

Where should all the trees go? – Appendices

Final Report - Appendices

Project Number: NY16005 (Completion: 25th May 2017)



Contents

I	Methodology	3
1	Introduction	4
2	Errors and features of analysing land cover for LGAs	4
2.1	Widely varying scales among LGAs	4
2.2	Changes to boundaries	5
2.3	Changing boundaries due to amalgamations	5
3	Human and definitional error	6
3.0.1	The importance of image timeliness	6
3.1	How the project's team mitigated these errors	7
3.1.1	Using high resolution images	7
3.1.2	Error checking	9
4	Sampling and standard error	10
4.1	Background	10
4.2	Sample data and error	10
4.2.1	Non-sampling error	10
4.2.2	Sampling error	10
4.3	Measuring standard error in the report	11
4.4	Comparisons between reports and the standard error of the difference	11
4.4.1	Hypothesis test through a two-Independent-Samples T Test	11
5	Producing and analysing the urban heat island data	12
5.1	Producing the data	12
5.2	Identifying urban hotspots	13
6	Combining all the information to produce an index of vulnerability	16
II	Results	22
1	State results of canopy and total green cover 2008-2013 – 2016	23
1.1	Summary	23
1.2	Figures for national canopy and green cover change	24
1.3	State by state changes in canopy and total green cover change	25
2	Urban Heat Island Results for Australian Cities	33
2.1	Introduction	33
2.2	Metro wide areas of heat	33
2.3	LGA level hot spots	35
2.4	State based Heat Maps	36
2.4.1	Estimation of UHI in Australian urban centres at the State level	37
2.5	LGA based Heat Maps	51
2.5.1	Urban Heat Islands in Strathfield NSW	52
2.5.2	Urban Heat Islands in Fairfield NSW overlaid with SEIFA IRSD	53
2.5.3	Urban Heat Islands in Fairfield NSW overlaid with on a streetmap NSW	54
3	Measuring risk from multiple variables	55
3.1	Results of the risk profile for Australia's LGAs	56

List of Figures

1	Screen shot from Q-GIS to illustrate the size of Cairns, Queensland with the white hexagon showing the approximate size of Blacktown, NSW and the red triangle showing the approximate size of Peppermint Grove, WA.	4
2	Screen shot from Q-GIS to illustrate the 1000 randomly located points coloured by land cover for Peppermint Grove, WA.	6
3	Screen shot of adjacent Google Earth imagery from different dates with the location of sample points in Queensland	7
4	Screen shot from Google Earth of a swimming pool in Peppermint Grove, Perth, WA at highest zoom level. Compare with Figure 5	8
5	Screen shot from Nearmap for the same pool as in Figure 4.	8
6	Screen shot from Q-GIS showing point 14 outside the edge of Nearmap coverage in Bendigo, the Google Earth service was used for point 14.	9
7	Flowchart of steps required to produce urban heat island maps	12
8	Distribution of frequency of cells according to temperature for Brisbane. Red lines show the temperature of a low level and a medium level hotspot	13
9	Distribution of frequency of cells according to temperature for Sydney. Red lines show the temperature of a low level and a medium level hotspot	14
10	Distribution of frequency of cells according to temperature for Melbourne. Red lines show the temperature of a low level and a medium level hotspot	15
11	Graph of % hotspot in each LGA by % canopy cover	17
12	Graph of Self-Assessed Health by ASR100 for each LGA by Prevalence of diabetes by ASR100	18
13	Graph of SEIFA Index of Relative Socio-Economic Disadvantage in each LGA by SEIFA Index of Economic Resources	19
14	Graph of the rate of total green loss in each LGA by canopy cover loss	20
15	Graph of the rate of % population under 5 in each LGA versus % population over 65 and living alone	21
16	Changes in Canopy and Shrubs for all LGAs in the study 2008-2013 – 2016	24
17	Changes in total green cover across all of the LGAs 2008-2013 – 2016. Red denotes a significant loss.	24
18	Changes in Canopy and Shrubs for the ACT 2008-2016	25
19	Changes in total green cover for the ACT 2008-2016	25
20	Changes in Canopy and Shrubs for NSW 2009-2016	26
21	Changes in total green cover for NSW 2009-2016	26
22	Changes in Canopy and Shrubs for NT 2009-2016	27
23	Changes in total green cover for NT 2009-2016	27
24	Changes in Canopy and Shrubs for Queensland 2009-2016	28
25	Changes in total green cover for Queensland 2009-2016	28
26	Changes in Canopy and Shrubs for SA 2013-2016	29
27	Changes in total green cover for SA 2013-2016	29
28	Changes in Canopy and Shrubs for Tasmania 2008-2016	30
29	Changes in total green cover for Tasmania 2008-2016	30
30	Changes in Canopy and Shrubs for Victoria 2013-2016	31
31	Changes in total green cover for Victoria 2013-2016	31
32	Changes in Canopy and Shrubs for WA 2011-2016	32
33	Changes in total green cover for WA 2011-2016	32
34	Contiguous areas of Urban Heat Island in Sydney coloured differently for each contiguous area.	34
35	Contiguous areas of Urban Heat Island in Melbourne coloured differently for each contiguous area.	34
36	Trendlines displaying the relationship between the different % land covers and % hot spot for each LGA.	35

Part I

Methodology

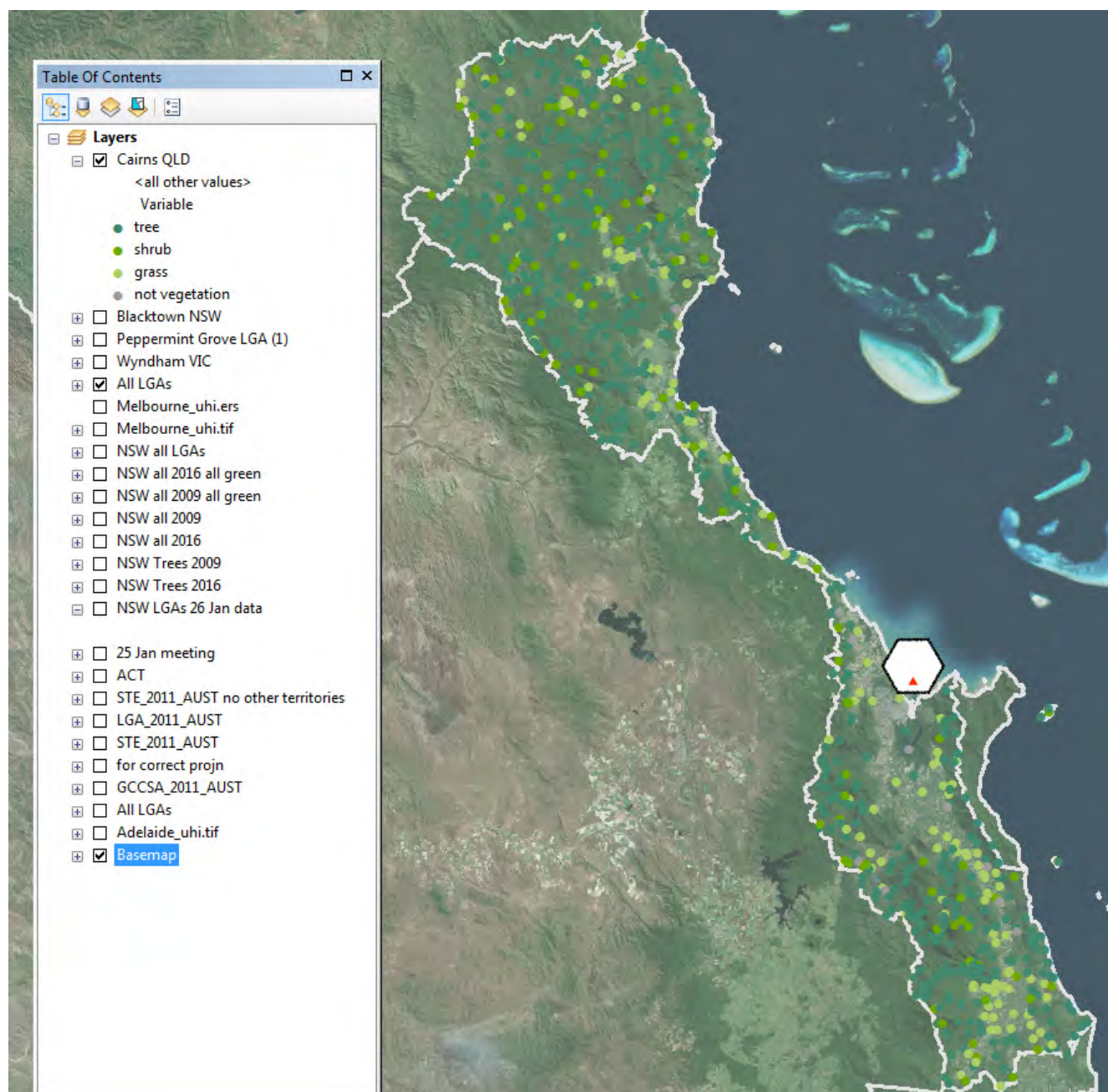
1 Introduction

In this part we provide some methodological notes to enable the developer of future benchmarks to understanding some aspects of using i-Tree.

2 Errors and features of analysing land cover for LGAs

2.1 Widely varying scales among LGAs

A feature of LGAs in Australia are their widely varying scales and locations. Figure 1 shows the variability of the size of LGAs (e.g. Cairns, Blacktown and Peppermint Grove).



Prepared by Kath Phelan: Screenshot from Q-GIS with points used and coloured by land cover type

Figure 1: Screen shot from Q-GIS to illustrate the size of Cairns, Queensland with the white hexagon showing the approximate size of Blacktown, NSW and the red triangle showing the approximate size of Peppermint Grove, WA.

Given the variability in size and land-covers for LGAs the i-Tree derived % change will hide a multitude of effects that range from changes in forestry management, to inner-city gentrification. A 5% change in land cover type identified by an i-Tree study can be very different in terms of causes, in terms of amount of change by surface area and likely effect on population.

2.2 Changes to boundaries

In a study that relies on random sampling such as this, data are only comparable when the boundaries from one period to the next are the same.

In the study by Jacobs et al. (2014)¹ the authors used Statistical Subdivision for Brisbane and the ACT because of the large sizes of these two LGAs. However by the time of the 2014 report the SSDs were obsolete. SSDs are a geography comprising one or more SLAs from the previous ABS ASGC. Geographies by ASGC are no longer in use by the ABS and since the 2011 census the ABS only produce statistics by ASGS. The current 2017 report will thus no longer present data by SSD.

Australian Capital Territory data presented by SA3 Due to the size of the ACT LGA, some land cover data by SA3 is also provided. Two SA3s out of eight SSDs from the 2014 report correspond exactly (Woden and Gungahlin-Hall) thus a comparison between report can be made for them.

Presenting data by SA3 will bring the report in line with the ABS ASGS and also enable time series comparisons between future canopy cover reports. It is recommended that releasing data by SA3 will also enable comparisons with other ABS and statistical releases such as from Public Health Information Development Unit (PHIDU).

