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THE AUSTRALIAN NATURAL DISASTER RESILIENCE INDEX

VOLUME II – INDEX DESIGN AND COMPUTATION

Chapter 6 – Uncertainty and sensitivity analysis

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CHAPTER 6 UNCERTAINTY AND SENSITIVITY ANALYSIS

<u>In this chapter</u>

Section 6.1	Explains the role of uncertainty and sensitivity analysis in composite index construction.
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6.1 INTRODUCTION

Uncertainty and sensitivity analysis is a form of mathematical modelling, insofar as mathematical calculations connect a set of inputs (in this case, indicators) with one or more outputs (in this case, the Australian Natural Disaster Resilience Index). The model can also be set up so that methodological choices, such as which form of aggregation to use, are also treated as inputs to the model.

Uncertainty analysis assigns probability distributions to the model inputs, representing the uncertainty associated with these inputs. By repeated sampling from these distributions and recalculating the model, the impact of input uncertainty on the model output can be quantified.

Sensitivity analysis apportions the variation in the model output among the model inputs, identifying, for example, the inputs for which uncertainty might have the greatest effect on the output.

Uncertainty and sensitivity analysis have not been widely used in the construction of composite indices. One possible reason for this is the demand on computing capacity, given that the number of combinations of input parameter values (representing indicators and methodological choices) increases rapidly with the number of choices to be tested. In addition, Monte Carlo simulations may be required, with large numbers of model runs needed to obtain accurate estimates of the distribution of the model output.

Given the large number of indicators used in the Australian Natural Disaster Resilience Index, and the relatively detailed transformation and aggregation procedures, a complete uncertainty analysis that includes all indicators and the many choices made in transforming and aggregating indicators is prohibitively demanding of computing power. The approach taken for the Australian Natural Disaster Resilience Index was firstly to reduce the number of potential model inputs by *a priori* reasoning about methodological choices. For example, min-max rescaling versus rescaling using the mean and standard deviation (termed here MSD rescaling) has been tested in some sensitivity analyses for composite indices (e.g. Saisana et al. 2005). However, there are grounds for preferring min-max rescaling (see Chapter 3), so for the Australian Natural Disaster Resilience Index uncertainty and sensitivity analysis, min-max rescaling vs MSD rescaling is not included as a model input.

The second approach used in the Australian Natural Disaster Resilience Index uncertainty and sensitivity analysis is to, where required, break the analysis down into manageable components. For example, the confidentialising adjustments used by the Australian Bureau of Statistics (ABS) mean that some Census cell counts used for calculating indicators are uncertain. If these adjustments can be shown to have negligible effect on the Australian Natural

Disaster Resilience Index, then this potential source of uncertainty can be omitted from subsequent analysis.

Included in this chapter is a third sensitivity analysis examining change in Census data over time. Since all the indicators used in the construction of the Australian Natural Disaster Resilience Index are likely to change over time, the question arises as to how frequently the Australian Natural Disaster Resilience Index should be updated. Of the indicators comprising the Australian Natural Disaster Resilience Index, it is only the Census based indicators that are readily available for more than one point in time. The social character theme is solely comprised of Census based indicators and the changes from the 2011 to the 2016 Census for the theme sub-index are analysed to inform the question of the frequency of updating of the Australian Natural Disaster Resilience Index.

6.2 UNCERTAINTY ANALYSIS

There are potential sources of uncertainty at every step in the construction of a composite index. These sources can be divided into those that affect the initial indicator values (indicator uncertainty), and those associated with the method of construction of the composite index from the indicators (methodological uncertainty).

6.2.1 Indicator uncertainty

6.2.1.1 Random perturbation in Census data

For the data released from the 2011 Census, the ABS protected confidentiality in tables with small cell counts by random rounding to base 3 in cells with counts less than 20 (ABS 2005; 2017). Counts less than 20 and a multiple of 3 are left unchanged. Zero counts are also left unchanged. Counts less than 20 and not a multiple of three are changed to either the multiple of 3 above or below with a probability that reflects the size of the adjustment. For example, a count of 13 is changed to 12 with a probability of 2/3 and to 15 with a probability of 1/3.

The adjustment of cells less than 20 by random rounding to base 3 resulted in discrepancies between actual marginal totals (which are large enough to be published without adjustment) and the marginal totals obtained by summing cells, some of which have been adjusted. The ABS reported that it used an “additivity” adjustment in the 2006 and 2011 Census tables to ensure that marginal totals corresponded with the relevant sum of cells in the table (ABS 2017). The additivity adjustment involved “further small adjustments”, however the algorithm used for the additivity adjustment has not been published. The additivity adjustment was discontinued after the 2011 Census (ABS 2017)

The effect of random rounding to base 3 is that all cell counts less than 20 are multiples of 3 and the probabilities of the possible initial counts resulting in a multiple of 3 can be quantified. For example, the initial cell count that results in a cell count of 15 after random rounding has a probability of 1/9 of being a 13, a probability of 2/9 of being 14, a probability of 1/3 of being 15, a probability of 2/9 of being 16 and a probability of 1/9 of being 17. The effect of any additivity adjustment on top of the random rounding is more difficult to quantify. If both random rounding and additivity adjustments are regarded as “small”, then the additivity adjustment, when applied, could be assumed to add or subtract no more than 1 to or from a cell count. For example, a cell count of 16 could be assumed to have had an additivity adjustment of +1 and was 15 before the adjustment. If it was 15 before the additivity adjustment, then it would have been 13, 14, 15, 16 or 17 before the random rounding adjustment, with probabilities of 1/9, 2/9, 1/3, 2/9 and 1/9.

This reasoning provided the basis for an algorithm to use in uncertainty analysis to quantify the effect of ABS confidentialising adjustments on small cells:

with n_1 = original count,

n_2 = count after random rounding to base 3

n_3 = count after possible additivity adjustment to n_2, then:

for $n_3 \in \{3,6,9,\ldots18\}$, $n_1 \in \{ n_3-2, n_3-1, n_3, n_3+1, n_3+2\}$ with probabilities of 1/9, 2/9, 1/3, 2/9, and 1/9 respectively.

for $n_3 \in \{2,4,5,7,8,10,11,13,14,16,17,19,20\}$, $n_2 = \text{round}_{(\text{base3})}(n_3)$ and

$n_1 \in \{ n_2-2, n_2-1, n_2, n_2+1, n_2+2\}$ with probabilities of 1/9, 2/9, 1/3, 2/9, and 1/9 respectively.

The social character theme sub-index is calculated from 15 indicators, all of which are derived from 2011 Census data and therefore subject to confidentialising adjustments on small cells. The sub-index was recalculated 1,000 times for each of the 2,084 SA2s, using the algorithm above to adjust, where required, cell counts to the values they may have had prior to confidentialising. This provided a distribution of possible values of the social character theme sub-index for each SA2, from which the 5th percentiles and 95th percentiles could be calculated, and from these, the 5-95 inter-percentile range.

It was found that, of the 2,084 SA2s, 2,073 SA2s had a 5-95 inter-percentile range less than 0.015, meaning that for these SA2s there was a 90 percent chance that the value of the social character theme sub-index prior to confidentialising was within 0.0075 of the value after confidentialising. For example, the SA2 of Bombala has a median social character theme sub-index value of 0.4048 and a 5-95 inter-percentile range of 0.015. This means that there is a 90 per cent chance that the pre-confidentialising value of the sub-index lies between 0.4123 and 0.3973.

There are ten SA2s for which the 5-95 inter-percentile range lies between 0.015 and 0.1, and one SA2 (Western) for which the 5-95 percentile is 0.19. These eleven SA2s are characterised by low populations and/or substantial numbers of indicators with very low values. This combination makes the incidence of cells with counts less than 20 more likely. The 5-95 inter-percentile range for uncertainty associated with the ABS confidentialising procedure is mapped in Figure 6.1. State/Territory and major metropolitan area resolution maps are provided in Appendix 6A

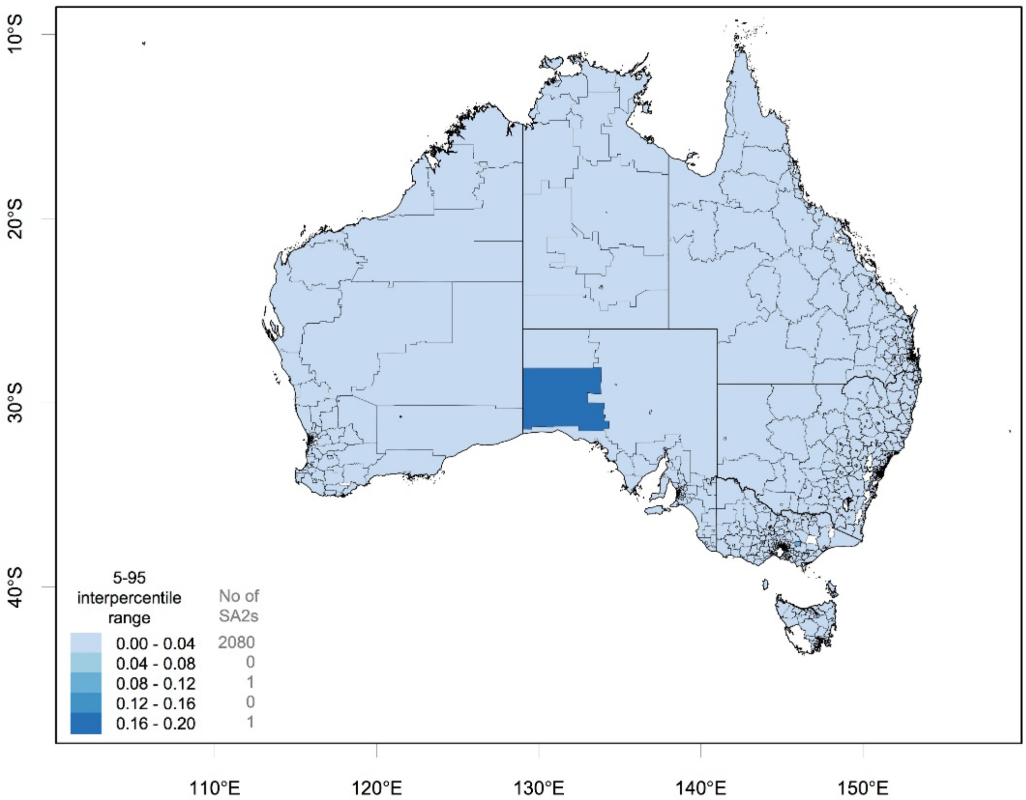

Figure 6.1: 5-95 inter-percentile range for the effect of ABS confidentialising procedures on the social character theme sub-index.

It is concluded that, for the social character theme, the ABS confidentialising procedure introduces negligible uncertainty in the vast majority of SA2s. The social character theme is the only theme where all indicators are derived from Census data and is therefore likely to represent the worst case for the impact of confidentialising procedures. Several other theme sub-indices use some Census-derived indicators, and it is likely that the impact of ABS confidentialising procedures on these themes will be negligible.

6.2.1.2 Evaluative uncertainty from document analysis

Several Australian Natural Disaster Resilience Index indicators are based on evaluations of planning and policy documents (see Chapter 2). The evaluations were of the extent to which particular criteria were met by government or other entities. The evaluations were coded numerically: 0 = not met, 1 = partly met, 2 = fully met. The indicators and number of items used to compute the indicator were:

Emergency Planning Assessment Score – 12 items;

Planning Assessment Score – 7 items;

Community Engagement Score – 7 items; and,

Governance, Policy and Leadership – 9 items.

The following assumptions were made about the probability of mis-evaluation for each item:

0 – probability of 1 or 2 is zero, i.e. there is complete certainty if the criterion for an item is not met;

1 – probability of 1 is 75%, probability of 2 is 25%; and,

2 – probability of 2 is 75%, probability of 1 is 25%.

As described in Chapter 2, the numerical evaluations were summed and expressed as a percentage of the maximum possible score obtainable. The greatest amount that mis-evaluations can cause an overall score to deviate from the true score is 50 percentage points. This occurs when all items were evaluated as 2 and should have been 1, or vice versa. Testing of synthetically generated indicators revealed that this relationship is approximately true for normalised and rescaled indicators. In this case, the maximum deviation due to mis-evaluation is 0.5.

From this, a probability density function to simulate evaluative uncertainty can be defined by a truncated normal distribution with a mean equal to the estimated indicator value and the following bounds:

the upper bound is the lesser of mean+0.5 or 1; and,

the lower bound is the greater of mean-0.5 or 0.

The Australian Natural Disaster Resilience Index value was calculated 1,000 times for each of the 2,084 SA2s, in each instance drawing at random an indicator value from the relevant truncated normal distribution for each of the four indicators that were derived by evaluation of planning and policy documents. The uncertainty analysis provided distributions of possible Australian Natural Disaster Resilience Index values for each of the 2,084 SA2s. The distributions are summarised in Figure 6.2. Evaluative uncertainty has a nonnegligible effect on the Australian Natural Disaster Resilience Index value, as much as approximately ±0.15.

The 5-95 inter-percentile range for the uncertainty associated with evaluation of planning and policy documents is mapped in Figure 6.3. State/Territory and major metropolitan area resolution maps are provided in Appendix 6B. The difference between Queensland and other States is a reflection of some of the evaluative indicators having been constructed from State planning and policy documents. Where an evaluative indicator has mid-range values, it will tend to have a higher 5-95 inter-percentile range for the simulated uncertainty, since the variation in mid-range values is not constrained by the minimum and maximum possible values of the indicator.

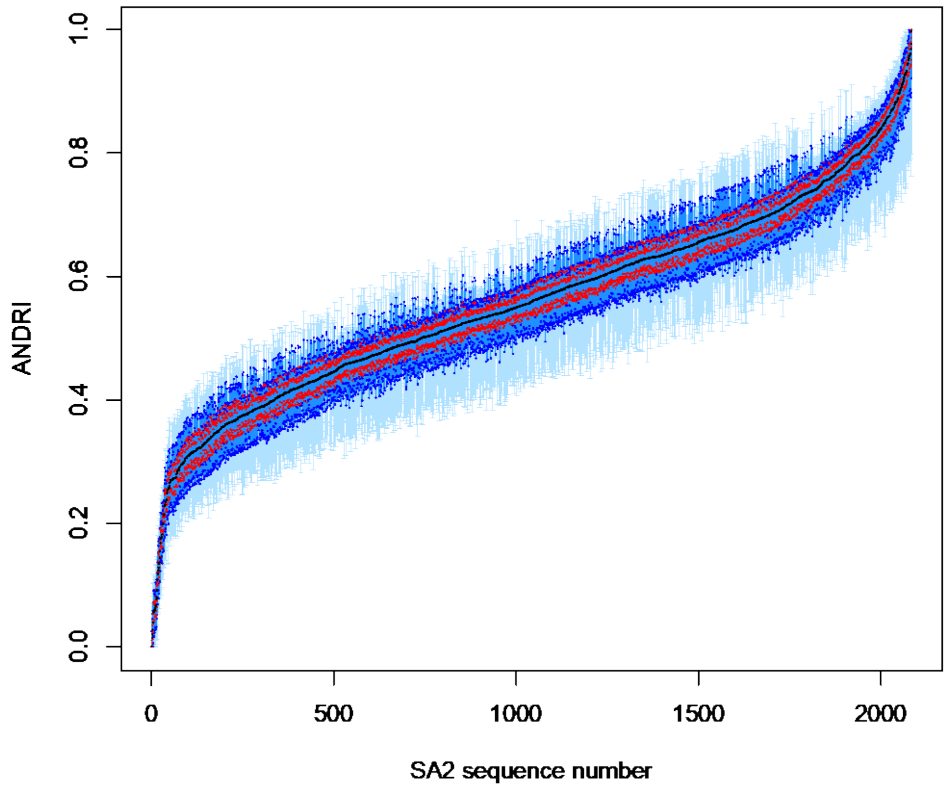

Figure 6.2: Effect of uncertainties in policy document evaluation shown as a sequence plot for simulated Australian Natural Disaster Resilience Index values- SA2s in increasing order of index value. Central black line = median, red dots = first and third quartiles, blue dots = 5th and 95th percentiles, light blue "whiskers" show the minimum and maximum values. 50% of values lie between the red dots, 90% of values lie between the blue dots.

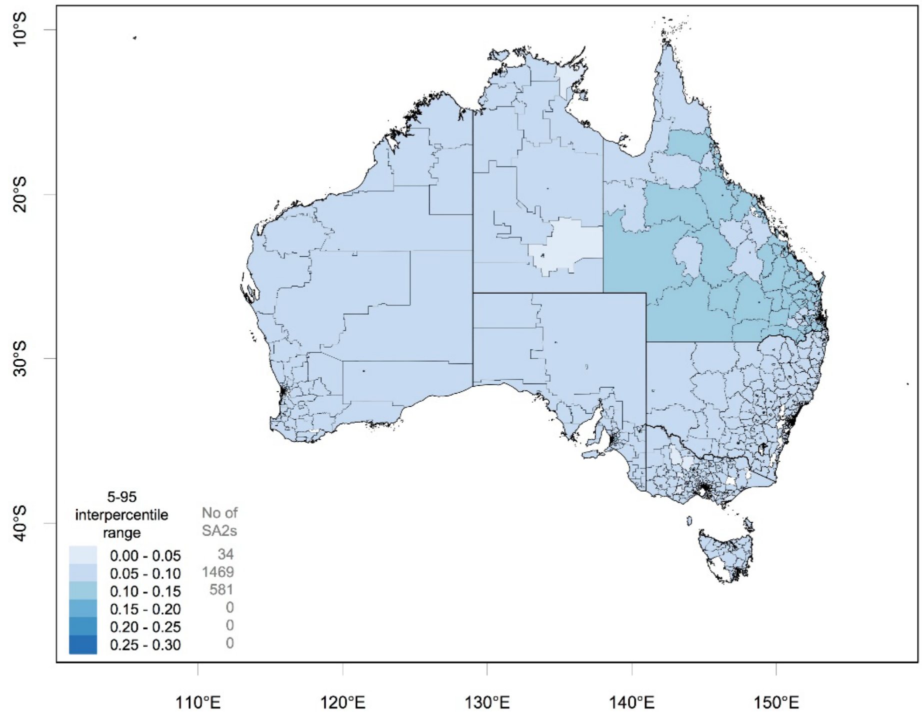

Figure 6.3: 5-95 inter-percentile range for the uncertainty in the Australian Natural Disaster Resilience Index caused by uncertainty in the evaluation of planning and policy documents**.**

6.2.1.3 Other indicator uncertainties

Some community capital indicators from Social Health Atlas are based on the ABS General Social Survey 2010 (see Chapter 2). The sample size for the latter is sufficient to ensure national, State and Territory estimates have an RSE less than 25%. ABS flags unreliable estimates, but it is not clear how the Social Health Atlas dealt with these. In the absence of this information, uncertainty analysis for the community capital indicators based on Social Health Data is not possible.

Several indicators used in the Governance and Leadership theme were supplied by the Regional Australia Institute (RAI), from its [In] Sight regional competiveness index. These indicators were derived by the Institute from ABS data and the Institute's own survey of local government websites. As such, the levels of uncertainty in the RAI indicators are likely to be low, and uncertainty analysis was not carried out for these indicators.

6.2.2 Methodological uncertainty

The main methodological uncertainties in the construction of the Australian Natural Disaster Resilience Index are associated with the disaggregation of data to SA2 level from larger geographical units, and the choice of orness values in the aggregation procedures. A number of methodological choices were made on substantive grounds and so are not candidates for uncertainty analysis. There are good grounds for preferring min-max rescaling over MSD rescaling (see Chapter 3). There are also good grounds for reducing the skewness and kurtosis of indicators prior to aggregation (see Chapter 3). The measurement model and aggregation strategy employed in the aggregation phase were also chosen on substantive grounds and so did not need to be included in an uncertainty analysis (see Chapter 3).

6.2.2.1 Disaggregation uncertainties

Data that are only available at a spatial resolution other than SA2, such as local government area (LGA) or State, has to be disaggregated to SA2 level so that it can be included in the construction of the Australian Natural Disaster Resilience Index. When disaggregation involves a characteristic that is spatially heterogeneous, this inevitably introduces uncertainty into the SA2 indicator values.

In determining the appropriate probability density function to reflect the uncertainty in an indicator value attributed to a target area (e.g. SA2) on the basis of the indicator values in constituent and/or surrounding source areas (e.g. LGA or State), it is necessary to consider whether indicators are spatially separable or non-spatially separable. If an indicator value can be meaningfully different in different parts of a source area, it can be considered to be spatially separable. For example, percentage of single parent families is spatially separable because different parts of a source area could feasibly have different percentages (Figure 6.4). In this situation, the area of overlap between the target SA2 and source LGA could contain all the single parent families in the LGA or none of them. Following from this, the minimum possible indicator value in the target SA2 would be 0% and the maximum possible value would be 100%. The true value would lie somewhere in between, depending on the vagaries of the spatial distribution of single parent families in the source LGAs.

If an indicator can only have one value across all parts of a source area, then it can be considered as non-spatially separable. For example, a local government financial sustainability rating is non-spatially separable because it is the same for all areas within an LGA. In this situation, the area of overlap between the target SA2 and source LGA can only take the value for the LGA, and there is no disaggregation uncertainty. If a target SA2 is comprised of several source LGAs then its local government financial sustainability rating, to the extent this is meaningful for an SA2, will be an area or population weighted mean of the ratings of the contributing source LGAs. There will be no disaggregation uncertainty.

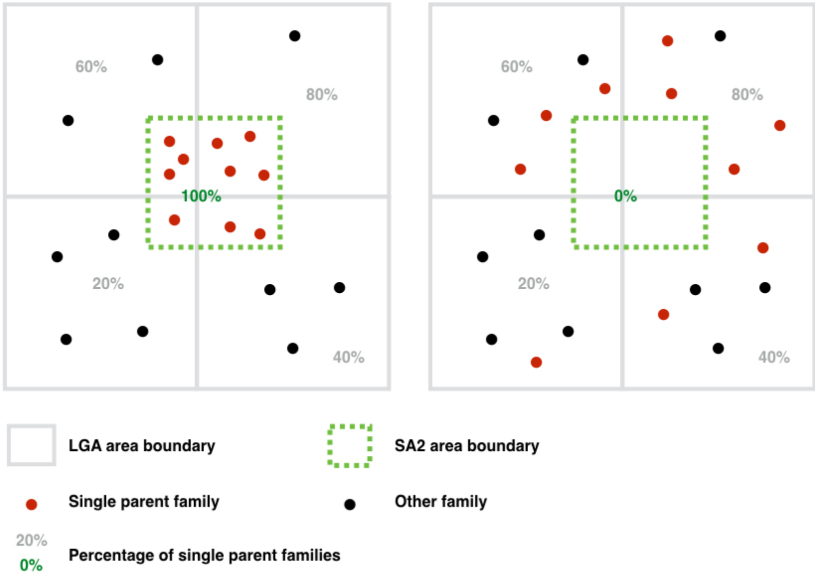

Figure 6.4: Schematic example of the disaggregation of an indicator (% single families) from four source LGAs to one target SA2. Each dot represents the geographic position of a family.

Having set maximum and minimum possible values for a target area indicator, it is then necessary to consider the shape of the probability density function between these two values. The probability density function summarises the distribution from which samples of possible indicator values are drawn in modelling the disaggregation uncertainty.

The greater the spatial heterogeneity of an indicator, the more likely are indicator values in the extremes of the probability density function, resulting in a flatter probability density function. For example, consider the indicator, hospital beds per 1,000 population, which has a value of 5 when measured across a large region that has a population of 25,000 people, making 125 beds altogether in the region. Obviously, hospital beds can only occur in hospitals and it is not known which SA2s within the region have a hospital. Suppose only one SA2 (population 1,000) has a hospital – then this SA2 will have an indicator value of 125 and all other SA2s in the region will have indicator values of zero. If there are two SA2s with hospitals, then these will have large indicator values (how large depends on their population), while the rest will have zero values. This illustrates how a wide range of indicator values are possible for SA2s, while still meeting the constraint that the larger region have an indicator value of 5 beds per 1,000 persons. This can be modelled by sampling from a distribution with a high standard deviation. The probability density function of this distribution will be relatively flat.

As a further example, consider the indicator, percent population between 15 and 65 years of age. This indicator will be relatively homogeneous across space. Areas with mainly children and the elderly are unlikely, as are areas with very few children or elderly. Consequently, the actual indicator values in SA2s are likely to be similar to the overall value across the larger region of which the SA2s are part. This can be modelled by sampling from a distribution with a low standard deviation. The probability density function will be peaked at the overall value for the larger region.

The SA2 target area values for disaggregated indicators represent the best estimate, given the information provided by the source area values and any other information brought into the estimation procedure. The true SA2 target area value is more likely somewhere in the vicinity of the estimated value – only slightly more likely where there is high spatial heterogeneity, and very much more likely where the indicator is spatially homogeneous. This suggests that disaggregation uncertainty could be represented by probability density functions that respect the minimum and maximum possible values and have a mode equal to the estimated value. The truncated normal distribution is suitable for this purpose. Figure 6.5 shows the probability density functions for indicator values of 0.2, 0.5 and 0.8, for three different levels of disaggregation uncertainty, represented by standard deviations of 0.7 (high uncertainty), 0.25 (moderate uncertainty) and 0.1 (low uncertainty).

Ideally, the analysis of disaggregation uncertainty would start with probability density functions representing the possible raw indicator values after disaggregation, for every indicator that was not available at SA2 level. Each set of indicator values drawn from these probability density functions would need to be transformed to normality and rescaled to a range of 0 to 1, before being combined with other non-disaggregated indicators to construct theme sub-indices and the Australian Natural Disaster Resilience Index. This approach is prohibitively computation intensive, but it is possible to gain some measure of the impact of disaggregation uncertainty on the Australian Natural Disaster Resilience Index with less computation by making the transformed and rescaled indicators the starting point for the analysis. In this case, the probability density functions used to model disaggregation uncertainty are all truncated at 0 and 1 (Figure 6.5). For each disaggregated indicator, the likely degree of spatial heterogeneity was considered and the disaggregation uncertainty characterised as high, moderate or low. The standard deviation of the truncated normal distribution was set to, respectively, 0.7, 0.25 or 0.1 (Figure 6.5).

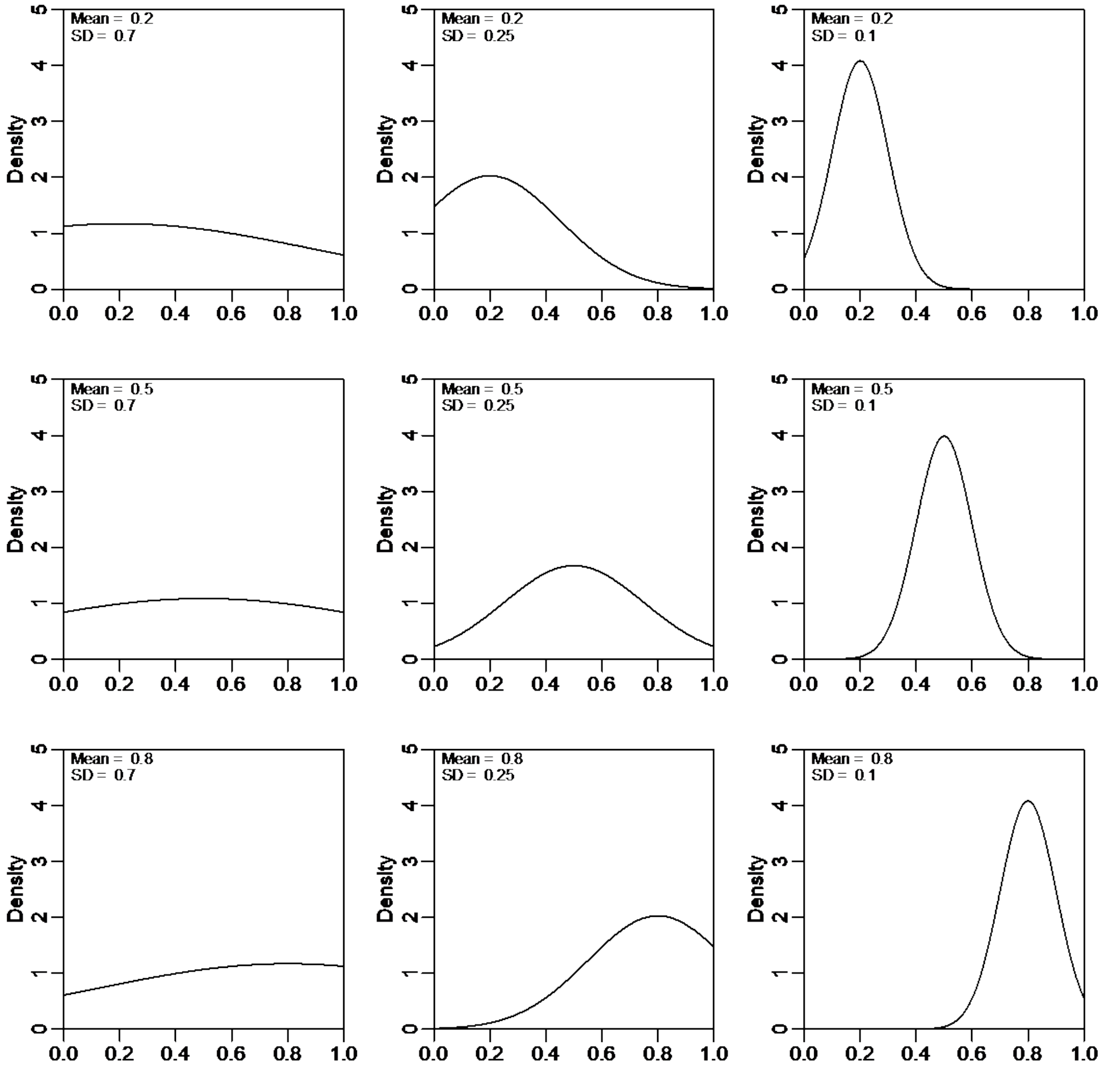

Figure 6.5: Example probability density functions for indicators with transformed rescaled values of 0.2 (top row), 0.5 (middle row) and 0.8 (bottom row). For each row, levels of uncertainty are high (SD = 0.7), moderate (SD = 0.25) and low (SD = 0.1).

The Australian Natural Disaster Resilience Index value was calculated 1,000 times for each of the 2,084 SA2s, in each instance drawing at random an indicator value from the relevant truncated normal distribution for each of the disaggregated indicators. For example, if the value of a disaggregated indicator in a particular SA2 had been determined to be 0.8, and this indicator was expected to have a high spatial heterogeneity, then a random sample of 1,000 indicator values was drawn from a truncated normal distribution with a lower bound of 0, an upper bound of 1, a mean of 0.8 and a standard deviation of 0.7 (Figure 6.5, lower left). The indicators for which SA2 values were arrived at by disaggregation are listed in Table 6.1. The rightmost column gives the standard deviations of the truncated normal distributions used in the disaggregation uncertainty analysis.

Table 6.1: Indicators for which the SA2 values were arrived at by disaggregation from other geographies.

Theme	Indicator	Source geography	Indicator type	Disaggregation method	SD of truncated normal distribution
Economic capital	Local government grant per capita	LGA	Non-spatially separable	Population weighted mean	NA
Planning and the built environment	Emergency plan assessment score	LGA	Non-spatially separable	Semi-quantitative	NA
	FTE council staff 14-15	LGA	Non-spatially separable	Semi-quantitative	NA
	Area (of LGA) km2/FTE	LGA	Non-spatially separable	Semi-quantitative	NA
	Dwellings/FTE	LGA	Non-spatially separable (FTE applies only to whole LGA)	Semi-quantitative	NA
	New dwellings (2012-16) as proportion of 2011 dwellings (%)	LGA	Spatially separable, high heterogenei ty	Semi-quantitative	0.7
	New dwellings per week (2015-16)	LGA	Spatially separable, high heterogenei ty	Semi-quantitative	0.7
	Planning assessment score	LGA	Non-spatially separable	Semi-quantitative	NA
Emergency Services	Medical practitioners per 1,000 population	SA3	Spatially separable, high heterogenei ty	Single SA3 value attributed to SA2s	0.7
	Registered nurses per 1,000 population	SA3	Spatially separable, high heterogenei ty	Single SA3 value attributed to SA2s	0.7
	Psychologists per 1,000 population	SA3	Spatially separable, high heterogenei ty	Single SA3 value attributed to SA2s	0.7
	Welfare support workers per 1,000 population	SA4	Spatially separable, high heterogenei ty	Single SA4 value attributed to SA2s	0.7
	Hospital beds per 1,000 population	Remoteness regions within States	Spatially separable, high heterogenei ty	Value for remoteness region within State attributed to SA2s	0.7

Table 6.1 (cont.)

Theme	Indicator	Source geography	Indicator type	Disaggregation method	SD of truncated normal distribution
Emergency services (cont.)	Ambulance officers and paramedics per 1,000 population	SA4	Spatially separable, high heterogeneity	Single SA4 value attributed to SA2s	0.7
	Fire and emergency workers per 1,000 population	SA4	Spatially separable, moderate heterogeneity	Single SA4 value attributed to SA2s	0.25
	Police per 1,000 population	SA4	Spatially separable, high heterogeneity	Single SA4 value attributed to SA2s	0.7
	Fire and emergency services and SES organisations, cost per 1,000 population	State	Non-spatially separable	Single State value attributed to SA2	NA
	Ambulance organisations, cost per 1,000 population	State	Non-spatially separable	Single State value attributed to SA2	NA
	Fire service volunteers per 1,000 population	State	Spatially separable, moderate heterogeneity	Single State value attributed to SA2	0.25
	SES volunteers per 1,000 population	State	Spatially separable, moderate heterogeneity	Single State value attributed to SA2	0.25
	Distance to a medical facility (km)	LGA	Spatially separable, high heterogeneity	Semi-quantitative	0.7
Community capital	Offences against persons, 2011-12, per 100,000 population	Police districts, LGAs, suburbs	Spatially separable, moderate heterogeneity	Semi-quantitative	0.25
	Offences against property, 2011-12, per 100,000 population	Police districts, LGAs, suburbs	Spatially separable, moderate heterogeneity	Semi-quantitative	0.25
	Safe walking in neighbourhood ASR, 2010, per 100	LGA	Spatially separable, moderate heterogeneity	Semi-quantitative	0.25

Table 6.1 (cont.)

Theme	Indicator	Source geography	Indicator type	Disaggregation method	SD of truncated normal distribution
Community capital (cont.)	Support in crisis ASR, 2010, per 100	LGA	Spatially separable, moderate heterogeneity	Semi-quantitative	0.25
	Difficulty accessing services ASR, 2010, per 100	LGA	Spatially separable, moderate heterogeneity	Semi-quantitative	0.25
	Poor self-assessed health ASR, 2010, per 100	LGA	Spatially separable, moderate heterogeneity	Semi-quantitative	0.25
	Raise $2,000 in week ASR, 2010, per 100	LGA	Spatially separable, high heterogeneity	Semi-quantitative	0.7
Information and access	Mean area weighted ADSL coverage	Raster	Spatially separable, low heterogeneity	Areal cover	0.1
	% area with mobile phone coverage	Raster	Spatially separable, low heterogeneity	Areal cover	0.1
	Community engagement and hazard education	State	Non-spatially separable	Single State value attributed to SA2	NA
Governance and leadership	Presence of research organisations	LGA	Spatially separable, moderate heterogeneity	Semi-quantitative	0.25
	Business Dynamo Sub-index	LGA	Spatially separable, high heterogeneity	Semi-quantitative	0.7
	Local economic development support	LGA	Non-spatially separable	Semi-quantitative	NA
	Governance, policy and leadership score	State	Non-spatially separable	Single State value attributed to SA2	NA
Social and community engagement	Participation in personal interest learning	State	Spatially separable, moderate heterogeneity	Single State value attributed to SA2	0.25

The uncertainty analysis provided distributions of possible Australian Natural Disaster Resilience Index values for each of the 2,084 SA2s (Figure 6.6). The uncertainty created by disaggregation from broader scale geographies to SA2 in obtaining indicator values has considerable impact on the Australian Natural Disaster Resilience Index value. Depending on the vagaries of spatial heterogeneity, the Australian Natural Disaster Resilience Index value could be as much as 0.2 either side of the derived value.

