartile range of rate multiples over a decade (by postcode and disease)



Notes: x-axis for postcode population (top chart) is cut-off at 10,000 and x-axis for average hospitalisations (bottom chart) is cut-off at 100 to improve readability. Postcode population peaks at 90,000 and average number of hospitalisations peaks at 925. Source: Grattan Institute analysis of VAED

#### 1.6 Exclusions

We applied a minimum size threshold to both our rate numerator (admissions) and denominator (population) because we found extreme rates among low-volume diseases and among low-population postcodes. Just one or a few hospitalisations can produce an extreme ACSC rate for a postcode when a disease is generally low incidence and/or the postcode has a very small population.

Postcodes vary greatly in size, between zero and over 90,000 people. We excluded postcodes with a population of less than 1000 people (Figure 3) and then excluded low-volume diseases based on an average count of hospitalisations of less than 10 across remaining postcodes (Figure 4).

These exclusions allowed us to make fair comparisons across different ACSCs. This left us with 459 Victorian postcodes and 10 diseases (9 ACSCs and our combined chronic measure) in which to identify potential hotspots.

After exclusions were applied, 70 per cent of areas in a given year had a rate between 0.5x and 1.5x the state average, with 15 per cent of areas distributed above and below these thresholds.

## Figure 3: Very small postcodes are excluded because just one or a few admissions can drive high rates

Rate multiple by postcode (all years, all diseases)



Notes: X-axis cut off at 10 (10,000 population) to improve readability. Postcode population peaks at 90,000. The most extreme rate multiples represent only one hospitalisation but in a very small postcode. Source: Grattan Institute analysis of VAED **Figure 4: Low hospitalisation incidence drives high rates in some postcodes so low-volume ACSCs are also excluded** Rate multiple at 98<sup>th</sup> percentile, by disease



Source: Grattan Institute analysis of VAED

### 2 Measuring persistence

In selecting hotspots, we aimed to identify places with persistently high rates because potentially preventable hospitalisations are rare events, health interventions take time to develop and areas with more entrenched problems should be highest priority. This chapter describes how we measured the persistence of hotspots.

We first present our rationale for evaluating persistence and a summary of the literature. We then show that persistence is rare but that persistent hotspots exist more often than expected by chance. The last section in this chapter looks at how much of the overall problem could be addressed through targeting persistent hotspots.

#### 2.1 Rationale for measuring persistence

With rare events like avoidable hospitalisation, high rates can be driven by chance. Persistence is a meaningful way of distinguishing entrenched area-based discrepancies from random, accidental or intermittently high rates that later revert to the mean.

Places with persistently high rates are also more amenable to action. As discussed in Chapter 1, health interventions take time so a place must be 'likely to stay hot' to be worth allocating resources.

Unfortunately many hotspot studies draw conclusions from a single year of data. The latest National Health Performance Authority report on potentially preventable hospitalisations

calculates rates for the year 2013-14.<sup>7</sup> NHPA's only previous report on this topic was for the year 2011-12<sup>8</sup> but the two datasets are not comparable because of changes to the specification of 'potentially preventable hospitalisation'.

Hotspot studies using multiple years of data have generally aggregated data across 3-10 years to identify hotspots.<sup>9</sup> More years of aggregate data are more likely to reveal entrenched problems, but also have their own biases. Data aggregated over long time periods can reflect past situations that no longer exist and miss current problems.<sup>10</sup> Naturally, aggregation hides temporal trends.

Longitudinal studies are rare, but two studies looked at rates of low birth weight over a decade across counties in Georgia and found evidence of persistent hotspots. One identified 3 out of 159 counties with significantly high rates for both the first three years and the last three years of their data period.<sup>11</sup> The other showed substantial variation across years within countries, but some areas with persistently high rates year-in-year-out.<sup>12</sup>

<sup>&</sup>lt;sup>7</sup> National Health Performance Authority (NHPA) (2015)

<sup>&</sup>lt;sup>8</sup> National Health Performance Authority (NHPA) (2013)

<sup>&</sup>lt;sup>9</sup> For example: Harrold, *et al.* (2014); Butler, *et al.* (2013); Crighton, *et al.* (2015); Ibañez-Beroiz, *et al.* (2014); South, *et al.* (2012).

<sup>&</sup>lt;sup>10</sup> Ocaña-Riola (2010)

<sup>&</sup>lt;sup>11</sup> Tian, *et al.* (2013)

<sup>&</sup>lt;sup>12</sup> Kirby, et al. (2011)

Other international studies looking at hotspot trends over time have compared two years of data, 10 years apart,<sup>13</sup> have averaged rates to identify hotspots<sup>14</sup> or have returned to aggregating data for hotspot identification.<sup>15</sup>

We used 10 years of annual rates of potentially preventable hospitalisations (2004-05 to 2013-14) to evaluate persistence. In evaluating persistence we considered variability in an area's rate over time, number of years an area was above our minimum heat threshold and likelihood of an area staying hot by chance.

We applied a minimum persistence threshold of three years, meaning an area must be hot for at least three consecutive years in the ten year window to be considered a persistent hotspot. Note that this does not necessarily mean the area is currently hot; simply that it persisted as a hotspot for at least three years.

#### Rates over time 2.2

Within a single year disease rates vary dramatically across postcodes (>10 fold) but most postcodes that are 'hot' in one year, lose their heat the next.

In any one year 15 per cent of postcodes are 'hot' (>1.5x state average).<sup>16</sup> But only 7 per cent of postcodes are hot for two years and nearly halved again for three years.

Put another way, just under half of postcodes (46 per cent) that are hot in one year (>1.5x) remain hot the next year. If the heat threshold is lifted to 2x the state average then only a third of areas maintain their heat for two consecutive years.

Over three consecutive years, only 3.9 per cent of postcodes maintain a rate >1.5x the state average. This proportion varies by ACSC being highest for COPD at 7 per cent, and lowest for CCF at 2 per cent.

After 2-3 years, hot areas are more likely to stay hot than not and if a postcode has been hot for 5 years its likelihood of remaining hot is almost 80 per cent (Figure 5).