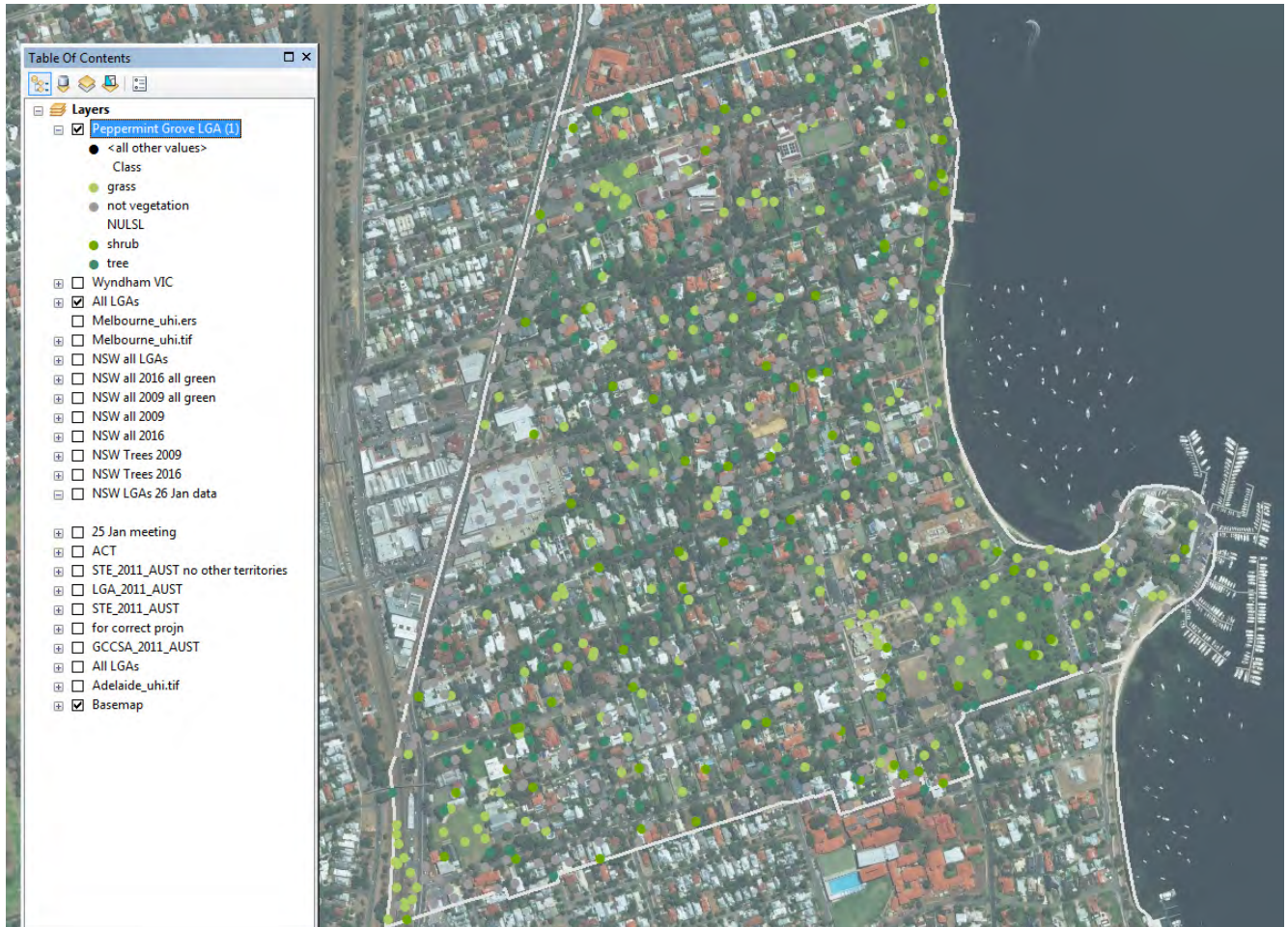
2.3 Changing boundaries due to amalgamations

This report was also produced while changes were underway in NSW to amalgamate LGAs. At the time of the production of this report, eight metro LGAs had been newly formed from old metro LGAs. In addition a further six had been proposed but were not yet confirmed and available in ABS geography. Data on land covers were produced for both sets of new NSW LGAs (14 in total).

¹Jacobs, B., Mikhailovich, N., and Moy, C. (2014) Benchmarking Australia's Urban Tree Canopy: An i-Tree Assessment, prepared for Horticulture Australia Limited by the Institute for Sustainable Futures, University of Technology Sydney.

3 Human and definitional error

Our study used the same definitions as the previous report which was based on the recommendations of the i-Tree Canopy software manual². In brief, an i-Tree Canopy software requires the use of satellite imagery overlaid with a layer of 1000 points that are randomly located within the boundaries of individual LGAs (Figure 2).



Prepared by Kath Phelan: Screenshot from Q-GIS with points used and coloured by land cover type, Nearmap base layer

Figure 2: Screen shot from Q-GIS to illustrate the 1000 randomly located points coloured by land cover for Peppermint Grove, WA.

Operators are required individually to zoom in on each point and identify whether the point represents one of four categories: Canopy, or anything that looks like a tree; Shrubs, landscaping and even agricultural crops such as vines; Grass, sports fields, paddocks and bare ground; Hard Surface, car parks, train lines etc. The full definition of these surfaces are available on page 11 of the Jacobs et al. (2014) report.

As with the 2014 study we employed 1000 points per LGA and aimed to record the land cover for all the LGAs that were used in the 2014 study (139 in total + 14 new NSW LGAs).

3.0.1 The importance of image timeliness

A feature of the standard i-Tree package is its reliance on freely available Google Earth imagery. While this saves on cost it mitigates against providing a precise time for setting a benchmark. This was demonstrated in the Jacobs et al. (2014) report where the year(s) of the Google Earth imagery used varied between 2008 and 2013 depending on the State being examined.

²Jacobs et al. (2014) Op Cit. Full details of the technical aspects of the i-Tree Canopy including user manuals are available at: [i-Tree tools](#)

In addition, as Figures 3 shows for points that are located very close to one another, the date can vary in Google Earth. It can also depend on the elevation or amount of zoom.



Prepared by Shirley Famelli: Screenshot from Google Earth

Figure 3: Screen shot of adjacent Google Earth imagery from different dates with the location of sample points in Queensland

3.1 How the project's team mitigated these errors

3.1.1 Using high resolution images

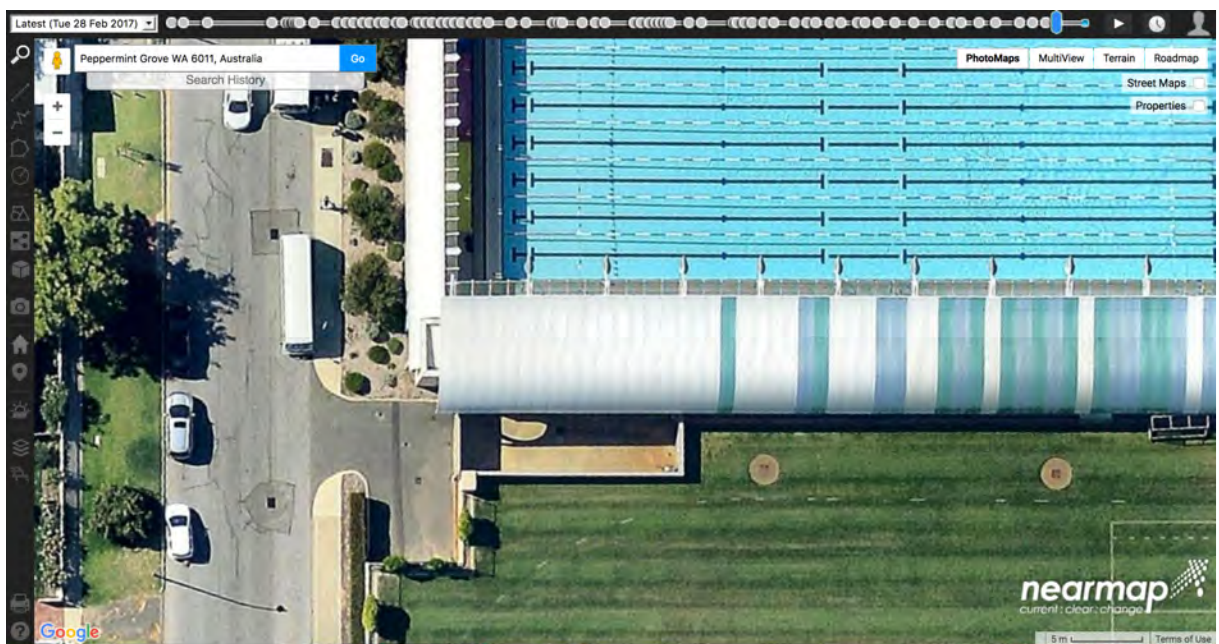
Instead of using the freely available imagery linked with the online i-Tree canopy tool, this project employed Nearmap imagery that were more recent and are captured at a higher resolution.

Figures 4 and 5 demonstrate this with images zoomed as close as possible on a swimming pool in Peppermint Grove, Perth, WA. As the images show the Nearmap outperforms Google Earth and arguably allows a more precise definition of the difference between shrubs and tree canopy, since this relies on the comparison with other objects to determine the height or the identification of a shadow.



Prepared by Marco Amati: Screenshot from Google Earth

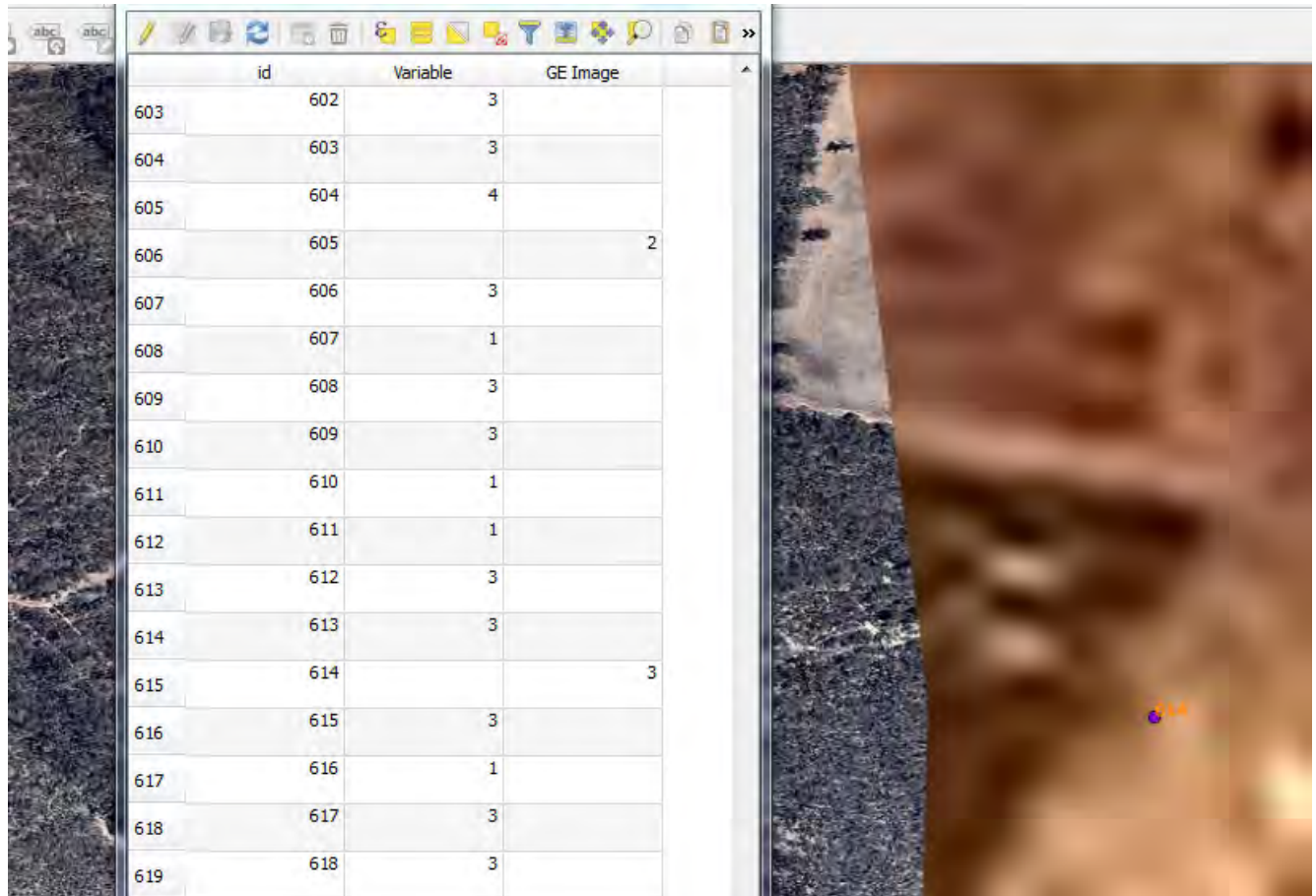
Figure 4: Screen shot from Google Earth of a swimming pool in Peppermint Grove, Perth, WA at highest zoom level. Compare with Figure 5, in particular the shrubs and trees on the footpath adjacent to the swimming pool.



Prepared by Marco Amati: Screenshot from Nearmap

Figure 5: Screen shot from Nearmap for the same pool as in Figure 4.

Nonetheless a limitation of using this approach is seen in some of the LGAs that include remote areas. This is highlighted in Figure 6 which shows an image for Bendigo, Victoria a large LGA that includes areas of National Park. Here point 14 falls in an area outside the Nearmap coverage. In these cases, Google Earth imagery was used as a surrogate. This however occurred in less than 2% of the points sampled and did not result in a significant level of error due to differences in resolution or time-liness of the imagery.



Prepared by Joe Kaspar: Screenshot from Q-GIS with Nearmap

Figure 6: Screen shot from Q-GIS showing point 14 outside the edge of Nearmap coverage in Bendigo, the Google Earth service was used for point 14.