The 5-95 inter-percentile range is mapped in Figure 6.7. State/Territory and major metropolitan area resolution maps are provided in Appendix 6C

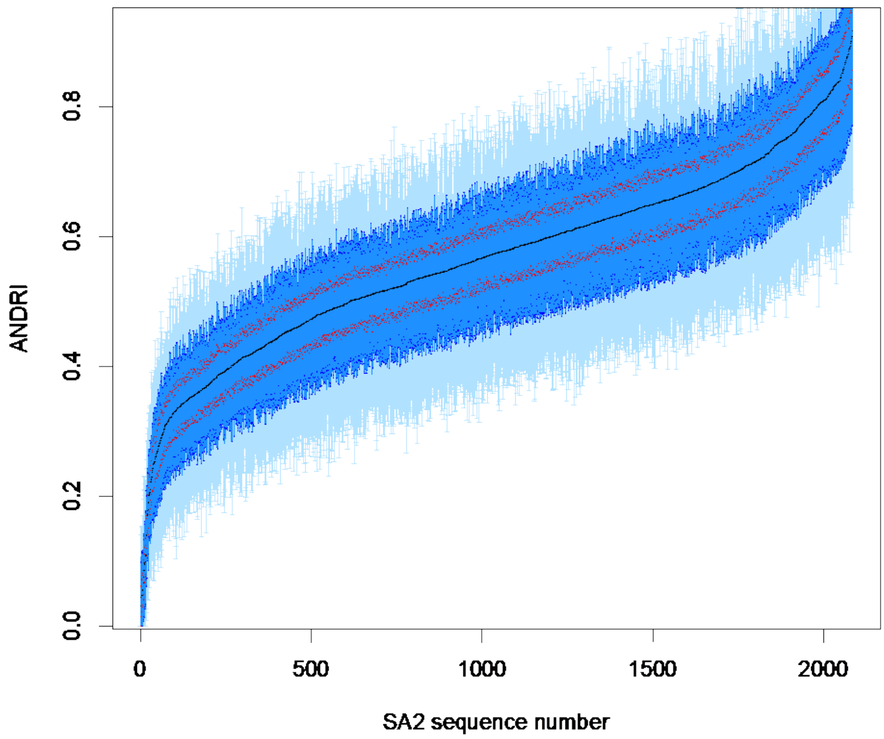

Figure 6.6: Effect of uncertainties in disaggregation shown as a sequence plot for simulated Australian Natural Disaster Resilience Index values – SA2s in increasing order of index values. Central black line = median, red dots = first and third quartiles, blue dots = 5th and 95th percentiles, light blue "whiskers" show the minimum and maximum values. 50% of values lie between the red dots, 90% of values lie between the blue dots.

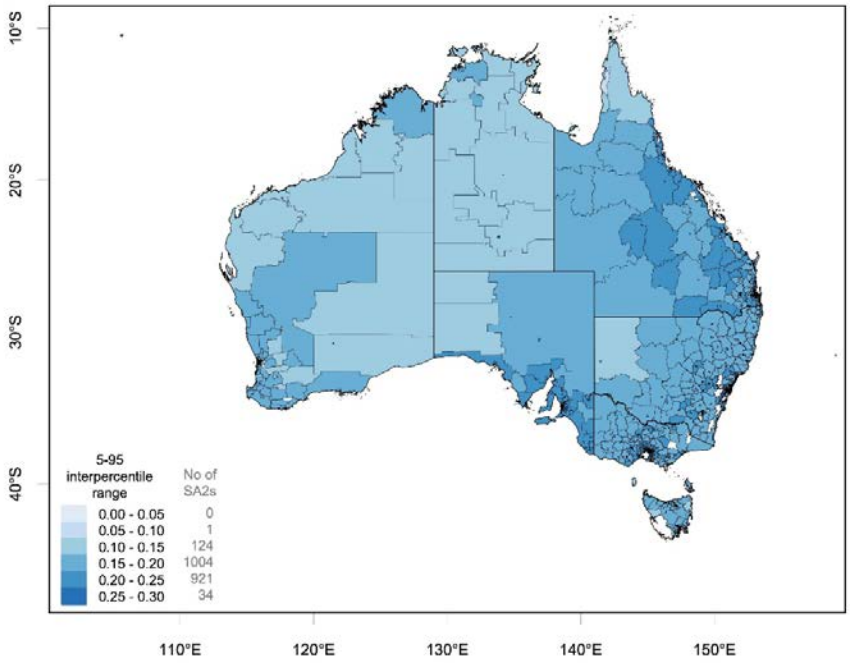

Figure 6.7: 5-95 inter-percentile range for the uncertainty in the Australian Natural Disaster Resilience Index caused by uncertainty in disaggregated indicator values.

6.2.2.2 Orness uncertainties

Aggregation of indicators by simple summation or averaging is common practice in the construction of composite indices but is also widely criticised for the implicit and unexamined assumption of unrestrained compensability between indicators (see Chapter 3). Ordered weighted averaging (OWA) and the discrete Choquet integral have been used in the construction of the Australian Natural Disaster Resilience Index and these aggregation procedures allow for the degree of compensability to be adjusted to reflect the current understanding of how the factors represented by the indicators might substitute for each other in determining resilience.

Central to this is the specification of the orness parameter, which determines the degree of restraint on compensability in the aggregation process. The degree of restraint can range from no restraint (orness = 0.5, equivalent to the arithmetic mean) to no compensability (orness = 0.0, equivalent to the minimum function). For example, aggregating two indicators with values 0.4 and 0.8, the value of the composite index will be the mean, 0.6 if the orness of the aggregation is 0.5, and the minimum, 0.4 if the orness of the aggregation is 0.0.

The current level of understanding as to how various characteristics of communities might combine to determine their resilience to natural disasters falls far short of what is required to specify the orness values that might reflect the degree of compensatory effects among these characteristics.

Accordingly, the Australian Natural Disaster Resilience Index aggregation procedures use just two orness values: 0.125 for situations where it can be reasoned that a fair degree of restraint should be placed on compensatory effects, and 0.375 for situations where it can be reasoned that some, but not completely unrestrained, compensatory effects can be allowed. The assumption of just two orness values introduces uncertainty into the Australian Natural Disaster Resilience Index, since the actual orness values needed to simulate the real compensatory effects between resilience characteristics could well be different to that implied by the chosen orness values.

So, it is possible, where limited compensatory effects is a reasonable assumption, that the required orness value lies anywhere between 0.0 and 0.25. Likewise, where it is reasoned that some compensatory effects are acceptable, the required orness value could lie anywhere between 0.25 and 0.5. These limits, then, will apply to the probability density function used to simulate the uncertainty in setting the orness value.

The assumed orness value used in the aggregation procedures to construct the Australian Natural Disaster Resilience Index are outlined in Table 6.2. There are 23 orness values, of which 5 are 0.125 and the remaining 18 are 0.375. Starting with the 77 rescaled and normalised indicators, the aggregation procedure was repeated 1,000 times. For aggregation by OWA, the orness values for each recalculation were drawn from truncated normal distributions. The distribution for the low orness value of 0.125 was truncated at 0.00 and 0.25, while the distribution for the high orness value of 0.375 was truncated at 0.25 and 0.50. In both cases, the truncated normal distributions were set to have a standard deviation of 10 per cent of the mean. For aggregation by discrete Choquet integral, the individual elements of the fuzzy measure were also drawn from truncated normal distributions. The parameters of these distributions were adjusted manually so that distribution of orness values for the fuzzy measures would be centred on 0.375 or 0.125 and truncated at 0.50 and 0.25, and 0.25 and 0.00, respectively, while preserving the relationships among the elements of the fuzzy measures.

The uncertainty analysis provided distributions of possible Australian Natural Disaster Resilience Index values for each of the 2,084 SA2s. The distributions are summarised in Figure 6.8. Uncertainty in the choice of orness values in the aggregation phase for the Australian Natural Disaster Resilience Index has some impact on the Australian Natural Disaster Resilience Index value. The range of orness values tested was quite wide: from 0.0 – 0.25 for the low orness value and from 0.25 to 0.50 for the high orness value. However, the range in resultant Australian Natural Disaster Resilience Index values is within 0.1 of the central value.

The 5-95 inter-percentile range is mapped in Figure 6.9. State/Territory and major metropolitan area resolution maps are provided in Appendix 6D

Table 6.2: Orness values used in the aggregation procedures for the construction of the Australian Natural Disaster Resilience Index.

Theme or sub-index	Model	Aggregation method	Orness	Intermediate sub-indices	Aggregation method	Orness
Social character	Two level formative	OWA	0.375	Household factors	OWA	0.375
				Socio-economic advantage	OWA	0.375
				Infirmity	OWA	0.375
				Familiarity with locality	OWA	0.375
Economic capital	Two level formative	OWA	0.375	Disposable income	OWA	0.375
				Ownership	OWA	0.375
				Economy	OWA	0.375
Planning and the built environment	Two level formative	Discrete Choquet integral	0.375	Local government capacity	OWA	0.375
				Infrastructure integrity	OWA	0.125
Emergency services	Two level formative	Discrete Choquet integral	0.125	Emergency response resources	OWA	0.125
				Proximity to medical services (single indicator		
Community capital	Single level formative	OWA	0.375			
Information and access	Single level formative	Discrete Choquet integral	0.375			
Governance and leadership	Single level formative	OWA	0.375			
Social and community engagement	Two level formative	OWA	0.125	Educational participation	OWA	0.375
				Life satisfaction and trust	OWA	0.125
				Gross in and out migration (single indicator)		
Coping capacity	Single level formative	OWA	0.375			
Adaptive capacity	Single level formative	Discrete Choquet integral	0.375			
ANDRI	Single level formative	Discrete Choquet integral	0.375			

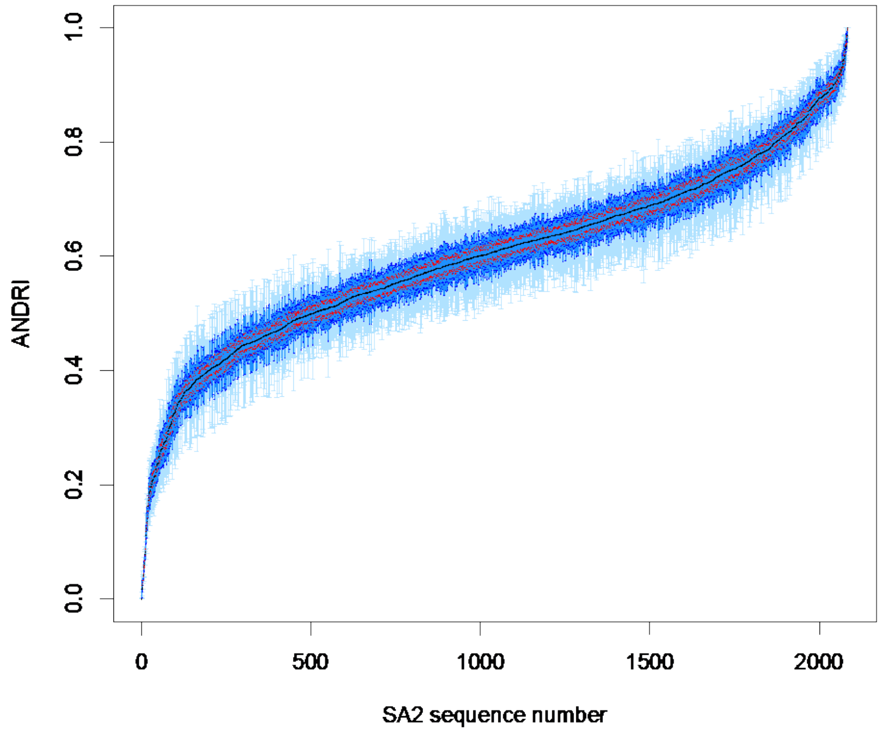

Figure 6.8: Effect of uncertainties in orness values shown as a sequence plot for simulated Australian Natural Disaster Resilience Index Values– SA2s in increasing order of index values. Central black line = median, red dots = first and third quartiles, blue dots = 5th and 95th percentiles, light blue "whiskers" show the minimum and maximum values. 50% of values lie between the red dots, 90% of values lie between the blue dots.

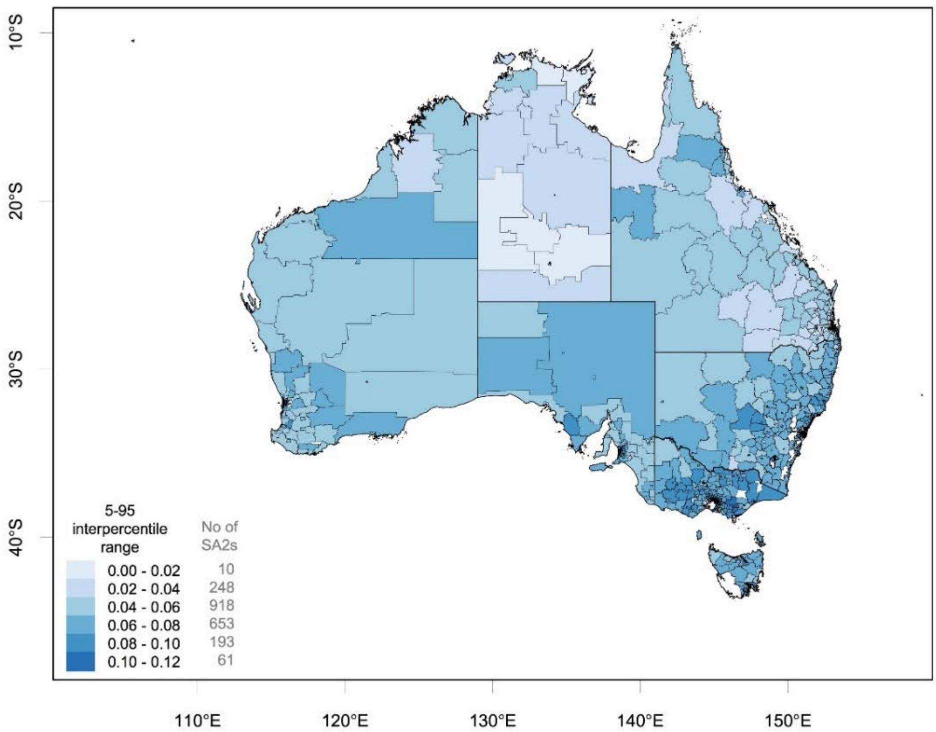

Figure 6.9: 5-95 inter-percentile range for the uncertainty in the Australian Natural Disaster Resilience Index caused by uncertainty in the orness values used in the aggregation procedure.

6.3 SENSITIVITY ANALYSIS

Given the complexity of the aggregation process in a hierarchically structured composite index, such as the Australian Natural Disaster Resilience Index, it is not unreasonable to expect that variation in some aggregation parameters (e.g. choice of orness value) might result in greater variation in the final index value, compared to the variation that results from other parameters. Alternatively, variation in some indicators might have a dominating effect on the variation of the index.

Sensitivity analysis provides a means of apportioning the variation in the Australian Natural Disaster Resilience Index to the indicators and aggregation parameters used in its construction. This enables the identification of indicators and/or parameters where variation will flow through to the index, versus indicators and/or parameters for which variation has negligible impact on the index.

Whether or not the domination of the Australian Natural Disaster Resilience Index variance by some indicators or aggregation parameters constitutes a problem for the validity of the index depends on the source of the indicator or parameter variation. For example, if an indicator has a wide range of valid values across Australia and the aggregation process is an accurate reflection of the actual compensatory effects among the factors that influence resilience, then its identification in sensitivity analysis as having a strong influence on the index value is nothing more than a reflection of reality.

On the other hand, if uncertainty in the construction of the index means that some indicators or parameters could potentially have values substantially different from their assigned values, then it is a matter of concern if sensitivity analysis identifies variation in these indicators or parameters as having a strong influence on the variation in the Australian Natural Disaster Resilience Index. This means that the uncertainty in these indicators or parameters flows through to uncertainty in the index. Uncertainty analysis and sensitivity analysis, together, are important tools for identifying the priority areas in which to attempt to reduce uncertainty, with a view to improving the accuracy of the Australian Natural Disaster Resilience Index.

6.3.1 Methods of sensitivity analysis

The simplest methods of sensitivity analysis are the so called local methods, generally based on derivatives, which calculate the change in model output (such as the Australian Natural Disaster Resilience Index value) relative to a change in an input factor (such as an indicator), while holding all other factors constant at their central values. While they have been widely used, these methods have the disadvantage that they leave large parts of the space of possible input factor values untested, are unable to discover interactions between factors and are limited in use to linear and/or additive models (Saltelli and Annoni 2010; Ferretti et al. 2016).

Global sensitivity analysis, on the other hand, and particularly the variance-based techniques that have been developed in the last few decades, requires no assumptions about model linearity and additivity, tests the space of input factor values much more comprehensively and deals specifically with interaction effects (Saltelli et al. 2008). However, these techniques have a prohibitively high demand on computing time and resources. Preliminary tests with Sobol' methods and the Australian Natural Disaster Resilience Index calculations (which involve 114 input factors) revealed that, with the computer resources available to the project, a single sensitivity analysis would take at least 11 days running time.

The Morris Elementary Effects method (Morris 1991) is a compromise, suited to large models, between the inadequacy of local methods and the impractical nature of the variance-based methods. A number of studies have demonstrated that it provides results that are consistent with the results from variance-based methods (Campolongo and Saltelli 1997; DeJonge et al. 2012; Herman et al. 2013), while still exploring much of the input factor space at low computational cost. The method calculates the mean and standard deviation of the effects of each input factor on the model output, varied one at a time while holding other factors at a range of values defined by various trajectories through the input factor space. A high standard deviation for an input factor signals that its effects vary substantially, depending on the values of other input factors. This is an indication of interaction effects in the model.

Campolongo et al. (2007) proposed a refinement of the Morris Elementary Effects method, wherein the mean of the effects (conventionally denoted "mu") is replaced by the mean of the absolute value of effects (conventionally denoted by "mu*"). This refinement reduces the probability of Type II error in the method, which could occur if large positive and negative effects cancel each other out in the calculation of mu.

6.3.2 Sensitivity analysis - Morris Elementary Effects method

The results from the application of the Morris Elementary Effects method to the Australian Natural Disaster Resilience Index calculation are shown in Figure 6.10 The small grey dots represent indicators and aggregation parameters that have negligible effect on the Australian Natural Disaster Resilience Index. The indicators that have a negligible effect on the Australian Natural Disaster Resilience Index might be considered for removal in future iterations of the index, although this purely mathematical criterion will have to be set against substantive reasons for retention. The 16 indicators with a mean absolute effect (mu*) less than 0.002 are listed in Table 6.3. A full list of all indicators and aggregation parameters is provided in Appendix 6E.

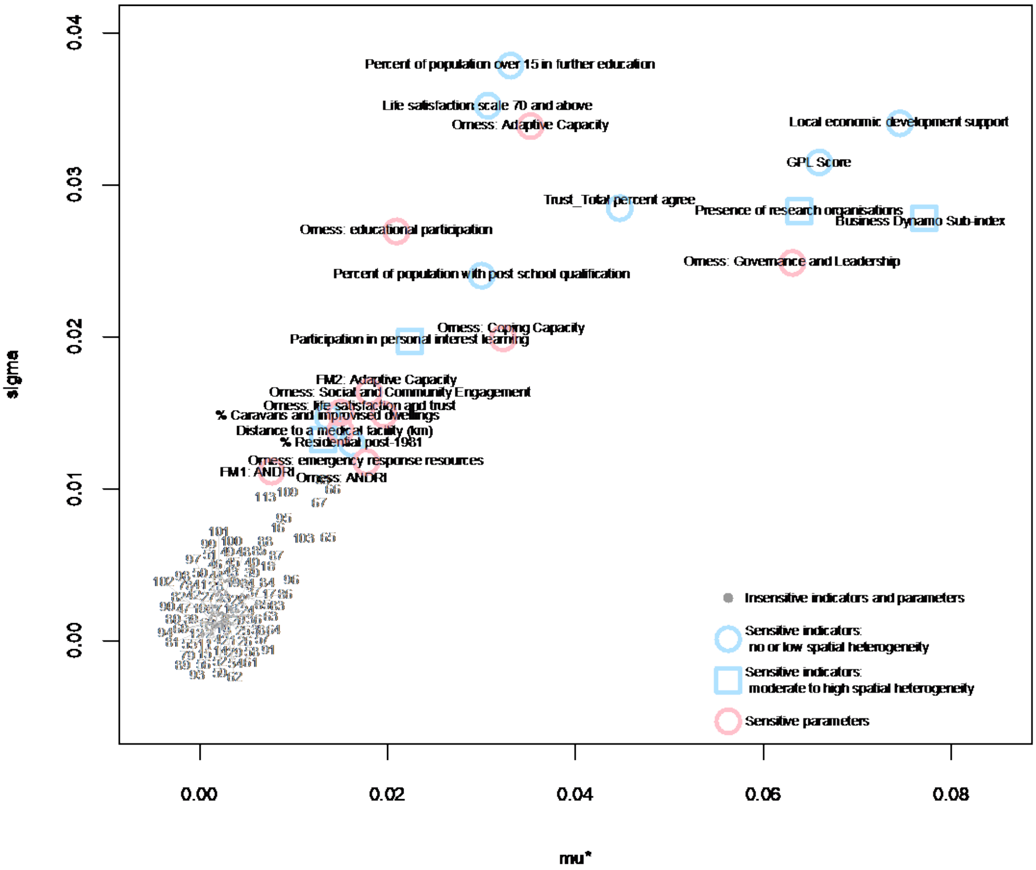

Figure 6.10: Scatter plot of the mean absolute effect and standard deviation of effects. The plotting symbols distinguish between indicators and methodological parameters and show the degree of spatial heterogeneity associated with indicators obtained by disaggregation. The numbers beside the dots relate to the listing of indicators and parameters in Appendix 6E.

Above and to the right of the grey dots are a group of indicators and parameters that have some effect on the Australian Natural Disaster Resilience Index (Figure 6.10). Of these, distance to a medical facility is associated with moderate to high disaggregation uncertainty and this will flow through to cause some uncertainty in the index.

The Australian Natural Disaster Resilience Index is most sensitive to variation in the indicators and parameters that plot in the top right area of the scatter plot (Figure 6.10). Two indicators: the business dynamo sub-index and the presence of research organisations, are also associated with relatively higher uncertainties, due to their likely higher levels of spatial heterogeneity and disaggregation from LGA to SA2. This means that these two indicators are likely to be important sources of any uncertainty in the Australian Natural Disaster Resilience Index. The relatively high values of sigma signal that the relationship between variation in the indicators and variation in the index is likely to be non-linear and involve interactions between indicators and/or parameters.

The Australian Natural Disaster Resilience Index values are also sensitive to variation in local economic development support and governance, policy and leadership score. However, while these indicators are disaggregated to SA2 level, spatial heterogeneity is low or non-existent, so that disaggregation uncertainty is minimal. These two indicators, therefore, are unlikely to introduce any significant uncertainty into the Australian Natural Disaster Resilience Index.

Overall, the sensitivity analysis illustrates the simple property of an aggregative hierarchy: the more aggregation calculations standing between an indicator at the bottom of the hierarchy and the Australian Natural Disaster Resilience Index at the top, and the more companion indicators included in the lowest level aggregation along with that indicator, the less effect it will have on the Australian Natural Disaster Resilience Index.

Table 6.3: List of the indicators with the least effect on the Australian Natural Disaster Resilience Index.

Indicator	mu*	Indicator	mu*
% of households with all or some residents not present a year ago	0.0011	% one parent families	0.0014
% managers and professionals	0.0012	Fire and emergency workers per 1,000 population	0.0014
Ratio of certificate and/or postgrad to year 8-12	0.0012	% lone person households	0.0016
% households with children	0.0013	% population aged over 75	0.0016
% population aged under 15	0.0013	Sex ratio	0.0017
% population with a core activity need for assistance	0.0013	Support in crisis ASR, 2010, per 100	0.0018
% not in labour force	0.0013	Medical practitioners per 1,000 people, 2011	0.0018
% group households	0.0013	% one parent families	0.0014

6.3.3 Sensitivity to Census data over time

The social character sub-index of the Australian Natural Disaster Resilience Index is based on 2011 Census data, as this was the most current during the indicator collection phase of the research. The data from the 2016 Census has since become available. This provides an opportunity to examine the change in the social character sub-index between 2011 and 2016, and the spatial distribution of this change.

6.3.3.1 Methods – comparison of 2011 and 2016 social character theme index

Of the 2,084 SA2s for which the Australian Natural Disaster Resilience Index was calculated, 1,770 SA2s had the same boundaries in 2016 as in 2011 (Figure 6.11). The remaining 314 SA2s had different boundaries in 2016 compared to 2011. These differences ranged from minor adjustments to the splitting of single 2011 SA2s into two or more SA2s in 2016 (Figure 6.11). Many of the SA2s where there have been changes to boundaries between 2011 and 2016 occur on metropolitan peripheries.

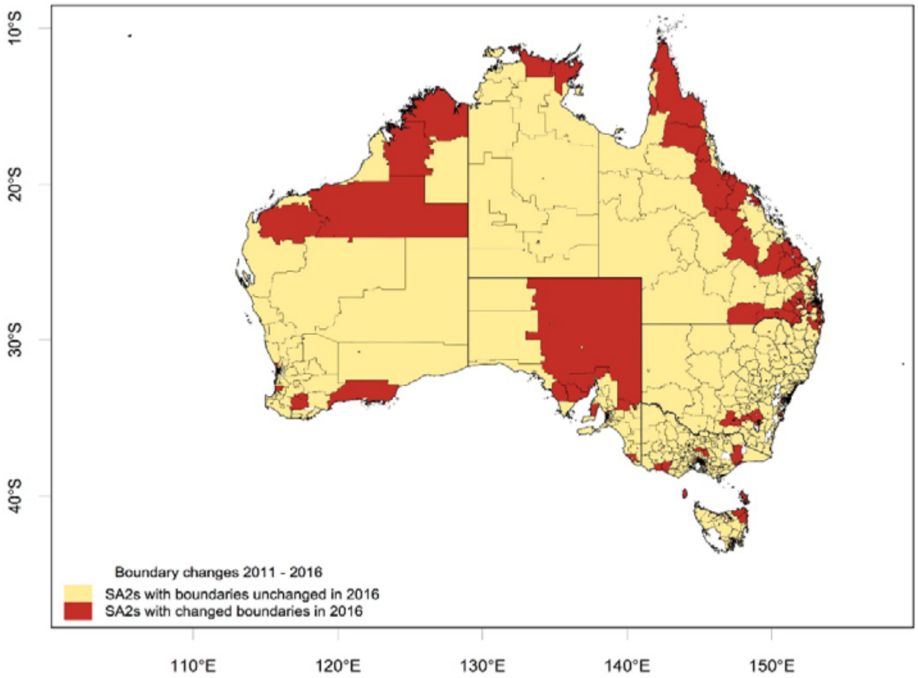

Figure 6.11: SA2 boundary changes between the 2011 and 2016 Census.

Boundary change complicates the comparison of 2011 and 2016 indicators and sub-indices on the same spatial basis. Where there have been boundary changes, 2016 Census indicator values can only be expressed on 2011 SA2 boundaries as estimates derived by population weighting using the 2011 SA2 – 2016 SA2 correspondence table (ABS 2016). The calculation of these estimates assumes population characteristics are uniformly distributed within SA2s, an assumption which may not be met in many cases.

For this reason, it might be argued that the comparison of 2011 and 2016 indicators or sub-indices should be confined to those SA2s that did not experience boundary changes. However, such a comparison might be misleading if many of the SA2s on metropolitan peripheries experienced boundary changes between 2011 and 2016 and would be omitted in the comparison. These metropolitan peripheries may have specific characteristics with respect to how the Australian Natural Disaster Resilience Index changes over time. For this reason, the mean indicator values in 2011 for SA2s whose boundaries changed, or did not change, in 2016 were compared (Table 6.4). The indicator values used were the normalised and rescaled values, to facilitate comparison of the indicators. The table rows are sorted in decreasing order of the absolute difference between the means for unchanged SA2s and the mean for changed SA2s.

Table 6.4: Mean indicator values for the 2011 SA2s that experienced no boundary change in 2016, and those 2011 SA2s that did experience a boundary change.

Indicator	Mean for unchanged SA2s	Mean for changed SA2s	Difference
% lone person households	0.713	0.664	0.050
% population aged under 15	0.493	0.536	-0.042
% households with children	0.500	0.540	-0.041
% population aged over 75	0.624	0.586	0.038
Sex ratio	0.394	0.431	-0.037
% of households with all or some residents not present a year ago	0.546	0.516	0.031
% managers and professionals	0.563	0.593	-0.030
Ratio of certificate and/or postgrad to year 8-12	0.491	0.518	-0.027
% population with a core activity need for assistance	0.720	0.702	0.019
% of labour force unemployed	0.481	0.500	-0.018
% not in labour force	0.565	0.548	0.017
% one parent families	0.664	0.649	0.015
% population arrived in Australia 2001 onwards	0.445	0.457	-0.012
% speaks English not well or not at all	0.486	0.481	0.006
% group households	0.365	0.361	0.003

The indicator % lone person households shows the greatest difference between 2011 SA2s whose boundaries were unchanged in 2016, and those 2011 SA2s which did experience boundary change (Table 6.4). If there is a problem with confining the comparison of 2011 and 2016 values to 2011 SA2s whose boundaries were unchanged in 2016, then it will be most evident with this indicator. For this reason, % lone person households was selected for further investigation of the question of whether 2011 – 2016 comparisons should include SA2s which experienced boundary changes in 2016.

The 2016 values of the % lone person households indicator for 2011 SA2s whose boundaries were changed in 2016 were calculated by population weighting using the ABS 2011 SA2 – 2016 SA2 correspondence table (ABS 2016). For example, 2011 SA2 Wollongong was split into Wollongong East with 45 per cent of the Wollongong population and Wollongong West with 55 per cent of the Wollongong population. In 2016 in Wollongong East, 37 per cent of households were lone person households, while in Wollongong – West 28 per cent of households were lone person households. The estimate of % lone person households in 2016 for the 2011 SA2 of Wollongong is 37 * 0.45 + 28 * 0.55 = 26.

Figure 6.12 compares the 2016 values of % lone person households with the 2011 values of % lone person households, with the 2016 values adjusted to 2011 SA2 boundaries by population weighting where necessary. The 2011 SA2s are divided into those which experienced boundary changes in 2016 and those that did not.

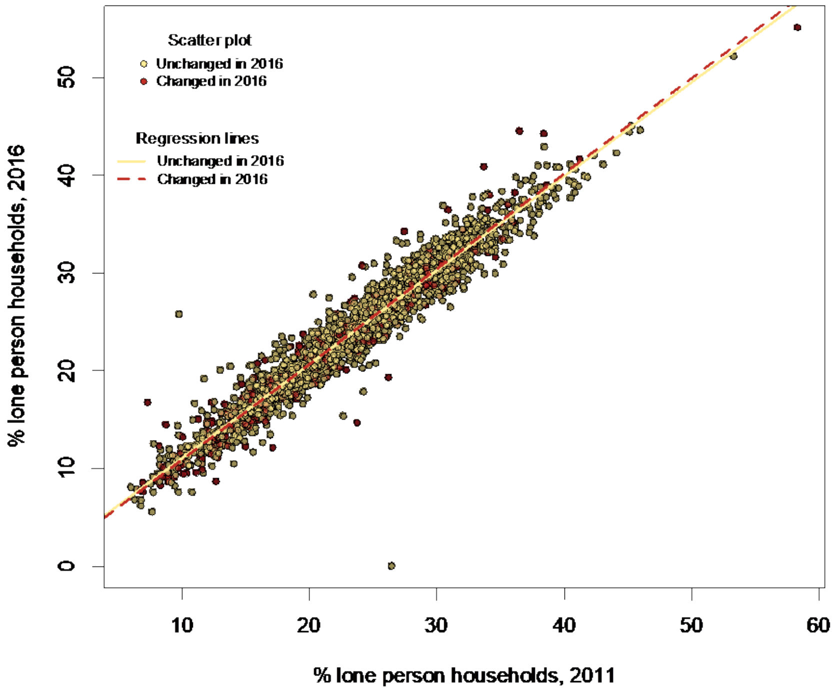

Figure 6.12: Relationship between % lone person households from the 2011 and 2016 Census, with the 2016 values adjusted to 2011 SA2 boundaries by population weighting where necessary.

For SA2s that kept the same boundaries in 2011 and 2016, the linear regression relationship between %lone person households in 2011 (lph11) and % lone person households in 2016 (lph16) is:

$$lph16 = 1.4 + 0.96 * lph11$$

The corresponding relationship for SA2s that experienced boundary changes in 2016 is:

$$lph16 =1.1 + 0.98 * lph11$$

There is negligible difference between the two groups of 2011 SA2s in the change in % lone person households from 2011 to 2016 (Figure 6.12). For this reason, the examination of the change of the social character theme sub-index between 2011 and 2016 is confined to the 1,770 2011 SA2s that retained their boundaries in 2016.

6.3.3.2 Comparison of 2011 and 2016 social character index

The 2016 raw indicators for the SA2s that did not change boundaries from 2011 were converted into normalised and rescaled indicators using exactly the same procedures as for the 2011 indicators. There were only minor differences from 2011 in the exponents and coefficients used to transform the raw indicators to normality.

The correlations between the transformed indicators showed slight differences from those obtained with 2011 indicators, and these differences were sufficient to cause a slight difference in the principal components analysis results used to guide the assignment of indicators to sub-indices in the two level formative model for aggregation to the social character theme sub-index. Specifically, the 2016 principal components analysis assigned % group households and % of households with all or some residents not present a year ago to the familiarity with locality component, rather than the household factors component. The aggregation of the 2016 indicators followed the same procedure as for the 2011 indicators, apart from adjustments to take account of the groupings of indicators suggested by the principal components' analysis.

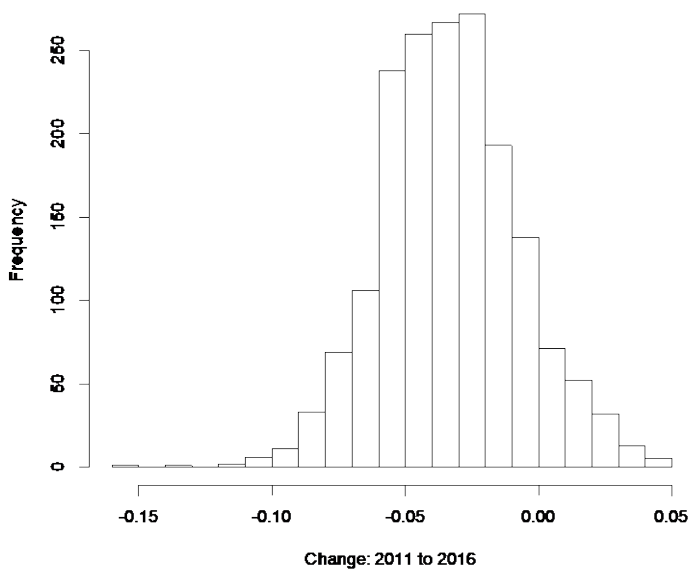

Figure 6.13: Distribution of the change in the social character theme sub-index from 2011 to 2016.

The majority of SA2s in the comparison changed less than 0.06 between 2011 and 2016 (Figure 6.13). The scatter plot (Figure 6.14) shows that 2016 values of the social character theme sub-index are, for most SA2s, reasonably well predicted by the 2016 values. Given that the social character theme sub-index is only one of eight theme sub-indices comprising the Australian Natural Disaster Resilience Index, these changes, by themselves, scarcely warrant the routine updating of the Census based indicators every five years. Obviously, changes in other indicators might be much more substantial and provide good reason for updating the Australian Natural Disaster Resilience Index outside of the Census cycle and updating of Census based indicators to the values of the most recent Census could occur at the same time.