The most persistent hotspots had rates >1.5x the state average in all 10 years of the data. These 25 postcodes were hot in every year of the data for at least one potentially preventable condition (Figure 6). Three of these postcodes were hot for two different conditions in all years of the data. The most persistent hotspots spanned 8 different diseases.

<sup>&</sup>lt;sup>13</sup> Basu, *et al.* (2014); Basu, *et al.* (2012)
<sup>14</sup> e.g. Berlin, *et al.* (2014) use a three-year average
<sup>15</sup> e.g. Will, *et al.* (2014) evaluated hospitalisation rates for hypertension across the US over six years and reported 'some instability in rates over time', but used only aggregate data to identify hotspots

<sup>&</sup>lt;sup>16</sup> 15 per cent is an average across ACSCs. The exact proportion varies by disease, ranging between 10 per cent for Urinary Tract Infections (UTI) and 20 per cent for Cellulitis.



**Figure 5: Likelihood of staying hot increases with persistence** Proportion of places that stay hot as a per cent of the previous year

Source: Grattan Institute analysis of VAED

Figure 6: Most places that are currently hot were not hot last year, but a few places have been persistently hot for a decade Number of hot postcodes in the latest year that were hot in each previous year



Source: Grattan Institute analysis of VAED

There is a trade-off between heat and persistence as Table 1 illustrates. Naturally areas drop off as you raise the heat threshold or raise the persistence threshold, and raising both leaves very few areas (or no areas for many diseases). We deliberately prioritise persistence over heat, taking a higher persistence threshold (at least 3 years of heat) rather than a higher heat threshold. This is because a place that is very hot in one year, but not the next, is likely to be a small postcode where rates are driven more by random chance. A place that is consistently above average could be any size, and demonstrates a more 'real' and certainly more actionable problem.

Table 1: How heat and persistence thresholds affect the selection of areas

Heat threshold	Number of areas (and admissions) in 2010-11	Number of areas (and admissions) still hot in 2011-12	Number of areas (and admissions) still hot in 2012-13	Number of areas (and admissions) still hot in 2013-14
. 0.4	73	16	3	2
>3X	1,751	670	72	61
0	277	86	37	22
>2X	7,766	3,141	1,462	1,093
	698	324	187	118
>1.5X	28,552	16,606	9,663	6,518
>1x	1,964	1,309	978	776
(average)	96,659	76,354	63,261	54,906

Notes: Table shows the count of areas and admissions across all ACSCs; some ACSCs are hotter and/or more persistent than others. An area is counted more than once if it meets the criteria for more than one ACSC. Source: Grattan Institute analysis of VAED.

#### 2.3 Persistence by chance

Hot places rarely stay hot but persistent hotspots do exist more often than expected by random chance.

The probability of a postcode being hot for three years by random chance is only  $\sim 0.34$  per cent<sup>17</sup>. This chance varies between 0.1-0.8 per cent depending on the disease. The actual proportion of postcodes hot for 3 years is more than 10 times greater at 3.9 per cent (again varying by disease between 2 per cent and 7 per cent, see Figure 7).

Persistently hot areas are 10 times more common than would be expected if driven by random events only.

<sup>17</sup> 15% chance in one year, so 0.15<sup>3</sup>

**Figure 7: Postcodes have a reasonable chance of being hot in any one year, but are very unlikely to be hot for three years by chance** Probability that a postcode is >1.5x state average rate for 1-3 years



Notes: All categories except 'Random' are actual probabilities. Random probabilities are calculated based on the average 15% chance of being hot in any one year across all diseases (so 0.15<sup>2</sup> to get random probability for 2 years and 0.15<sup>3</sup> to get random probability for 3 years).

Source: Grattan Institute analysis of VAED

#### 2.4 Size of the problem

Having established that persistent hotspots exist – places that are hot for at least three consecutive years – we wanted to understand the size of the problem they represent.

Persistent hotspots capture around 6,000 potentially preventable hospitalisations annually,<sup>18</sup> representing a large health burden and high costs for patients and taxpayers.

Persistent hotspots are areas with a higher concentration of admissions (i.e. more admissions per person) but not necessarily a large proportion of total admissions.

If the aim is to reduce potentially preventable admissions in Victoria, then what proportion of all admissions do persistent hotspots capture?

Persistent hotspots represent between 3 per cent and 15 per cent of hospitalisations for each of the high-volume ACSCs (Table 2). If a random 10 per cent of the population were targeted, then we might expect to capture 10 per cent of admissions by chance, with an efficiency index of 1. The performance of persistent hotspots on this efficiency index varies from only slightly better than random (1.16 for CCF), to more than twice as good for Angina (2.32), Cellulitis (2.32) and ENT (2.11).

In reality, we would not be able to prevent *all* hospitalisations for target ACSCs within persistent hotspots. But an intervention

<sup>&</sup>lt;sup>18</sup> Average annual total for all persistent hotspots in the most recent three years of the data (2011-12 to 2013-14)

designed for one ACSC could potentially help to reduce hospitalisations for another ACSC.

Clearly targeting prevention through persistent hotspots alone will not markedly reduce Victoria's potentially preventable hospitalisations. But persistent hotspots still represent a greater density of potentially preventable hospitalisations so should offer efficiency benefits in targeting prevention.

Table 2: Proportion of admissions in persistent hotspots vs.proportion of population targeted, by ACSC

ACSC	Percentage of admissions in persistent hotspots	Percentage of population in persistent hotspots	Efficiency index (admissions % / population %)
COPD	14.5%	7.9%	1.84
Dental	7.1%	3.7%	1.89
Cellulitis	6.9%	3.0%	2.32
Epilepsy	6.3%	3.3%	1.92
Diabetes	4.5%	2.5%	1.86
Angina	3.4%	1.5%	2.32
ENT	3.1%	1.5%	2.11
UTI	3.1%	2.3%	1.33
CCF	2.7%	2.3%	1.16

Notes: Persistent hotspots were taken to be those areas hot (>1.5x state average) for the most recent 3 years of the data (2011-12 to 2013-14). Admissions and population were calculated as the average across those three years. Source: Grattan Institute analysis of VAED.