3.1.2 Error checking

Two strategies were used to mitigate against the errors caused by different operator definitions of the classes (e.g. a shrub versus a tree canopy) as well as blunders. The latter could include miskeys in the results, LGA name confusion (e.g. Campbelltown, NSW and Campbelltown, SA) or confusion in the image identification (e.g. a point that landed on a wall with a climbing plant or a point that landed in the middle of a mine shaft).

The first strategy was to assume stability from one period of sampling to the next and therefore to identify all those classes that had had a +/- 5% point swing. The points for these classes were resampled resulting in an additional 50,000 points to check by the team in addition to the initial 139,000 points.

The second strategy was to ensure that no operator would be rechecking their own work and that 'classification' fatigue was limited.

4 Sampling and standard error

Author: Joe Kaspar

4.1 Background

An additional source of error to those noted above was the error produced in the statistical analysis. This was calculated by first considering that we want to calculate several core statistical metrics:

1. Create a simple random sample of points for each LGA for summer 2016 and assess the category of land cover under each point;
2. Calculate the proportion of points for each category as well as the standard error for each proportion for each LGA in 2016; and
3. Compare the sample derived land cover for each category as a proportion from 2. with the sample derived canopy cover proportion from the 2014 report.

In order to compare the sample derived canopy cover proportions from 2014 and 2016, a different standard error needed to be calculated for the difference between each proportion, similarly a significance test needed to be conducted to test that the difference between the two sample proportions was actual and not through sampling error.

4.2 Sample data and error

Two types of sampling error can occur: non-sampling error and sampling error.

4.2.1 Non-sampling error

Non-sampling error can occur at any stage of data collection and is primarily a result of processing error by coders, time period bias for the Nearmap imagery, image parallax or inconsistency of the classification of points between reports. These issues can be mitigated through checking, careful training of coders and improving image time consistency however some non sampling errors are unavoidable.

4.2.2 Sampling error

As data are collected from a sample but inferences are made about the whole area, the data are thus subject to 'sampling' error. Sampling error thus reflects the difference between the estimate derived in the report from the sample and the 'true value' if a full census of the LGA canopy cover were actually to be conducted.³

The two core factors affecting sampling error in this report include:

- Sample size: Larger samples give rise to smaller sampling error;
- Sample/canopy proportion ratio: The larger the sample is as a proportion of the actual canopy cover, the smaller will be the sampling error.⁴

With minimal non-sampling error we can be confident that, if significant, the sample statistic within the standard error range will be within the actual 'true value' due to the central limit theorem.

³McLennan, W. (1999) An Introduction to Sample Surveys: A User's Guide. ABS Catalogue no. 1299.0

⁴Parmehr EG, Amati M, Taylor EJ and Livesley SJ (2016) Estimation of urban tree canopy cover using random point sampling and remote sensing methods, Urban Forest Urban Greening, 20, 160–171.

4.3 Measuring standard error in the report

Sampling error can be measured mathematically and in this report we primarily present sampling error through the standard error. A standard error is used to present the range of values on the sample statistic that is expected to contain the 'true value' that is being measured by the sample, thus any estimate derived from a sample has a standard error associated with it.⁵

In this report we measure two slightly different types of standard error:

1. The standard error of the canopy cover for each LGA as a result of a sample; and
2. The standard error of the difference between the canopy cover proportions from two different independent samples i.e. the 2014 report p_1 and the current 2017 report p_2 .

4.4 Comparisons between reports and the standard error of the difference

If the proportion of canopy cover between reports is different for each LGA, this does not necessarily mean that there has been a change, the difference may be due to statistical error. Both the 2014 report and the 2017 report used different simple random samples within the same sample frame (i.e. LGA), thus each sample was considered an 'Independent sample'. When comparing the proportions between two independent samples (i.e. p_1 and p_2) a hypothesis test should additionally be conducted to ascertain that there has in fact been a change. When describing the change between the reports a standard error of the difference should also be presented.⁶

In this report the standard error for the difference between each proportion was calculated in two discrete equations.

Step 1: Calculate the pooled standard deviation (weighted average) for the difference between each report LGA: when comparing two proportions for both independent samples, the variances (and therefore the standard deviations) for each sample will be similar, thus a pooled standard deviation (i.e. a weighted average) is used in the equation⁷.

$$\hat{p} = \frac{\hat{p}_1 n_1 + \hat{p}_2 n_2}{n_1 + n_2}$$

Step 2: Calculate the standard error of the difference between the two proportions

$$SE_0 = \sqrt{\frac{\hat{p}(1-\hat{p})}{n_1} + \frac{\hat{p}(1-\hat{p})}{n_2}} = \sqrt{\hat{p}(1-\hat{p})\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}$$

4.4.1 Hypothesis test through a two-Independent-Samples T Test

The null hypothesis for each canopy cover proportion will be that the difference between each time periods i.e. 2014 (p_1) and 2017 (p_2) is 0.

H_0 : p_1 canopy cover % = p_2 canopy cover %

H_1 : p_1 canopy cover % \neq p_2 canopy cover %

To calculate the p value the z score is first needed.

$$z = \frac{(\hat{p}_1 - \hat{p}_2) - 0}{SE_0}$$

If $p < 0.05$ then we can reject the null hypothesis and can assert that there is a difference between the two sample statistics (i.e. 2014 and 2017 are different with a 95% certainty).

⁵McLennan 1999 Op Cit.

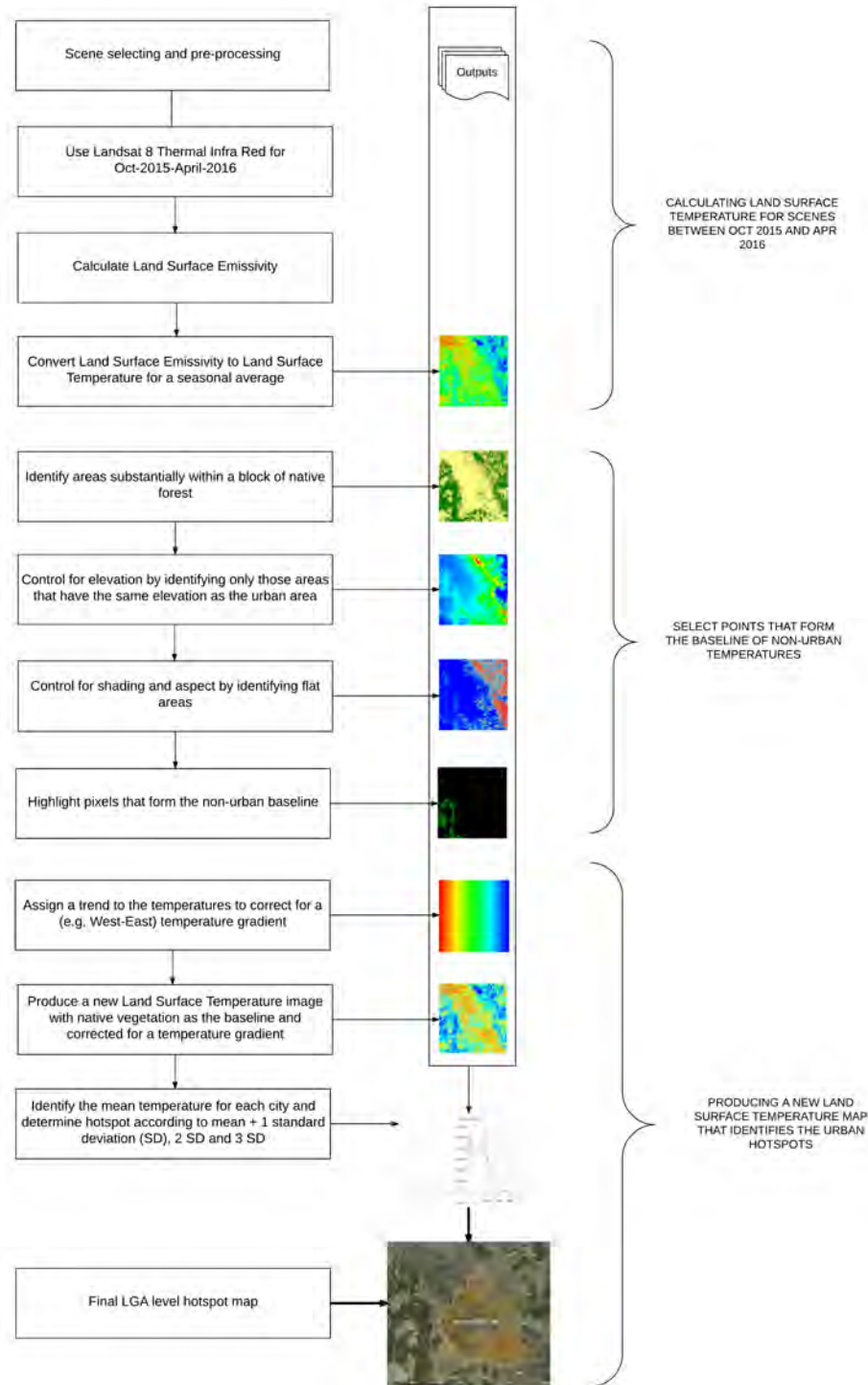
⁶Gravetter, F. & Wallnau, L. (2000) Statistics for the Behavioural Sciences 5th edn. Wadworth Tomas Learning: USA.

⁷Gravetter & Wallnau 2000 Op Cit.

5 Producing and analysing the urban heat island data

5.1 Producing the data

A key part of the project was the production of urban heat island data for all of the LGAs studied (Figure 7). Devereux and Caccetta (2017) detail the full version of the methodology.⁸



Prepared by Marco Amati based on Devereux and Caccetta (2017)

Figure 7: Flowchart of steps required to produce urban heat island maps

⁸Devereux D and Caccetta PA (2017) Estimation of Land Surface Temperature and Urban Heat Island effect for Australian urban centres. Report CSIRO Data61, Australia.

5.2 Identifying urban hotspots

Various approaches were trialled to allow the mapping and identification of hotspots, including setting the hotspot definitions by quintiles. A significant challenge here was the variability in the locations that were mapped. These include tropical locations or large LGAs with relatively uniform land cover. In these cases dividing the temperature into quintiles produced an unrealistic hotspot map that ‘forced’ the identification of hotspots when in reality the temperature differences were quite minor.

Figures 8, 9 and 10 demonstrate the variability of the temperatures across the three largest cities in the study: Brisbane, Melbourne and Sydney. For Brisbane as noted in the report by Devereux and Caccetta (2017)⁹, artefacts were created as part of the identification of temperature. This leads to a small number of extreme temperatures. To allow the spread of data to be better visualised the axes were set at the same limits.

Consistent with a tropical climate, Brisbane shows a much lower spread of temperatures than either Sydney or Melbourne. Sydney and Melbourne both have peaks of temperature frequency that are outside 0 degree centigrade for native vegetation. To take account these different histogram shapes and the ranges of temperature, while adopting an approach that is consistent across all of the sample areas it was decided to use mean + 1 standard deviation (SD) to set the level of a hotspot with +2 SD and +3SD for the extremes. This results in a slightly different hot spot temperature for each metropolitan area.