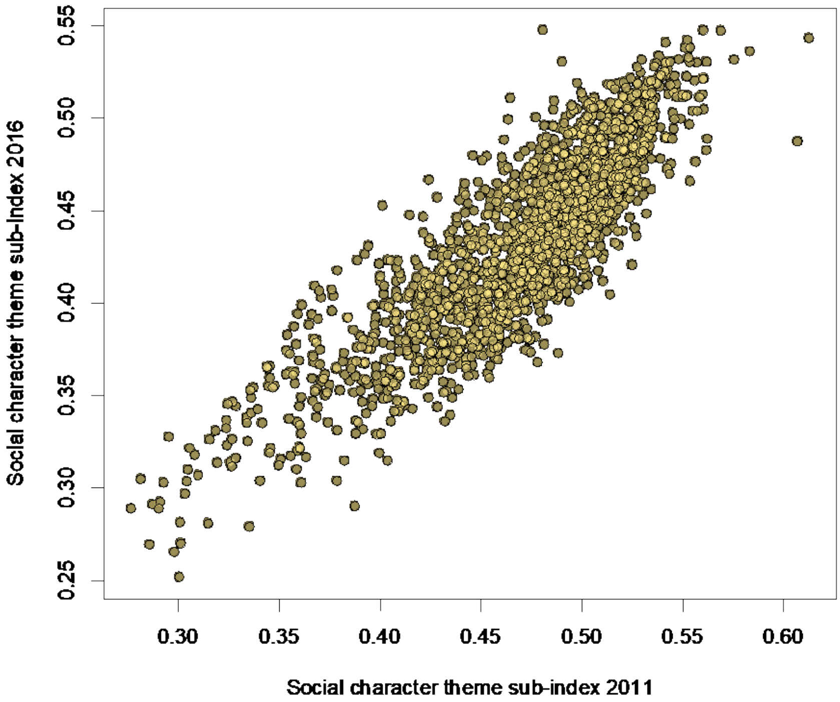

Figure 6.14: Scatter plot comparing values of the social character theme sub-index derived from 2011 and 2016 Census data.

6.3.3.3 Geographic coherence in sub-index changes

The geographic distribution of the social character theme has implications for the planning of updates to the Census based indicators. If the changes in indicators from one Census to the next are just the result of demographic “churn”, so that change in one direction might well be reversed in the next inter-Censal period, this would favour longer time periods between updates. However, if the indicator changes are part of well-defined long-term trends, and particularly if the changes have some geographic coherence, then long term trends in the social character theme sub-index, and the Australian Natural Disaster Resilience Index itself, are a possibility. Understanding the causes and spatial disposition of these trends would be improved by more frequent updating of the indicators that comprise the Australian Natural Disaster Resilience Index. It is this understanding that could inform natural hazard preparation and mitigation.

When the 2011-2016 change in the social character theme sub-index is mapped nationally, it shows a geographic coherence that suggests long term trends in demography might be occurring (Figure 6.15). It is worth noting that the 2011-2016 increase in the value of the social character theme sub-index mostly occurs in remote areas with higher proportions of indigenous people. This might reflect a lessening of the levels of social disadvantage in these areas over the period.

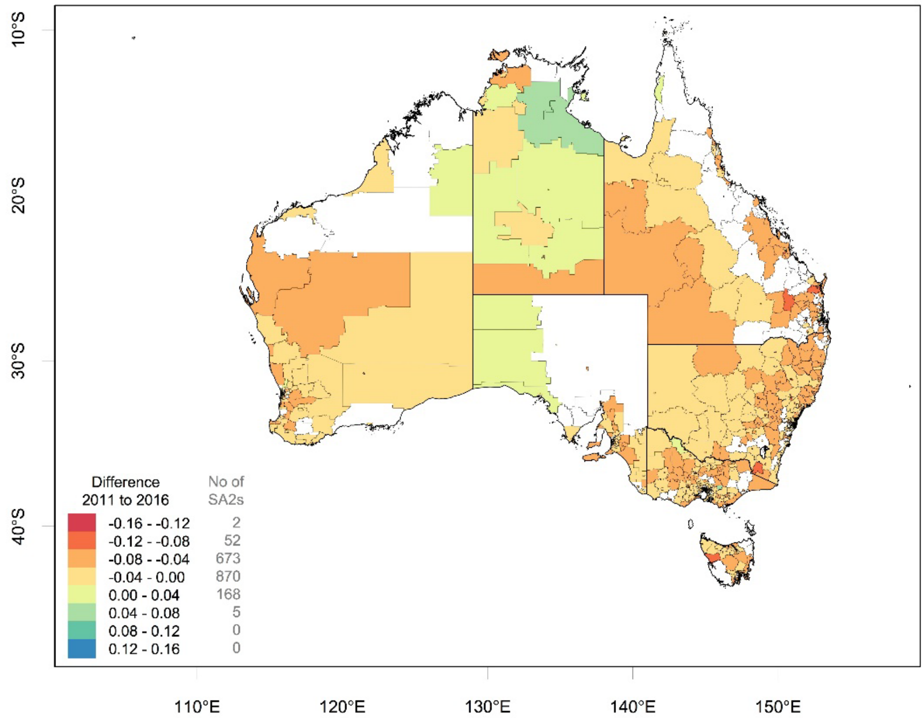

Figure 6.15: Map of change in the social character theme sub-index between 2011and 2016 Census data. SA2s in white experienced boundary changes in 2016 and were excluded from analysis.

An analysis of which indicators might be driving the changes in the social character theme sub-index was inconclusive. Rather, it highlighted the importance of understanding the compensatory relationships between indicators, as these are critical in determining how indicator changes feed through to sub-index changes. For example, it appeared that, for some SA2s, an influx of skilled migrants between 2011 and 2016 may have increased the proportion of non- or poor English speakers, but also improved education levels. These two indicators have opposite effects on the sub-index, so an influx of skilled migrants could either increase or decrease the aggregate of these two indicators, depending on how compensatory effects are understood and incorporated in aggregation procedures.

6.4 CONCLUSIONS

Four sources of uncertainty were analysed: that due to ABS confidentialising procedures, that due to derived evaluative indicators of planning and policy documents, that due to disaggregation from broader scale geographies and that due to the choice of orness values used in aggregation calculations. It was found that the uncertainty introduced into the final Australian Natural Disaster Resilience Index values by ABS confidentialising procedures is negligible for the great majority of SA2s, and minimal for a small number of SA2s that have low cell counts.

Evaluative uncertainty had a modest impact on final Australian Natural Disaster Resilience Index values; however the sensitivity analysis did not identify any particular evaluative indicator as having undue influence on the index.

Disaggregation uncertainty was shown to have considerable impact on the final Australian Natural Disaster Resilience Index values. For this reason, the refinement of disaggregation techniques used in the Australian Natural Disaster Resilience Index, and/or the location of data at SA2 level should be considered in future iterations of the index. The sensitivity analysis showed that disaggregation uncertainty the business dynamo sub-index and presence of research organisations indicators, had the greatest impact on the final index values. Investigation of alternatives to disaggregation from broader geographies for these two indicators should be a priority in future iterations of the Australian Natural Disaster Resilience Index.

The sensitivity analysis identified several choices of orness values used in aggregation by OWA that had greater influence on the final Australian Natural Disaster Resilience Index values. The uncertainty analysis showed that, while there were differences among the orness choices, overall the impact of orness choices on the index was fairly modest. Three aggregations and their orness values that should receive attention in future iterations of the Australian Natural Disaster Resilience Index are:

- aggregation of six theme sub-indices to give coping capacity,
- aggregation of two theme sub-indices to give adaptive capacity; and,
- aggregation of four indicators to give the governance and leadership theme sub-index.

Future re-examination of the orness values used in aggregation could follow either, or both, of two approaches. The first is to review the natural disaster resilience literature for evidence of the extent of compensatory effects among factors affecting natural disaster resilience and use this evidence to refine the orness values for OWA and the fuzzy measures used with the discrete Choquet integral. The second approach is to obtain orness values or fuzzy measures from a structured elicitation with an expert panel. Methods of doing this have been pioneered in the construction of the FEEM Sustainability Index (FEEM 2011; Cruciani et al. 2012).

The analysis of 2011-2016 change in the social character theme showed that the comparison is not straight forward, given that 15 per cent of SA2s had their boundaries changed in 2016. It was found that comparisons based on the 1,770 SA2s that did not change boundaries were unlikely to differ substantially from comparisons based on all 2,084 SA2s, although using the latter would have the disadvantage of introducing uncertainty in estimating 2016 indicator values for 2011 SA2s.

The comparison based on the 1,770 SA2s that did not change boundaries suggested that the change in the Social Character theme sub-index was not large enough to warrant routine updating of the Australian Natural Disaster Resilience Index after every Census. Of course, if other indicators used in the Australian Natural Disaster Resilience Index undergo substantial changes that warrant updating the index, then it would be worth updating Census based indicators to the most recent Census values at the same time.

6.4.1 Data quality summary

The maximum 5-95 inter-percentile range for disaggregation uncertainty, evaluation uncertainty and orness uncertainty can be taken as a data quality indicator. The wider the 5-95 inter-percentile range, the more likely are these uncertainties to result in a calculated Australian Natural Disaster Resilience Index value that deviates from the true value.

The uncertainty in the Australian Natural Disaster Resilience Index due to ABS confidentialising procedures is negligible. For most SA2s, the maximum 5-95 inter-percentile range will be that for the disaggregation uncertainty. The 5-95 inter-percentile range for a particular SA2 is the difference between the 95th percentile and 5th percentile for the distribution of possible Australian Natural Disaster Resilience Index values when taking account of the uncertainties in the constituent indicators or calculations. Ninety per cent of Australian Natural Disaster Resilience Index values will lie within the 5-95 inter-percentile range. The 5-95 inter-percentile range is centered around the median value of the Australian Natural Disaster Resilience Index. For example, for a 5-95 inter-percentile range of 0.2, 90 per cent of Australian Natural Disaster Resilience Index values will lie within 0.1 either side of the median.

The distribution of the maximum 5-95 inter-percentile range across Australia is shown in Figure 6.16. State/Territory and major metropolitan area resolution maps are provided in Appendix 6F.

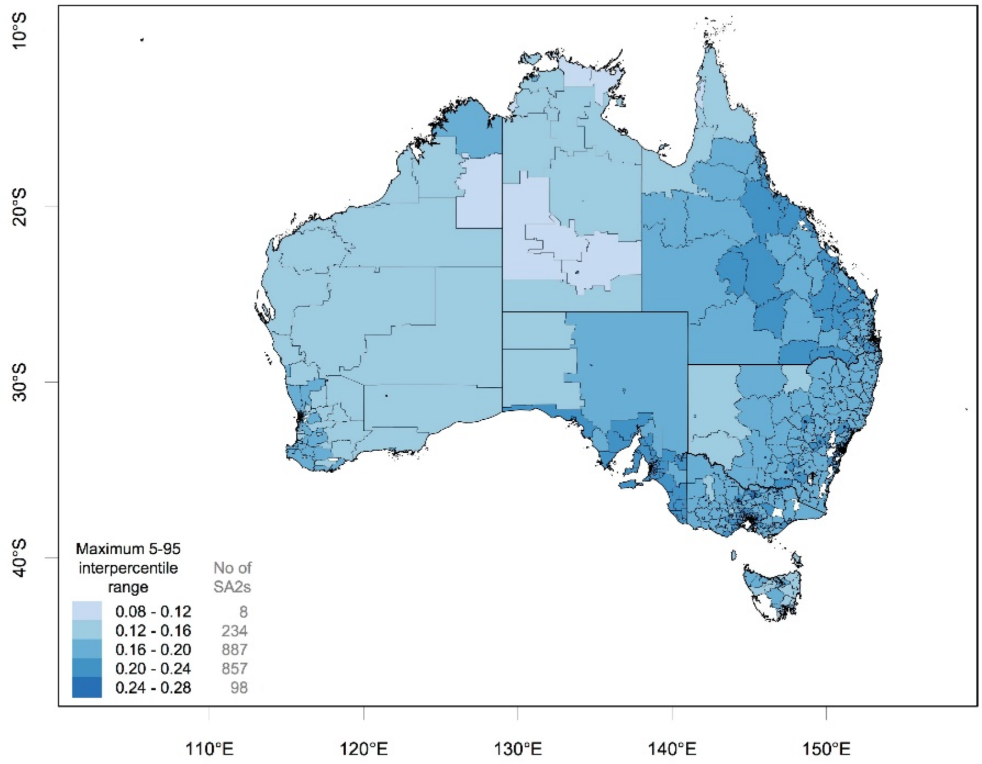

Figure 6.16: Maximum 5-95 inter-percentile range for the uncertainty in the Australian Natural Disaster Resilience Index caused by evaluation, orness and disaggregation uncertainties in the calculation of the index.

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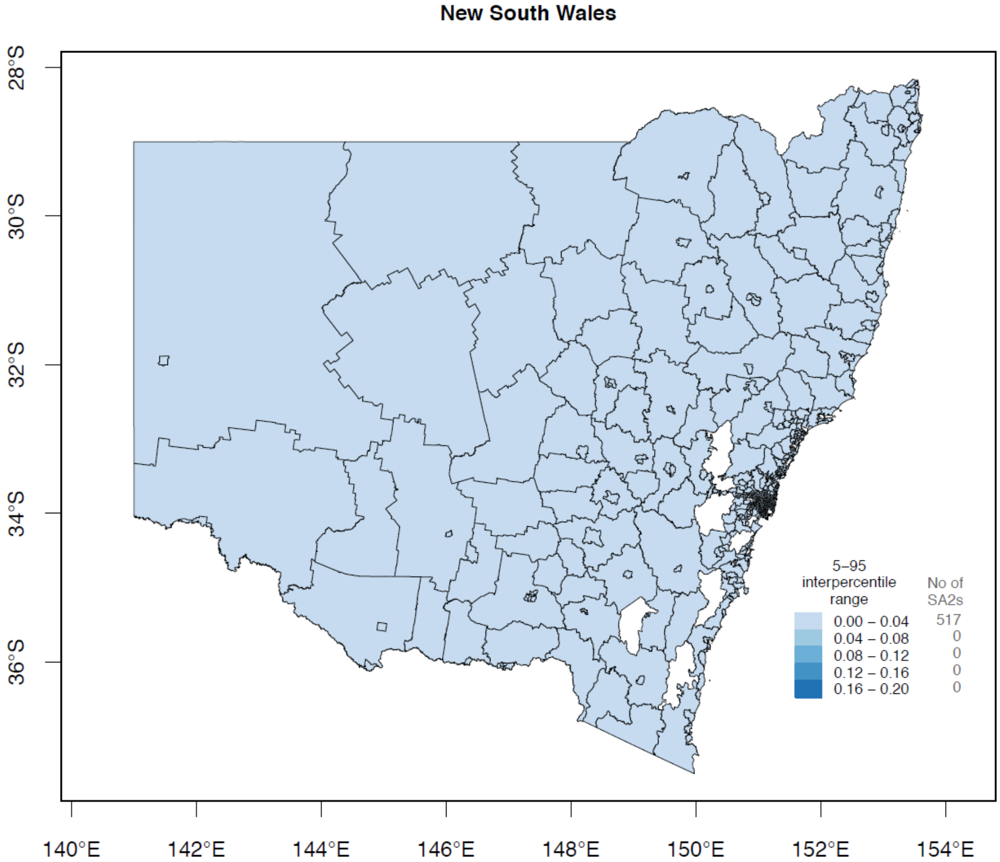
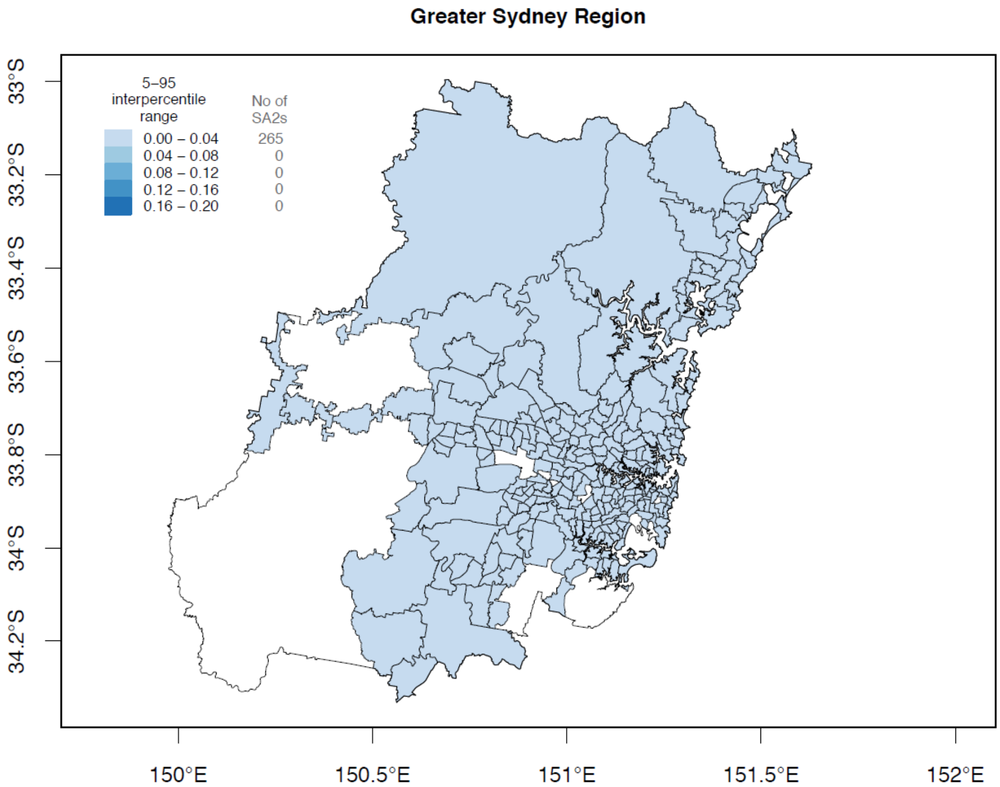
APPENDIX 6A – 5-95 INTER-PERCENTILE RANGE: ABS CONFIDENTIALISING PROCEDURE

Appendix 6A shows the State/Territory and major metropolitan-area resolution maps of the 5-95 inter-percentile range for uncertainty associated with the ABS confidentialising procedure.

Appendix 6A (cont.)





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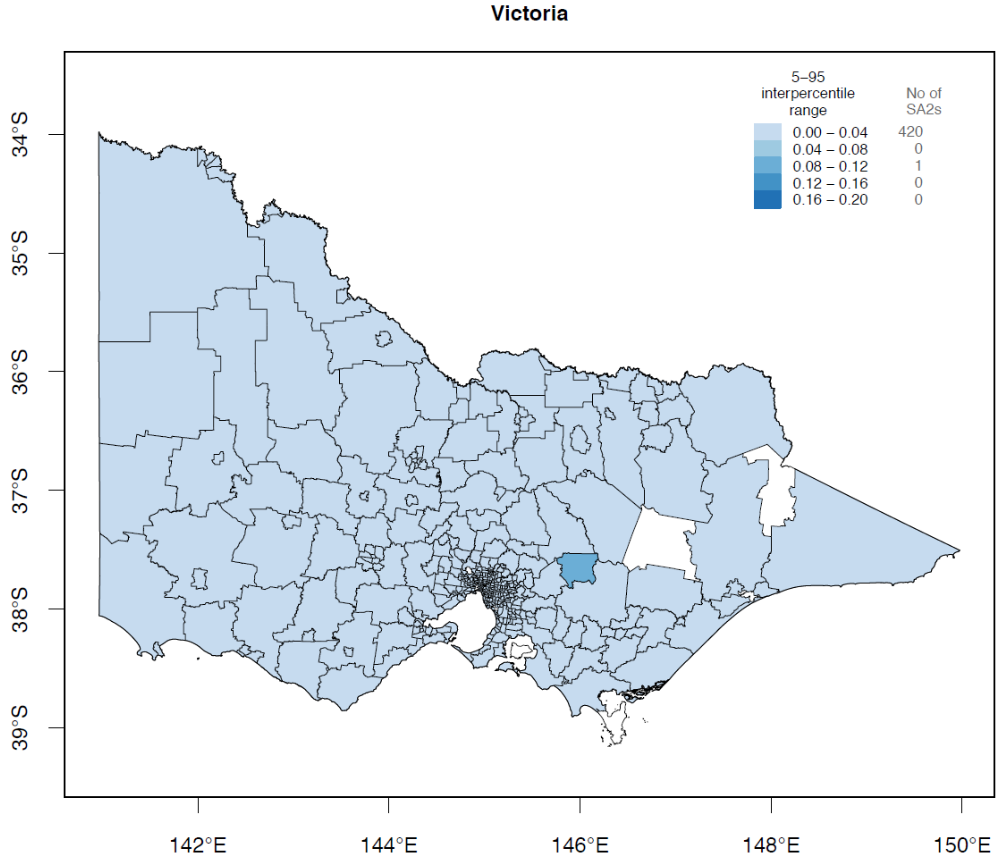

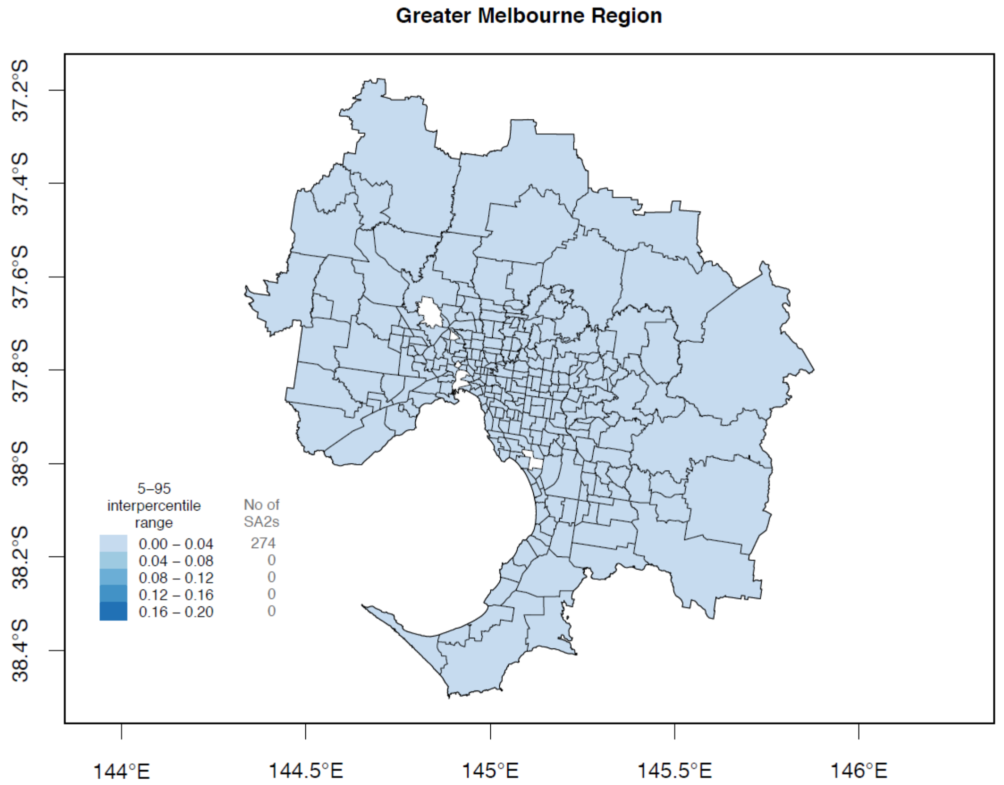

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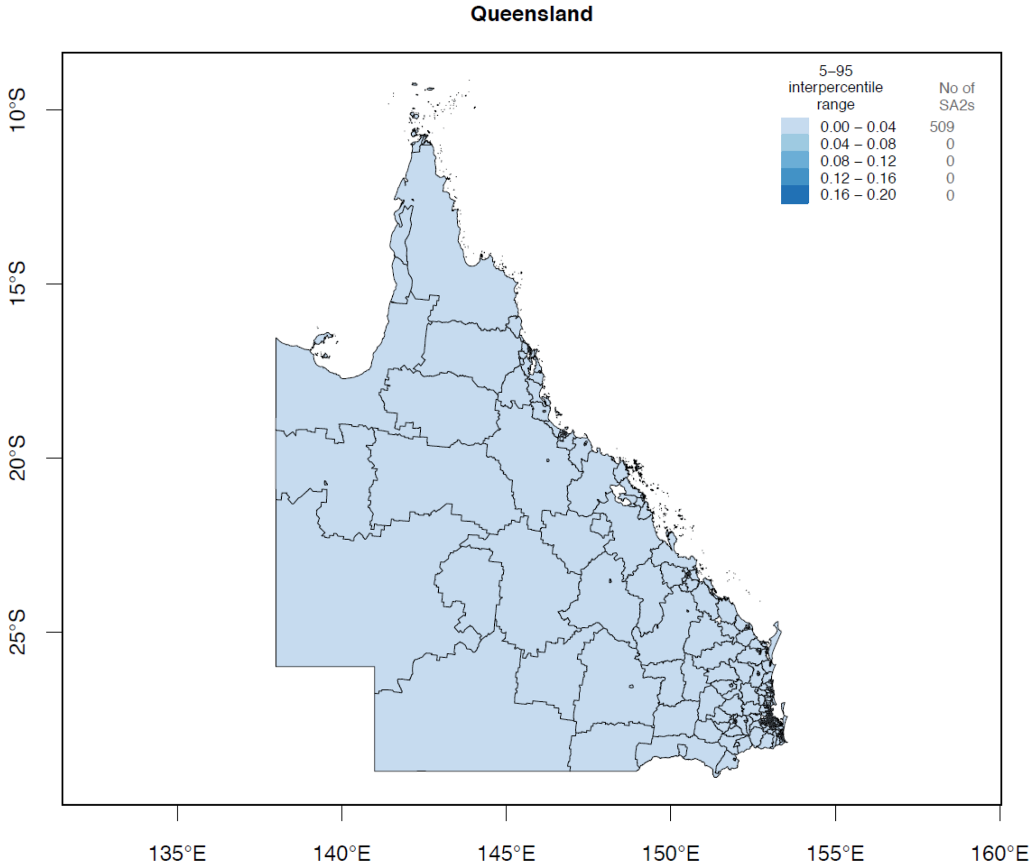

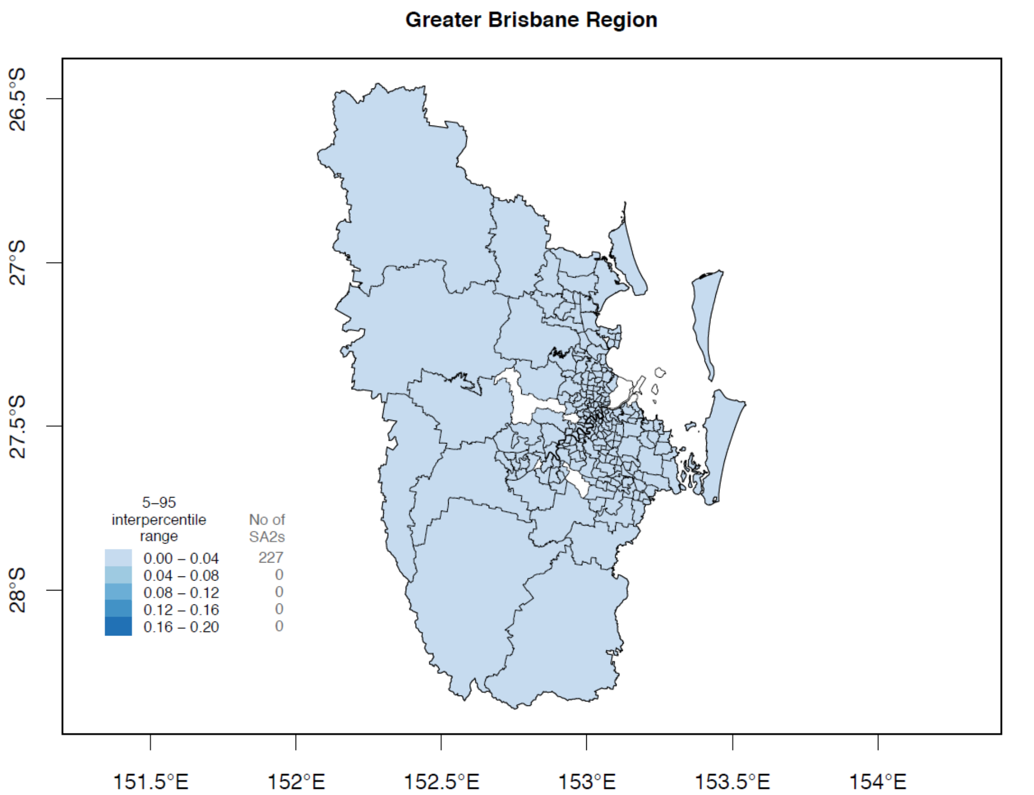

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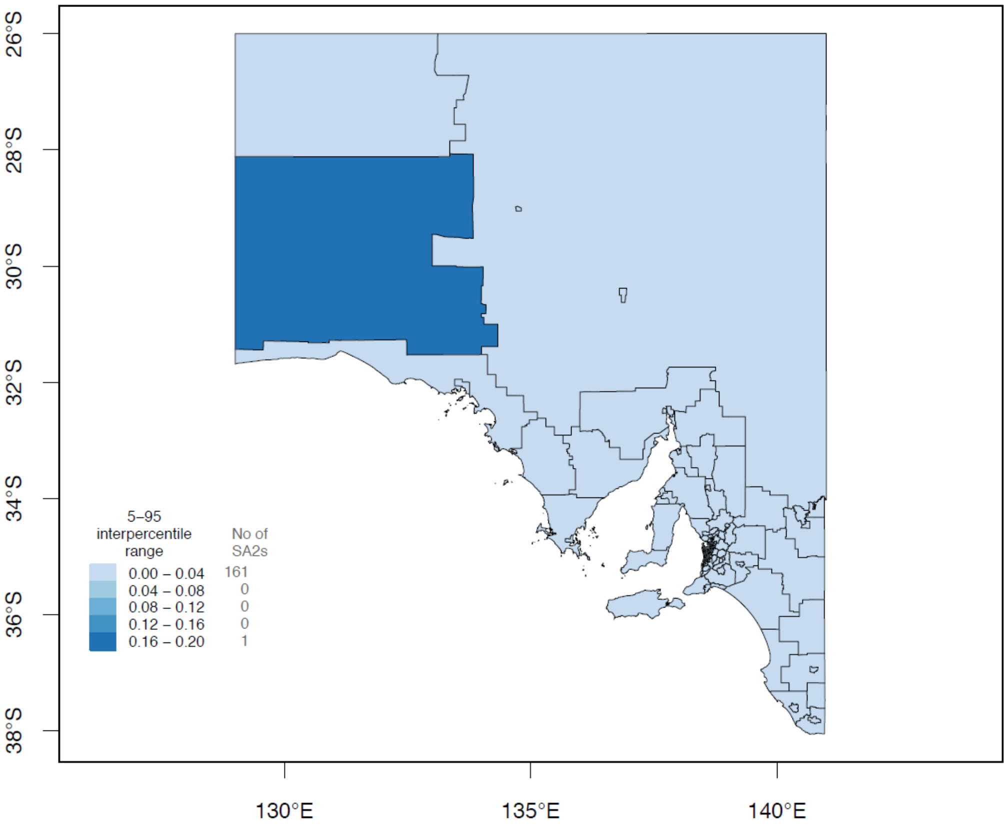
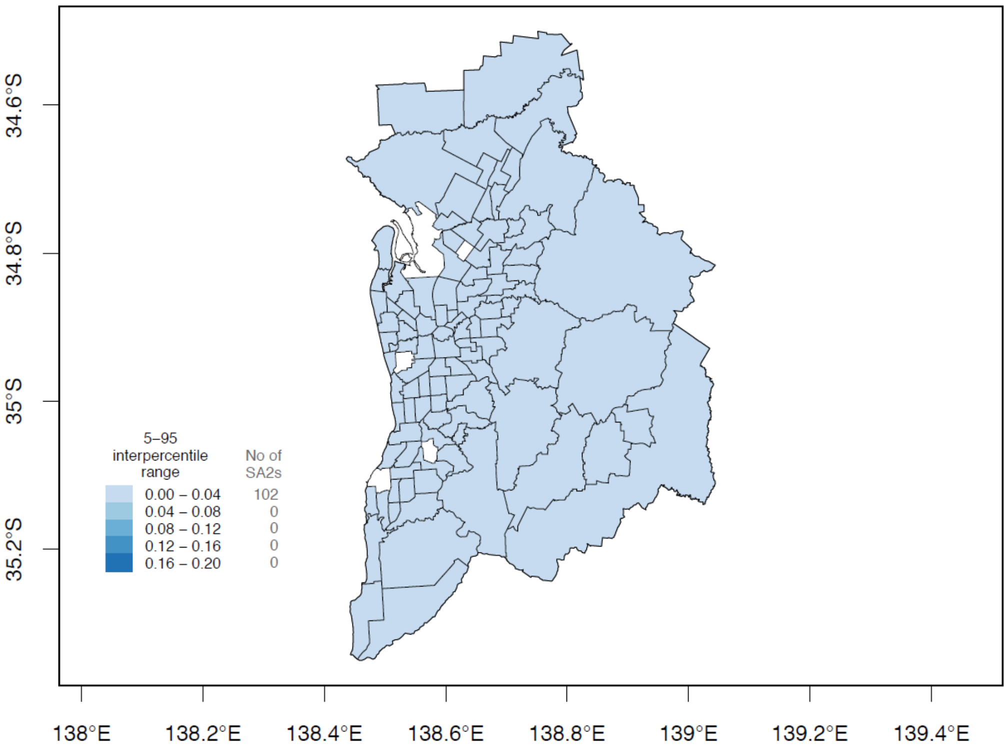
South Australia



Greater Adelaide Region



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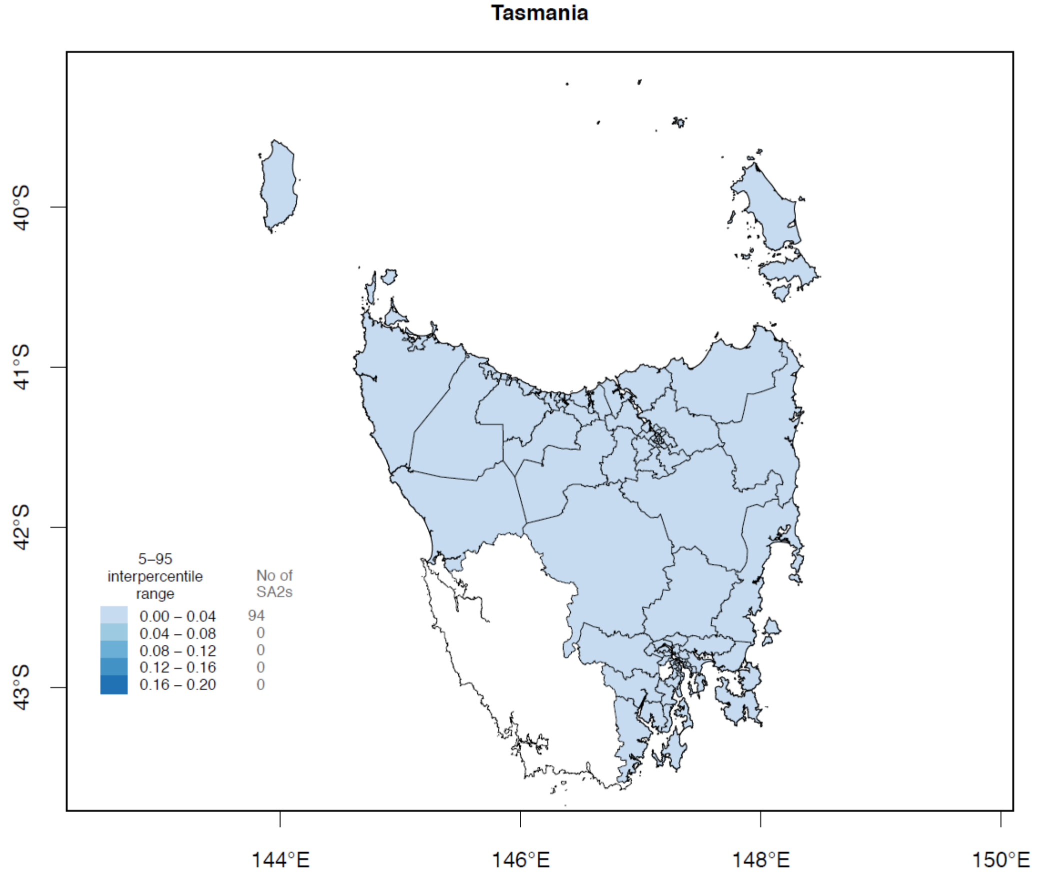