### 3 Evaluating predictability

To be amenable to action, persistent hotspots must be predictable. Investment decisions occur in the present, but usually take effect in a few years' time, so we need to be able to accurately predict future hotspots based on information we have today. This chapter describes how we evaluated the predictability of persistent hotspots.

We first explore the characteristics of persistent hotspots to identify common indicators of places that stay hot. We then evaluate the proportion of hotspots 'likely to stay hot' based on different combinations of predictors.

#### 3.1 Characteristics of persistent hotspots

In order to predict future hotspots we want to understand characteristics that persistent hotspots share.

Persistent hotspots have certain characteristics in common as a group, *on average*, when compared to all other areas. They are:

- Lower SES
- More remote
- Higher proportion Indigenous

There is large rate variation even when comparing among similar areas (see Figures 8 and 9). For example, some of the 'hottest' postcodes are low SES, but we see the complete spectrum of rates among low SES postcodes (Figure 8).

Figure 8: Lower SES and more remote postcodes have higher rates on average

10-year average rate multiple by postcode



Note: Y-axis cut-off at 5 to improve readability (one area hidden). We define high SES as an IRSAD score >1050, and low SES as <950. We define "regional" as all areas with an ABS remoteness classification other than Major City.

Source: Grattan Institute analysis of ABS Census 2011, ABS remoteness index and VAED

## Figure 9: Persistent hotspots are higher proportion Indigenous on average

Percentage of postcode population that identifies as Indigenous



Note: Chart includes all postcodes and diseases for a single year (2011-12). Places labelled persistent hotspots stayed hot for the next three years 2011-12 to 2013-14. Source: Grattan Institute analysis of ABS Census 2011 and VAED

#### 3.2 Characteristics of admissions in persistent hotspots

In some places, just a few people account for many ACSC hospitalisations. We investigated the relationship between total admissions and total persons admitted, by area, for persistent hotspots compared to non-hotspots (Figure 10).

In Figure 10, Areas A and B are highlighted to illustrate that the two areas have the same number of admissions, but in Area A only 15 people account for 80 admissions, whereas in Area B 80 people account for the same number of admissions. Area A therefore has a high rate of readmissions (patients returning to hospital within the same year), whereas Area B has no readmissions (each admission is a unique patient).

Readmissions are more common in persistent hotspots than other areas, but there is no linear relationship between an area's heat (rate) and the proportion of admissions that are readmissions (Figure 11).

Each hotspot will have its own drivers. For example, among persistent hotspots, some areas have a very high proportion of readmissions while others have few (Figures 10 and 11). This varies by disease too, where readmissions have little influence in dental hospitalisation hotspots, while in some COPD hotspots, most hospitalisations are readmissions (Figure 12).

Readmissions are only part of the problem though: 22 per cent of persistent hotspots had no readmissions at all and in only 10 per cent of persistent hotspots were readmissions more than half of all admissions.



Figure 10: Readmission rates vary substantially between areas, for example, Area A has many readmissions while Area B has none Total admissions, 2011-12

Notes: Both axes are cut-off at 300 to improve readability. 'Persistent hotspot' refers to all places with rates at least 50% higher than state average in the most recent three years of the data (2011-12 to 2013-14).

Source: Grattan Institute analysis of VAED

Figure 11: Readmissions do not drive high rates Average rate multiple, 2011-12 to 2013-14



Notes: Y-axis cut-off at 5 to improve readability (six areas hidden). 'Persistent hotspot' refers to all places with rates at least 50% higher than state average in the most recent three years of the data (2011-12 to 2013-14). A random sample of 1000 other areas in the same time period is displayed. Source: Grattan Institute analysis of VAED

# Figure 12: Readmissions make up a larger proportion of chronic ACSC admissions (e.g. Angina, COPD and Diabetes) than for other ACSCs (e.g. Cellulitis and Dental)

Proportion of an area's total admissions attributable to individuals with three or more admissions



Notes: Black line represents the average of all areas by ACSC. Persistent hotspot' refers to all places with rates at least 50% higher than state average in the most recent three years of the data (2011-12 to 2013-14). A random sample of 500 other areas in the same time period is displayed to reduce congestion. Source: Grattan Institute analysis of VAED (single year, 2011-12)

#### 3.3 Predicting persistent hotspots

Predictive success depends on being able to predict a reasonable proportion of all future hotspots (good sensitivity) while avoiding predicting lots of places that revert to the mean or 'lose their heat' (good specificity).

Large variation in rates – even when comparing among similar areas (as per Figures 8-10) – makes it hard to predict persistent hotspots both accurately and precisely.

For example many of the lowest-SES postcodes are persistent hotspots (good accuracy/high sensitivity), but targeting low SES postcodes would capture lots of places that are not hotspots (poor precision/low specificity). Table 3 illustrates the trade-off between sensitivity and specificity for different predictors.

The best single predictor of future heat is past heat. As discussed in Chapter 2 and illustrated in Figure 5, places that have been hot for at least 3-5 years have a better than even chance of staying hot into the future.

Using past heat to predict future hotspots, Figure 13 shows that shorter forecasts and longer datasets (more years of past data) improve the predictability of future hotspots.

A key question is therefore how far into the future do you need to be able to predict? This is dependent on how long it takes to intervene and how long the intervention lasts.