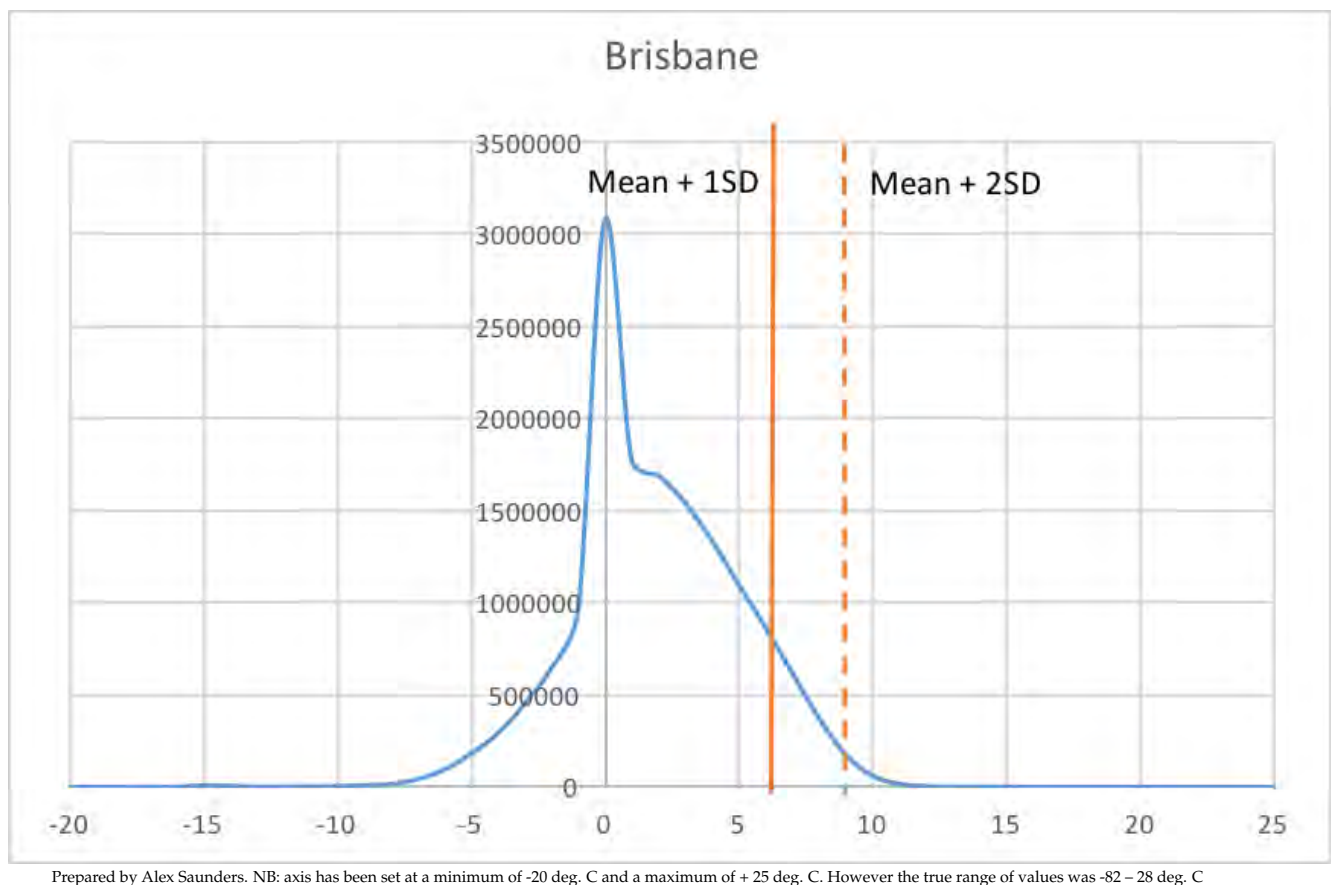
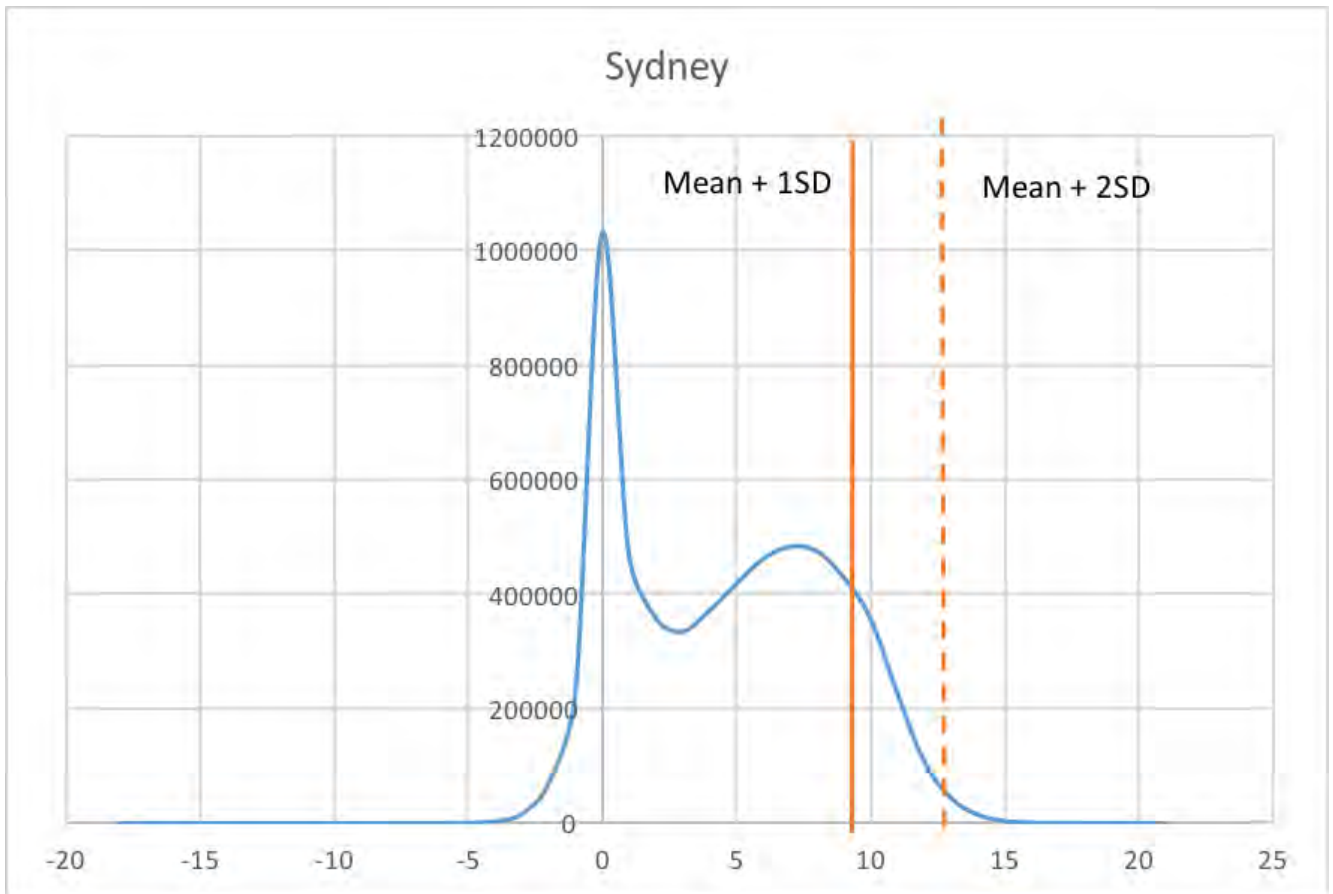


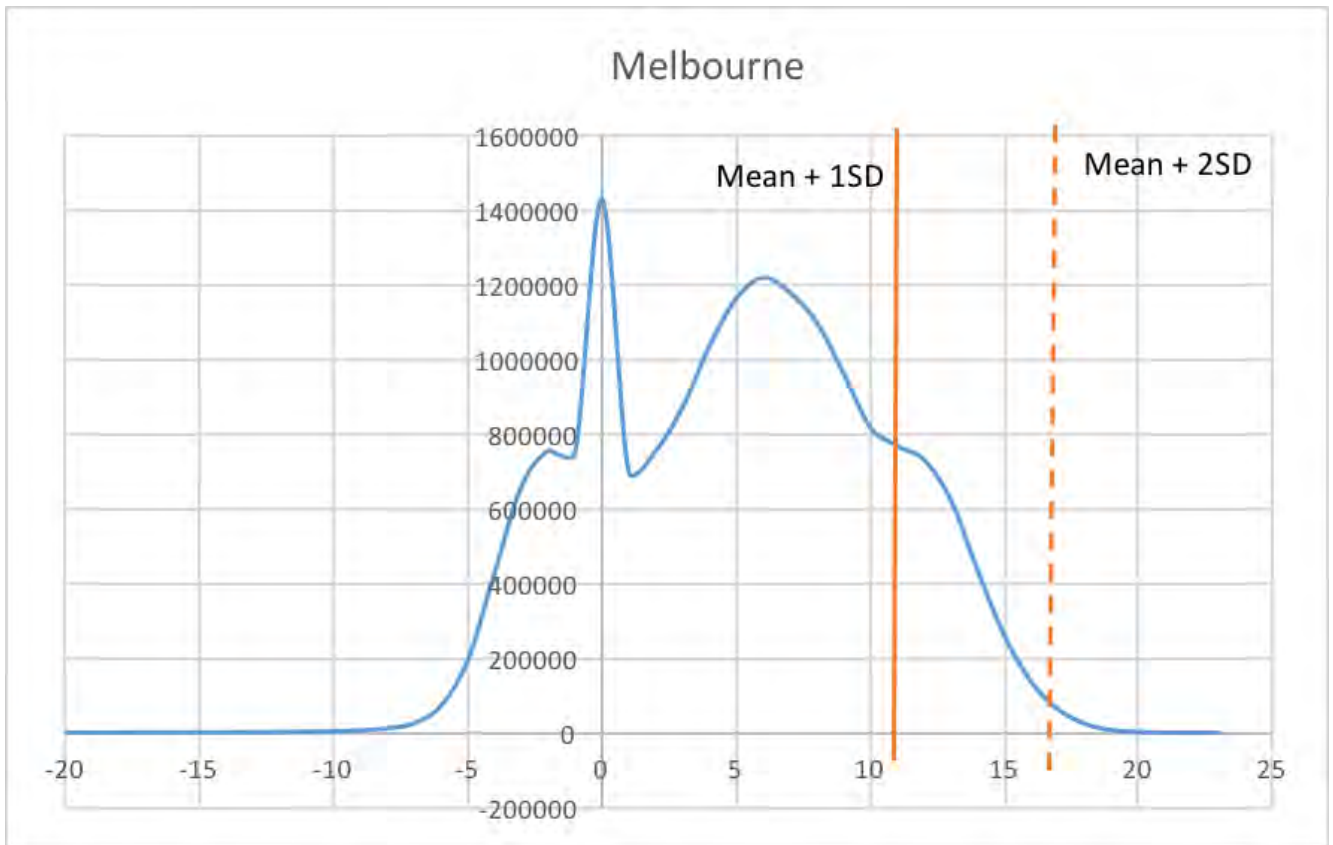
Figure 8: Distribution of frequency of cells according to temperature for Brisbane. Red lines show the temperature of a low level and a medium level hotspot

⁹Op Cit.



Prepared by Alex Saunders. NB: axis has been set at a minimum of -20 deg. C and a maximum of + 25 deg. C. However the true range of values was -18 – 21 deg. C

Figure 9: Distribution of frequency of cells according to temperature for Sydney. Red lines show the temperature of a low level and a medium level hotspot



Prepared by Alex Saunders. NB: axis has been set at a minimum of -20 deg. C and a maximum of + 25 deg. C. However the true range of values was -41 – 23 deg. C

Figure 10: Distribution of frequency of cells according to temperature for Melbourne. Red lines show the temperature of a low level and a medium level hotspot

6 Combining all the information to produce an index of vulnerability

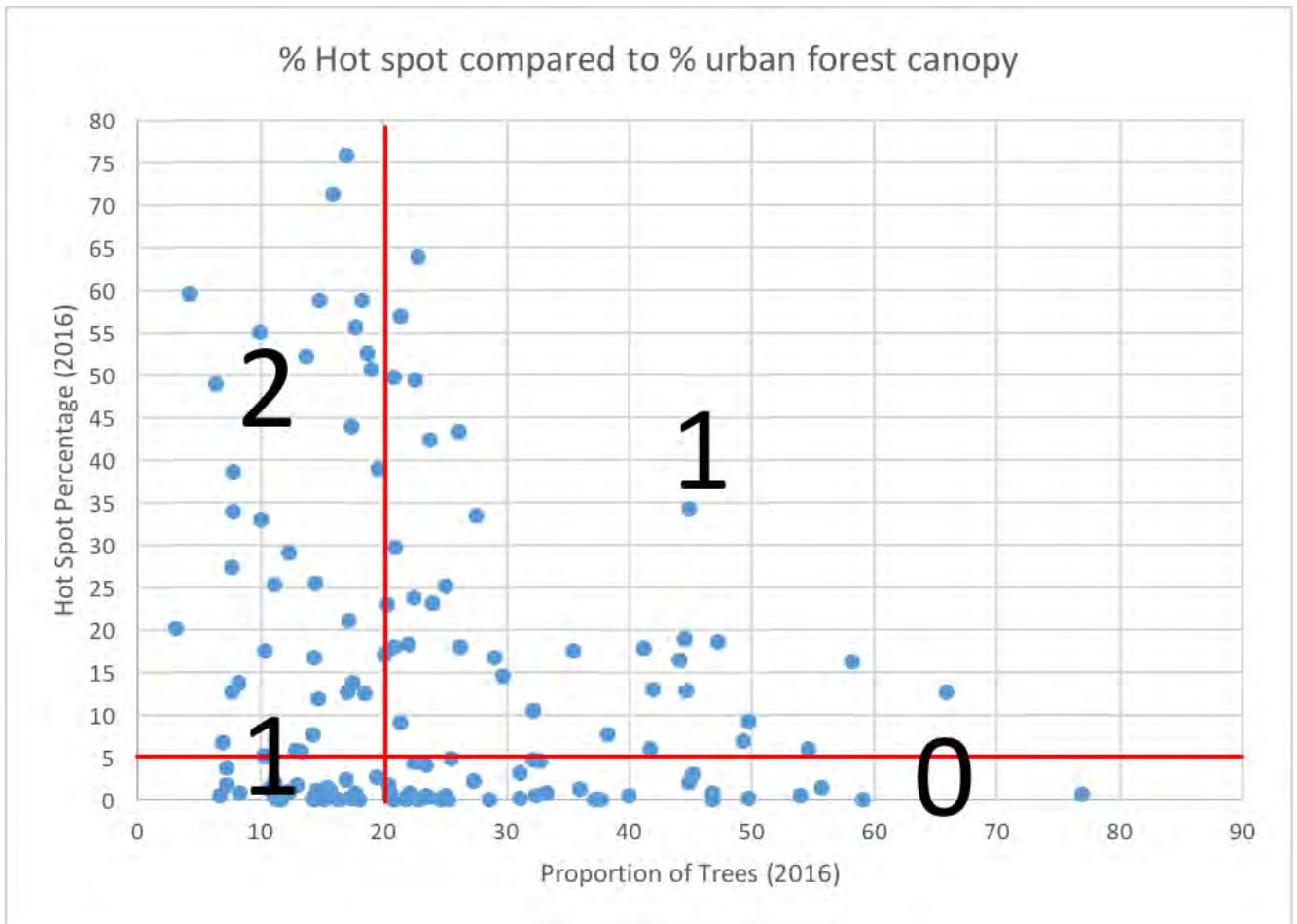
A significant challenge was identified early on in the project with combining the key data sets that represent different scales, different time periods and are produced at different time scales. For example, health data is generated as a result of complex patterns of lifestyle and opportunity over the course of years. Land cover data may only be a small part of that variability.