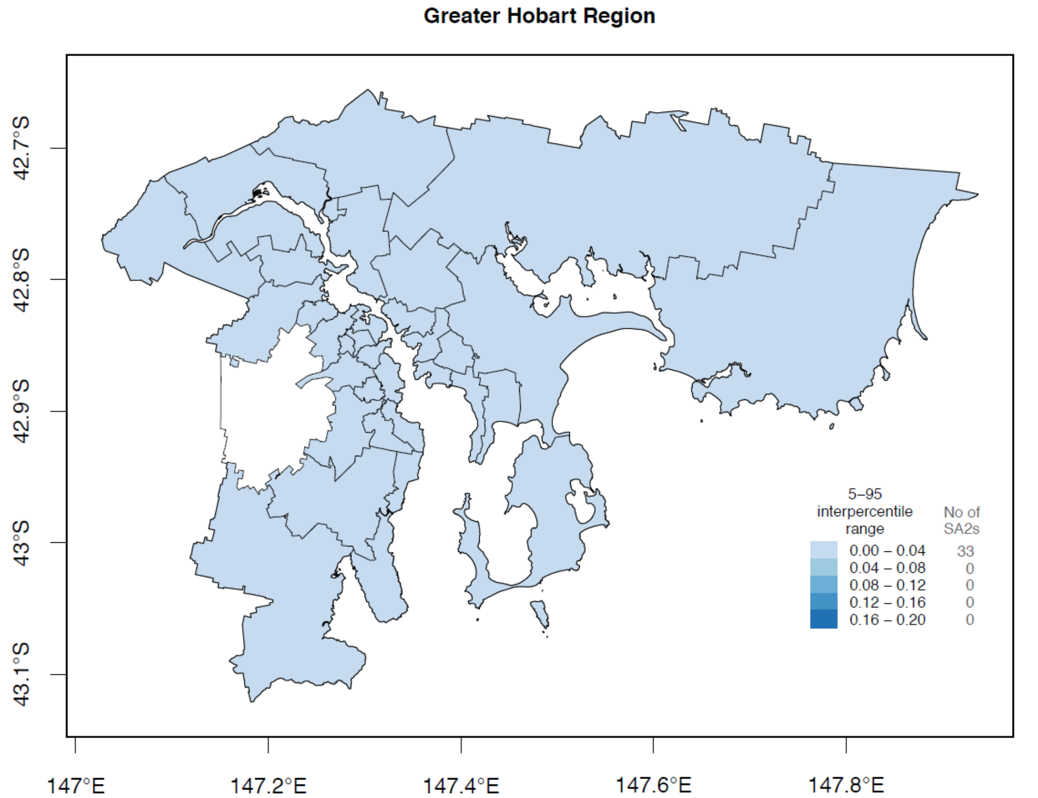

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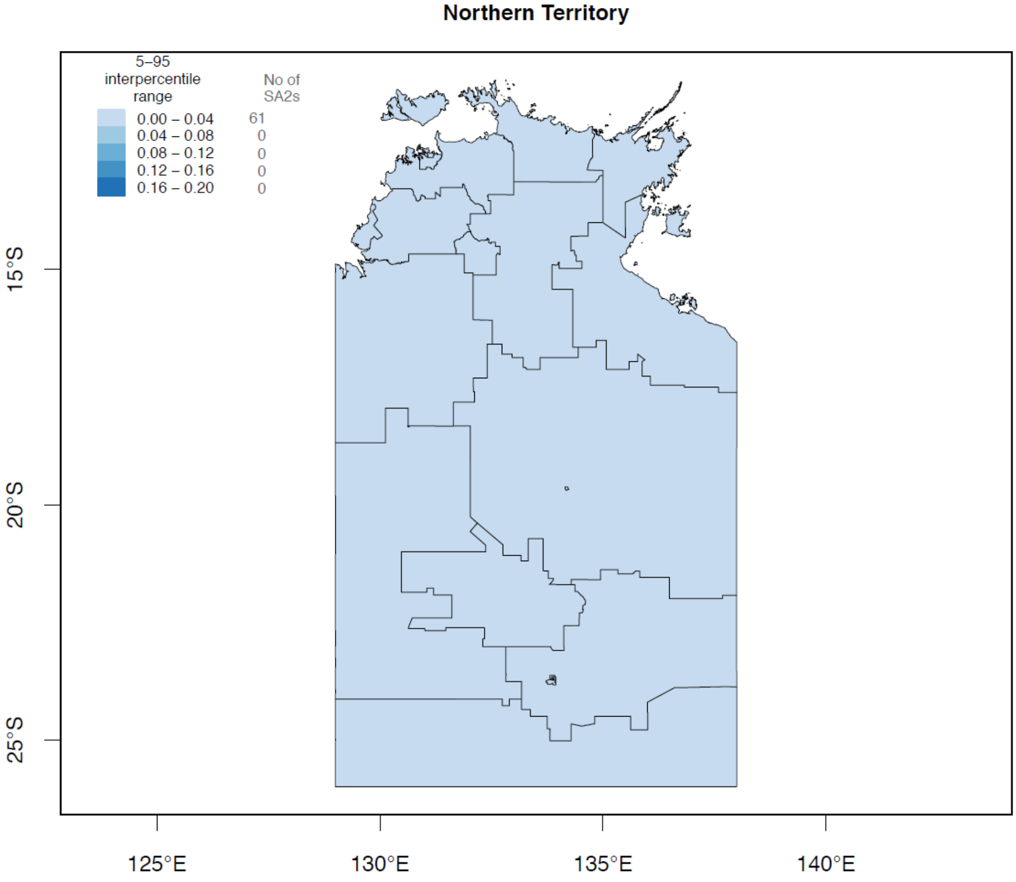

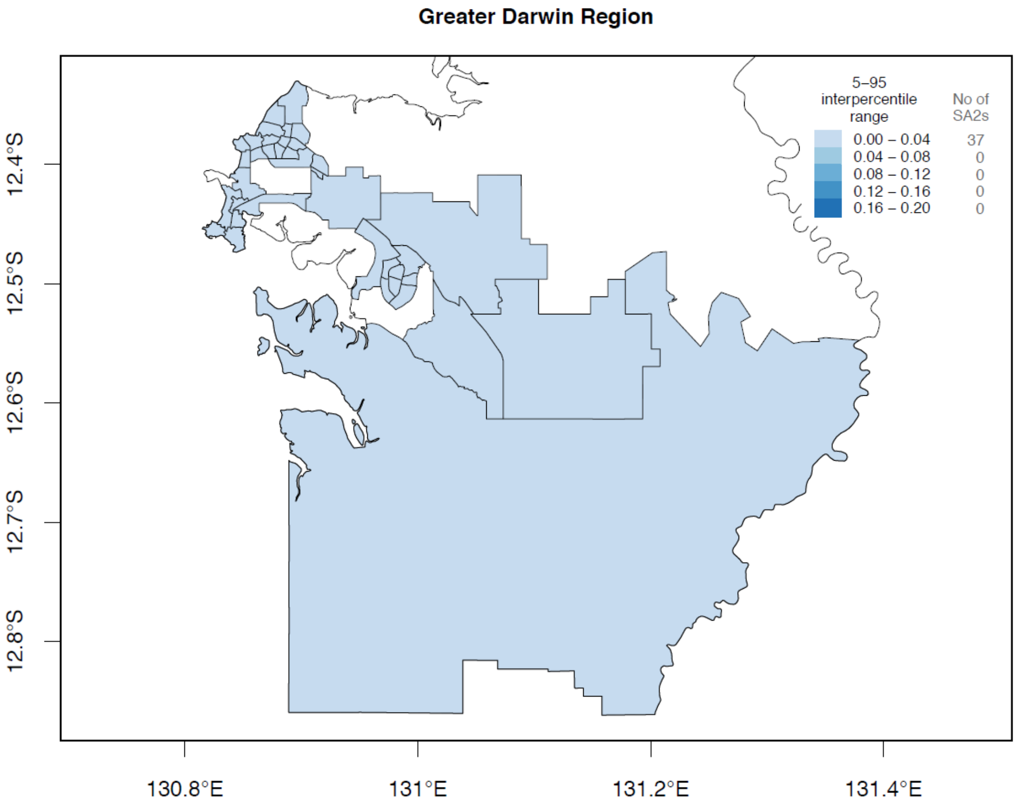

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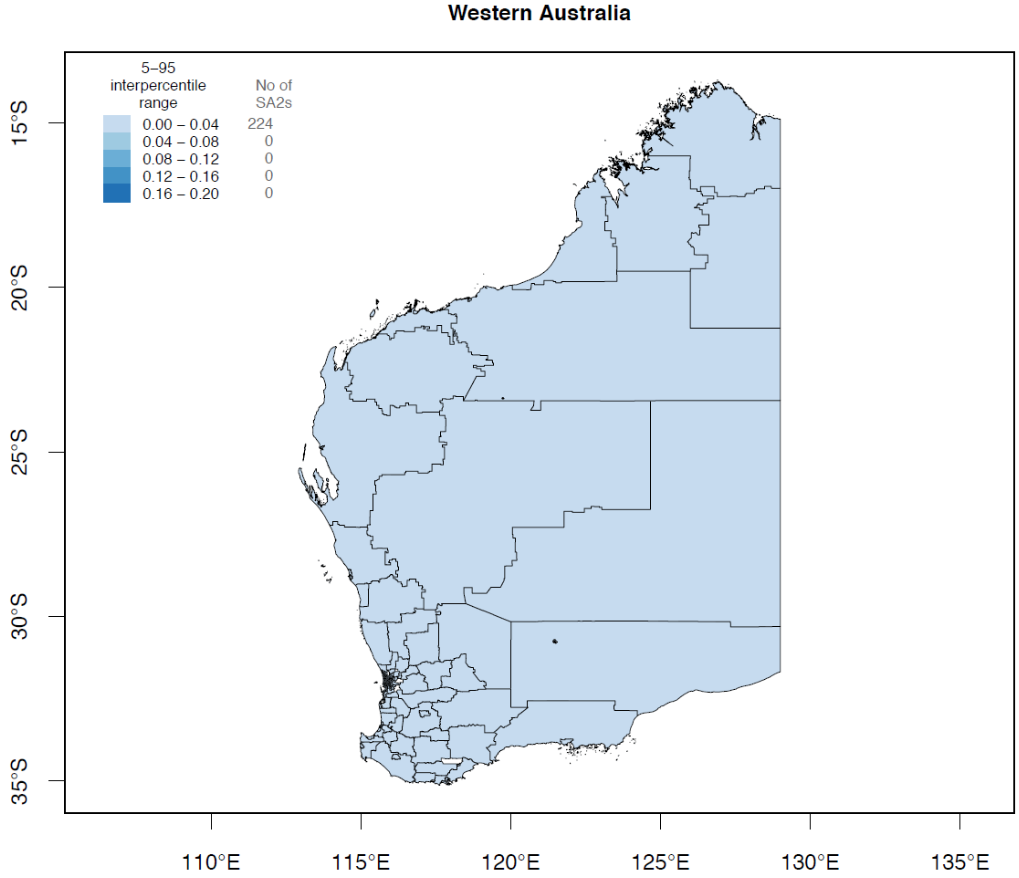

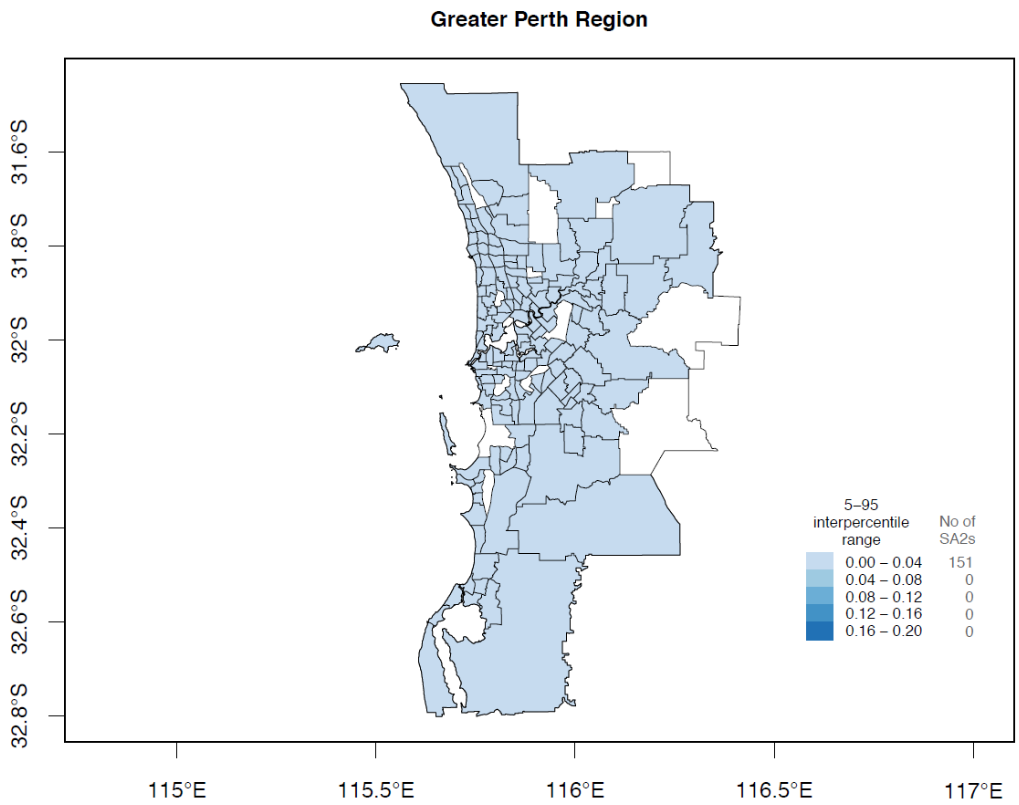

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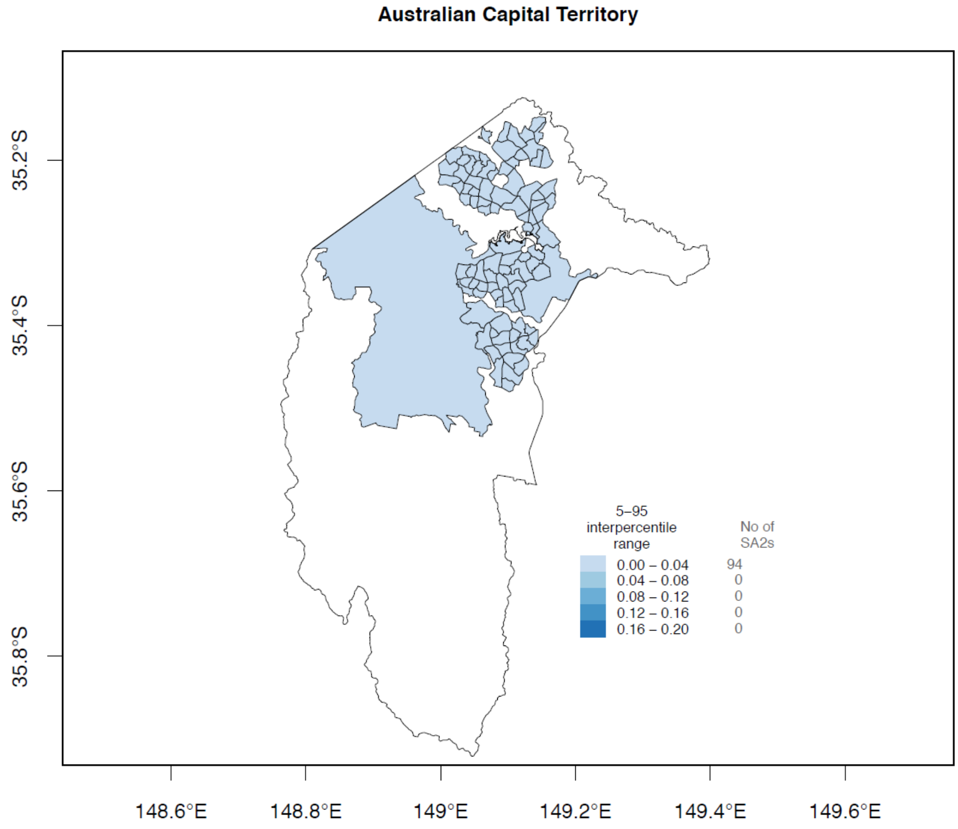
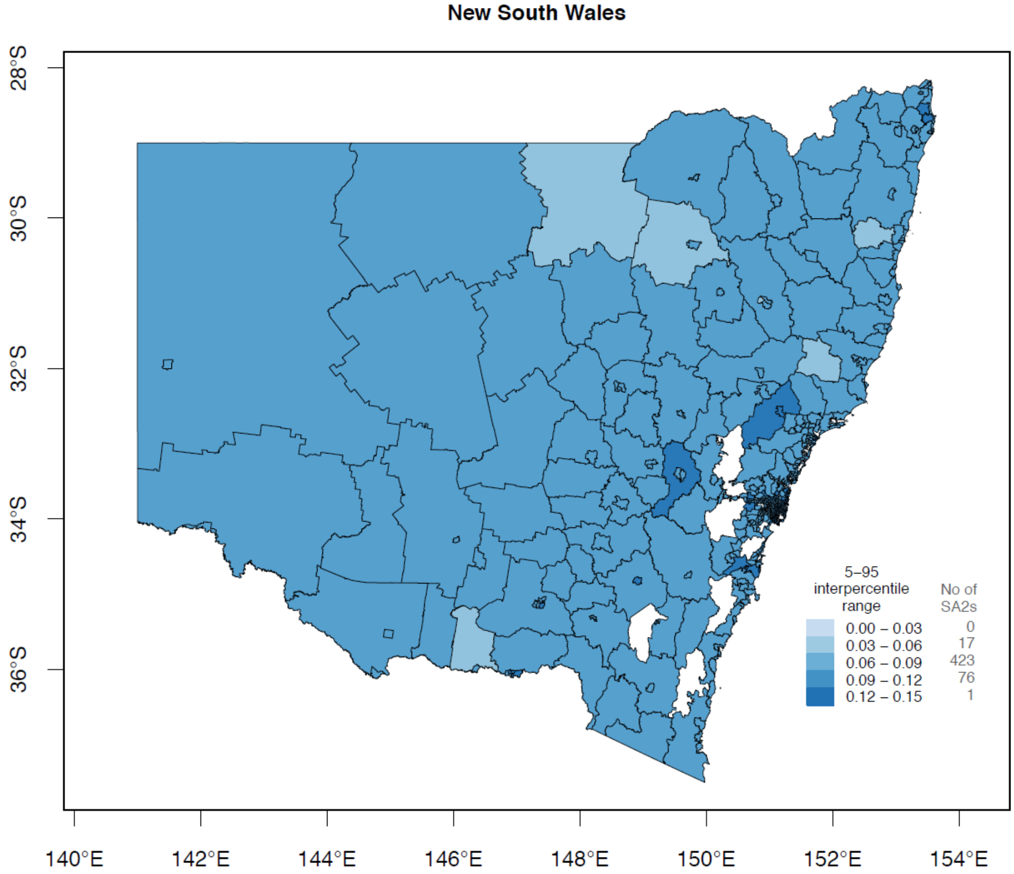
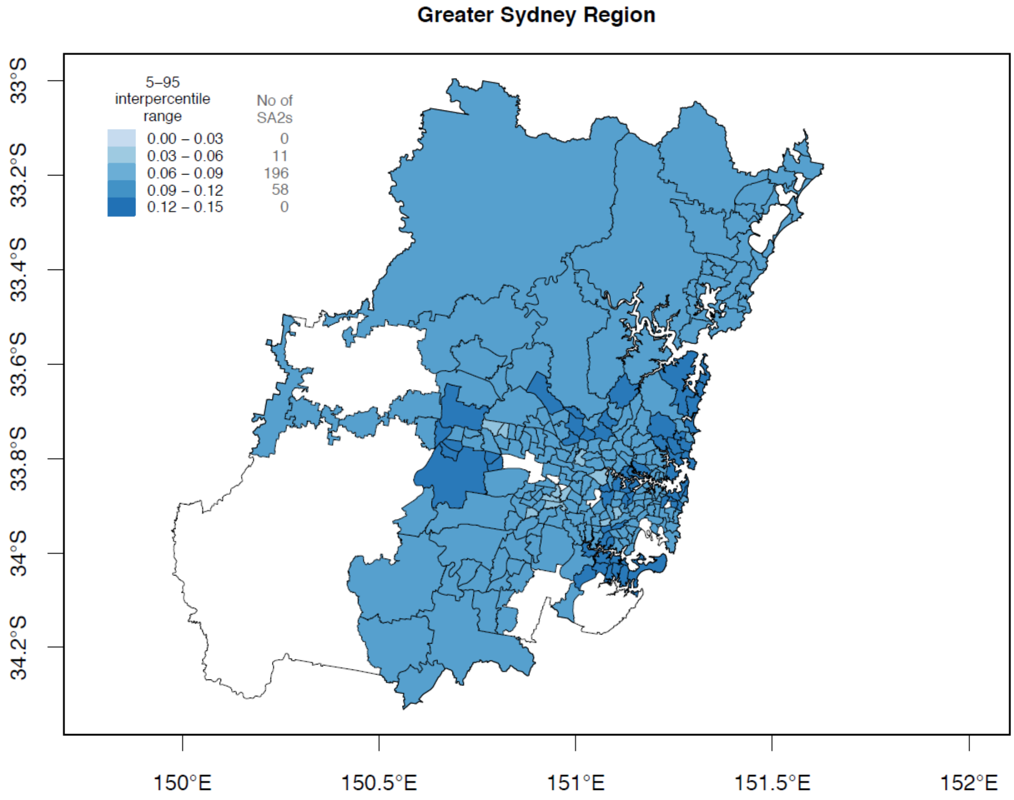


APPENDIX 6B – 5-95 INTER-PERCENTILE RANGE: EVALUATION OF PLANNING AND POLICY DOCUMENTS

Appendix 6B shows the State/Territory and major metropolitan-area resolution maps of the 5-95 inter-percentile range for the uncertainty associated with evaluation of planning and policy documents.

Appendix 6B (cont.)





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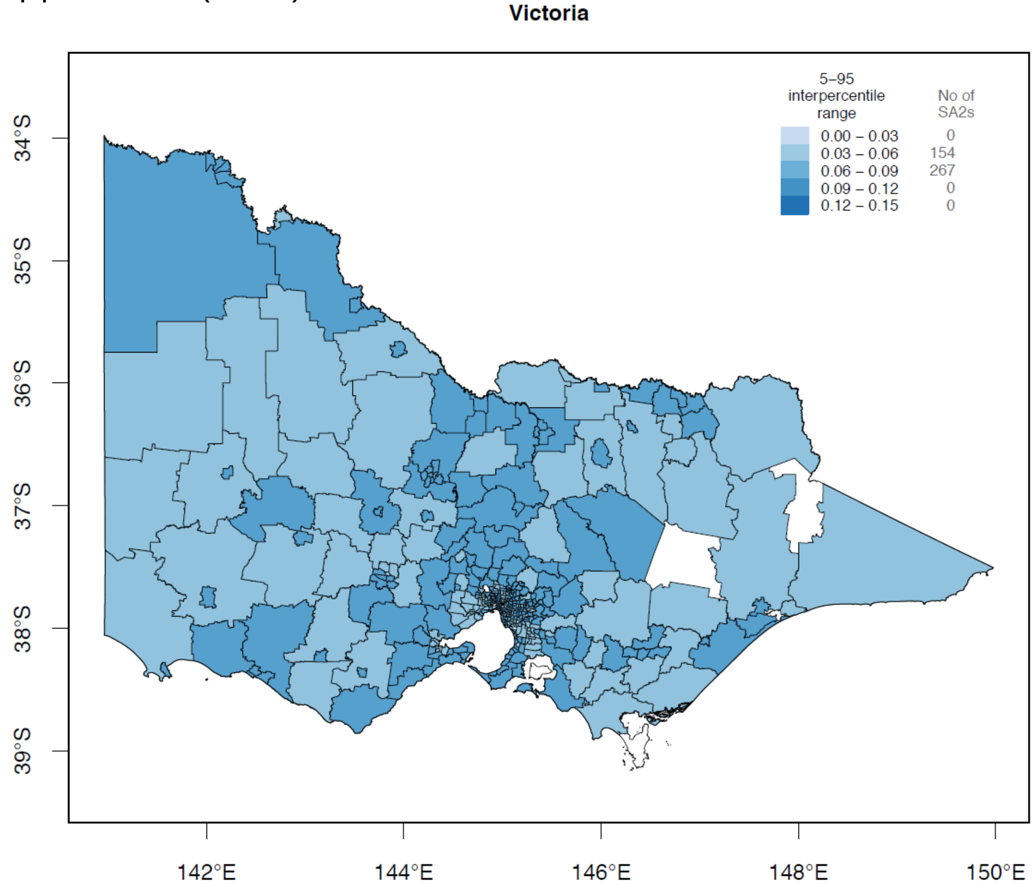

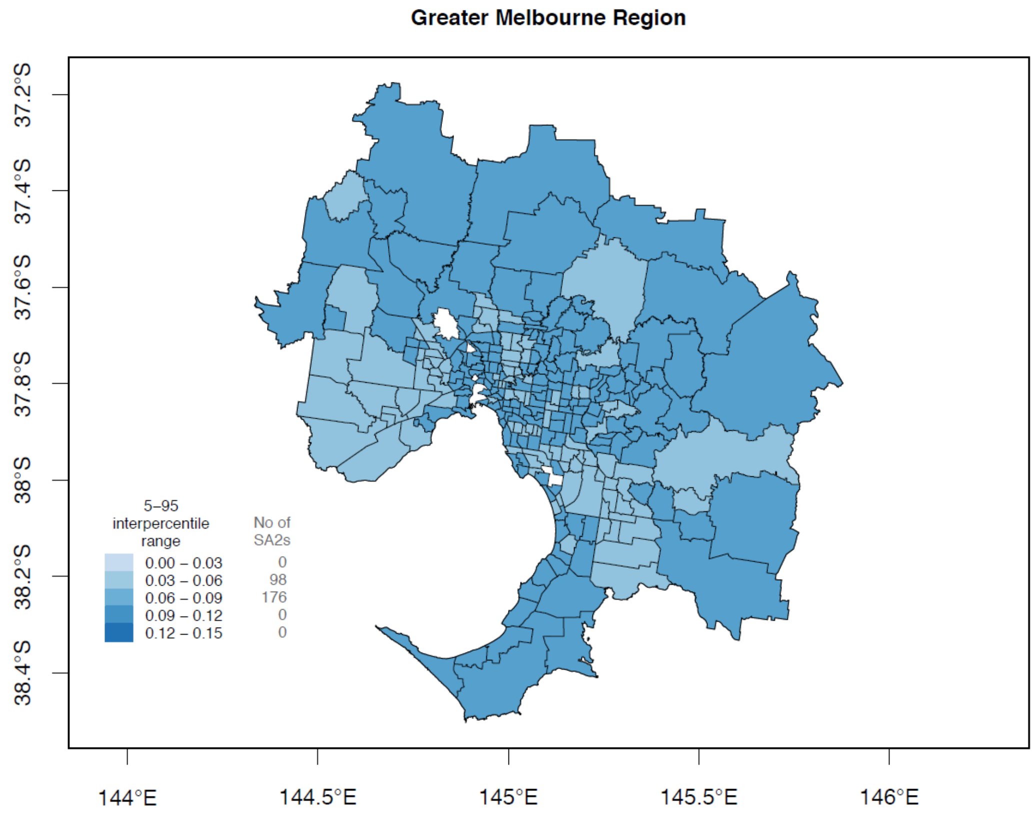

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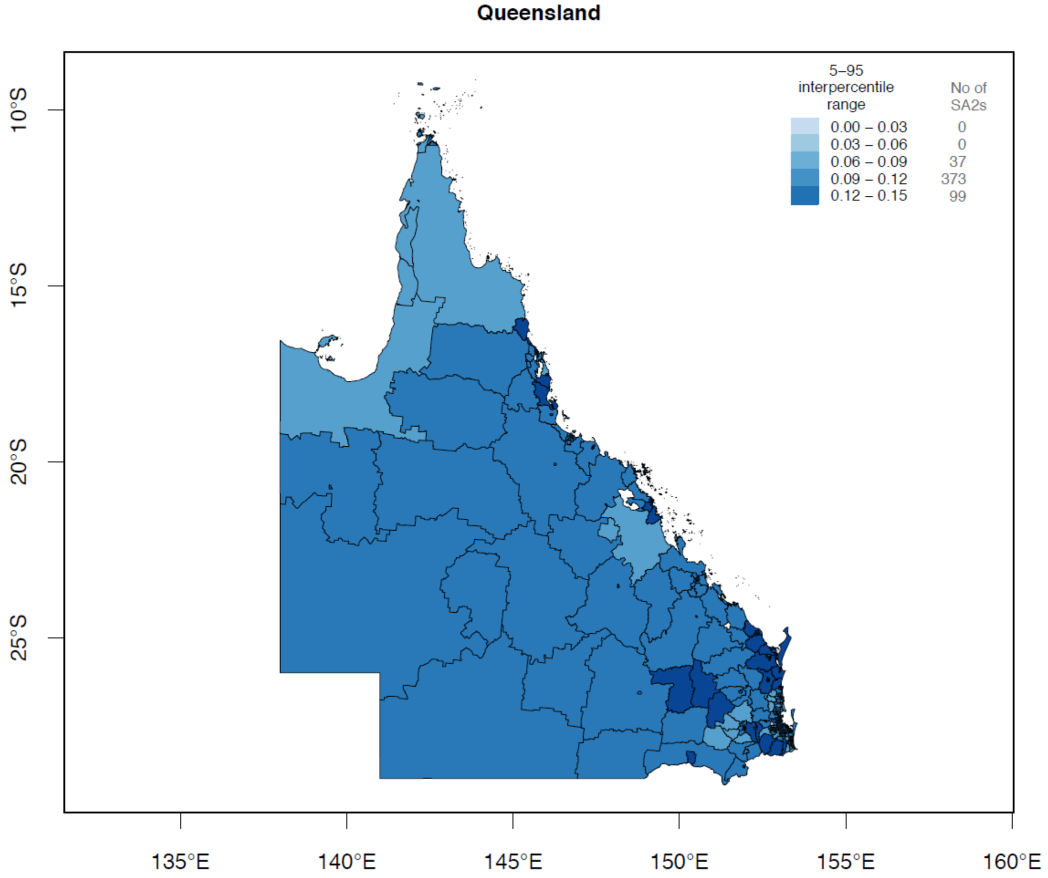

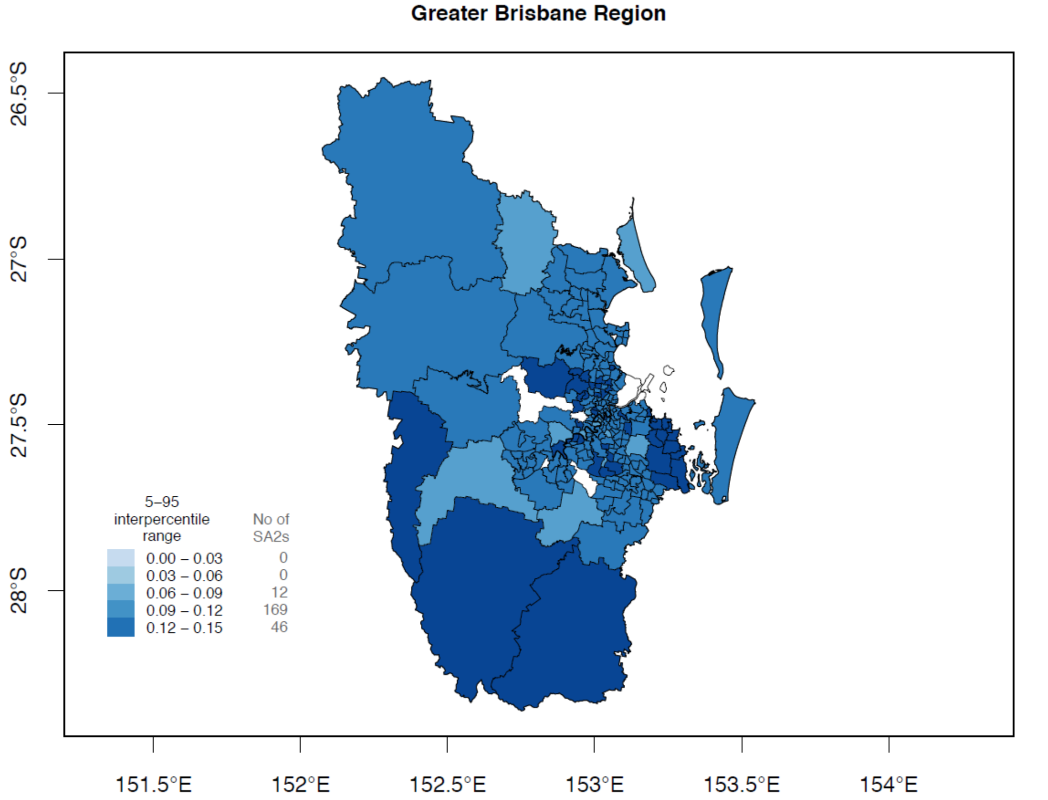

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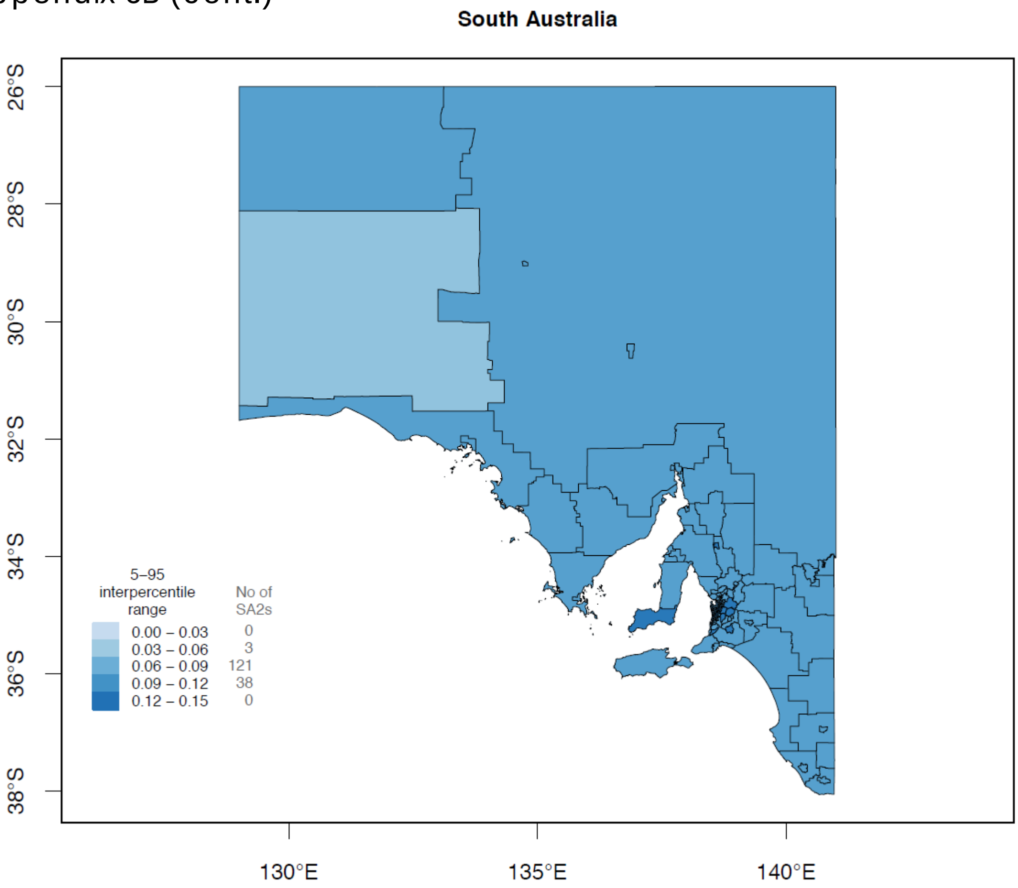