4.040) .0. 4	( prodicto				
		Low SES	No	Sensitivity	Specificity
Hotspot for the		100	140	500/	
next 3 yrs (2011-	Yes	104	76	58%	
12 to 2013-14)	No	862	3,328		79%
	Lows	SES, Region	nal &	Sensitivity	Specificity
	Hig	gh Indigenou	IS		, ,
Hotspot for the		Yes	No		
nevt 3 vrs (2011-	Vac	38	1/1	21%	
$12 \text{ to } 2013_1/$	No	221	2 957		0.20/
12 (0 2013-14)	NO	551	3,857		92 /0
	Past hea	at (1 year, 20	010-11)	Sensitivity	Specificity
l latarat far tha		Yes	No		
Holspol lor line	Vaa	110	60	66%	
10 to 0010 11)	res	118	60	0070	000/
12 to 2013-14)	NO	572	3,521		86%
	Pas 2008	t heat (3 yea 8-09 to 2010-	nrs, .11)	Sensitivity	Specificity
	2000	Voo	No		
Hotspot for the		res	INO		
next 3 yrs (2011-	Yes	67	111	38%	
12 to 2013-14)	No	110	3,975		97%
	Pas	t heat (5 yea	ars	Sensitivity	Specificity
	2006	6-07 to 2010-	-11)		opcomony
Hotspot for the		Yes	No		
next 3 yrs (2011-	Yes	43	135	24%	
12 to 2013-14)	No	48	4,035		99%

 Table 3: Prediction sensitivity and specificity (in terms of number of areas) for different predictors

Notes: An area can be counted up to 10 times if it meets the criteria for all 10 ACSCs. Socio-Economic Status (SES) is defined on the ABS Index of Relative Socioeconomic Advantage and Disadvantage (IRSAD). We define low SES as an IRSAD score <950 (bottom quartile). We define "regional" as all areas with an ABS remoteness classification other than Major City. We define "High Indigenous" as top quartile for the state in terms of the proportion of the population that identifies as Indigenous. Source: Grattan Institute analysis of VAED. Three to five years is a likely time-frame for an intervention to be developed, rolled-out and take effect, so we consider it necessary to be able to predict places that will still be hot in 3-5 years' time.

Choosing areas for intervention based on one year of data (i.e. places that are currently hot) leaves only 20 percent of places still hot after three years and only 10 per cent after five years (Figure 13). However choosing areas for intervention based on three or more years of data (places that have been hot for the last three or more years) dramatically improves prediction success.

If three years of past data is used to predict places that will be hot in 3-5 years' time, 25-40 per cent of predicted places stay hot. If five years of data is available, 40-55 per cent of predicted places stay hot (Figure 13).

It's a case of 'the more data the better' in identifying hotspots, and cost-benefit analyses for hotspot interventions must factor in that many selected areas will not stay hot (with the exact likelihood depending on both the data inputs and the forecast window).

In predicting persistent hotspots, past heat should be the first criterion: the longer a place has been hot, the more likely it is to stay hot. Other characteristics might be used though, in combination with past heat.

Areas that are low SES, regional and have a high Indigenous population are also more likely to be hotspots. Prediction based on a combination of factors performs similarly to prediction based on past heat alone, as an average across all ACSCs (Figure 14). However for some individual ACSCs (e.g. COPD) a combination of predictors performs much better (Figure 15).



### Figure 13: Predictability of future hotspots improves with more years of data but declines the longer the forecast

Proportion of postcodes correctly predicted to stay hot

Note: Figure represents all ACSCs, predictability varies by disease. This analysis is based on a selection of hotspots chosen in 2009-10 from 1-5 previous years of data (1 year of data = 2008-09, 5 years = 2004-05 to 2008-09). Future heat "Year 1" to "Year 5" is taken from real data in the years 2009-10 to 2013-14. Source: Grattan Institute analysis of VAED

#### Figure 14: Predictability of future hotspots using a combination of predictors (all ACSCs)

Proportion of postcodes correctly predicted to stay hot



Note: Figure represents all ACSCs, predictability varies by disease. Socio-Economic Status (SES) is defined on the ABS Index of Relative Socioeconomic Advantage and Disadvantage (IRSAD). We define low SES as an IRSAD score <950. We define "regional" as all areas with an ABS remoteness classification other than Major City. Source: Grattan Institute analysis of ABS Census 2011, ABS remoteness index and VAED



## Figure 15: Predictability varies by disease, for example predictability is better for COPD hotspots

Proportion of postcodes correctly predicted to stay hot

Note: Socio-Economic Status (SES) is defined on the ABS Index of Relative Socioeconomic Advantage and Disadvantage (IRSAD). We define low SES as an IRSAD score <950. We define "regional" as all areas with an ABS remoteness classification other than Major City.

Source: Grattan Institute analysis of ABS Census 2011, ABS remoteness index and VAED

### 4 Selecting hotspots

Few places pass the dual tests of persistence and predictability. But exactly how many places pass these tests depends on the thresholds required for heat, persistence and predictability, which are naturally context-dependent. There will be situations where the intervention horizon is much shorter than the 3-5 years considered here, and/or where forecasts and priorities can be refreshed each year.

*Perils of place* considers a conservative selection of hotspots. We select only the most persistent hotspots: places with high ACSC rates year-in-year-out. These places clearly have a consistent long-term problem with potentially preventable hospitalisations.

#### 4.1 The most persistent hotspots

We define the most persistent hotspots (or 'priority places') as the postcodes with rates >1.5x the state average in every year of our 10-year dataset. There are 25 postcodes that are hot in every year of the data, some of which are hot for more than one condition (in every year of the data). This is unacceptable place-based inequality.

Priority places are lower SES and higher proportion Indigenous on average, even when compared to persistent hotspots (see Figures 17 and 18). Priority places are also more remote on average (although no more remote than persistent hotspots). **Figure 16: Priority places are spread throughout Victoria** Map of Victoria with Melbourne inset, priority postcodes labelled by disease



Source: Grattan Institute analysis of VAED in ArcGIS

## Figure 17: Priority places are lower SES on average, even when compared to persistent hotspots

ABS indicator of relative socio-economic advantage and disadvantage (IRSAD) by postcode



Source: Grattan Institute analysis of ABS 2011 SEIFA indicators and VAED (2011-12)

**Figure 18: Priority places are higher proportion Indigenous on average, even when compared to persistent hotspots** Percentage of postcode population that identifies as Indigenous



Source: Grattan Institute analysis of ABS Census 2011 and VAED (2011-12)

In some priority places, as few as 8 people represent more than 50 admissions for a single year (see Figure 19). Readmissions are particularly common for COPD and our combined measure of Chronic ACSCs, but readmissions represent only a small part of the problem in most priority places. Some priority places for acute conditions (such as cellulitis, dental and ENT) had no readmissions.

Figure 19: Tackling readmissions will be part of the solution in some priority places, but more of the problem lies elsewhere Victoria: all priority places



#### Other selection approaches

The most persistent hotspots are not necessarily the only places worthy of special attention, but they are good places to start.