After extensive consultation with the research team and with the 2020 Vision team it was decided to adopt a quadrant approach to developing the index. This consisted of:

1. Pairing two variables to examine their relationship using an X Y scatter plot.
2. Identify the median value on both axes.
3. Divide the scattered data into a quadrant.
4. Identify the direction of the variables that represent lower vulnerability.
5. Give two points to those LGAs that fall into the quadrant that is lowest vulnerability.
6. Give one point for those LGAs that are in the quadrant next to the one with lowest vulnerability (i.e. that have high vulnerability for one variable and low vulnerability for the other).
7. Give no points for LGAs that are in the quadrant that is highest risk.

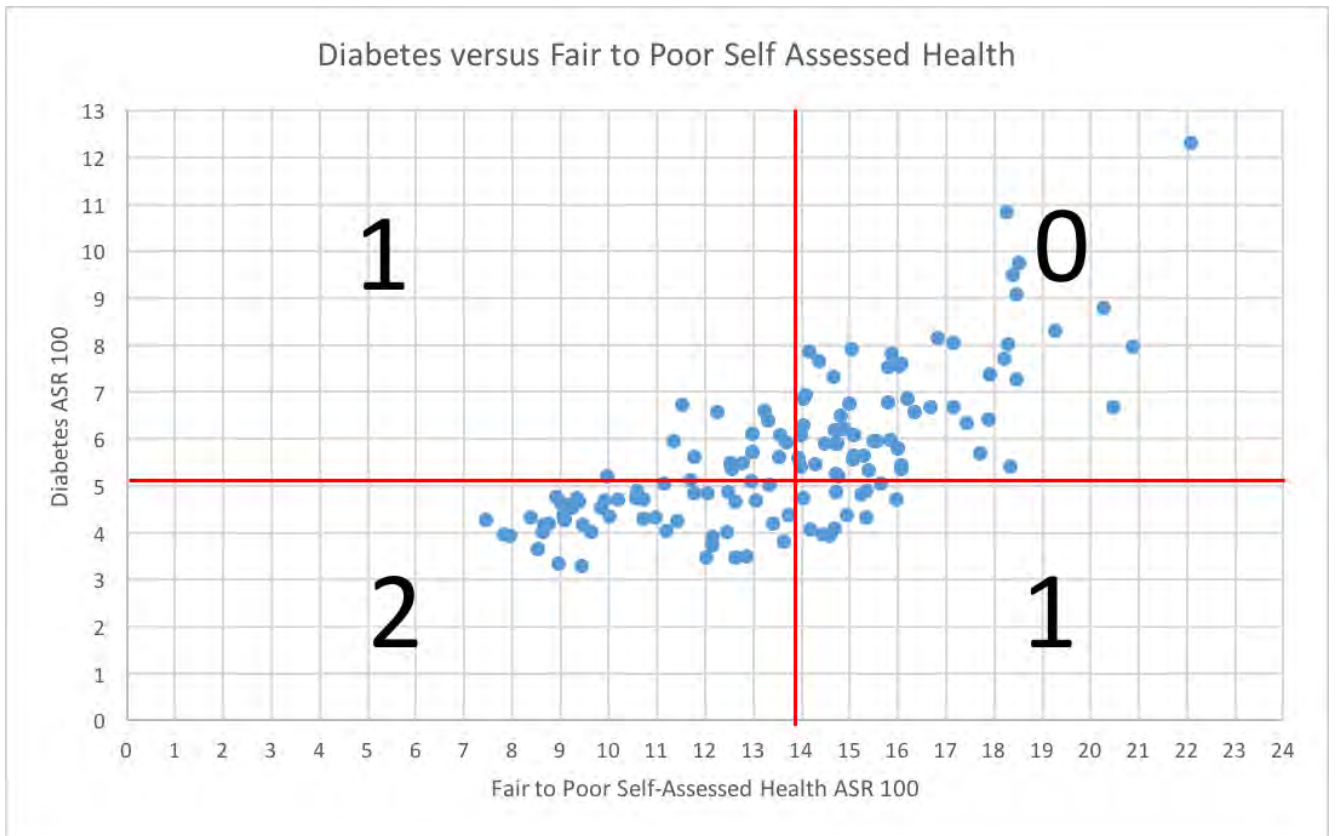
Figure 11 illustrates this method using the data from canopy % and urban hotspot %. It shows the trend as expected is downward with LGAs that have low canopy cover experiencing a greater coverage of urban hotspots. However at the same time, there are many LGAs that have no hotspots despite having little canopy cover. This is because the % urban hotspots are due to the influence of other types of greenery such as shrubs and the presence of water bodies. There is a clear association between the presence and size of hotspots and the roofs of large warehouses and pieces of infrastructure. It may be that only a small amount of canopy cover in residential areas and a lack of large pieces of unshaded infrastructure is what is needed to ensure the coolness of an area.

Figure 12 shows a similar process with the rate of self-assessed fair to poor health rising with the prevalence of diabetes. The SEIFA indices also show that they rise together. This is not surprising since SEIFA IRSD and SEIFA IER share 4 variables (Figure 13). The graph of rate of change of canopy loss versus total green cover loss does not show any evident trend (Figure 14). Finally, the % population under 5 is plotted against the % population greater than 65 who live alone to identify the sections of the population with a greater risk of vulnerability (Figure 15).



Prepared by Marco Amati

Figure 11: Graph of % hotspot in each LGA by % canopy cover



Prepared by Marco Amati

Figure 12: Graph of Self-Assessed Health by ASR100 for each LGA by Prevalence of diabetes by ASR100