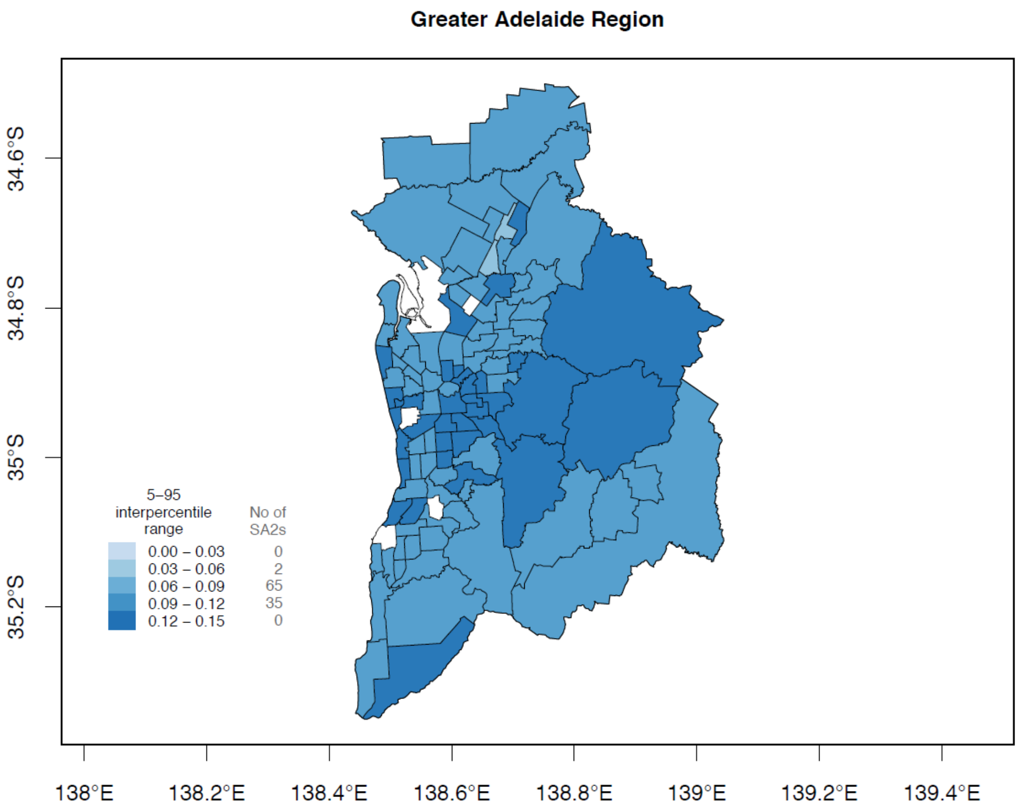

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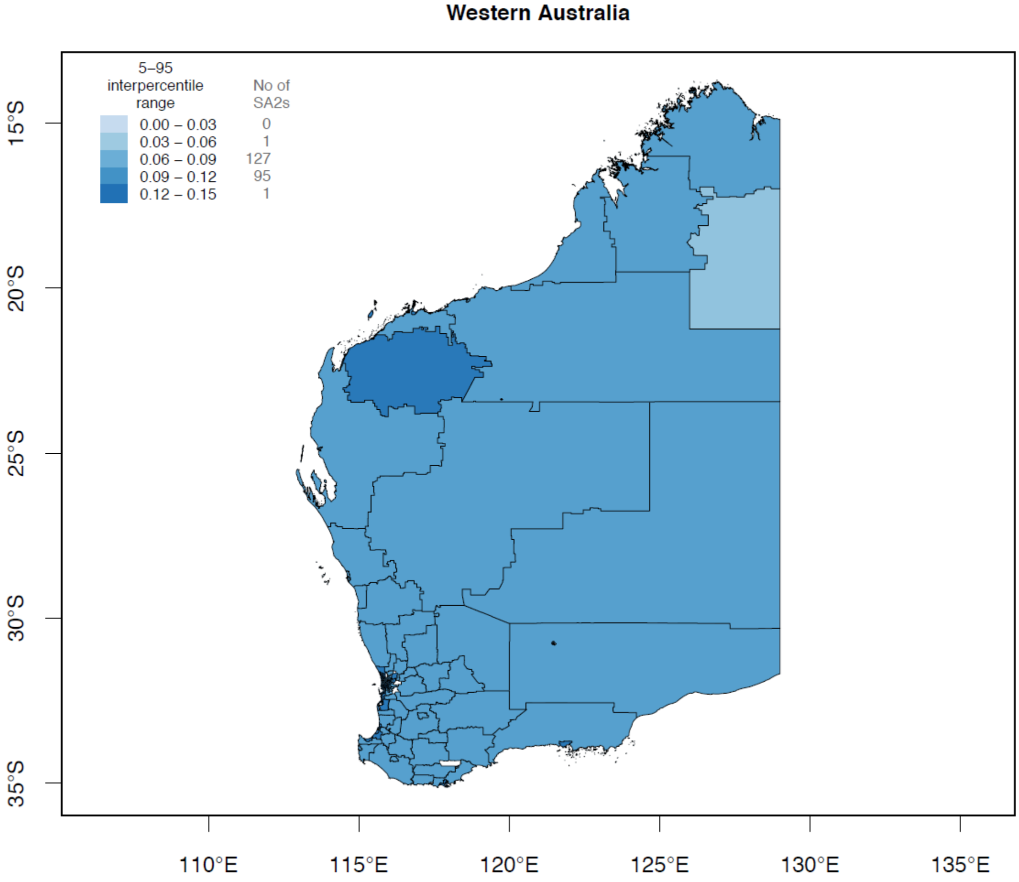

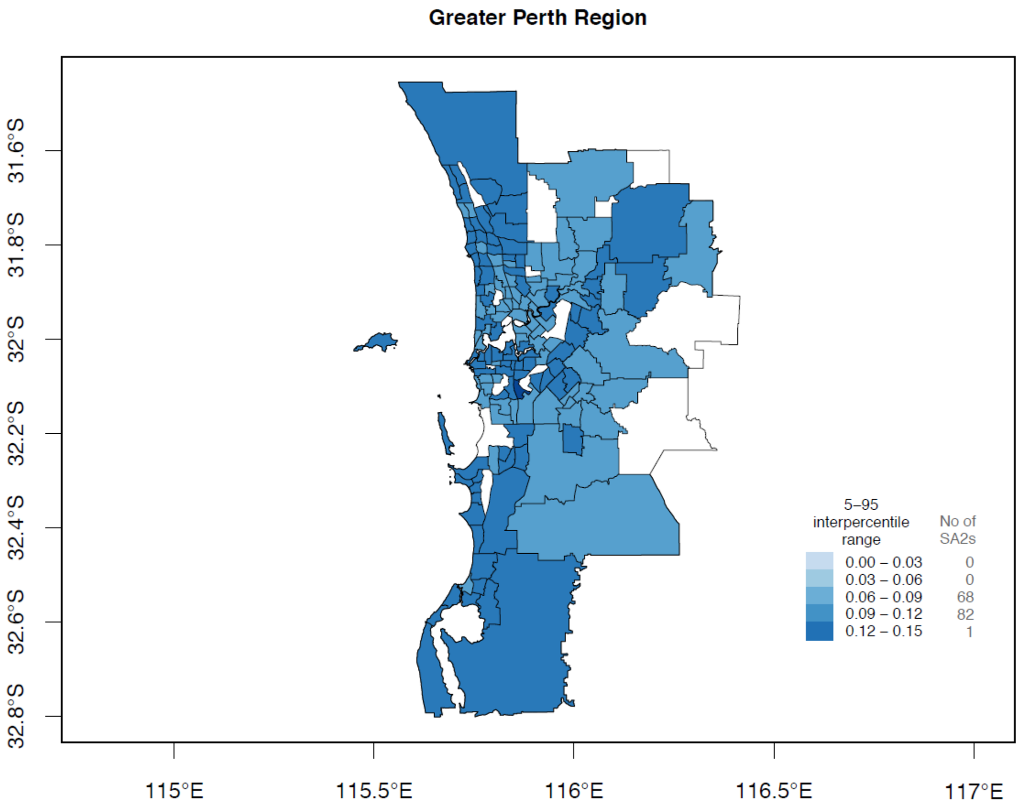

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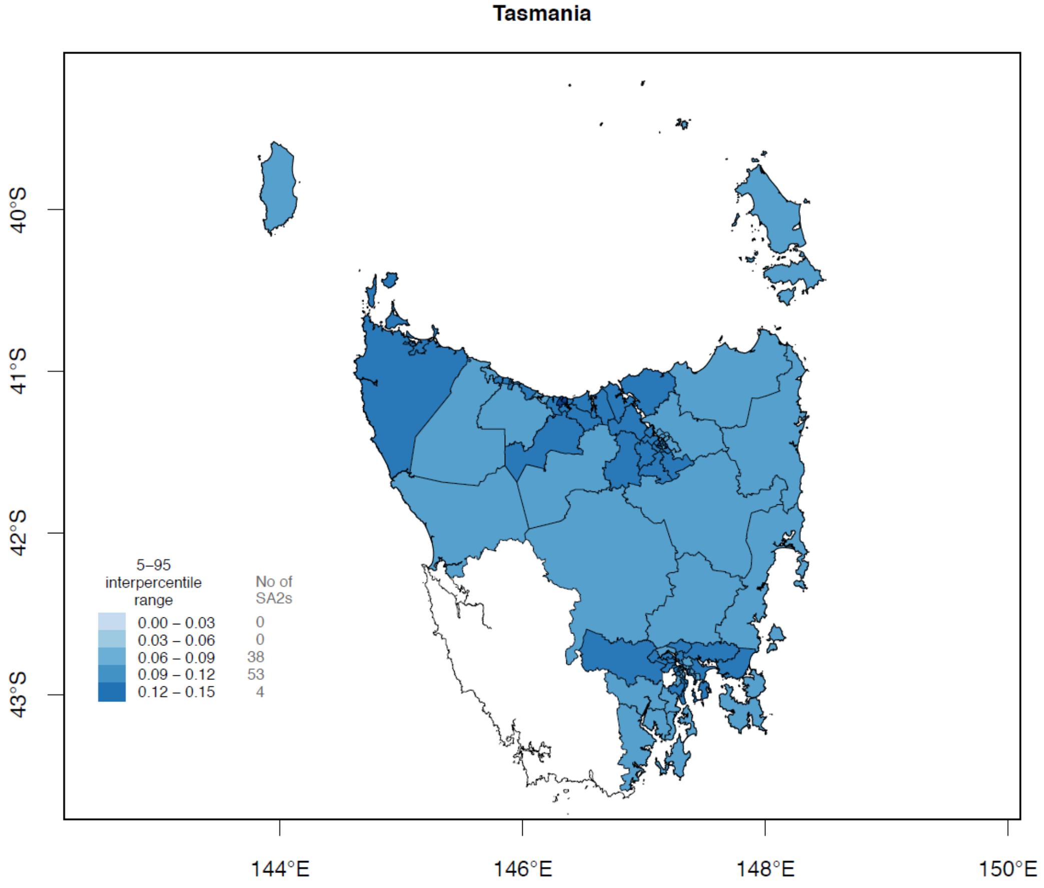

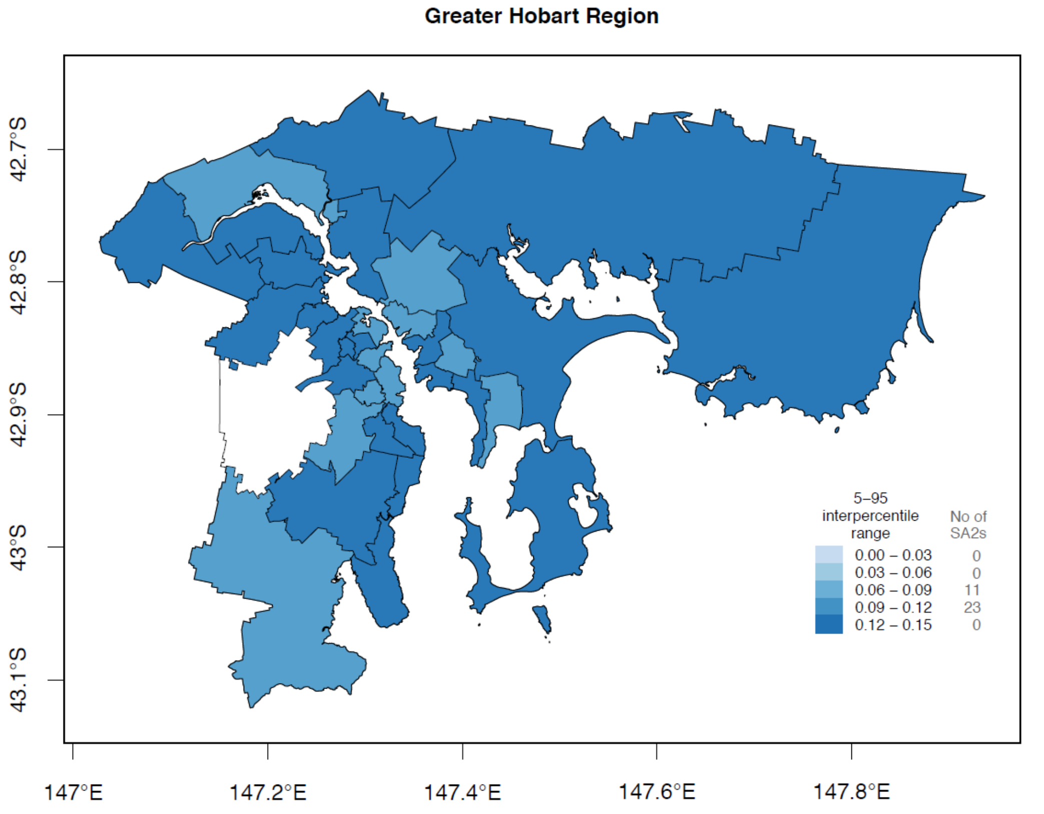

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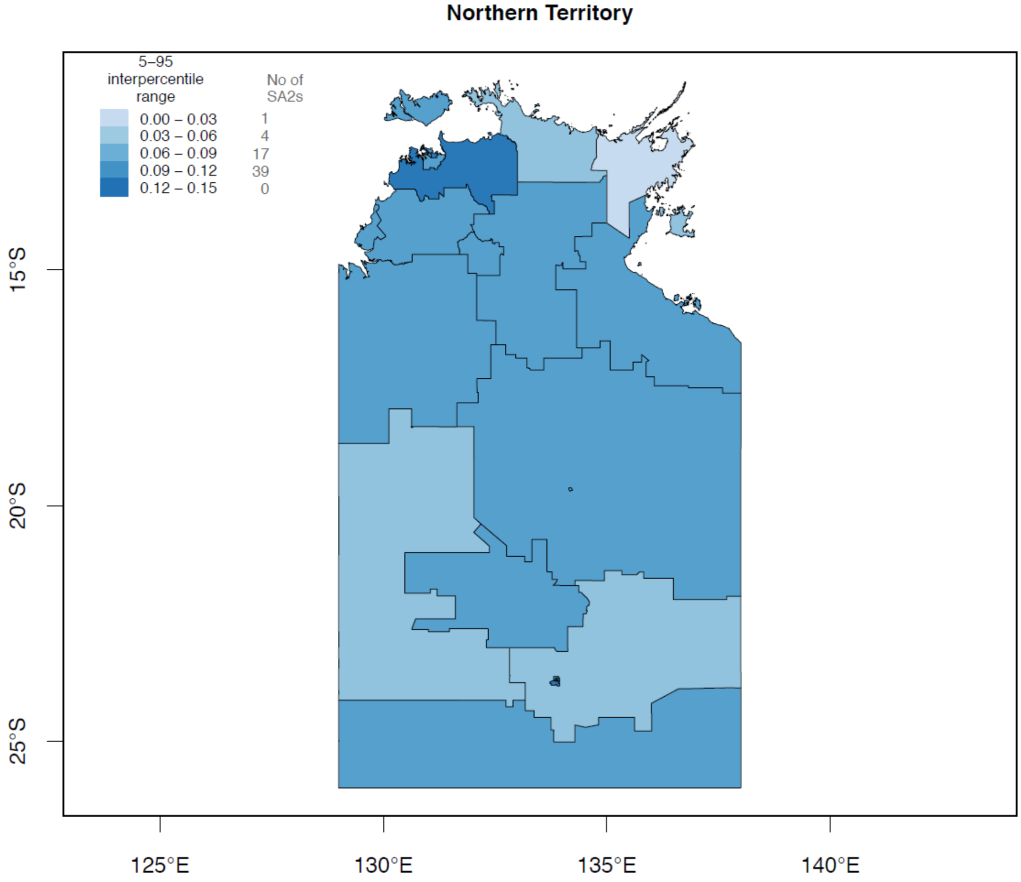

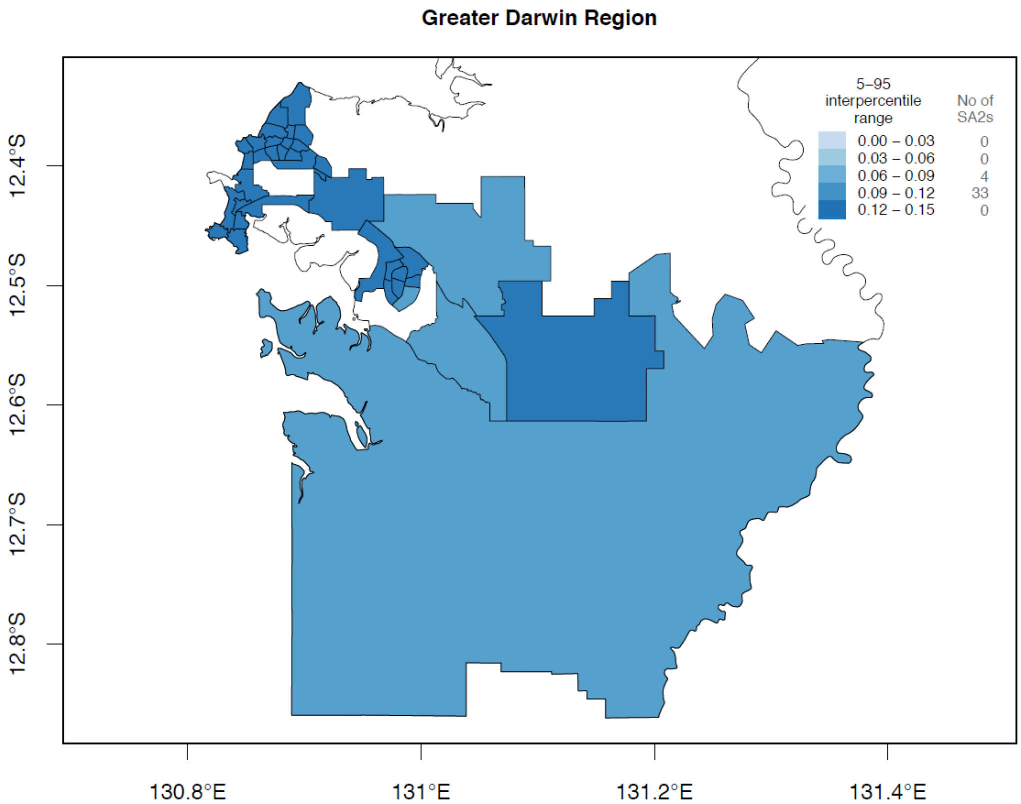

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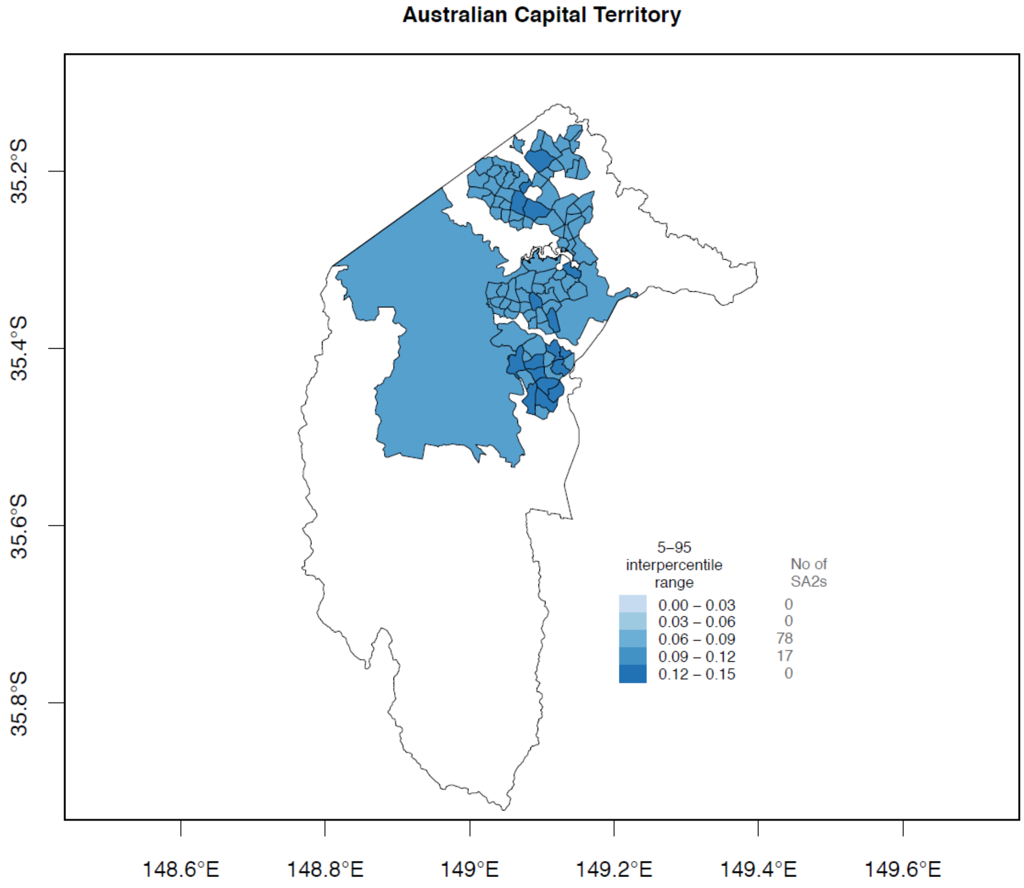
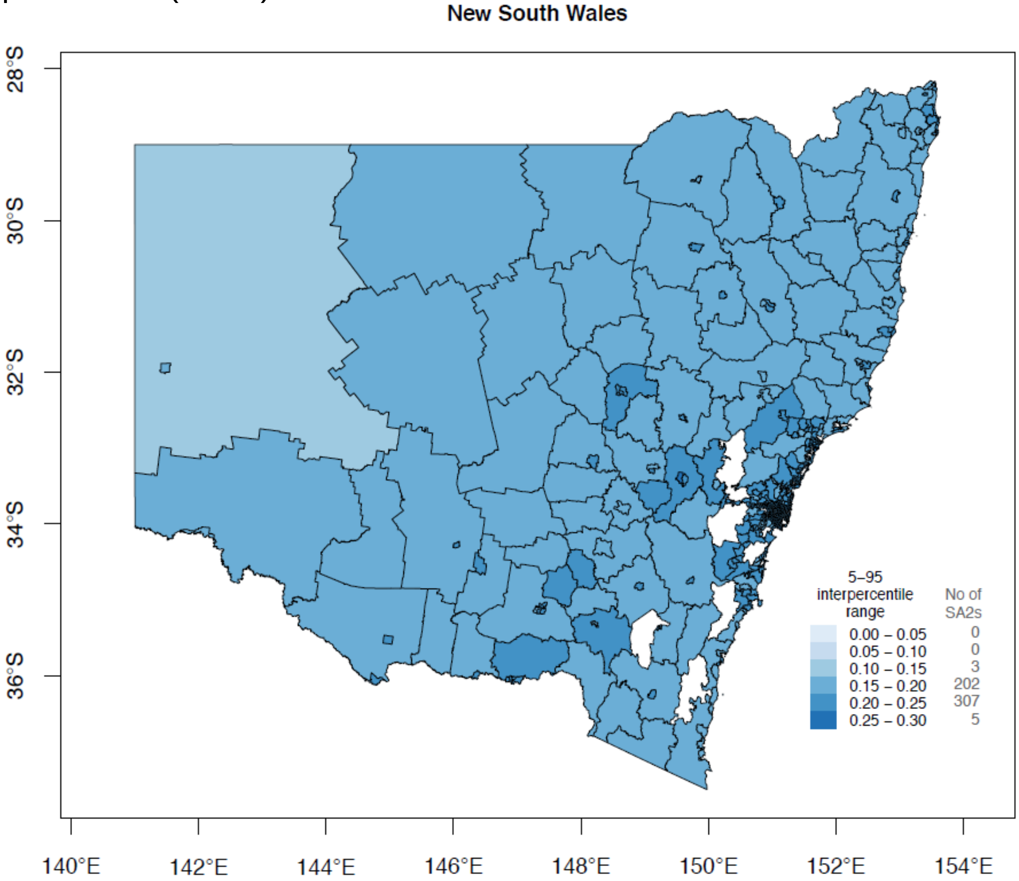
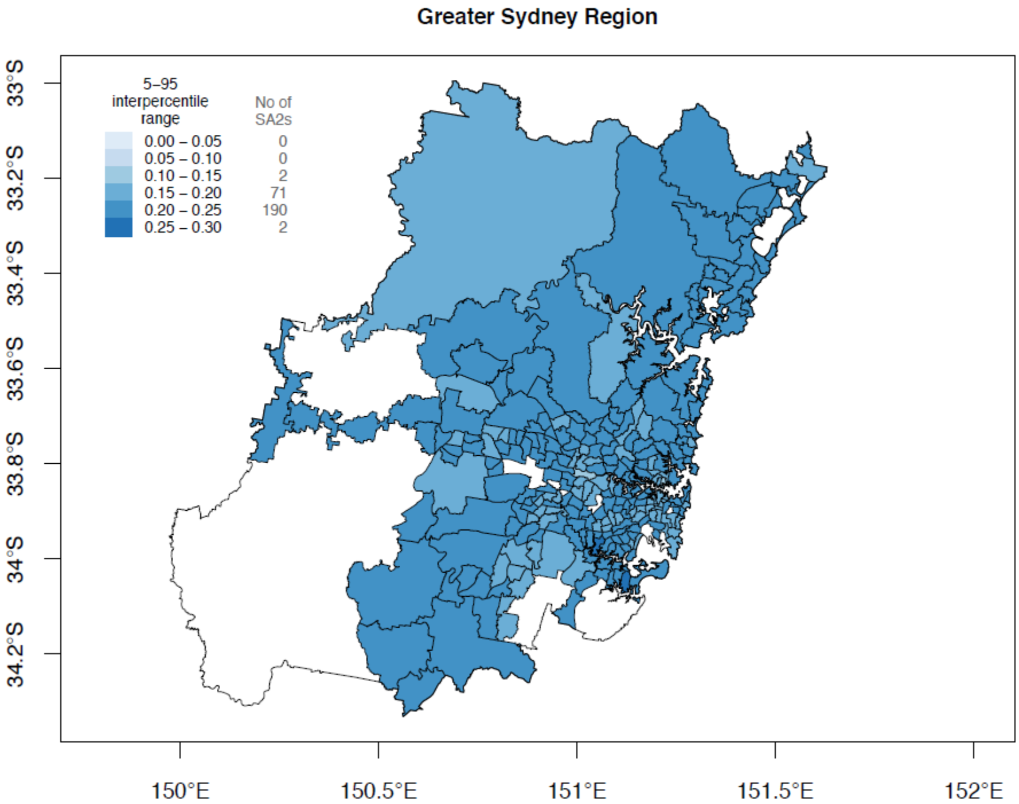


APPENDIX 6C – 5-95 INTER-PERCENTILE RANGE: INDICATOR DISAGGREGATION

Appendix 6C shows the State/Territory and major metropolitan-area resolution maps of the 5-95 inter-percentile range for the uncertainty associated with indicator disaggregation.

Appendix 6C (cont.)





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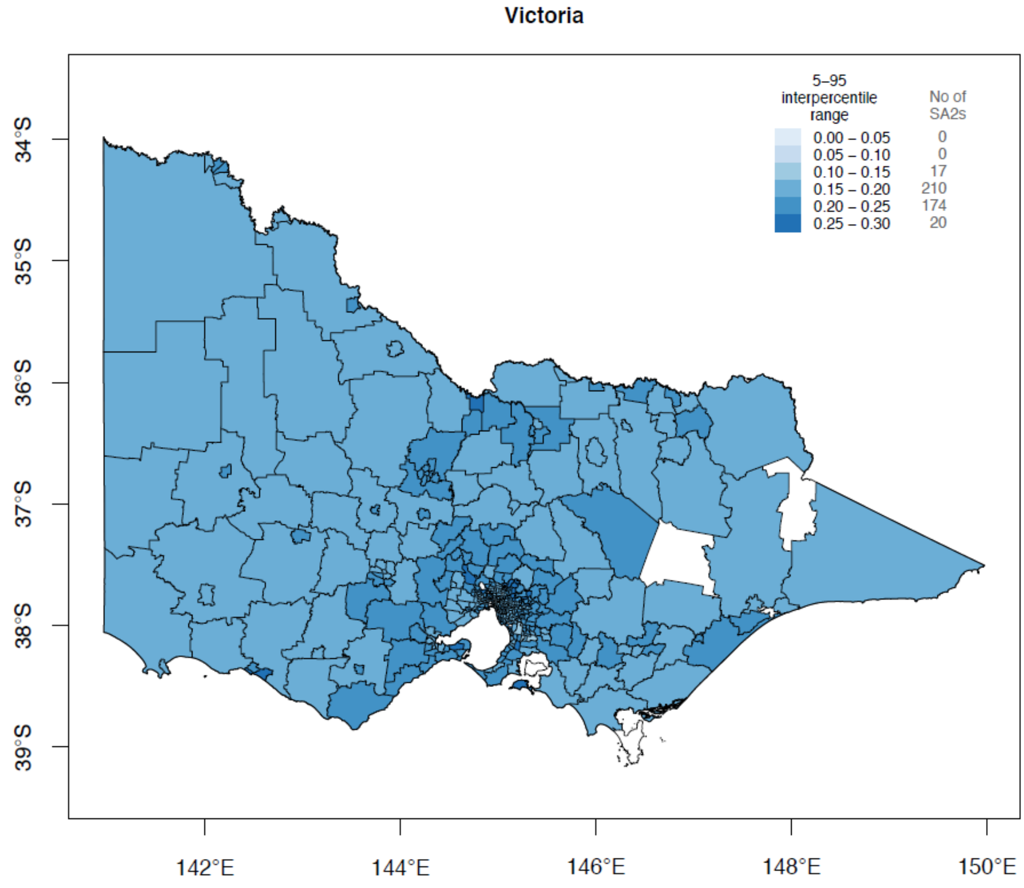

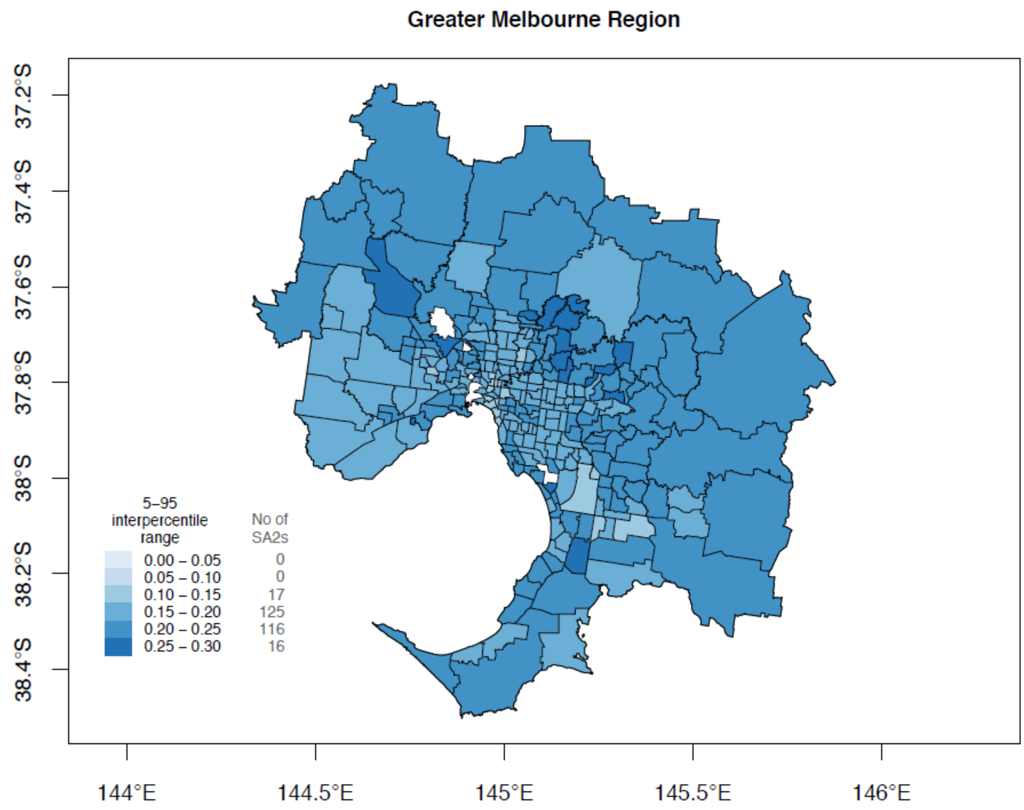

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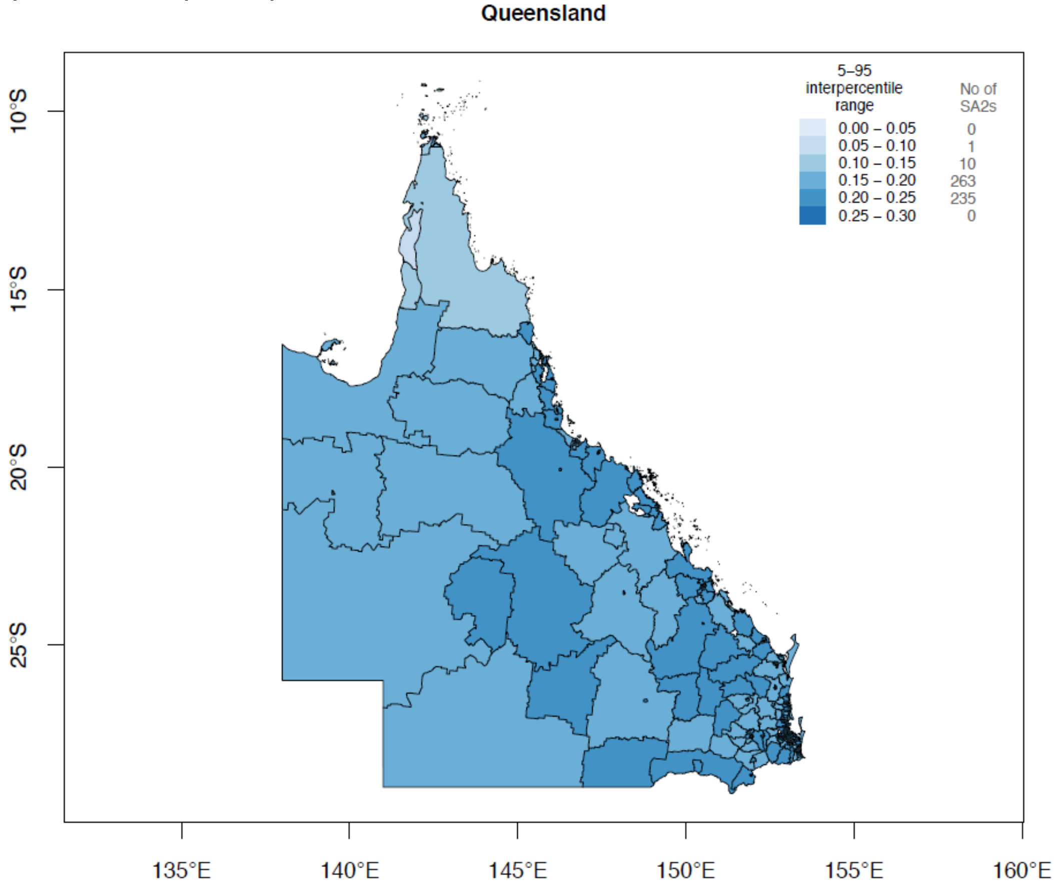