Expanded definitions to identify the areas next most in need of attention might include places that were hot in a certain proportion of years, or places that were hot based on an average of all years. Selection should include a measure of recent heat though to ensure target areas are still hot, not just hot in the past.

Two examples of potential expanded definitions are presented, including their impact on hotspot selection:

- A definition of "hot in at least 7 out of 10 years <u>and</u> hot on average over the most recent three years of data" identifies 115 postcodes, some of which meet the definition for multiple ACSCs
  - Among areas selected under this definition, the minimum 10-year average is 1.5x the state average (max 4.5x, median 2x)
  - The average minimum rate in 10 years is 1.1 (range 0-2.2)
  - The average maximum rate in 10 years is 3.4 (range 1.8-15.8)
- 2. A definition of "hot on average over the last 10 years and hot on average over the most recent three years of data" identifies 170 postcodes, some of which meet the definition for more

than one condition

- Among areas selected under this definition, the minimum number of hot years is 2 (max 10, median 7) if an area can be hot for just 2 out of 10 years, it suggests this definition is too broad
- The average minimum rate in 10 years is 0.9 (range 0-2.2)
- The average maximum rate in 10 years is 3.5 (range 1.8-17.6)

Another approach to selecting areas for intervention is to prioritise places that have multiple problems, for example, postcodes that are hotspots for more than one preventable condition.

Three of our 'priority places' were hot for two different ACSCs in all 10 years. Thirty per cent of persistent hotspots met the criteria for more than one ACSC, and one postcode met the persistent hotspot criteria for six different ACSCs.

### 5 Applicability to other states

The previous sections outline our method for determining if and when hotspots are amenable to action, and identifying priority places for preventive action in Victoria. Having developed this method exclusively on the Victorian data set, we then tested the stability of the findings and its broader applicability on a similar data set for Queensland.

The key questions we tested in Queensland were:

- Do we identify a similar proportion of priority places using the same method in a different state?
- Do we capture a similar proportion of potentially preventable hospitalisations through a hotspots approach?
- Are hotspots in Queensland more or less amenable to action than those in Victoria?

Queensland and Victoria are similar in population size (4.8 million and 5.9 million in 2015 respectively) but have quite different health systems, geographies and population demographics. We might expect these differences to influence the distribution and concentration of potentially preventable hospitalisations.

The main difference between state data sets was the spatial unit. ACSC rates were calculated by postcode for Victoria and by SA2 for Queensland. The difference in spatial unit was a consequence of data availability but this difference allowed us to test whether our method held up for different area-boundary definitions.

SA2 units and postcodes are similar in average size, but postcodes are more variable (with both much smaller and much larger areas) and are not statistically standardised.<sup>19</sup> Postcode population in Victoria in 2013 ranged between zero and 90,000 with a mean of 8,600 (median 2,700) while SA2 population in Queensland in 2013 ranged between zero and 30,500 with a mean of 8,800 (median 8,100).

#### 5.1 The Queensland data set

Queensland Health provided a data extract from the Queensland Hospital Admitted Patient Data Collection (QHAPDC) – a comprehensive set of records for all admitted patient episodes in all public and private hospitals in Queensland.

The data extract comprised 10 years of admissions data (2005-06 to 2014-15) with information on patient diagnosis, SA2 of residence, age-group (5 years) and sex. The data extract included a linkage identifier to enable identification of readmissions.

#### 5.2 Comparison of Queensland and Victoria

Priority places were identified in Queensland following the same method as Victoria (all areas with rates of at least 1.5 times state average in every year for a decade). In Victoria, 5 per cent of postcodes were classified as priority places for one or more

<sup>&</sup>lt;sup>19</sup> ABS (2011a)

ACSCs. In Queensland, 7 per cent of all SA2s in the state were identified as priority places for one or more ACSCs.<sup>20</sup>

Thirty-eight priority places were identified in Queensland (Figure 20), of which 23 qualified for multiple ACSCs. One priority place met the definition for all nine high-volume ACSCs and another had a decade average rate of 20 times the state average for COPD hospitalisation.

Potentially preventable hospitalisations were more concentrated in Queensland than Victoria, making Queensland hotspots more amenable to action. Priority places in Queensland represent 4 per cent of the state's total ACSC admissions, compared to 1 per cent in Victoria.

Persistent hotspots – places with ACSC rates of at least 1.5 times state average for three (or more) years consecutively – were more common in Queensland (6 per cent on average across ACSCs) than Victoria (4 per cent). Persistent hotspots were also hotter in Queensland, averaging rates of 3 times higher than state average, compared to 2.3 times state average in Victoria.

Persistent hotspots are also more predictable in Queensland (as a result of being more common). In Queensland, a place is 80 per cent likely to stay hot if it has been hot the last three years, whereas in Victoria the same likelihood is only reached after 5 years of 'being hot' (Figure 21).

Table 4: Comparison of hotspots in Queensland and Victoria

Key statistics	Queensland	Victoria
Spatial area	SA2	Postcode
Total number of areas in the state	526	679
Number of areas in analysis (after exclusions)	508	457
Chance of an area being hot in any 1 year, average across all ACSCs (range by disease)	16 per cent (12-19)	15 per cent (10-20)
Persistent hotspots: total number of areas hot for the last 3 years (or more) consecutively	120	114
Persistent hotspots: proportion of all areas, any ACSC	24 per cent	25 per cent
Persistent hotspots: proportion of all areas, range by ACSC	4-8 per cent	2-7 per cent
Persistent hotspots: average rate multiple (heat)	3.0	2.3
Persistent hotspots: admissions captured by ACSC, average (range in brackets)	12 per cent (6-18)	6 per cent (3-15)
Priority places: total number of areas	38	25
Priority places: average rate multiple (heat)	4.2	2.5
Priority places: proportion of all areas, any ACSC	7 per cent	5 per cent
Priority places: proportion of all areas, range by ACSC	1-4 per cent	0-2 per cent
Priority places: admissions captured as a proportion of the state's total ACSCs	4 per cent	1 per cent

<sup>&</sup>lt;sup>20</sup> In both states, selection of priority places was based on only the nine highest volume ACSCs (and these were the same ACSCs in both states).