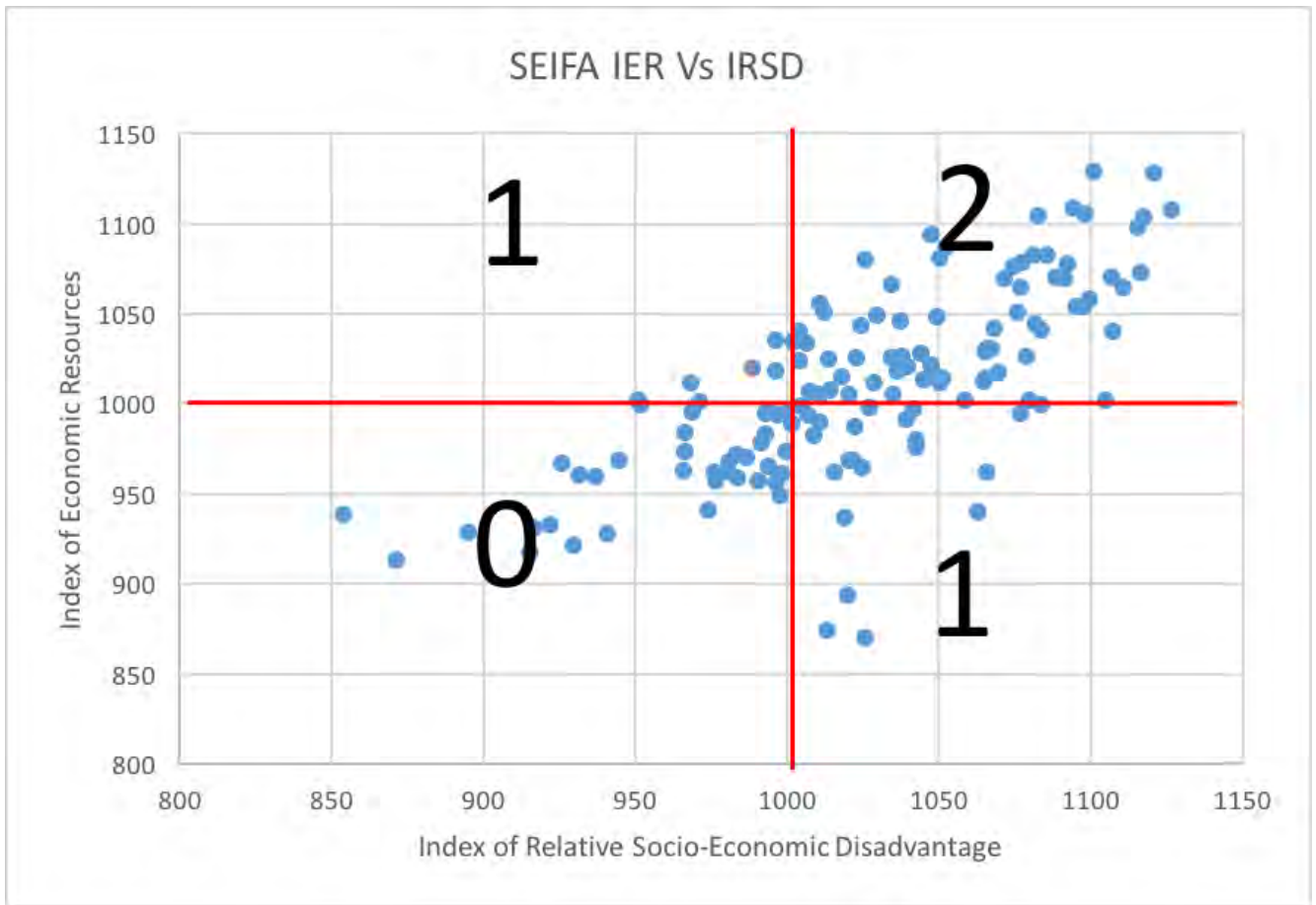
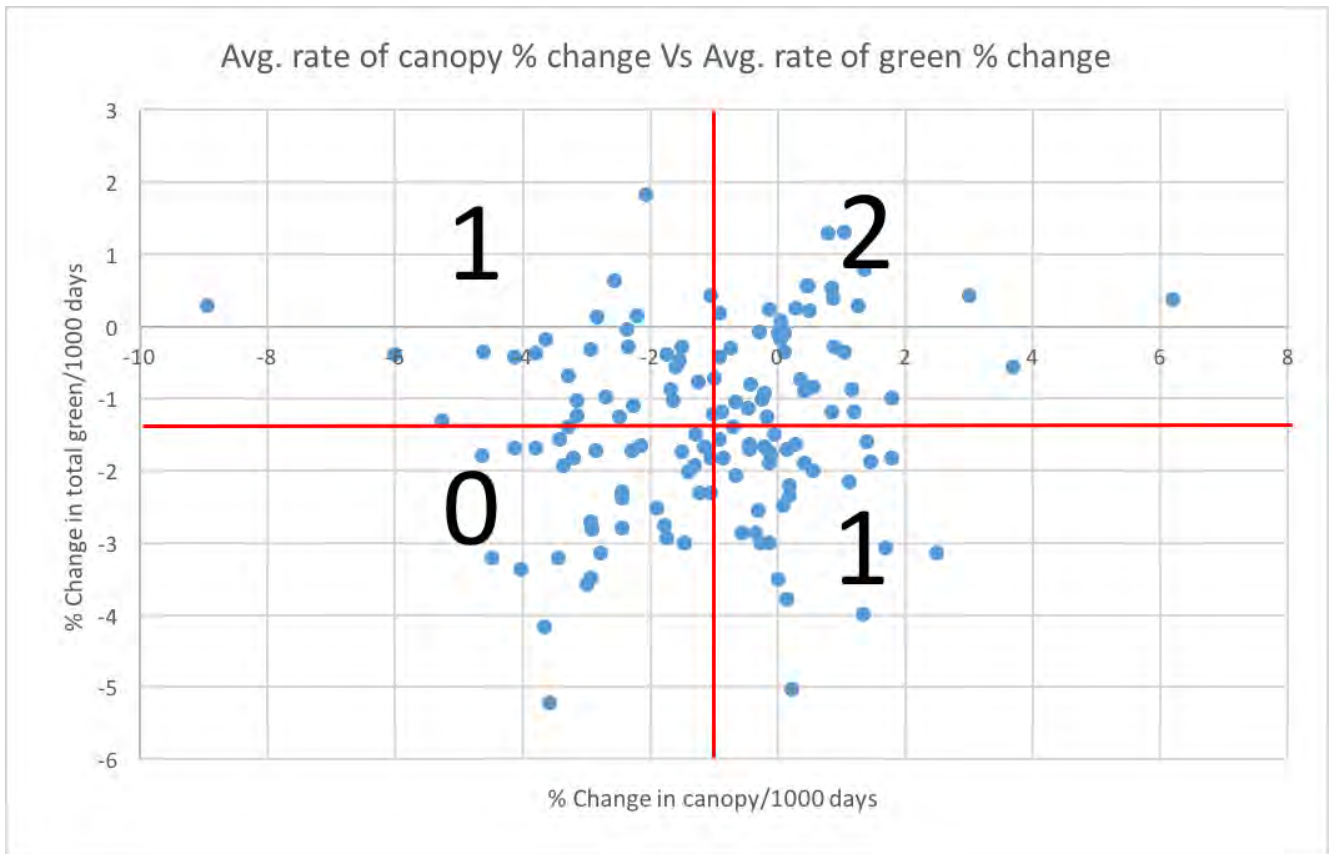
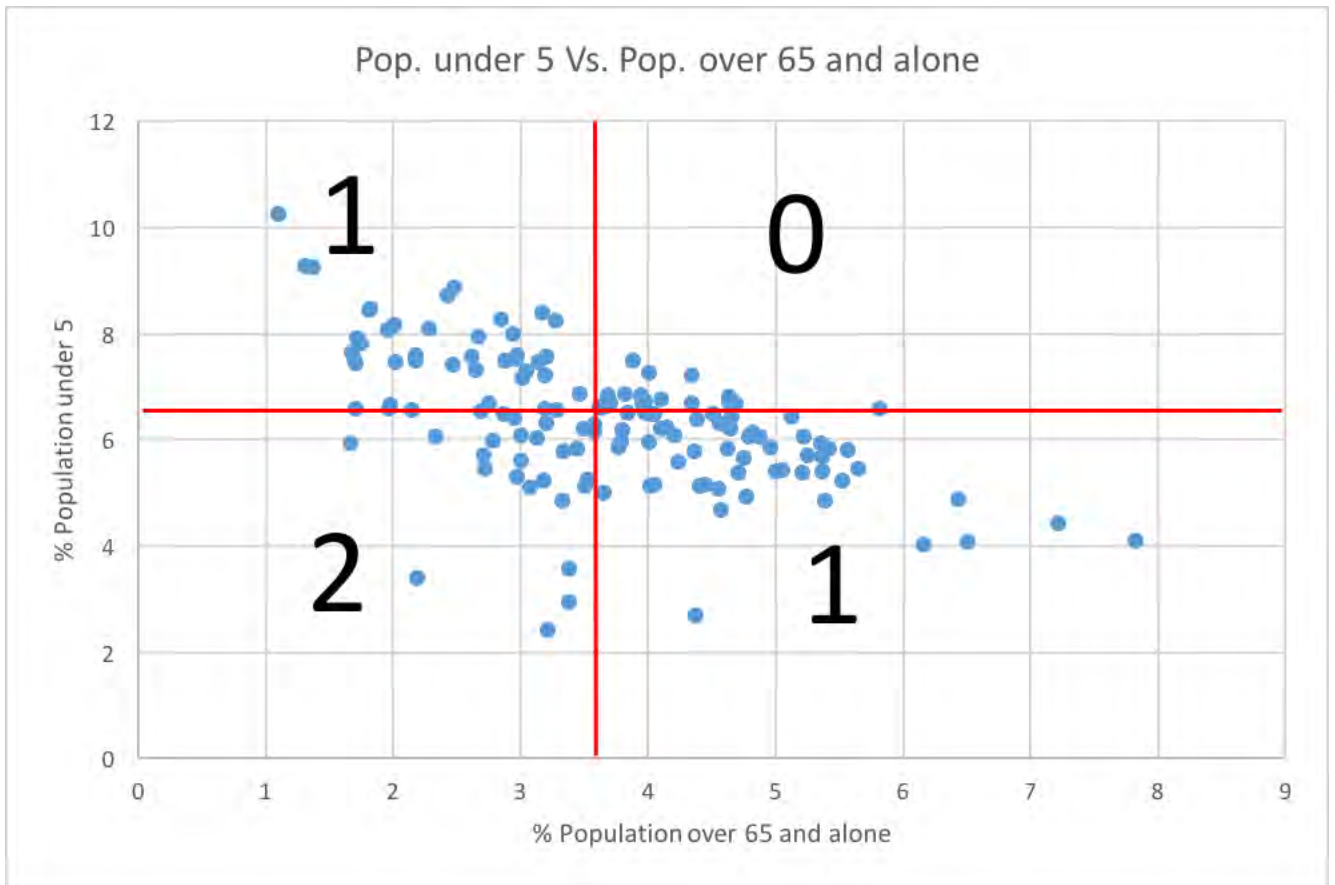


Figure 13: Graph of SEIFA Index of Relative Socio-Economic Disadvantage in each LGA by SEIFA Index of Economic Resources



Prepared by Marco Amati

Figure 14: Graph of the rate of total green loss in each LGA by canopy cover loss



Prepared by Marco Amati

Figure 15: Graph of the rate of % population under 5 in each LGA versus % population over 65 and living alone

Part II

Results

1 State results of canopy and total green cover 2008-2013 – 2016

1.1 Summary

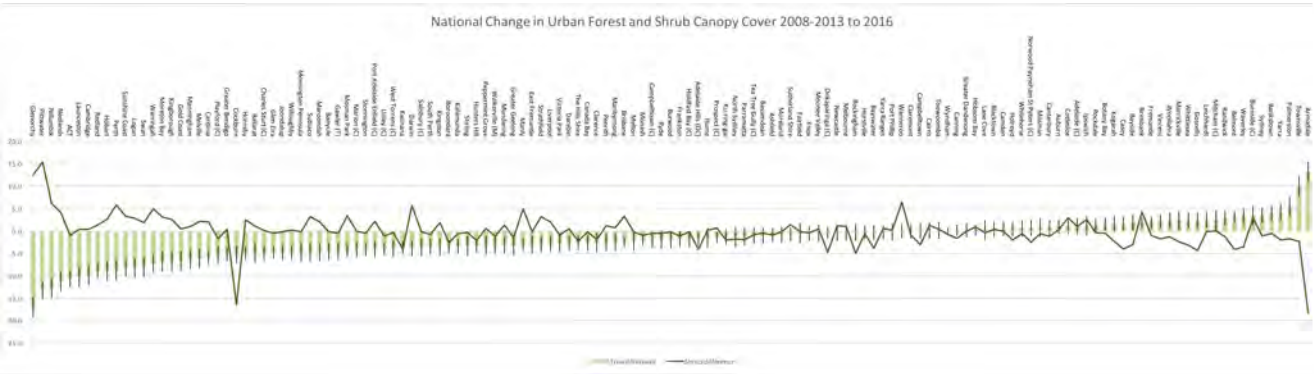
Overall the results display two consistent trends across both set of graphs for canopy and green cover change. For tree canopy there is evidence of natural exchange between the canopy class and the shrubs. This is shown nationally for the loss of canopy in Figure 16, page 24 and Figure 20, page 26. They show, for example, that Pittwater and Warringah LGAs both lost significant amounts of canopy cover during the five years from 2009–2016. However, these losses are offset by gains in shrub cover (or saplings) during the same period.

Interpreting tree canopy as an indicator of urban greening should be treated with caution, especially in an i-Tree study such as this. As well as the differences between operators differentially identifying trees and shrubs, there is a natural exchange between shrubs and trees over a given period. Trees and shrubs are subject to dieback and so will leave opportunities for the growth of one or the other. A bushfire or drought will reduce the canopy cover but allow shrubs or juvenile trees that look like shrubs to grow back. Since many of the metro LGAs in Australia contain extensive areas of national park some are particularly susceptible to these natural fluctuations.

While canopy cover can be argued in a few limited cases to be increasing (factoring in losses of shrubbery) the figures for total green cover paint a starker picture. None of the LGAs have increased their green land cover over the period studied by a significant amount (Figure 17, page 24). and the majority have lost green cover. For example the total surface area of all the LGAs studied is 61,001 square kilometers. In total the green surface area declined by 2.6% over the period studied. This equates to a total loss of 1,586 square kilometres, or an area equivalent to the size of the City of Brisbane.

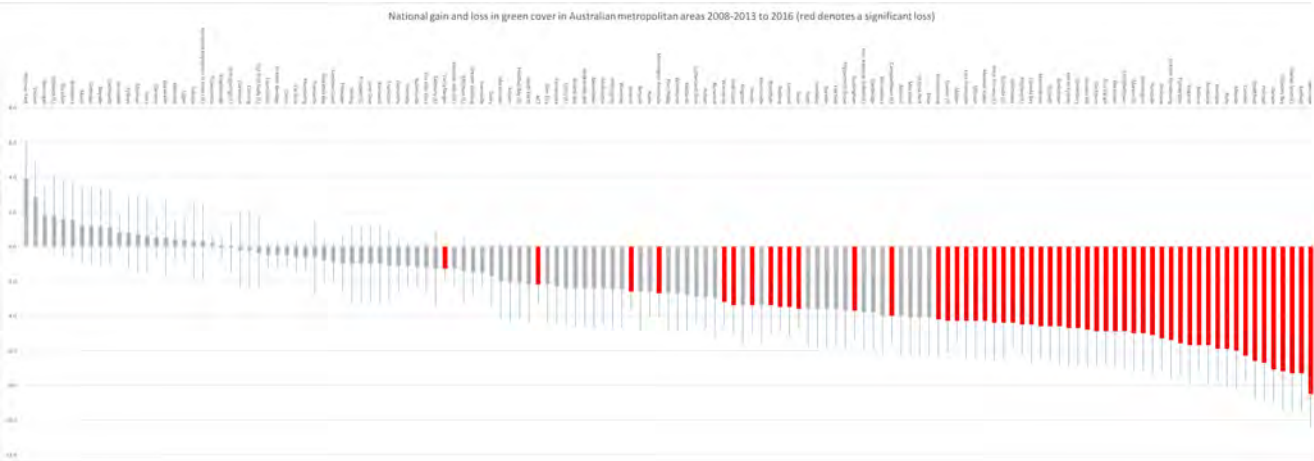
Just as remarkably, looking through the LGAs that have lost green cover there appears to be no consistent trend for where these losses are coming from. For example, the largest percentage decreases are not happening in peri-urban or inner-city areas but are happening in all the States and in all variety of different LGA location. This green cover loss would therefore be resultant from a variety of processes that range from legislation to reduce tree cover in the event of a bushfire; subdivision of large suburban blocks; consumer trends in housing towards smaller gardens; risk aversion of local governments towards trees and falling branches and green field development on the edge of urban areas.