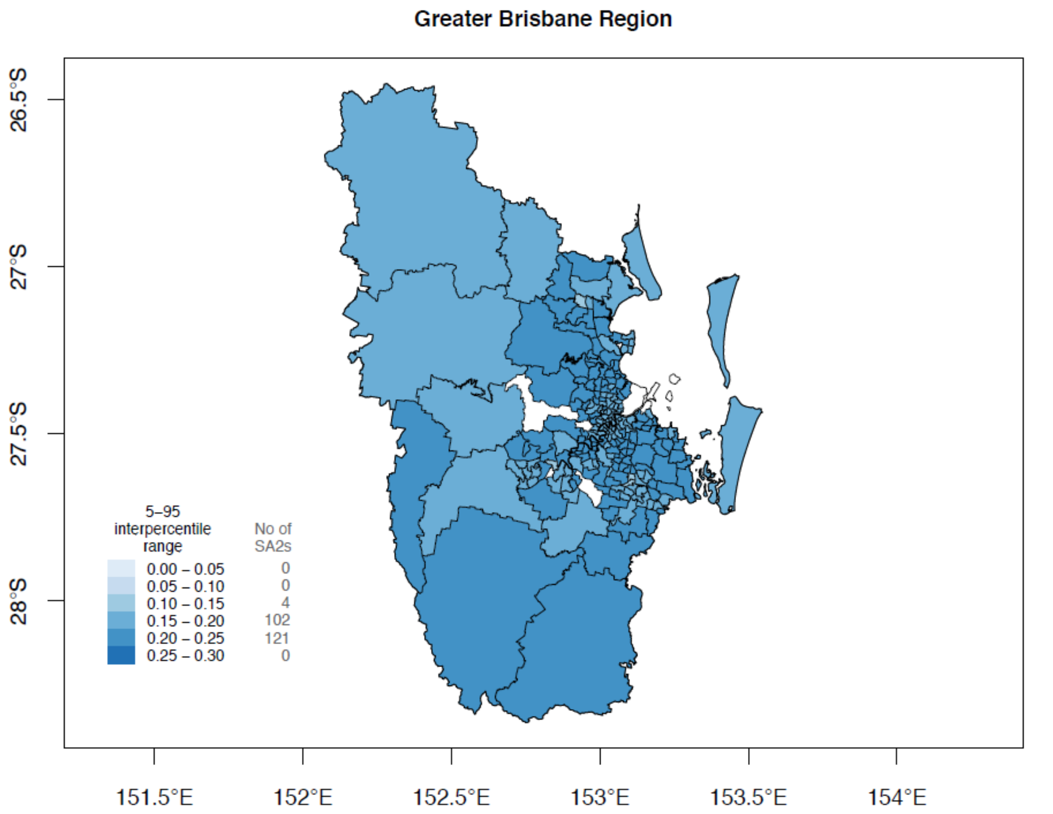

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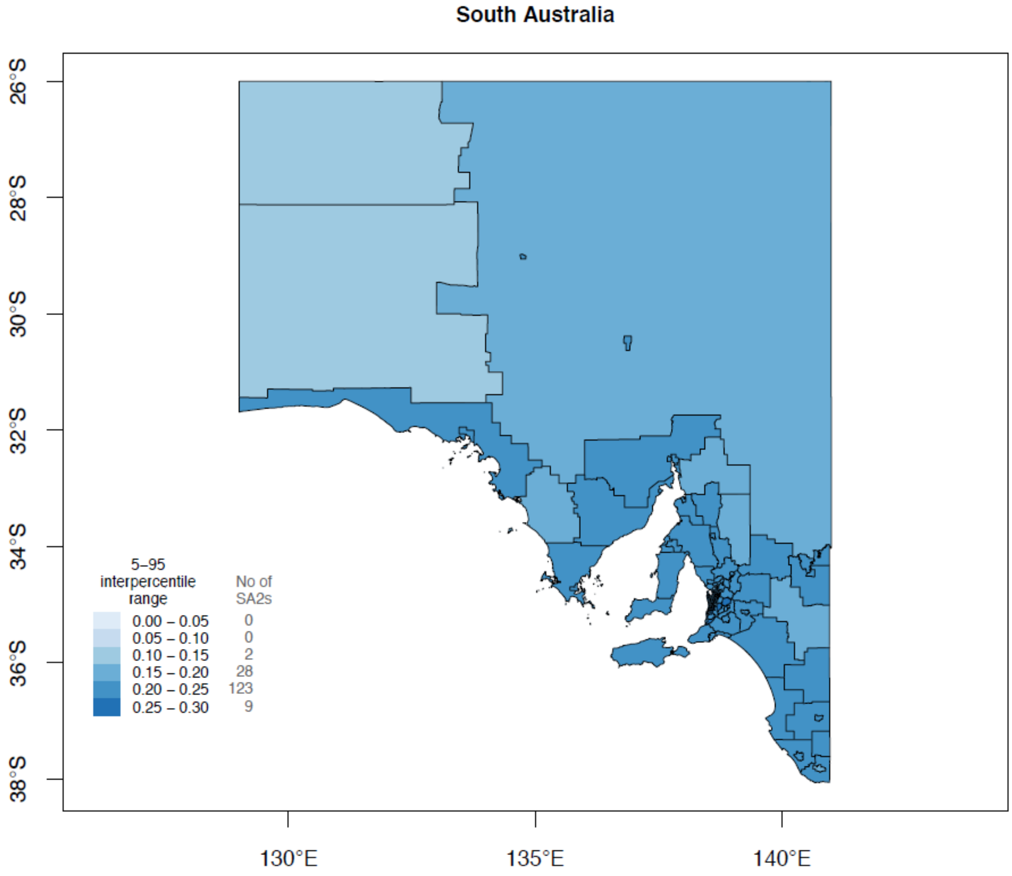

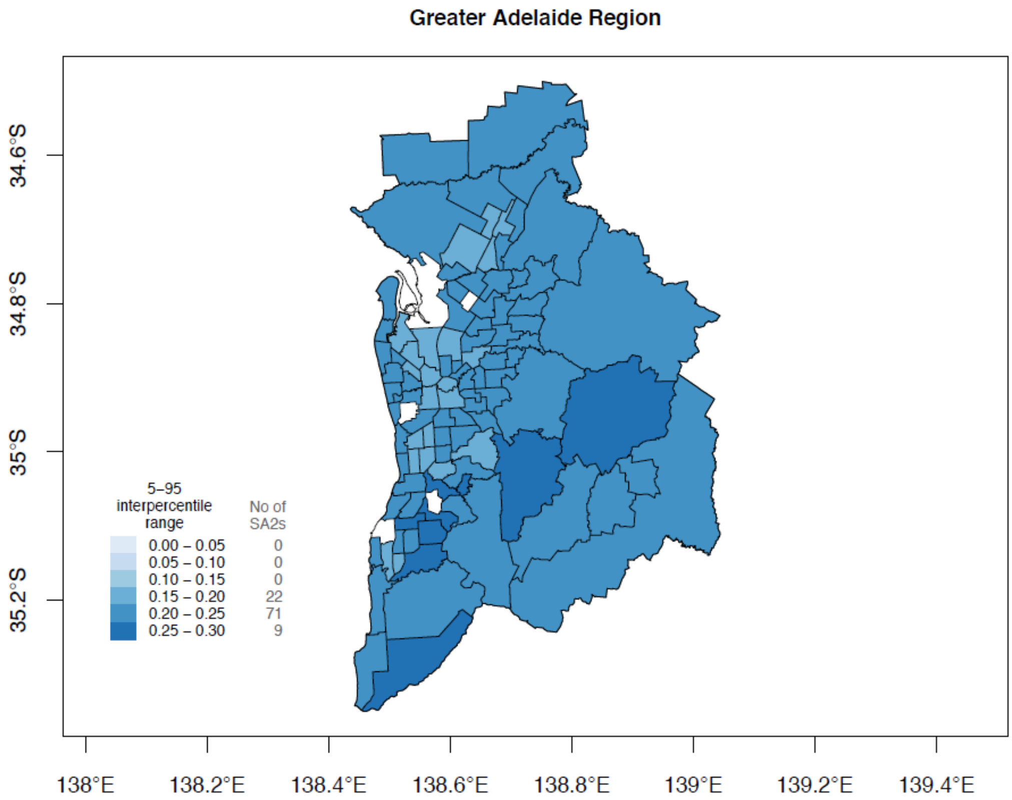

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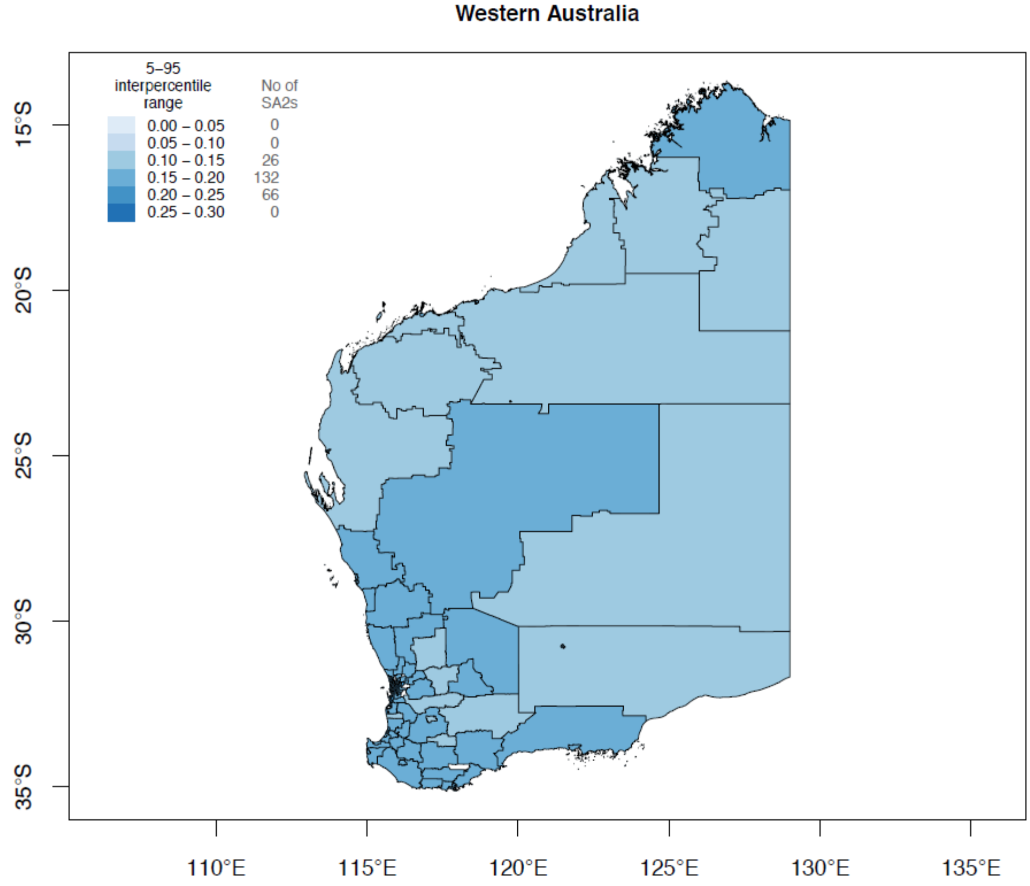

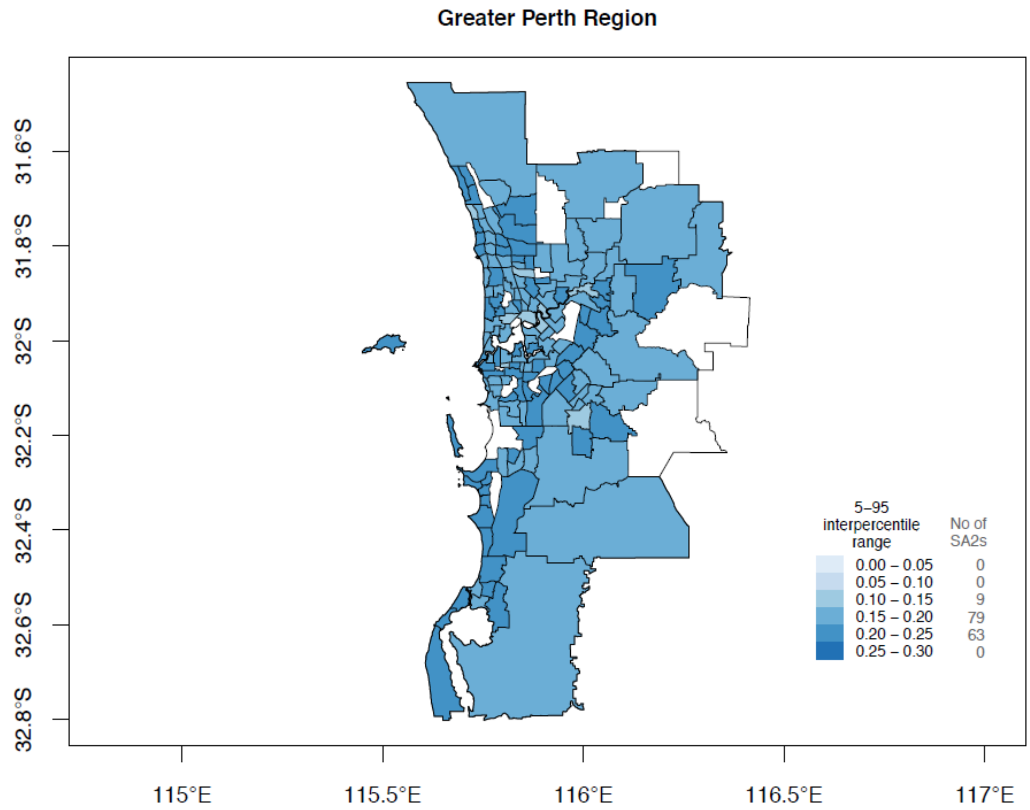

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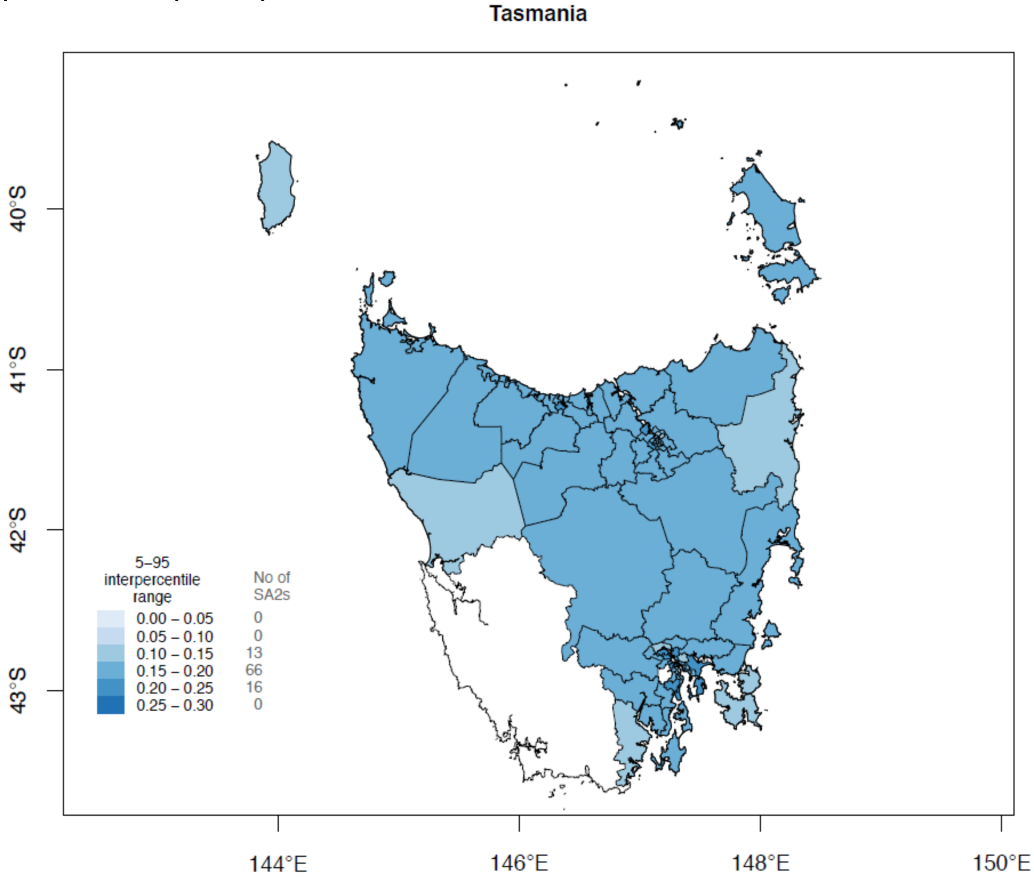

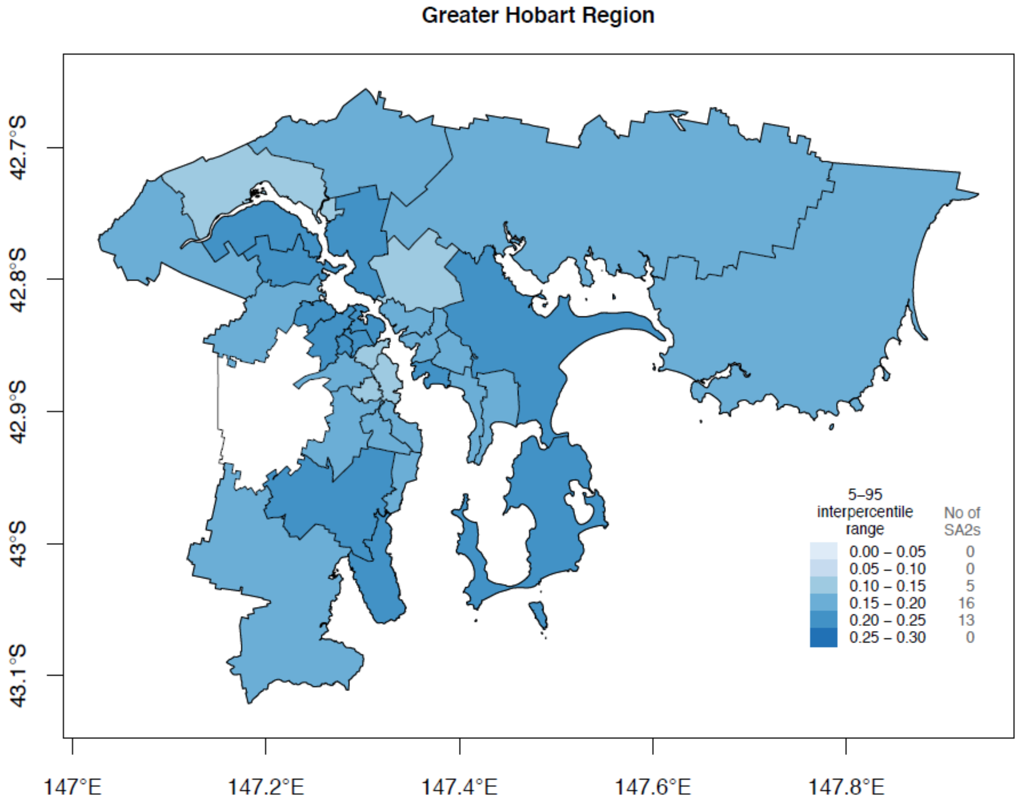

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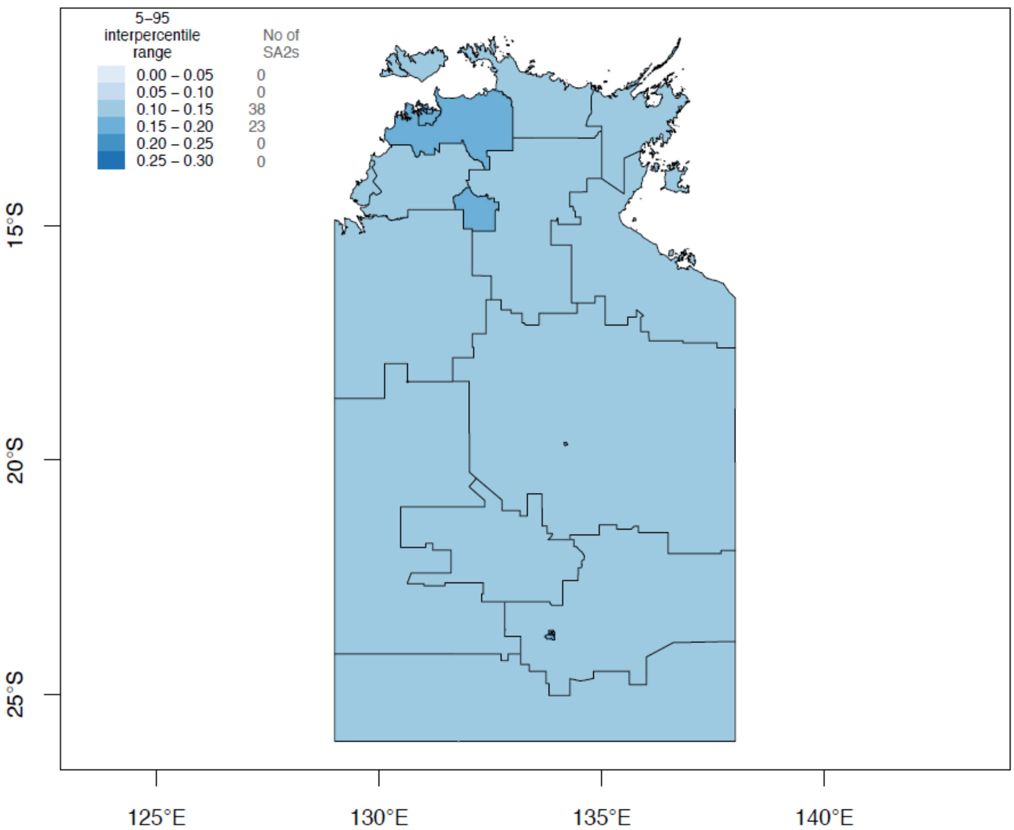
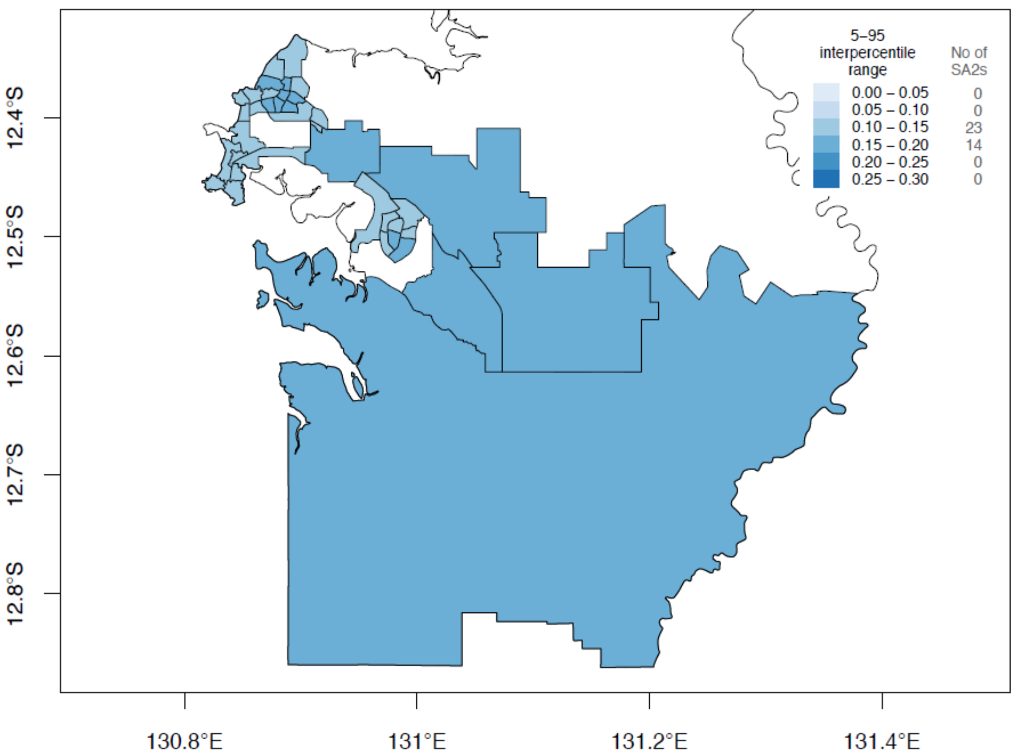


Greater Darwin Region



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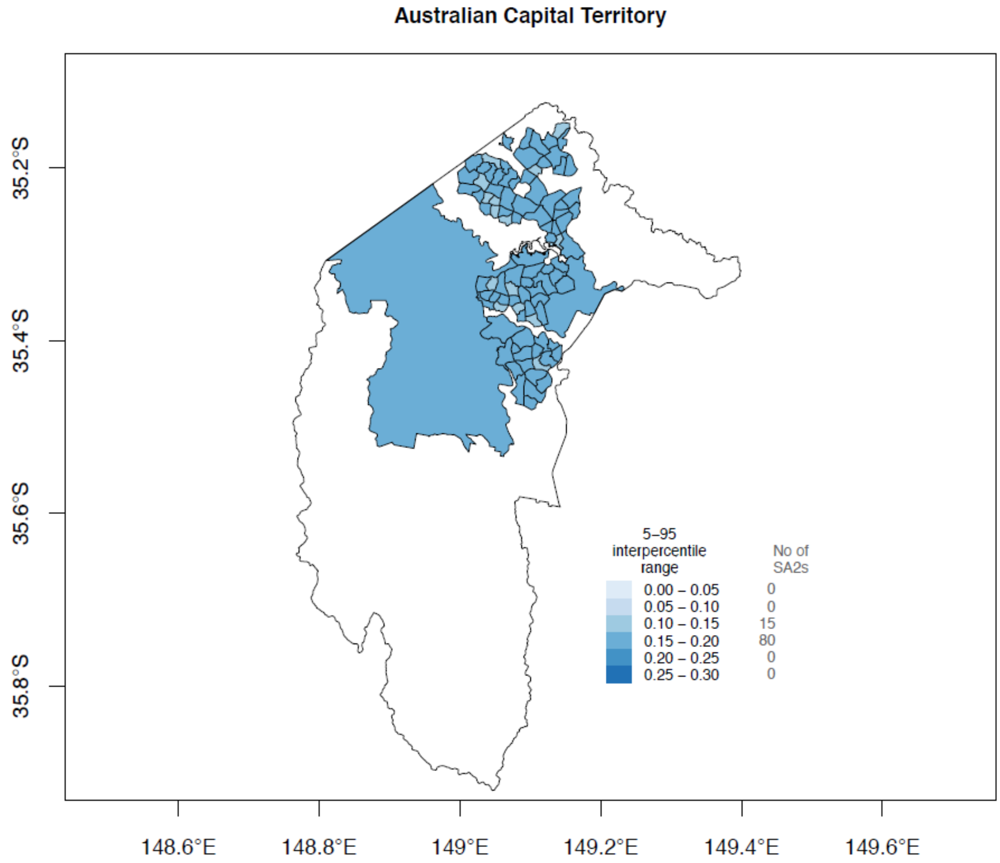

APPENDIX 6D – 5-95 INTER-PERCENTILE RANGE: ORNESS VALUES

Appendix 6D shows the State/Territory and major metropolitan-area resolution maps of the 5-95 inter-percentile range for the uncertainty associated with the orness values used in the aggregation procedure.

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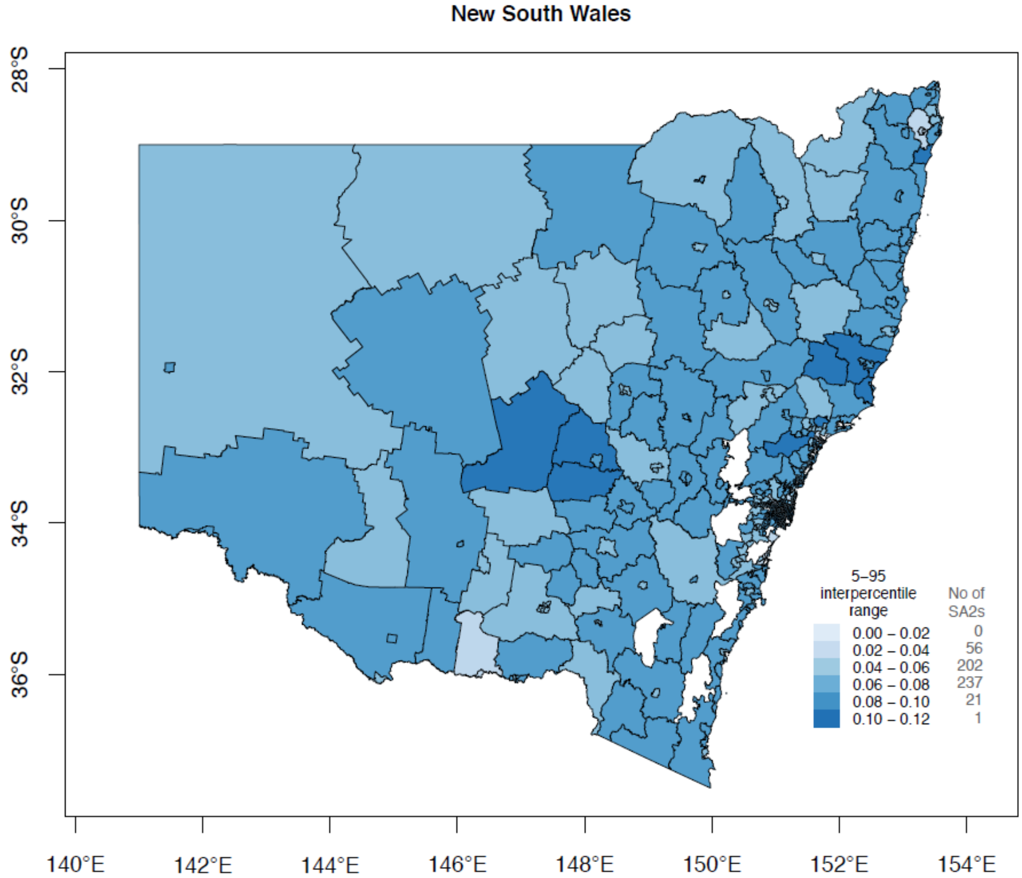

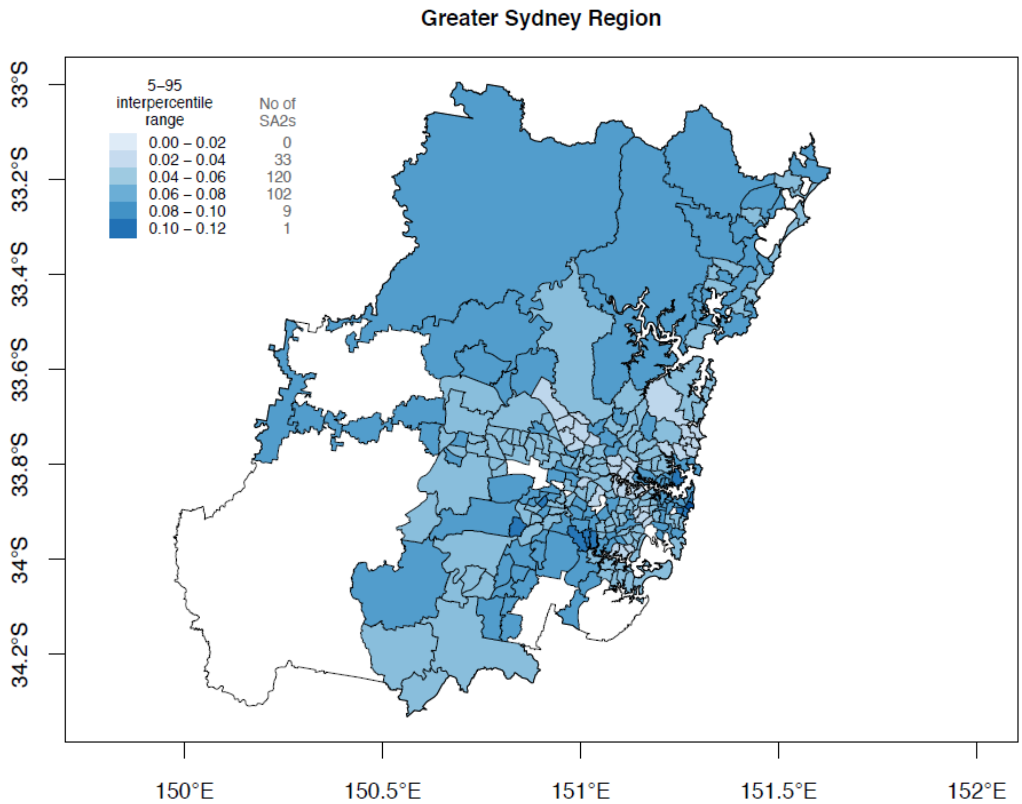

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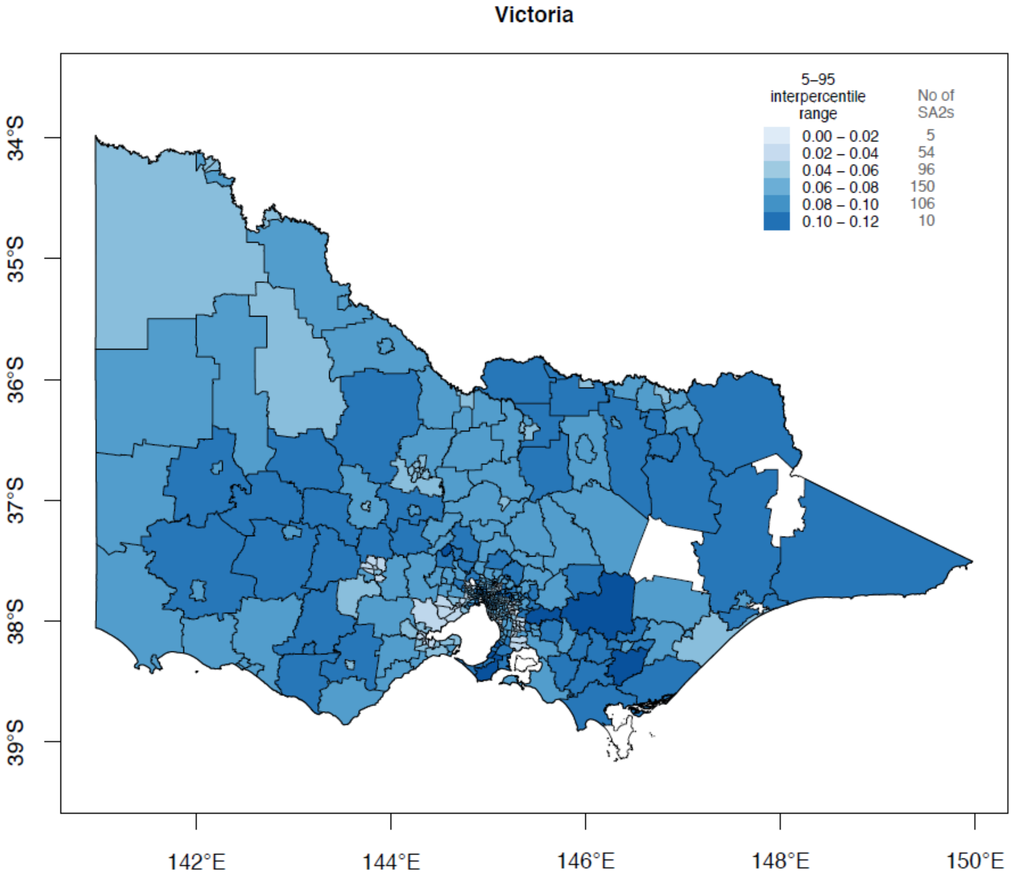