Figure 20: Most priority places qualify for multiple ACSCs Map of Queensland with Brisbane inset

Source: Grattan Institute analysis of QHAPDC in ArcGIS

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## Figure 21: Persistent hotspots are more predictable in Queensland than in Victoria

Proportion of places that stay hot as a percentage of the previous year 100%  $\neg$ 



Source: Grattan Institute analysis of VAED and QHAPDC

We conducted a regression analysis to compare the marginal value of different predictors. Specifically we used a probit model to predict places that would be hot in the *next* year based on information about whether or not an area was: hot in the past (last 1, 3 and 5 years), low SES (bottom quartile), regional (outside the major cities), or high Indigenous population (top quartile for the state in terms of the proportion of the population that identify as Indigenous). The proportion of areas correctly predicted to be hot in the next year for each variable individually and combined is displayed in Table 5.

Table 5: Proportion of areas correctly predicted to be hot in the next year

Predictors individually						
State	5 years past heat	3 years past heat	1 year past heat	High % Indigenous	Low SES	Regional
VIC	74%	68%	46%	26%	28%	21%
QLD	83%	77%	56%	36%	33%	25%

	Predictors combined					
State	1 year past heat	+ Low SES	+ Regional	+ High % Indigenous	+ 2 years past heat (3yrs total)	+ 2 years past heat (5yrs total)
VIC	46%	56%	59%	61%	81%	85%
QLD	56%	66%	69%	71%	85%	88%

Note: The proportion of areas correctly predicted to be hot in the next year varies by disease. Values represent predicted probabilities from probit models where the dependent variable is always whether or not an area has a rate >=1.5x state average in the following year.

Source: Grattan Institute analysis of VAED.

Table 5 illustrates that in both states past heat is the best predictor of heat in the next year. Figures 21-24 illustrate the impact of these predictors over time (predicting up to 5 years into the future).

Figure 22 shows the predictability of future hotspots in Queensland, over time, based on past heat. Three years is probably the minimum plausible time period for an intervention to be developed, rolled-out and take effect. If a 3-year intervention was conducted in places that had been hot the past 5 years, then two-thirds of areas invested in would remain hotspots. A two-thirds success rate is likely to be sufficient for many interventions.

Figure 23 shows the proportion of places that are hot for three consecutive years based on other area characteristics in the two states. In both Victoria and Queensland, areas that are lower SES, outside the major cities and/or have a high Indigenous population are more likely to be persistent hotspots. In Queensland, one in four areas with these characteristics is a persistent hotspot compared to the average area, which has just a 6 per cent chance of being a persistent hotspot (Figure 23).

Figure 24 shows the predictability of future hotspots in Queensland, over time, based on all predictors combined. However, the best predictors and their success rates vary by disease, so Figure 25 illustrates predictability of hotspots for one of the more predictable ACSCs in Queensland – hospitalisation for Ear, Nose and Throat (ENT) disorders.



Figure 22: The predictability of future hotspots in Queensland based on past heat alone

Proportion of SA2s correctly predicted to stay hot

Note: Figure represents all ACSCs, predictability varies by disease. This analysis is based on a selection of hotspots chosen in 2010-11 from 1-5 previous years of data (1 year of data = 2009-10, 5 years = 2005-06 to 2009-10). Future heat "Year 1" to "Year 5" is taken from real data in the years 2010-11 to 2014-15. Source: Grattan Institute analysis of QHAPDC

## **Figure 23: Low SES, regional and Indigenous areas are much more likely to be persistent hotspots, particularly in Queensland** *Probability of an area being a persistent hotspot, given certain area characteristics*



Note: Probability of being a persistent hotspot refers to the probability of achieving an ACSC rate at least 50% higher than state average in three consecutive years. Socio-Economic Status (SES) is defined on the ABS Index of Relative Socioeconomic Advantage and Disadvantage (IRSAD). We define low SES as an IRSAD score <950 (bottom quartile) and high SES as >1050 (top quartile). We define "metro" as all areas with an ABS remoteness classification of Major City and "regional" as all other areas. We define high and low proportion Indigenous as the top and bottom quartiles for the state. Source: Grattan Institute analysis of VAED, QHAPDC and ABS Census 2011 data



## Figure 24: The predictability of future hotspots in Queensland based on a combination of predictors

Proportion of SA2s correctly predicted to stay hot

Note: Figure represents all ACSCs, predictability varies by disease. Socio-Economic Status (SES) is defined on the ABS Index of Relative Socioeconomic Advantage and Disadvantage (IRSAD). We define low SES as an IRSAD score <950 (bottom quartile). We define "regional" as all areas with an ABS remoteness classification other than Major City. We define high proportion Indigenous as >4% of the population (top quartile for the state). Source: Grattan Institute analysis of ABS Census 2011, ABS remoteness index and QHAPDC Figure 25: Predictability varies by disease, for example predictability is better for ENT hotspots in Queensland Proportion of SA2s correctly predicted to stay hot



Note: Socio-Economic Status (SES) is defined on the ABS Index of Relative Socioeconomic Advantage and Disadvantage (IRSAD). We define low SES as an IRSAD score <950 (bottom quartile). We define "regional" as all areas with an ABS remoteness classification other than Major City. We define high proportion Indigenous as >4% of the population (top quartile for the state).

Source: Grattan Institute analysis of ABS Census 2011, ABS remoteness index and QHAPDC

In summary:

- Our method identified a similar proportion of priority places in a different state
- Priority places captured a low proportion of total preventable hospitalisations in both states (although more in Queensland than in Victoria)
- Hotspots in Queensland are more amenable to action than those in Victoria – they are more persistent, more predictable and more likely to have high rates for multiple ACSCs.

The methods developed for Victoria held up in Queensland in terms of identifying the highest priority places for preventive action. Our selection of priority places may be too conservative for Queensland though with persistent hotspots being more identifiable and actionable in Queensland than in Victoria.