1.2 Figures for national canopy and green cover change



Prepared by Marco Amati

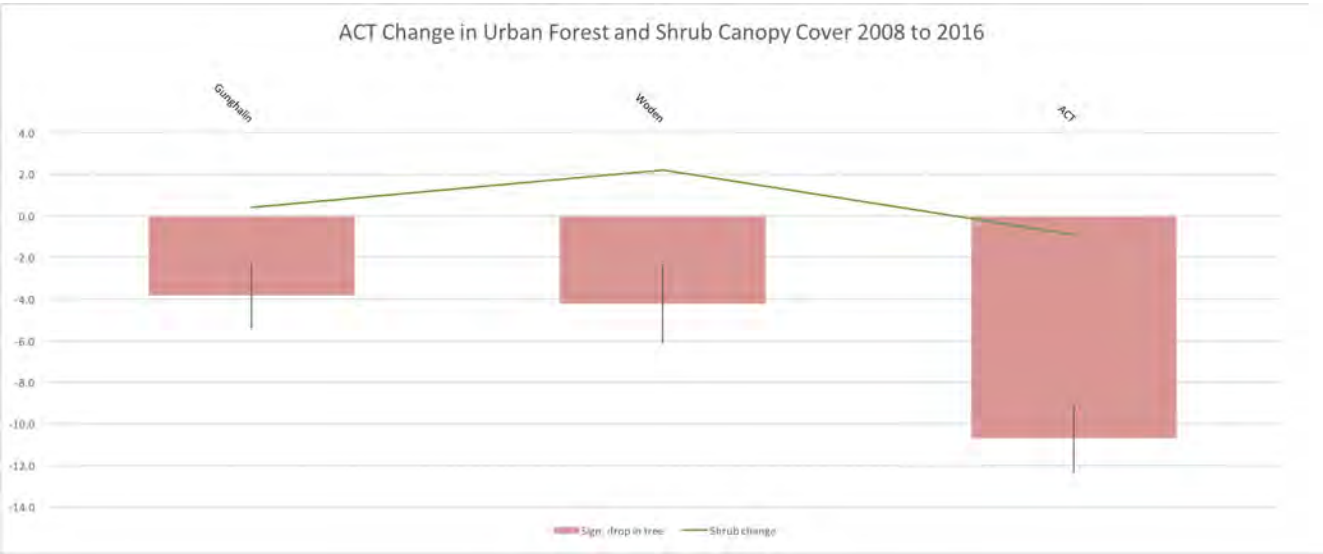
Figure 16: Changes in Canopy and Shrubs for all LGAs in the study 2008-2013 – 2016



Prepared by Marco Amati

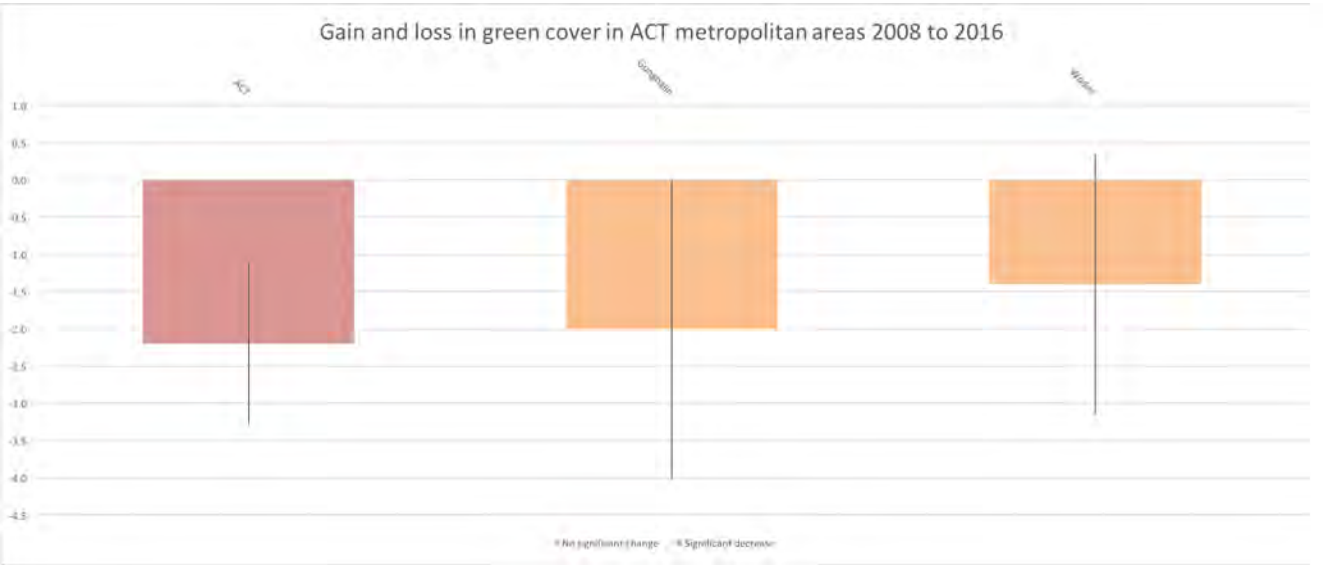
Figure 17: Changes in total green cover across all of the LGAs 2008-2013 – 2016. Red denotes a significant loss.

1.3 State by state changes in canopy and total green cover change



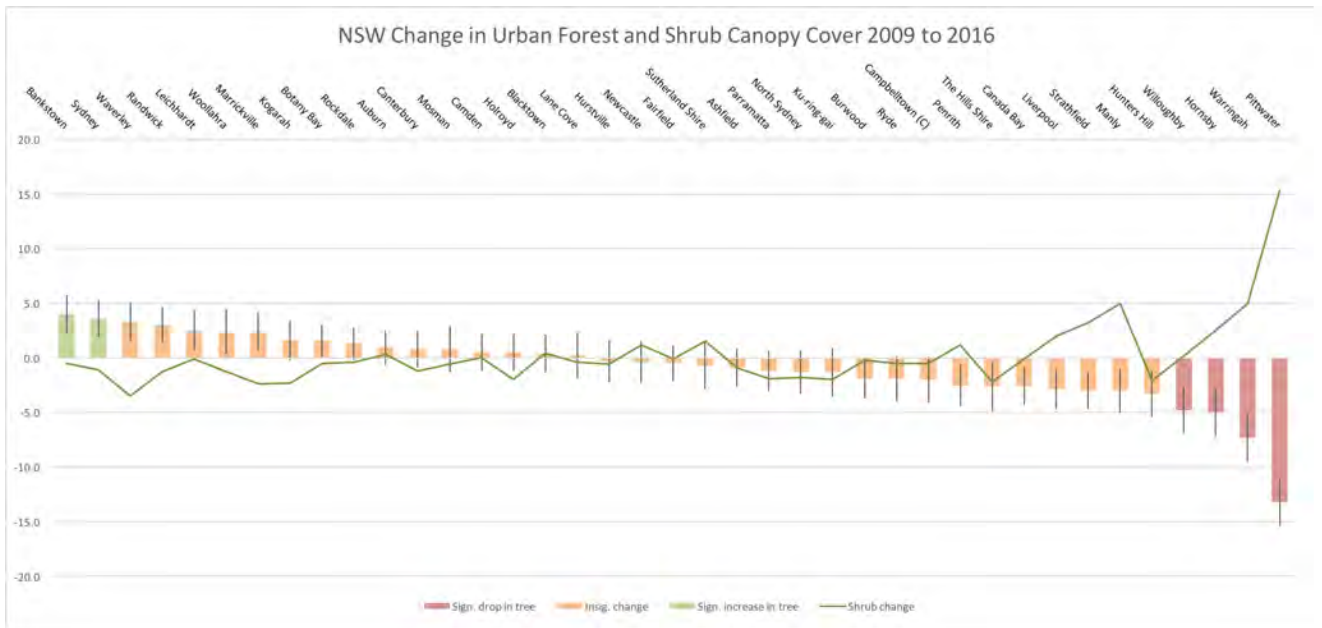
Prepared by Marco Amati

Figure 18: Changes in Canopy and Shrubs for the ACT 2008-2016



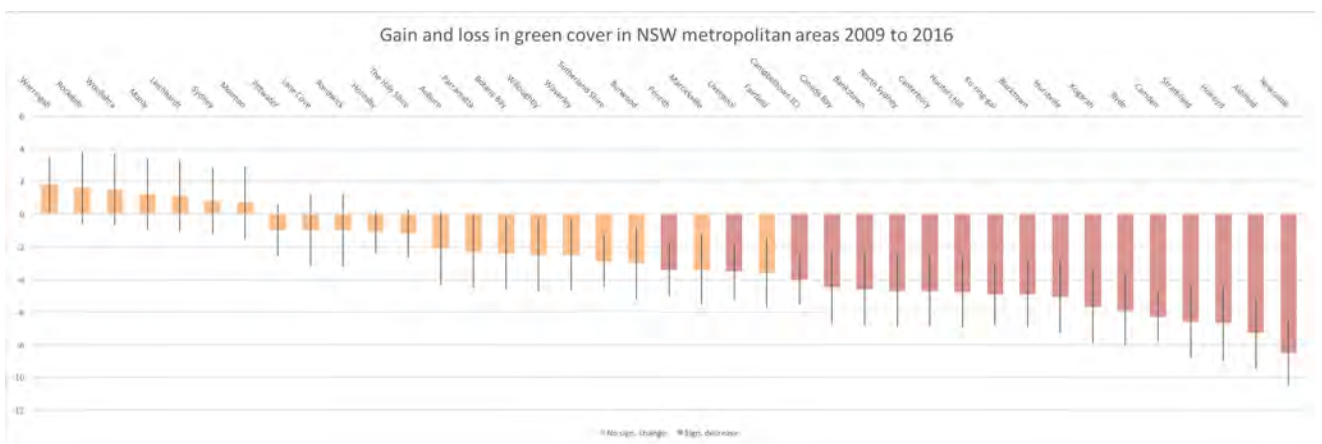
Prepared by Marco Amati

Figure 19: Changes in total green cover for the ACT 2008-2016



Prepared by Marco Amati

Figure 20: Changes in Canopy and Shrubs for NSW 2009-2016



Prepared by Marco Amati

Figure 21: Changes in total green cover for NSW 2009-2016

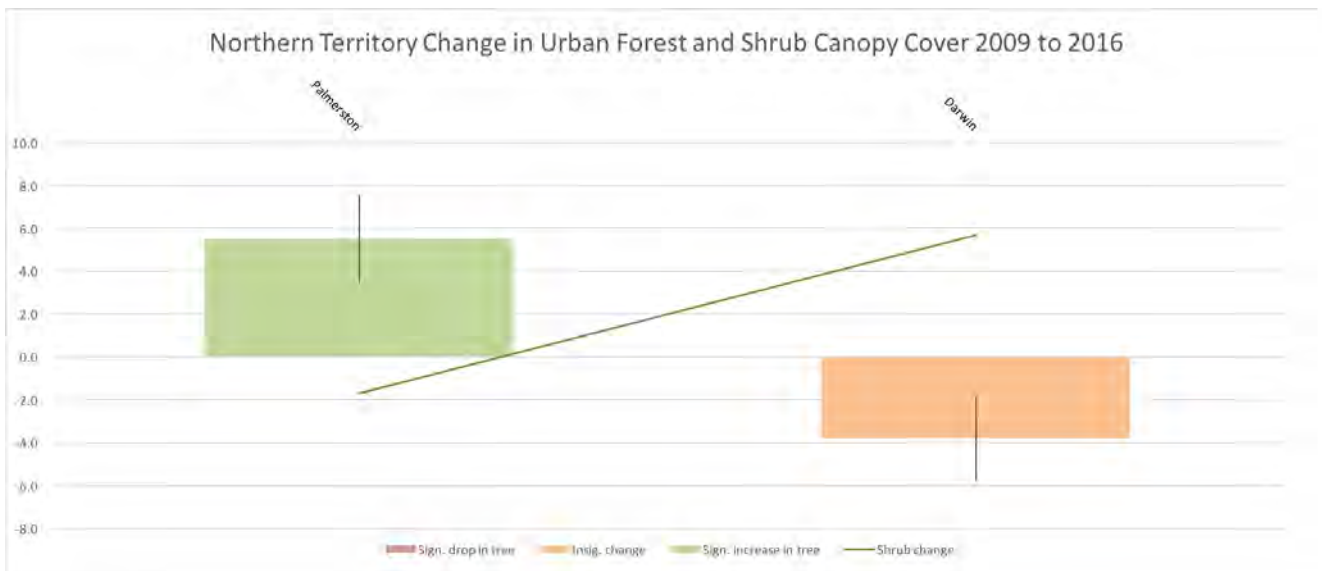
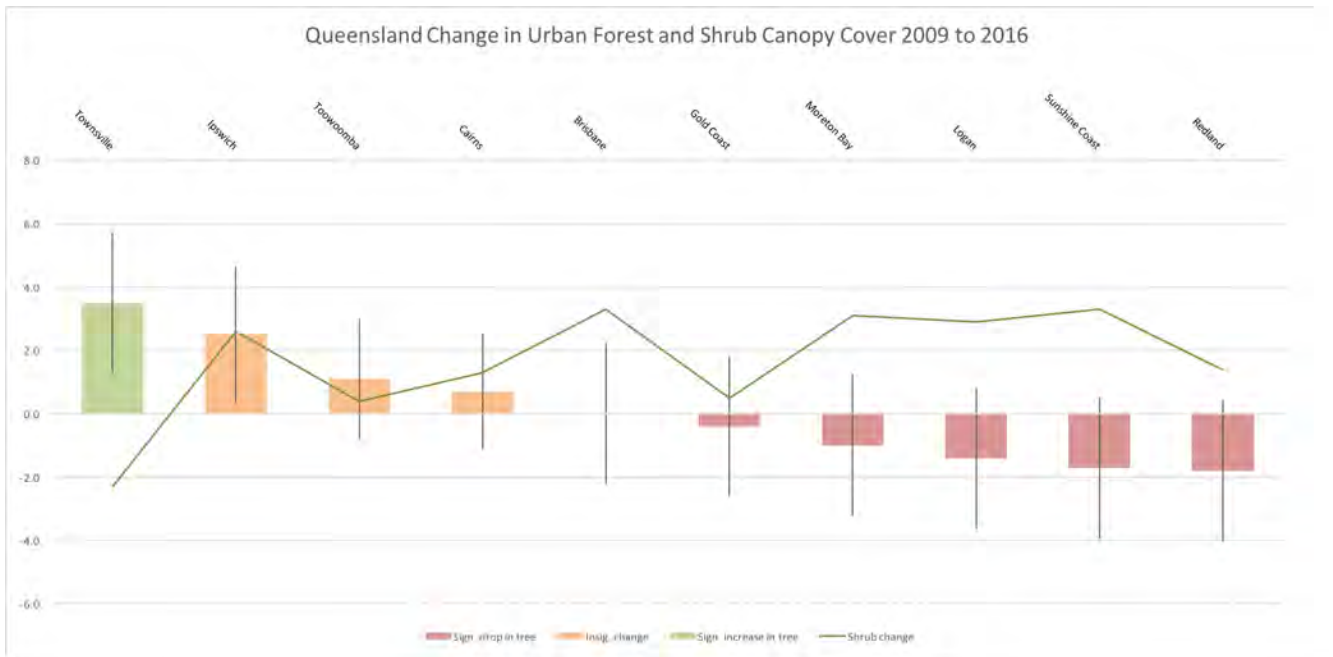