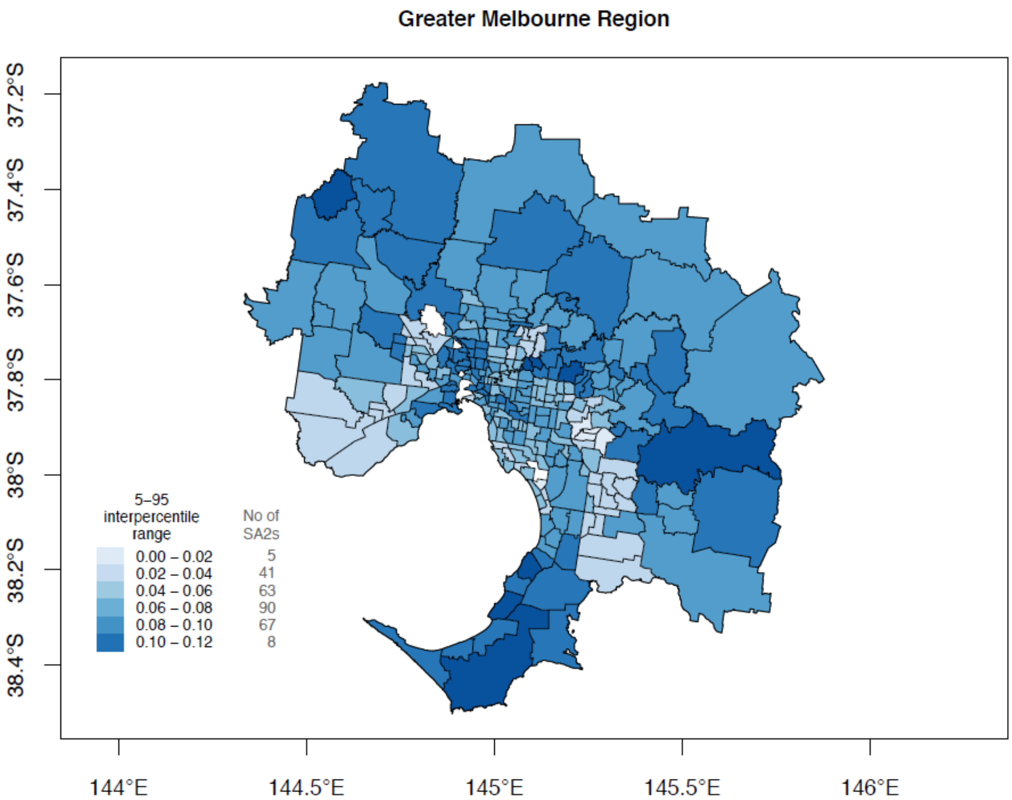

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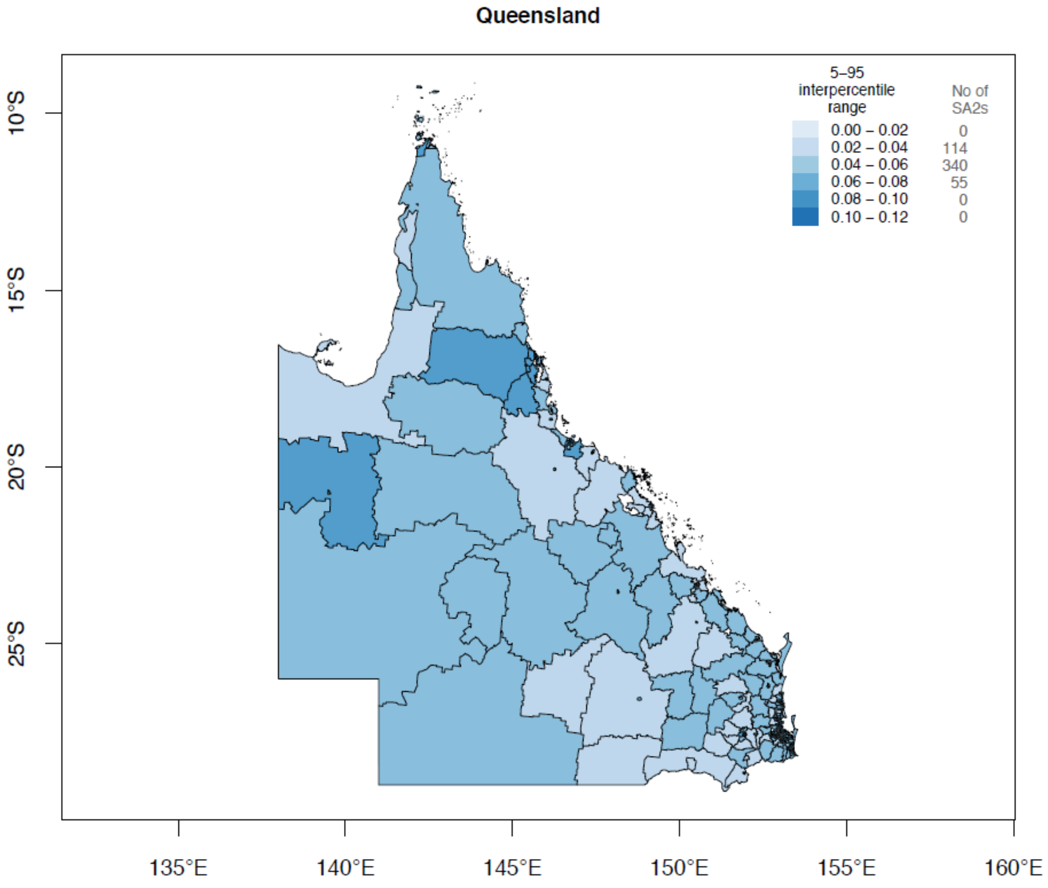

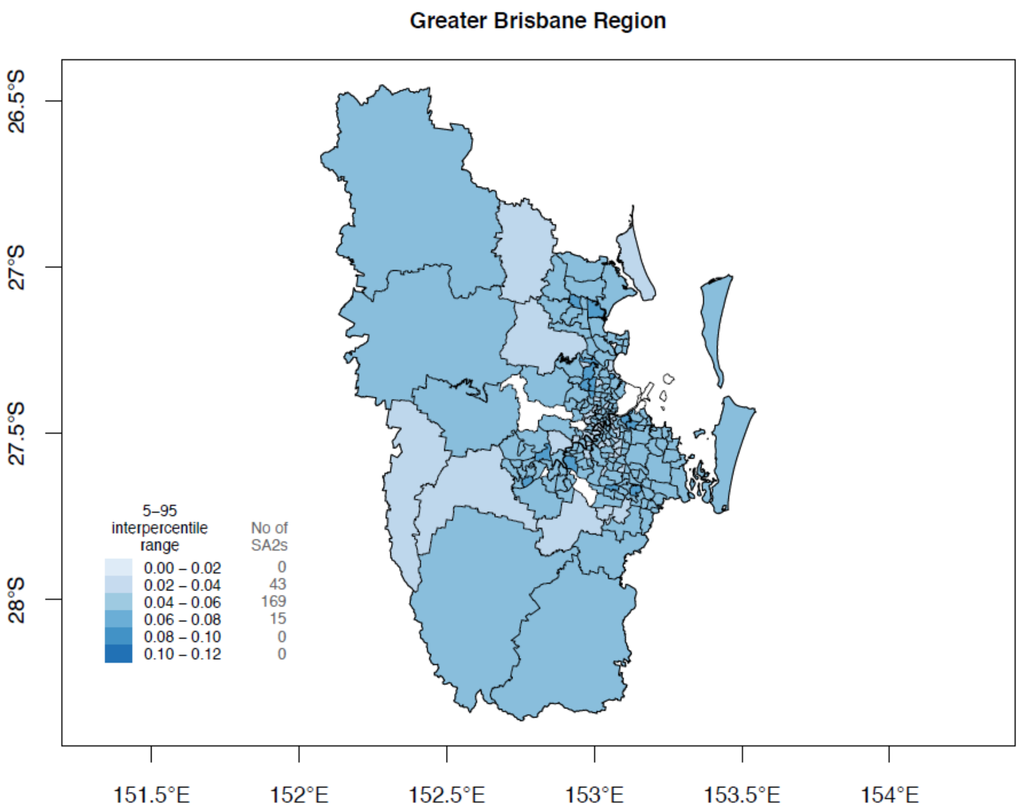

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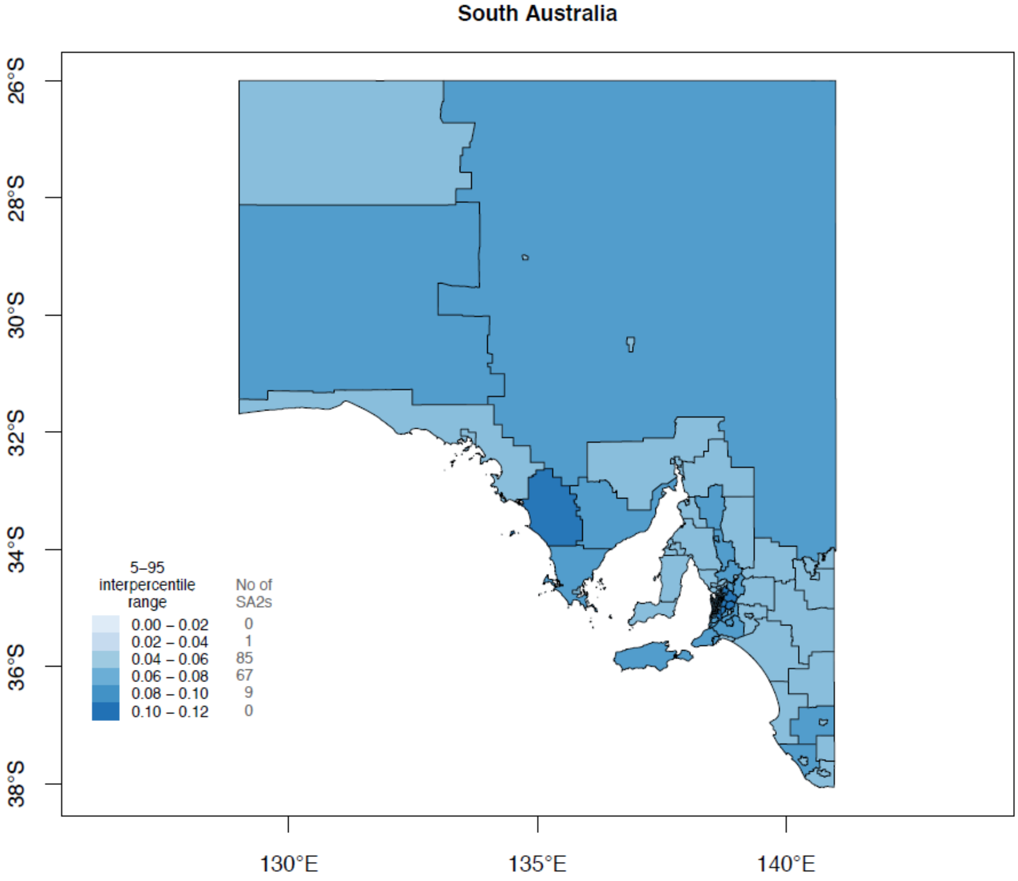

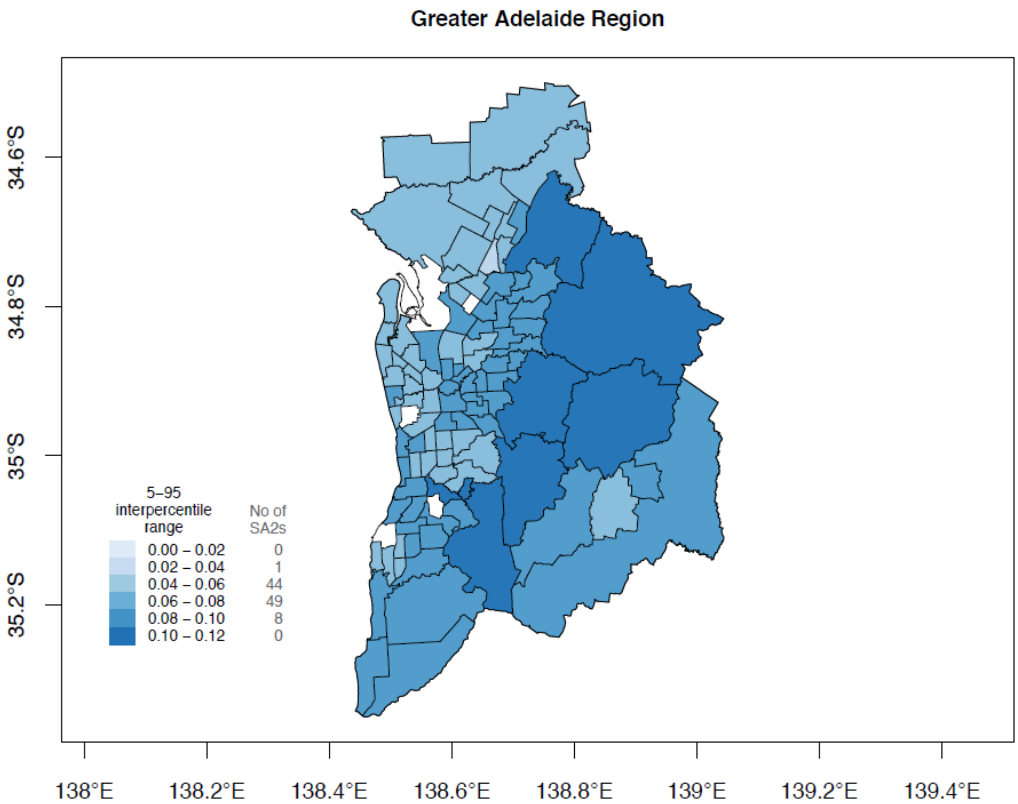

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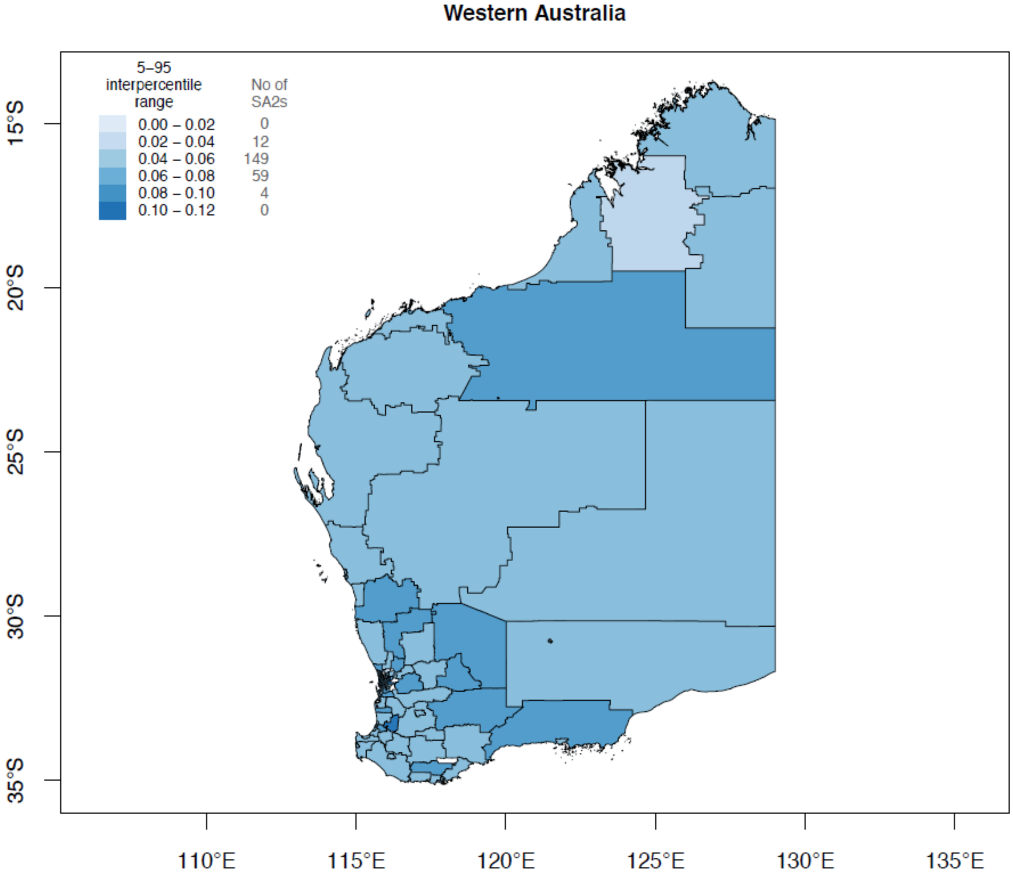

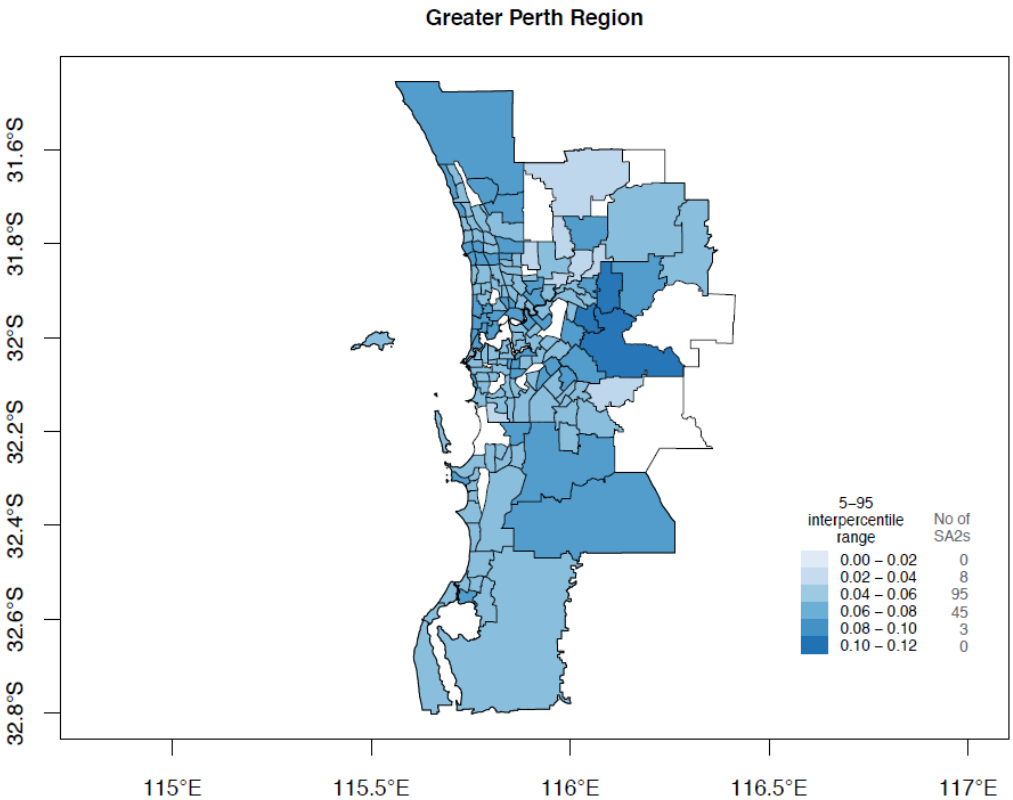

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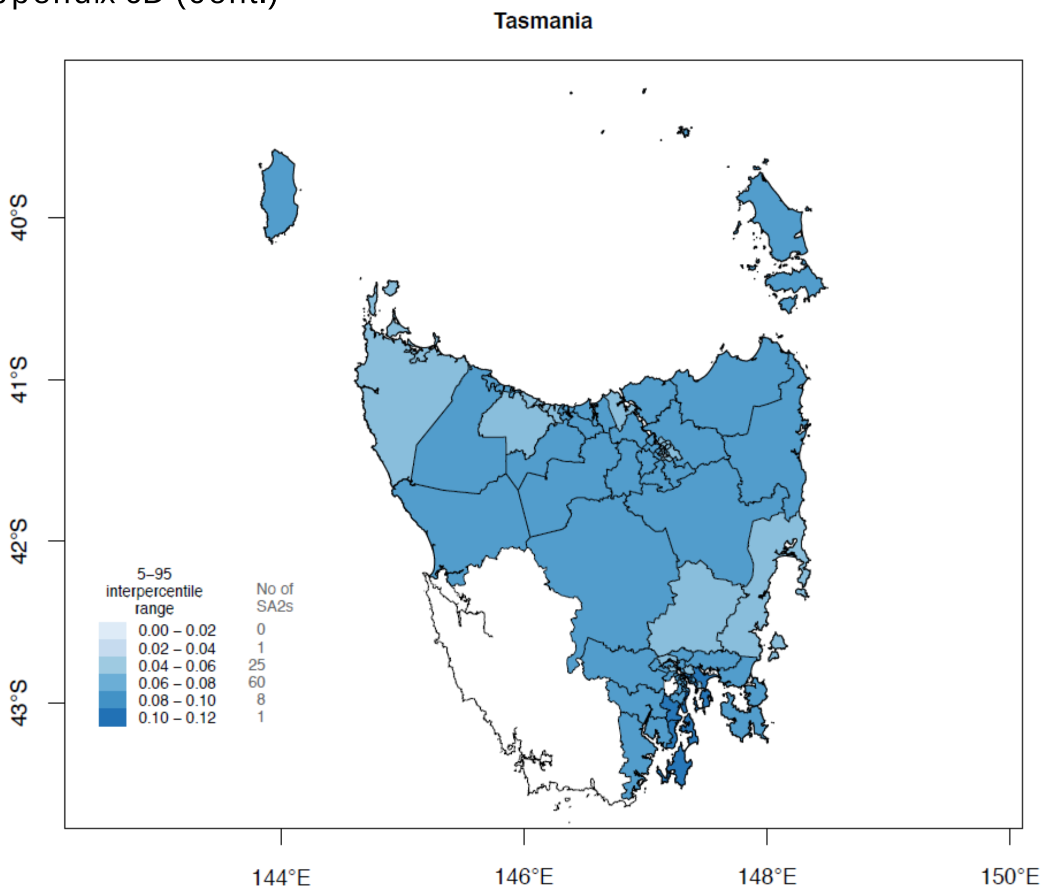

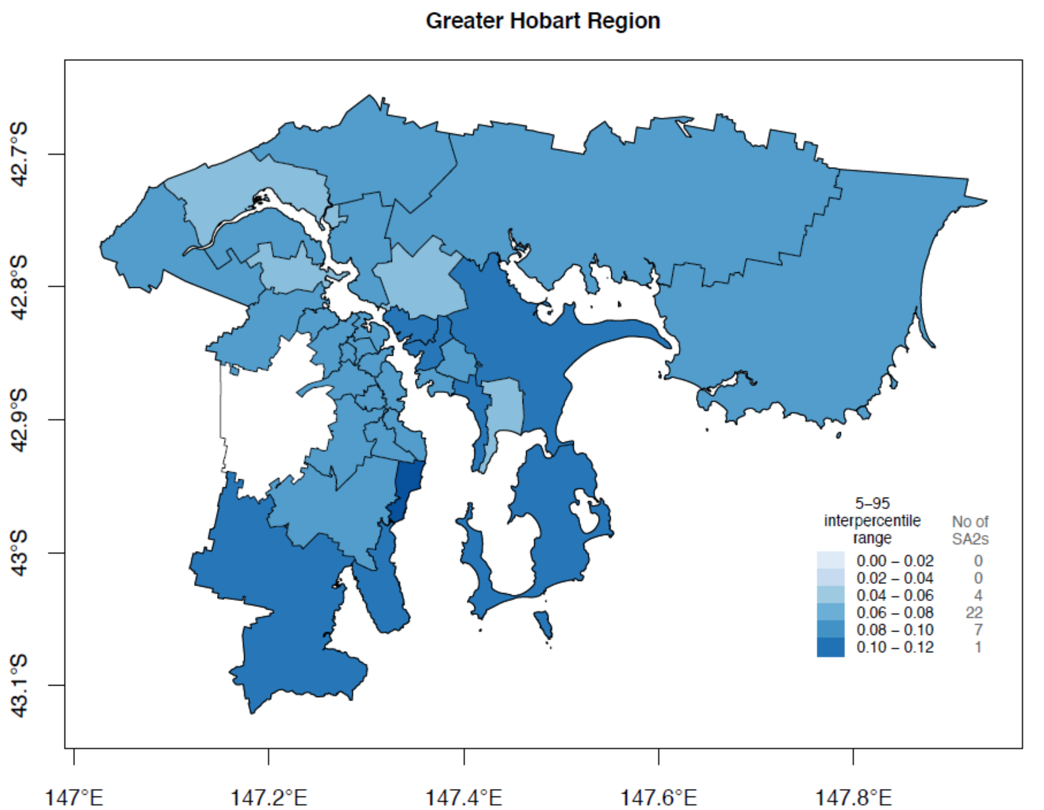

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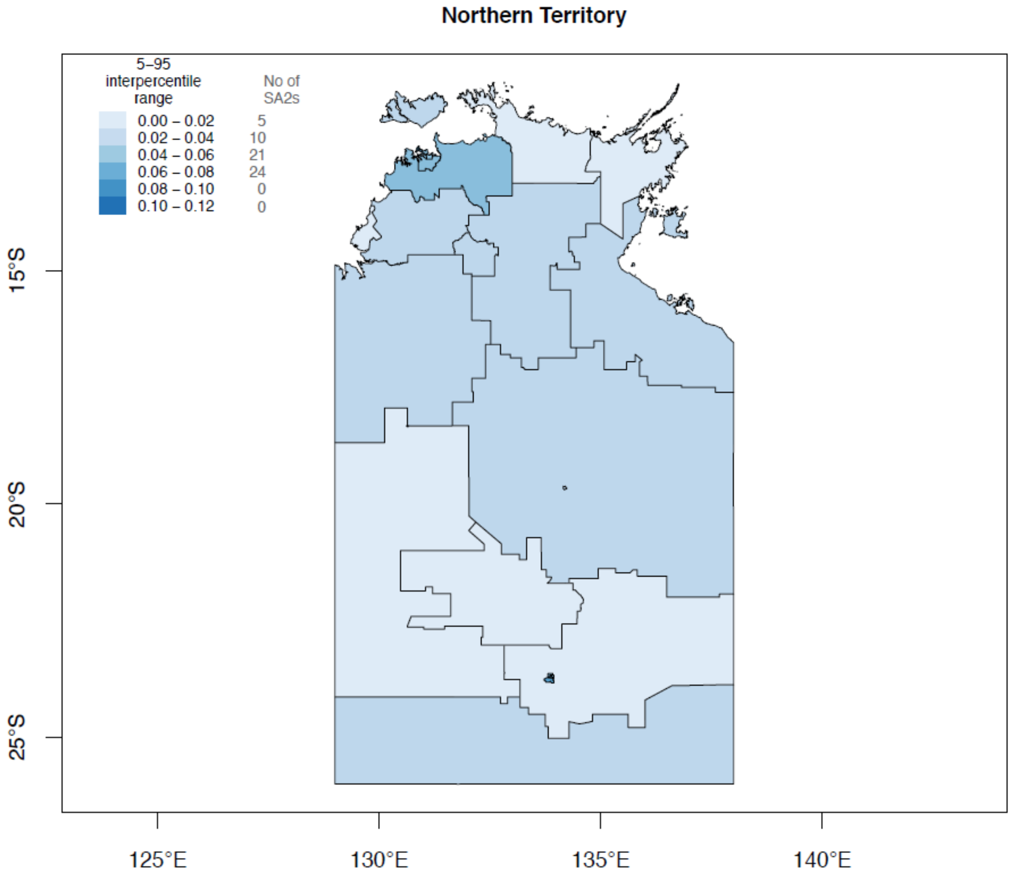

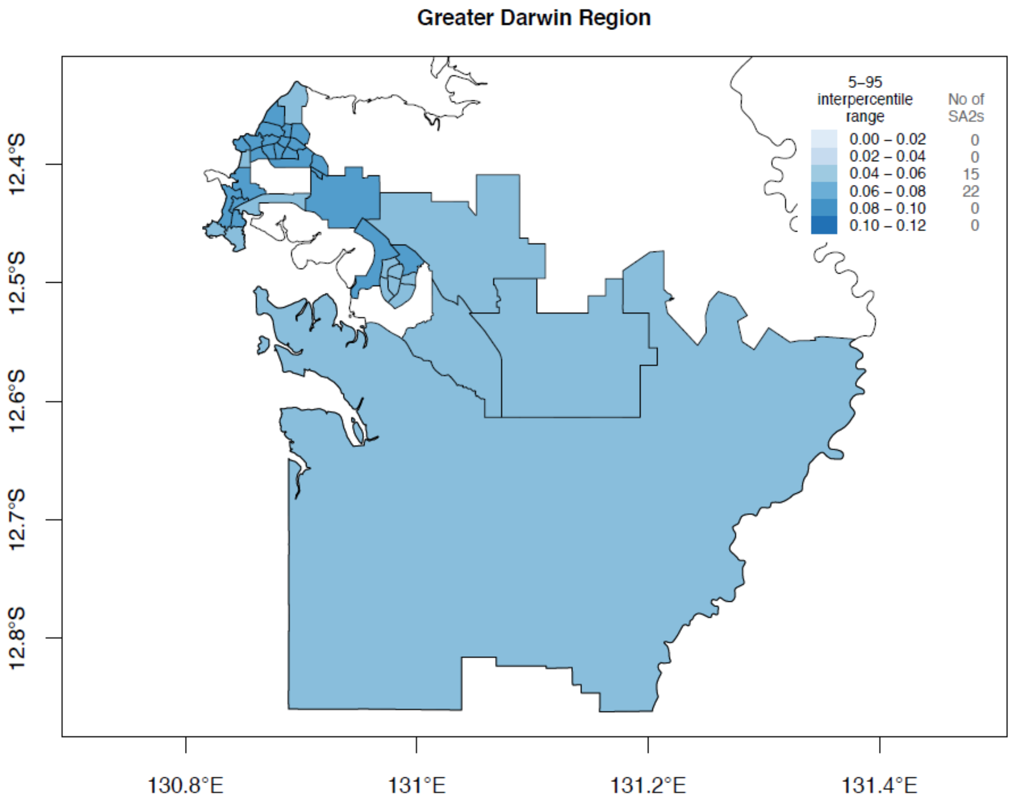

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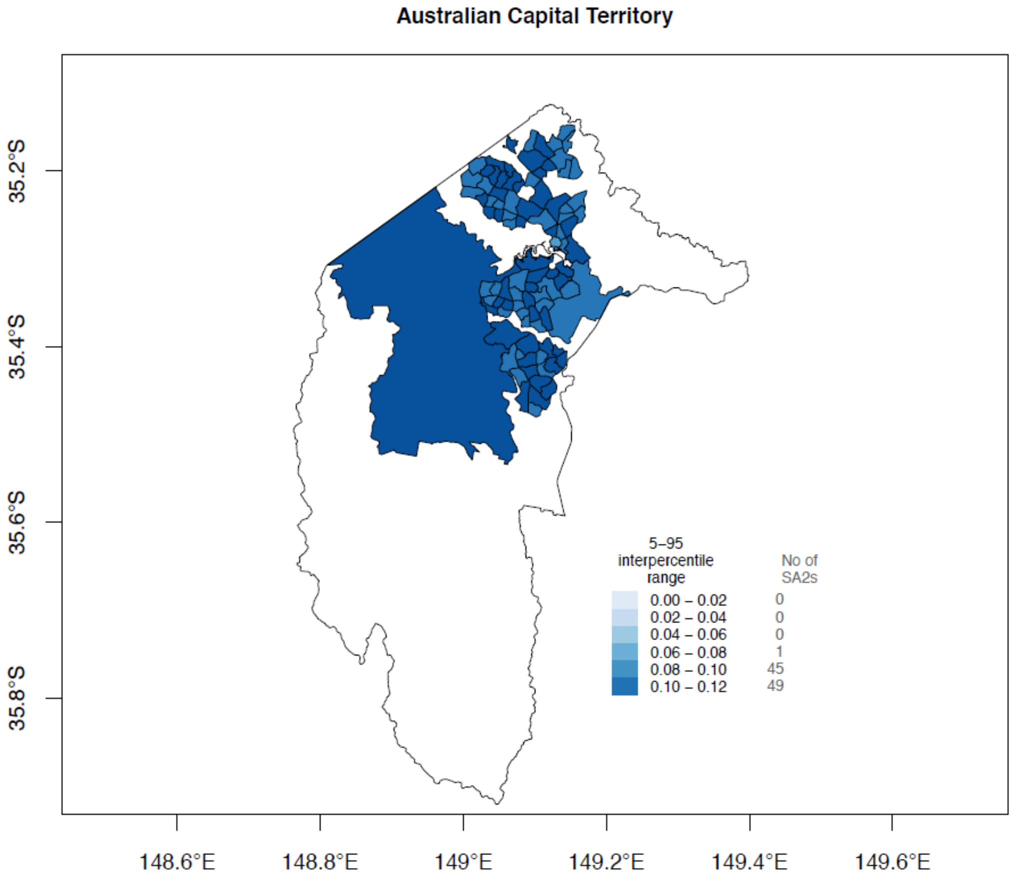


APPENDIX 6E – INDICATOR CODES AND AGGREGATION PARAMETERS USED IN THE MORRIS ELEMENTARY EFFECTS METHOD

Appendix 6E shows the indicator codes and aggregation parameters used in the Morris Elementary Effects Method of sensitivity analysis. Indicator codes refer to Figure 6.10.

Appendix 6E.

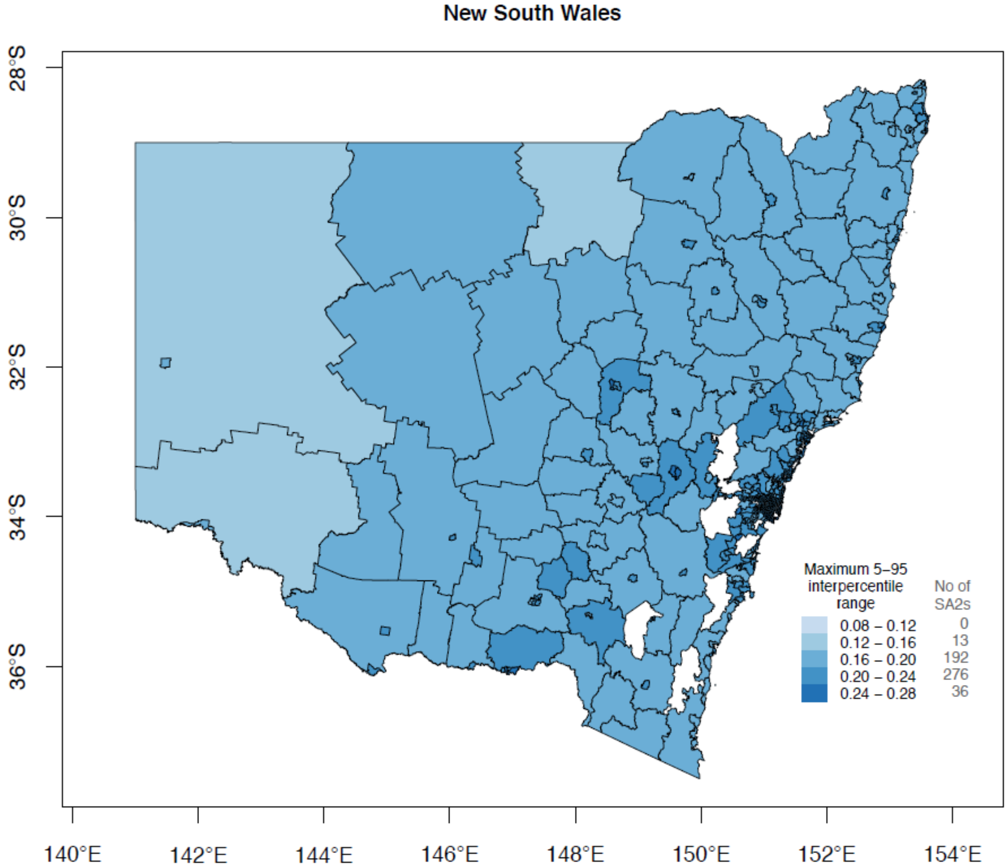
% population arrived in Australia 2001 onwards	1	New dwellings per week (2015-16)	39	Participation in personal interest learning	77
% of households with all or some residents not present a year ago	2	Planning assessment score	40	Orness: household factors	78
% speaks English not well or not at all	3	Medical practitioners per 1000 people 2011	41	Orness: socio-economic advantage	79
% population with a core activity need for assistance	4	Registered nurses per 1000 people 2011	42	Orness: infirmity	80
% one parent families	5	Psychologists per 1000 people 2011	43	Orness: familiarity with locality	81
% households with children	6	Available hospital beds per 1000 population	44	Orness: Social Character	82
% lone person households	7	Welfare support workers per 1000 population	45	Orness: disposable income	83
% group households	8	Ambulance officers and paramedics per 1000 population	46	Orness: ownership	84
Sex ratio	9	Fire and emergency workers per 1000 population	47	Orness: economy	85
% population aged over 75	10	Police per 1000 population	48	Orness: Economic Capital	86
% population aged under 15	11	Fire Emergency SES organisations cost per 1000 population	49	Orness: local government capacity	87
Ratio of certificate and/or postgrad to year 8-12	12	Ambulance organisations cost per 1000 population	50	Orness: infrastructure integrity	88
% of labour force unemployed	13	Fire service volunteers per 1000 people	51	FM1: Planning and the Built Environment	89
% not in labour force	14	SES volunteers per 1000 people	52	FM2: Planning and the Built Environment	90
% managers and professionals	15	Distance to a medical facility (km)	53	Orness: Planning and the Built Environment	91
% residents owning own home outright	16	Offences against persons 2011-12 per 100000 population	54	Orness: emergency response resources	92
% residents owning own home with a mortgage	17	Offences against property 2011-12 per 100000 population	55	FM1: Emergency Services	93
% residents renting their home	18	Support in crisis ASR 2010 per 100	56	FM2: Emergency Services	94
Median weekly rent	19	Safe walking in neighbourhood ASR 2010 per 100	57	Orness: Emergency Services	95
Median monthly mortgage repayments	20	Difficulty accessing services ASR 2010 per 100	58	Orness: Community Capital	96
Median weekly personal income	21	Poor self assessed health ASR 2010per 100	59	FM1: Information and Access	97
Median weekly family income	22	Raise $2000 in week ASR 2010 per 100	60	FM2: Information and Access	98
% families with less than $600 p.w. income	23	% Residents in same residence > 5 years	61	FM3: Information and Access	99
% families with more than $3000 p.w. income	24	% Households with no motor vehicle	62	FM4: Information and Access	100
% employment in largest single sector	25	% Population undertaking voluntary work	63	FM5: Information and Access	101
Economic diversity index	26	% Jobless families	64	FM6: Information and Access	102
% businesses employing 20 or more people	27	Mean area weighted ADSL coverage	65	Orness: Information and Access	103
Retail and/or commercial establishments per 1000 people	28	% area with mobile phone coverage	66	Orness: Governance and Leadership	104
% population change 2001 to 2011	29	Community engagement score	67	Orness: educational participation	105
Local government grant per capita	30	Presence of research organisations	68	Orness: life satisfaction and trust	106
% Caravans and improvised dwellings	31	Business Dynamo Sub-index	69	Orness: Social and Community Engagement	107
% Residential post-1981	32	Local economic development support	70	Orness: Coping Capacity	108
% Commercial and industrial post-1981	33	GPL Score	71	FM1: Adaptive Capacity	109
Emergency plan assessment score	34	Life satisfaction scale 70 and above	72	FM2: Adaptive Capacity	110
FTE council staff 14-15	35	Trust_Total percent agree	73	Orness: Adaptive Capacity	111
Area km2/FTE	36	Gross in and out migration as percent of population	74	FM1: ANDRI	112
Dwellings/FTE	37	Percent of population with post school qualification	75	FM2: ANDRI	113
New dwellings (2012-16) as proportion of 2011 dwellings (%)	38	Percent of population over 15 in further education	76	Orness: ANDRI	114

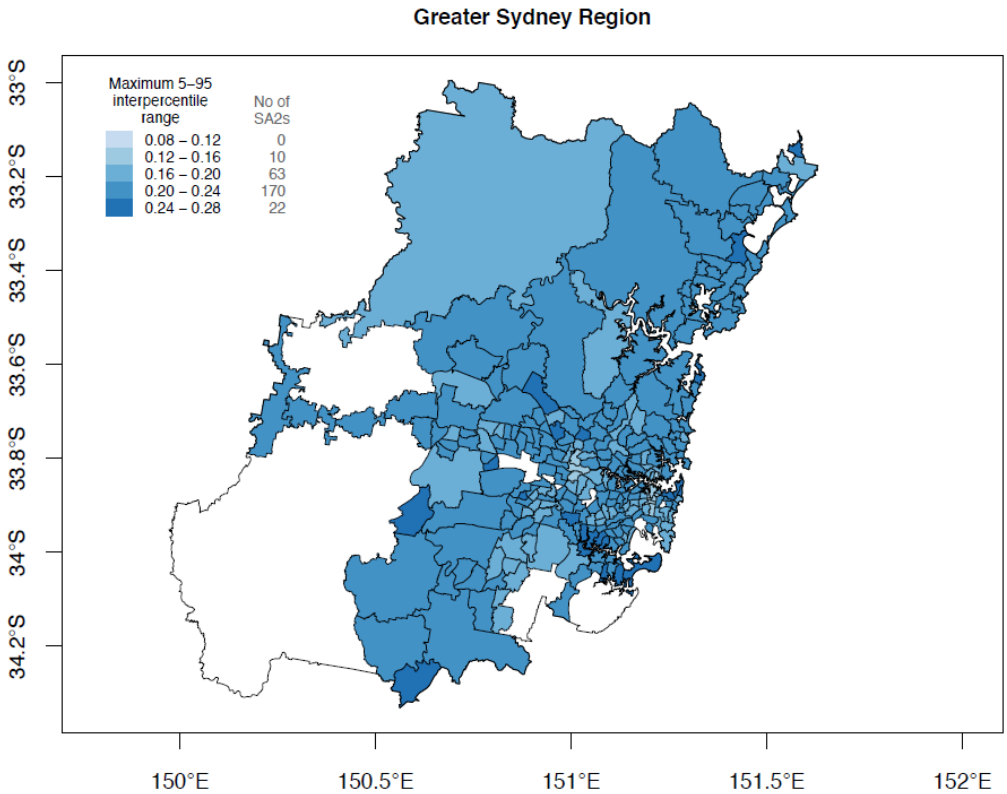
Note: FM1, FM2 etc., refer to the elements of a fuzzy measure.