### 6 Estimating potential savings

*Perils of place* recommends developing, testing and evaluating tailored interventions to reduce potentially preventable hospitalisations in a conservative selection of priority places before broader roll-out. This chapter outlines our approach to estimating potential savings from reducing ACSC hospitalisations in priority places.

The analysis has two parts:

- 1. Estimating the number of hospital admissions that could likely be avoided in priority places; and
- 2. Estimating the cost attributable to those avoidable admissions (the potential savings)

Note that our analysis does not try to estimate flow-through or wider benefits to these communities as a result of reducing hospitalisations or any other additional benefits of specific interventions.

#### Part 1: How many hospitalisations could be avoided?

We assume that an appropriate intervention will reduce ACSC admissions to average levels or better in each priority place. Priority places are identified for specific ACSCs so we assume only the ACSC or ACSCs that make a place a 'priority place' are reduced.

The appropriate 'average level' for ACSC admissions is different in each priority place because it is affected by the age-sex profile of the area. Priority places were selected based on their age-sex adjusted ACSC rate, expressed as a multiple of state average. We divide the actual number of hospitalisations in a priority place by the area's rate multiple to get the number of hospitalisations expected for an average area given its age-sex profile.

The difference between the actual and expected admissions is the avoidable admissions. For example an area with 100 admissions and a rate multiple of 2 (an age-sex adjusted rate of twice the state average), we would expect to have only 50 admissions if it were an average area, and would therefore expect to be able to avoid at least 50 admissions through appropriate intervention.

We calculate avoidable admissions for each priority place in each of the most recent three years of the data.

#### Part 2: How much do these avoidable admissions currently cost?

We calculate the typical cost of an admission for nine ACSCs using the Victorian Weighted Inlier Equivalent Separation (WIES).<sup>21</sup> WIES is a cost weight that is adjusted for the diagnosis group (DRG) and time spent in hospital (LOS). This weight is then multiplied by the state efficient price (which varies by provider group).

<sup>&</sup>lt;sup>21</sup> WIES20 pricing from Department of Health and Human Services (Victoria) (2013a). WIES20 cost weights from Department of Health and Human Services (Victoria) (2013b).

To calculate the typical cost of an admission we analysed the DRG and LOS profile of all admissions across Victoria for each ACSC. For each ACSC, 80-95 per cent of admissions fell into 2-4 DRGs. We included all DRGs that represented more than 10 per cent of admissions for a particular ACSC. Most ACSC admissions are same-day or 1-2 days in hospital. WIES sets specific boundaries for length of stay, by DRG. Admissions outside these boundaries are considered outliers and are priced differently. We ignored outliers in calculating the typical cost of an admission.

We calculated a single 'typical' cost weight per ACSC, taking into account the distribution of total admissions across DRGs and LOS (using WIES20 weights by DRG and LOS). This cost weight was then multiplied by the WIES20 price for major providers of \$4,248 to give a typical cost per admission for each ACSC (see Table 6).

We use the Victorian WIES for both Victorian and Queensland priority places because our Victorian dataset included DRG and LOS information while our Queensland dataset did not.

Queensland uses the National Weighted Activity Unit (NWAU) and national efficient price. WIES is a variant of the NWAU for Victoria. DRG and LOS information are critical to calculating both WIES and NWAU. We chose WIES because we could more accurately calculate the typical cost of an admission for each of the nine ACSCs.

ACSC	WEIS per admission	Price per admission	Avoida admis: Vio	able sions	Potentia (\$000) Vio	al savings
Angina	0.626	\$2.661	VIC	144	VIC	383
Angina	0.020	φ2,001	-	144	-	303
CCF	1.167	\$4,958	21	76	104	377
Cellulitis	0.720	\$3,058	103	840	315	2,569
COPD	1.035	\$4,397	351	506	1,543	2,225
Dental	0.512	\$2,175	187	254	407	552
Diabetes	0.865	\$3,673	43	285	158	1,047
ENT	0.345	\$1,466	36	346	53	507
Epilepsy	0.551	\$2,341	-	279	-	653
UTI	0.661	\$2,808	24	330	67	927
TOTAL			765	2,730	\$2.6m	\$9.2m

 Table 6: Typical cost per admission, 2013-14

Note: Based on WEIS20 (2013-14). Avoidable admissions are also for 2013-14. Source: Grattan Institute analysis of VAED and QHAPDC.

Table 6 illustrates potential savings \$12 million for one year (2013-14). We estimated potential savings across three years and calculated a potential savings range using the lowest and highest number of avoidable admissions in each priority place across the three years.

We estimate direct savings of at least \$10-15 million annually. Our estimate is very conservative for a number of reasons:

 Firstly, we do not attempt to quantify indirect benefits and savings from reducing potentially preventable hospitalisations, such as improved well-being, workforce participation, or neighbourhood renewal.

- Secondly, we assume interventions will only reduce admissions in priority places to average levels. Given that interventions are absent for most areas we might expect appropriate interventions to do better than average.
- Thirdly, we limit avoidable admissions and the estimation of savings to the particular ACSC for which the priority place was chosen, but interventions introduced for one type of ACSC may help to reduce other ACSC admissions.
- Fourthly, we apply the WIES price for major providers, which is the lowest price. The WIES price is higher for outer metro, regional and rural providers and many priority places are regional or remote. However we cannot identify in the data which hospital patients were admitted to.
- Fifthly, the state efficient price for Victoria is lower than the national efficient price. Savings from Queensland admissions are estimated using the Victorian pricing, which may be an under-estimate.
- Finally, long-stay admission outliers were excluded from weight calculations. Long stays in hospital are more costly but are also less likely to be preventable.

## 7 Limitations of geographic analysis

The methodology described here has three main limitations:

- The scale of analysis (size of geographic unit)
- Accuracy in the allocation of individuals to geographic units (including both the geocoding of hospital data and the statistical estimation of population data)
- The arbitrary nature of spatial unit boundaries

Geographic units are simple proxies for the individuals that reside there, so naturally smaller spatial scales more accurately reflect the underlying distribution of a problem.