APPENDIX 6F – MAXIMUM 5-95 INTER-PERCENTILE RANGE

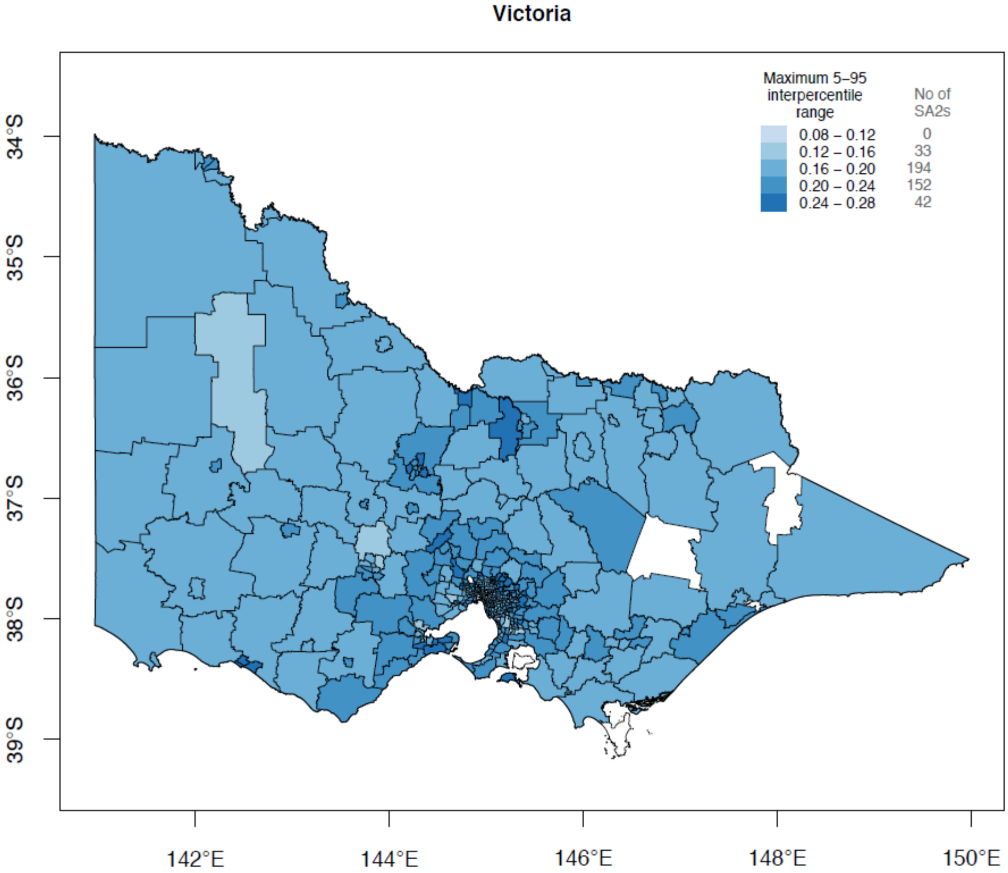
Appendix 6F shows the State/Territory and major metropolitan-area resolution maps of the maximum 5-95 inter-percentile range for the uncertainty in the Australian Natural Disaster Resilience Index associated with evaluation of planning and policy documents, indicator disaggregation and choice of orness values.

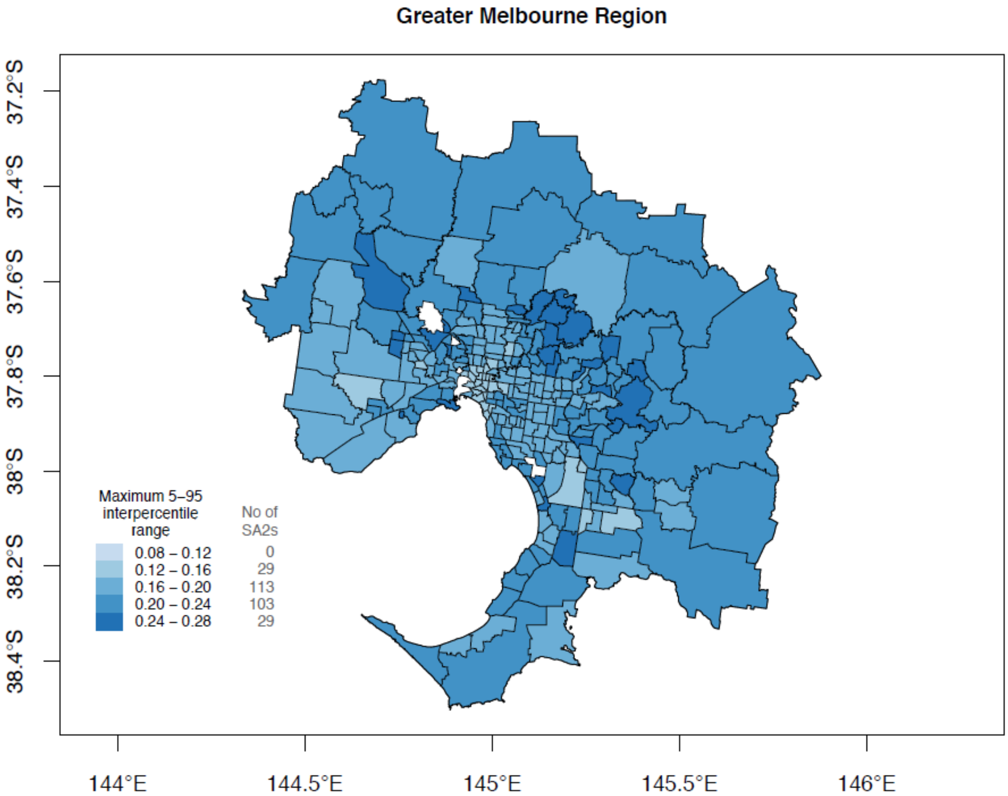
Appendix 6F (cont.)





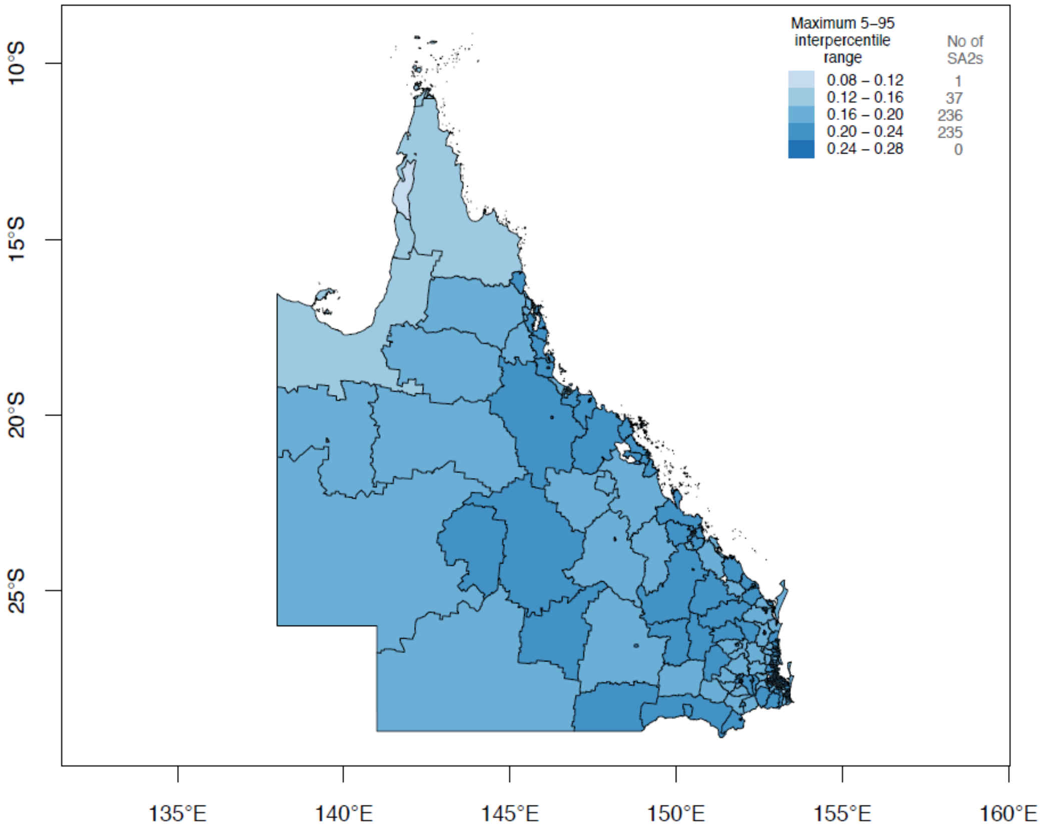
Appendix 6F (cont.)



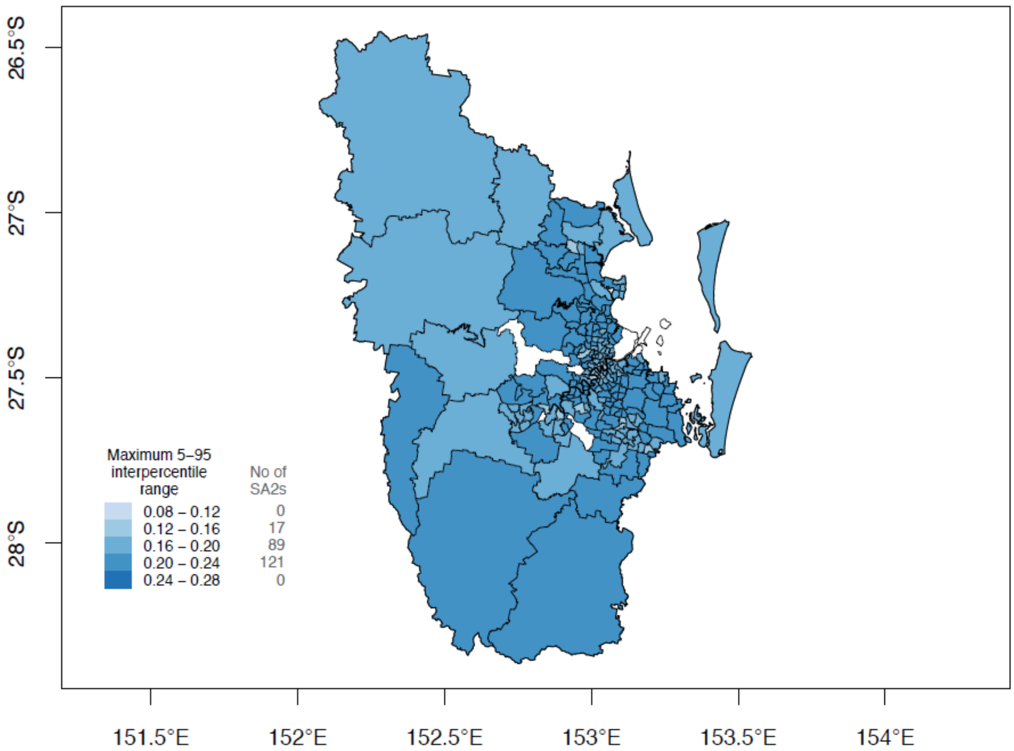


Appendix 6F (cont.)

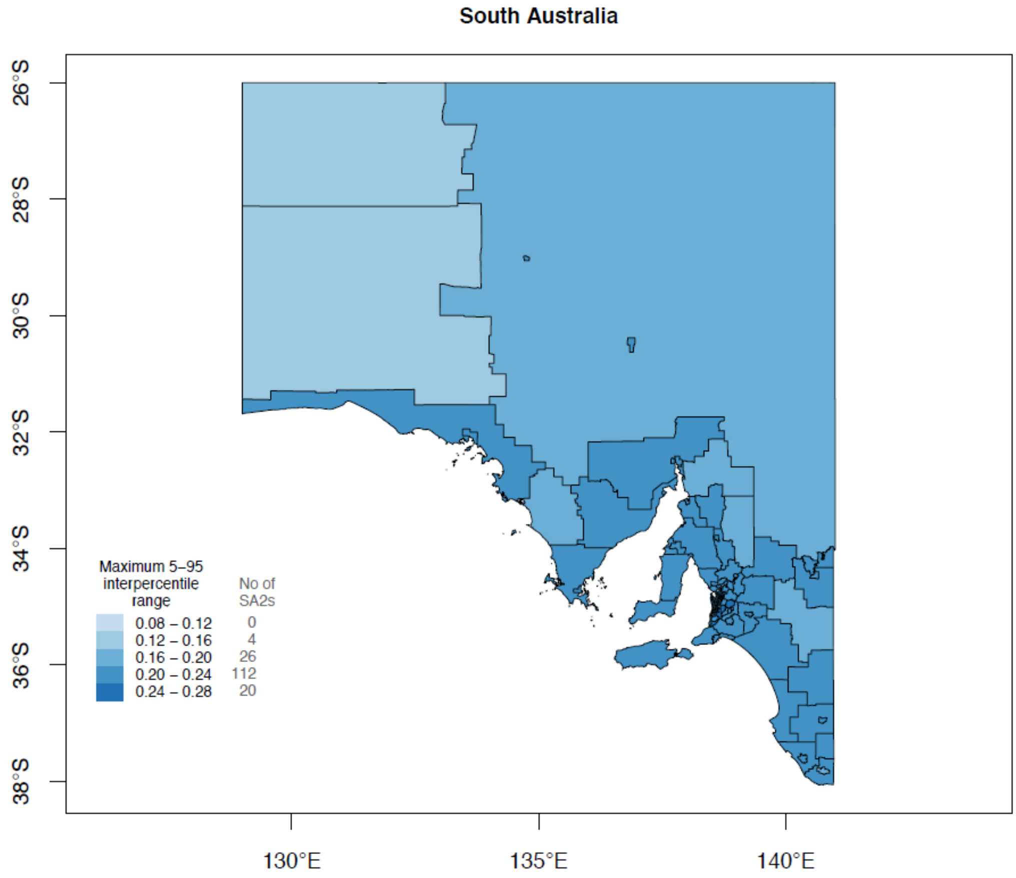
Queensland

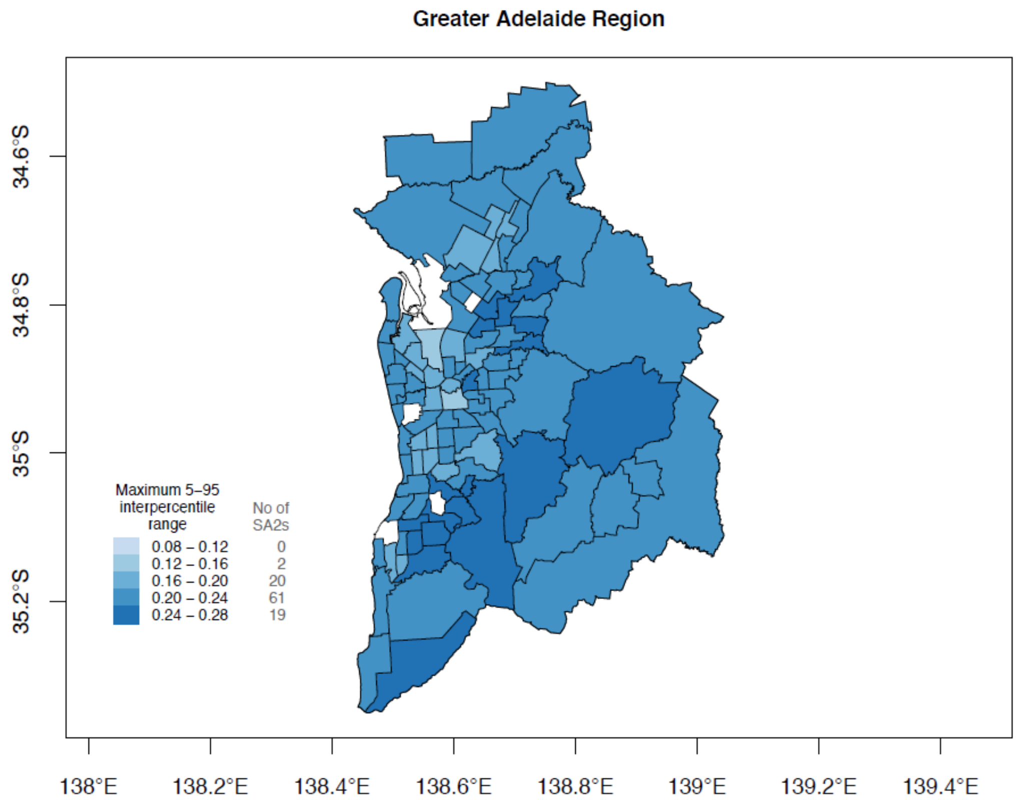


Greater Brisbane Region

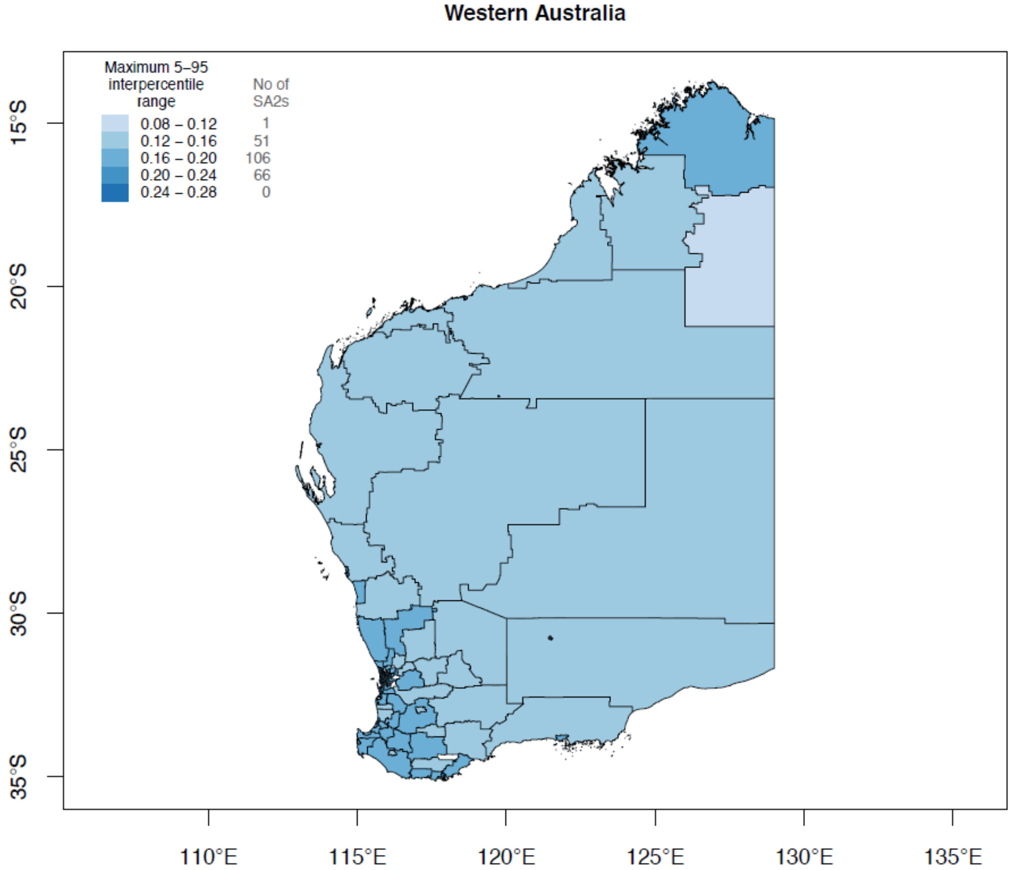


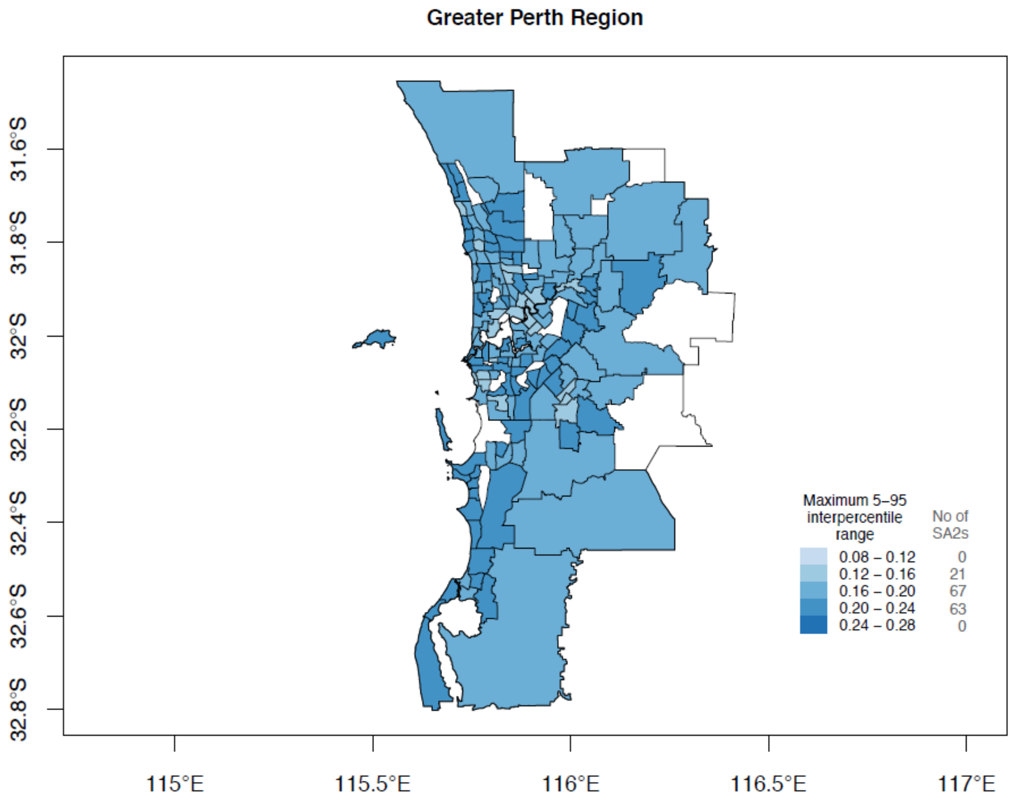
Appendix 6F (cont.)



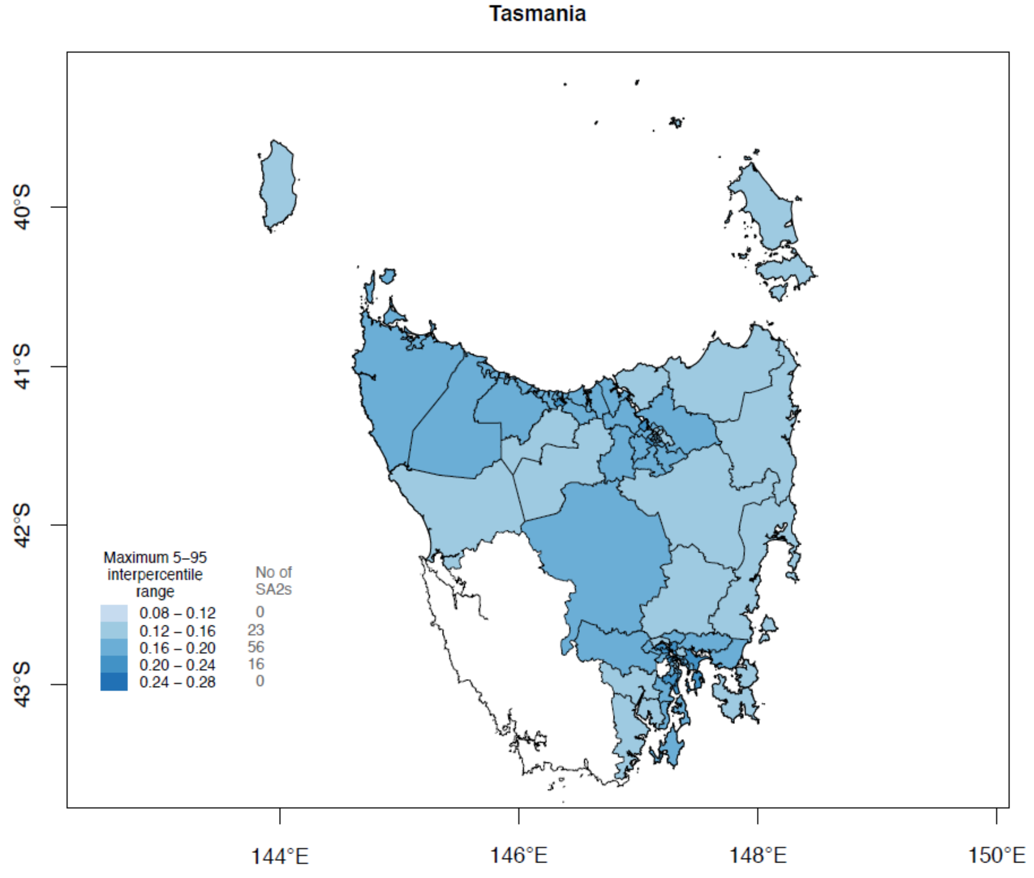


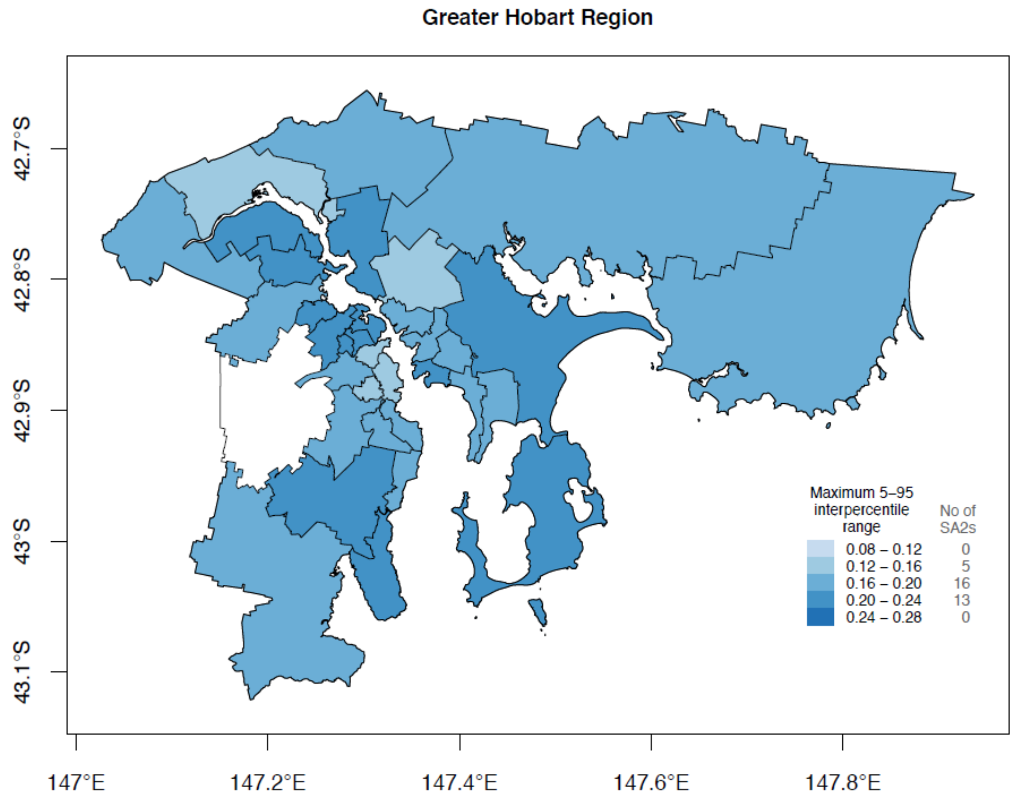
Appendix 6F (cont.)





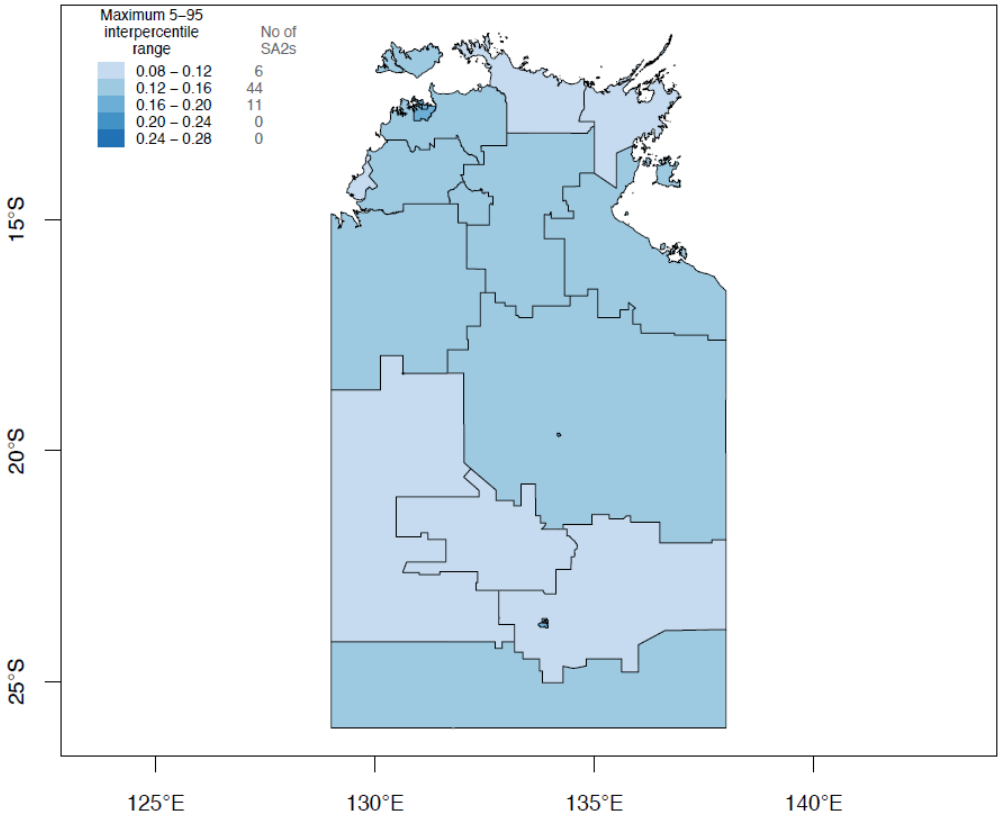
Appendix 6F (cont.)



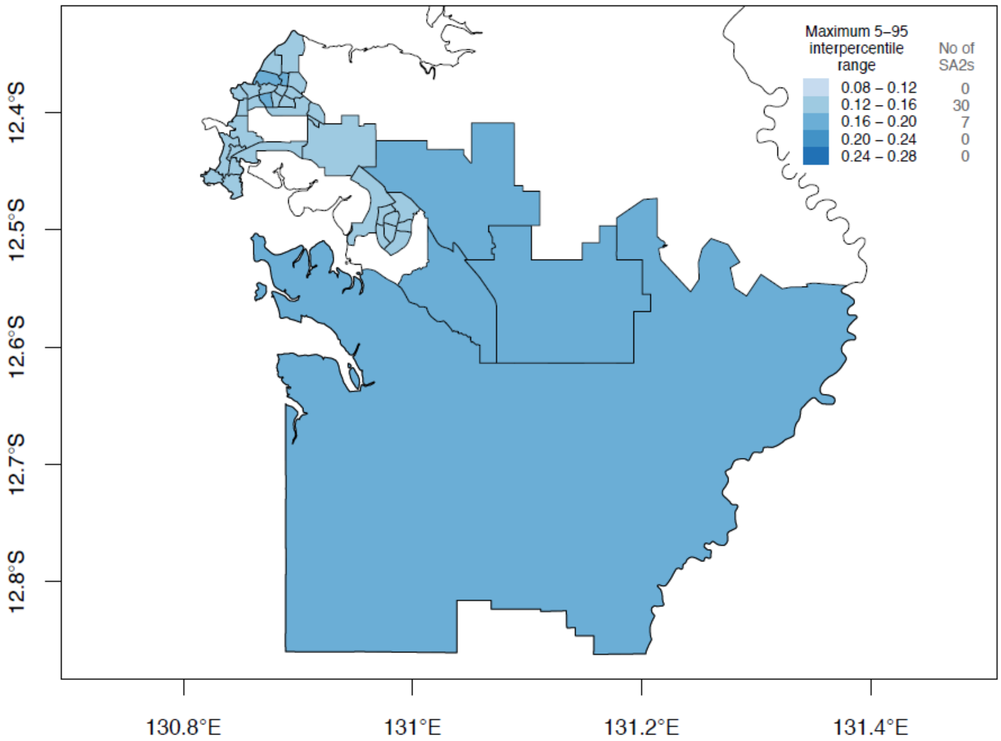


Appendix 6F (cont.)

Northern Territory



Greater Darwin Region



Appendix 6F (cont.)