We identify hotspots using postcode and SA2-level data but smaller spatial units exist. Mesh blocks are the smallest geographic region in the Australian Statistical Geography Standard (ASGS), containing about 30-60 dwellings,<sup>22</sup> and are therefore the best geographic indicator of individual-level phenomena available.

Small spatial scales are also more likely to identify individuals though, so to protect the individual right to privacy, data for research is usually restricted to larger spatial units.

As data quality and availability improves, including access to mesh block level data, it will be important to test whether the high rates observed in priority places identified here are largely attributable to just one or a few smaller units within (or indeed, whether other smaller units with persistently high rates exist outside the priority places identified here).

Mesh block level data may even be small enough to enable application of density estimation techniques such as kernel density estimation, which predicts the distribution of risk across an area.<sup>23</sup>

Our analysis in Victoria is built on rates of potentially preventable hospitalisations that were calculated at the postcode-level. There is however no national consensus on the geographic boundaries of postcodes, and therefore no perfect estimation of population by postcode. Our rate numerator (number of ACSC hospitalisations) is allocated to postcodes based on patients' residential addresses. Our rate denominator (postcode population) is the ABS's Estimated Resident Population by Postal Area.

Postal Areas were created by the ABS to approximate Australia Post postcodes in the absence of published postcode boundaries. ABS Postal Areas are constructed from SA1s using the best available information on postcode boundaries.<sup>24</sup> Mesh block

<sup>&</sup>lt;sup>23</sup> Kernel density estimation is designed for point data; however urban mesh blocks may be sufficiently small to enable random attribution of hospitalisations within a mesh block (or to the mesh block centroid) and thereby estimate the distribution of risk within much larger areas. <sup>24</sup> ABS (2011a)

<sup>&</sup>lt;sup>22</sup> ABS (2011b)

dwelling counts are used where there is a poor geographic match with SA1s.

Estimated Resident Population is an approximation too. A full Census of Population and Housing is conducted only once every five years, so population data between Censuses are derived by estimating population changes (births, deaths, immigration and emigration).

The postcodes most likely to be affected by inaccuracies in postcode boundaries and/or population estimates are the smallest postcodes. Very small postcodes (population less than 1000 people) were excluded in our analysis. Persistence (high rates in every year) is also an important way that we control for potential inaccuracies or variations in boundaries.

Finally, the boundaries of spatial units may not reflect boundaries of relevance to the incidence or management of potentially preventable hospitalisations. *Perils of place* identifies 63 priority places; however the driving forces causing high rates of potentially preventable hospitalisations in these places may not lie within the same exact bounds. Risk of potentially preventable hospitalisation might spill over into neighbouring areas and therefore interventions in priority places should not necessarily be confined to their boundaries. Each priority place identified in our analysis marks a high concentration of potentially preventable hospitalisations to inform further interrogation of the problem and prioritise intervention activities.

## **Appendix A: Cluster analysis**

This appendix presents a cluster analysis of Chronic ACSC rates in Victoria. Here we use a statistical test of spatial association, Local Moran's I,<sup>25</sup> to identify clusters – groups of postcodes – with significantly higher rates than expected by chance alone.

High rate clusters identified in each of the 10 years are illustrated for the Melbourne region (Figure A1) and the rest of Victoria (Figure A2). We detail rates for the five main persistent clusters identified for Victoria in Table A1.

Table A1 illustrates, many postcodes within clusters have average rates themselves but are surrounded by higher rate areas, suggesting they may still be at risk of higher rates of potentially preventable hospitalisations if the causes of high rates in neighbouring areas play out over a broader area.

PHNs might use cluster analysis as one of many tools to understand the distribution of potentially preventable hospitalisations within their regions. However cluster analysis using postcode data or larger spatial units is unlikely to be sufficiently precise to guide prioritisation of place-based interventions. 

 High-High Cluster
 Output Cluster
 Output Cluster
 Output Cluster

 Cluster number
 2013-14
 2012-13

 2011-12
 2010-11
 2009-10
 2008-09

 2007-08
 2006-07
 2005-06
 2004-05

Figure A1: Statistically significant clusters of high Chronic ACSC

rates in the Melbourne region

Notes: Local Moran's I analysis was applied to Chronic ACSC rates by postcode in each individual year as well as to each area's average rate over 10 years (top left). Distance method applied was contiguity (edges and corners). Source: Grattan Institute analysis of VAED postcode data in ArcGIS

<sup>25</sup> Anselin (1995)

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Figure A2: Statistically significant clusters of high Chronic ACSC rates in regional Victoria



Notes: Local Moran's I analysis was applied to Chronic ACSC rates by postcode in each individual year as well as to each area's average rate over 10 years (top left). Distance method applied was contiguity (edges and corners). Source: Grattan Institute analysis of VAED postcode data in ArcGIS

Table A1: Statistically significant clusters of high Chronic ACSC rates in Victoria

#	Cluster	Postcode	Rate (10-yr avg)	Rate (2013-14)	Persistent hotspot or priority place?
1	Melton area	3022 3023 3024	2.17 1.32 1.33	1.86 0.93 2.16	Priority place
		3335 3338	1.75 1.19	2.19 1.30	Persistent hotspot
2	Broadmeadows area	3047 3048 3049 3060 3061	1.85 1.73 1.11 1.22 1.28	1.71 1.71 1.06 1.28 0.79	Priority place
3	Frankston, Cranbourne and surrounds	3175 3197 3198 3199	1.32 1.12 1.28 1.30	1.61 0.96 1.25 1.29	
		3200 3201 3803 3805 3806 3809 3810 3910	2.06 1.56 1.22 1.24 1.14 0.84 1.26 1.28	2.05 1.40 1.37 1.26 1.02 1.15 1.50 1.34	Priority place
		3911 3915 3933 3975	2.68 1.51 1.56 1.19	1.88 1.56 1.22 1.19	Priority place
		3976 3977 3978 3981	1.53 1.45 0.96 1.16	1.71 1.48 1.88 2.36	Persistent hotspot
4	Terang and surrounds	3264 3265	2.07 1.29	1.95 0.82	Priority place
5	Morwell area	3840 3842 3869	1.50 1.40 1.70	1.49 1.48 0.80	

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