Figure 22: Changes in Canopy and Shrubs for NT 2009-2016



Figure 23: Changes in total green cover for NT 2009-2016



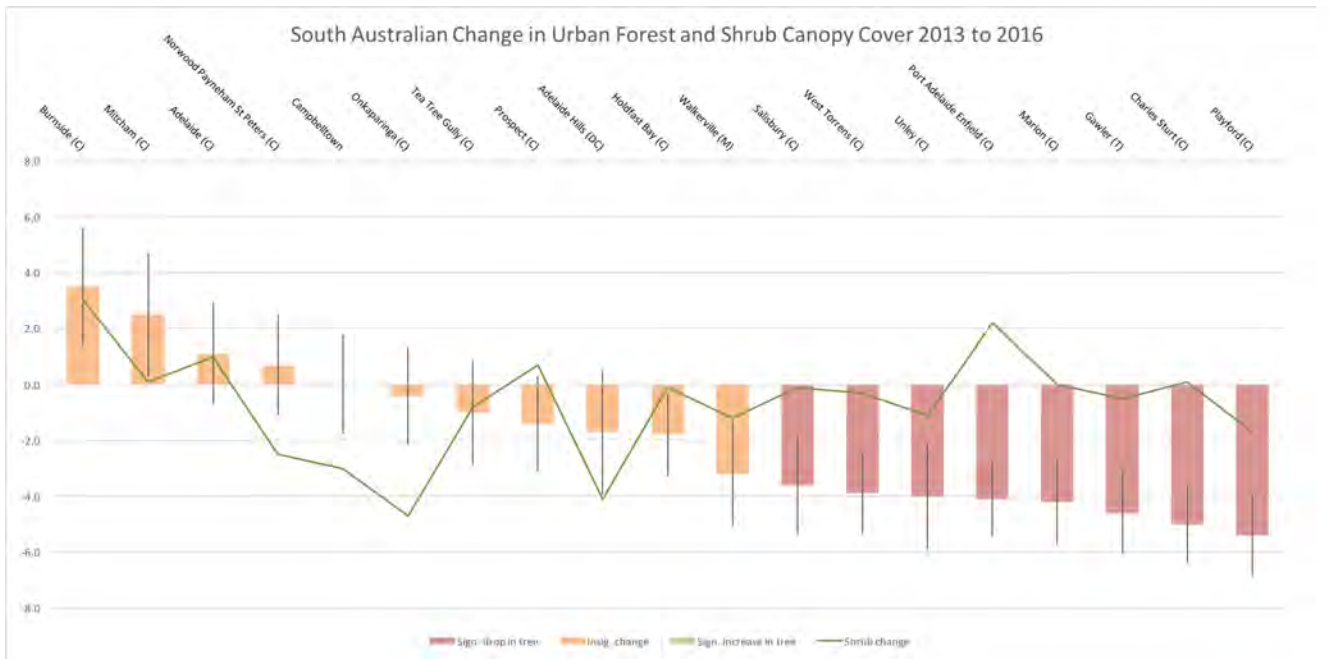
Prepared by Marco Amati

Figure 24: Changes in Canopy and Shrubs for Queensland 2009-2016



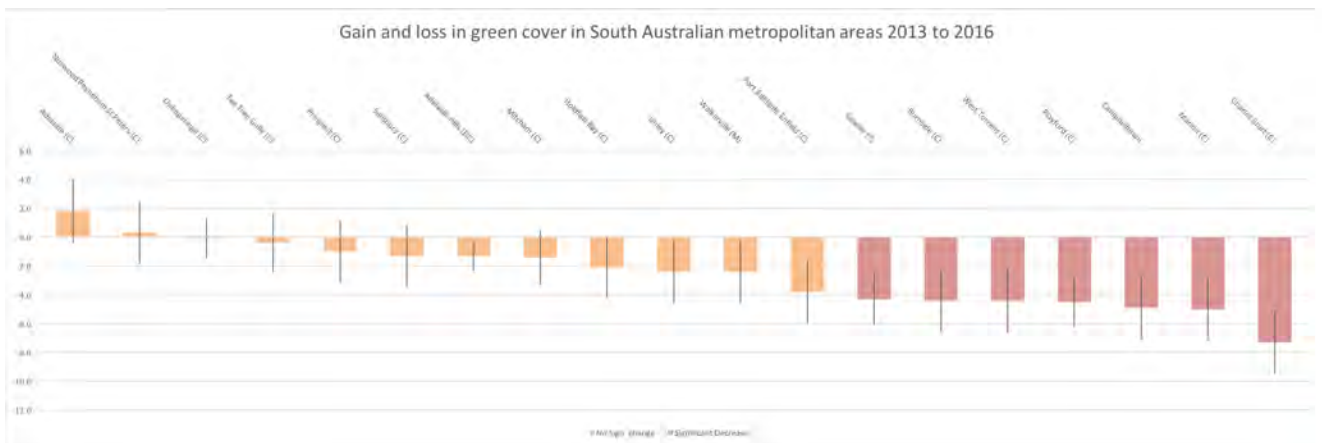
Prepared by Marco Amati

Figure 25: Changes in total green cover for Queensland 2009-2016



Prepared by Marco Amati

Figure 26: Changes in Canopy and Shrubs for SA 2013-2016



Prepared by Marco Amati

Figure 27: Changes in total green cover for SA 2013-2016

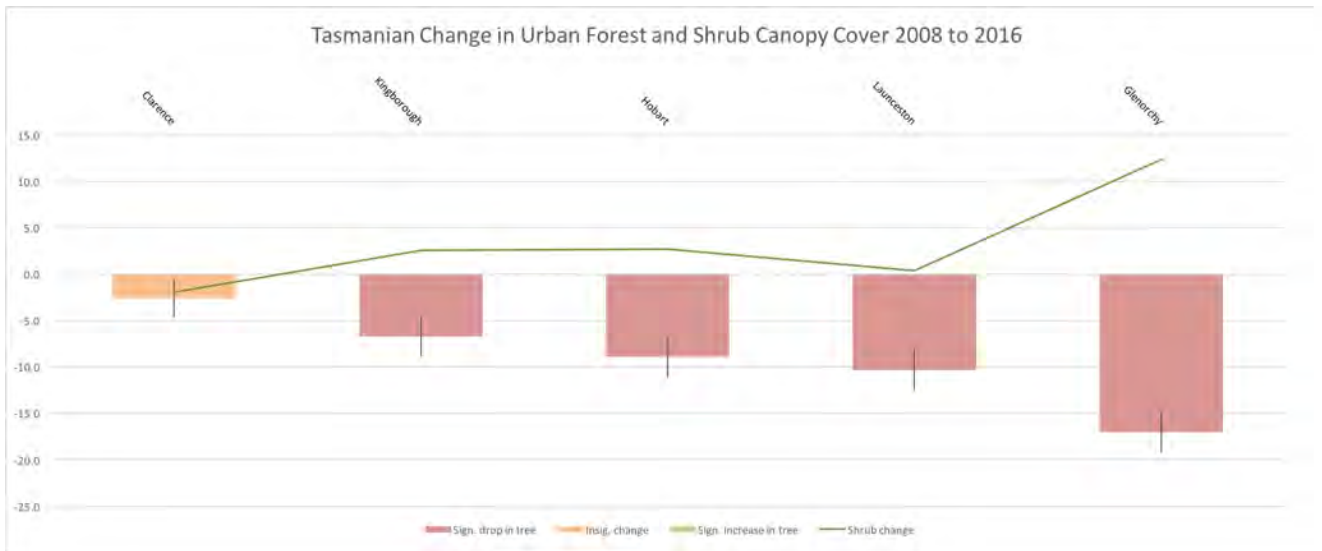


Figure 28: Changes in Canopy and Shrubs for Tasmania 2008-2016

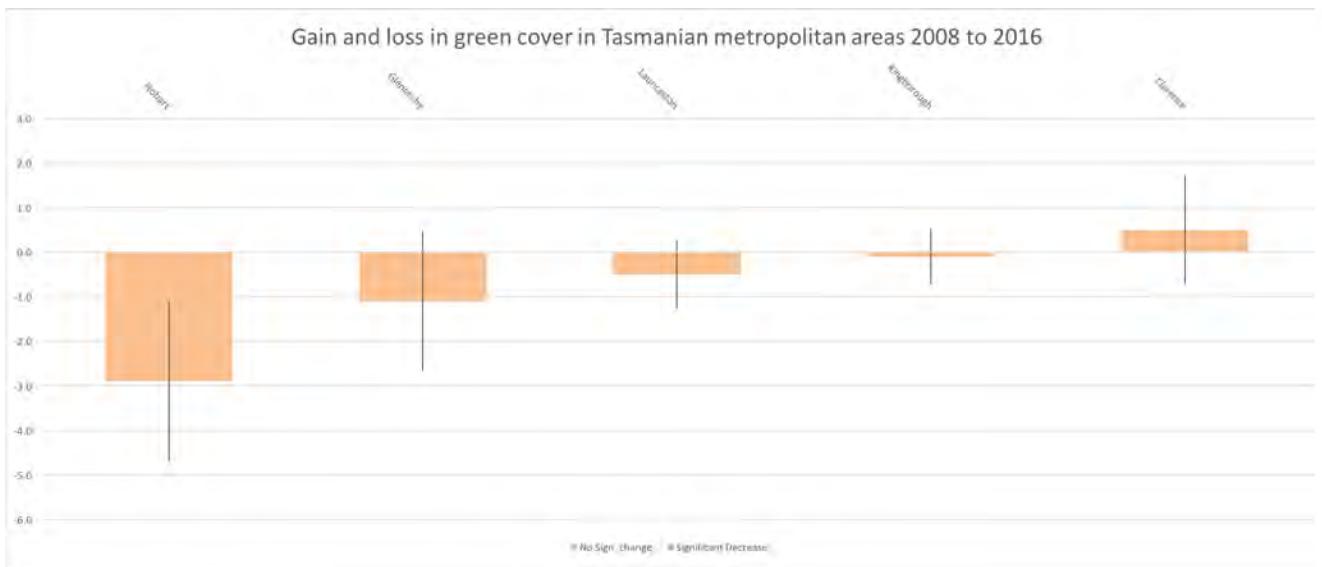
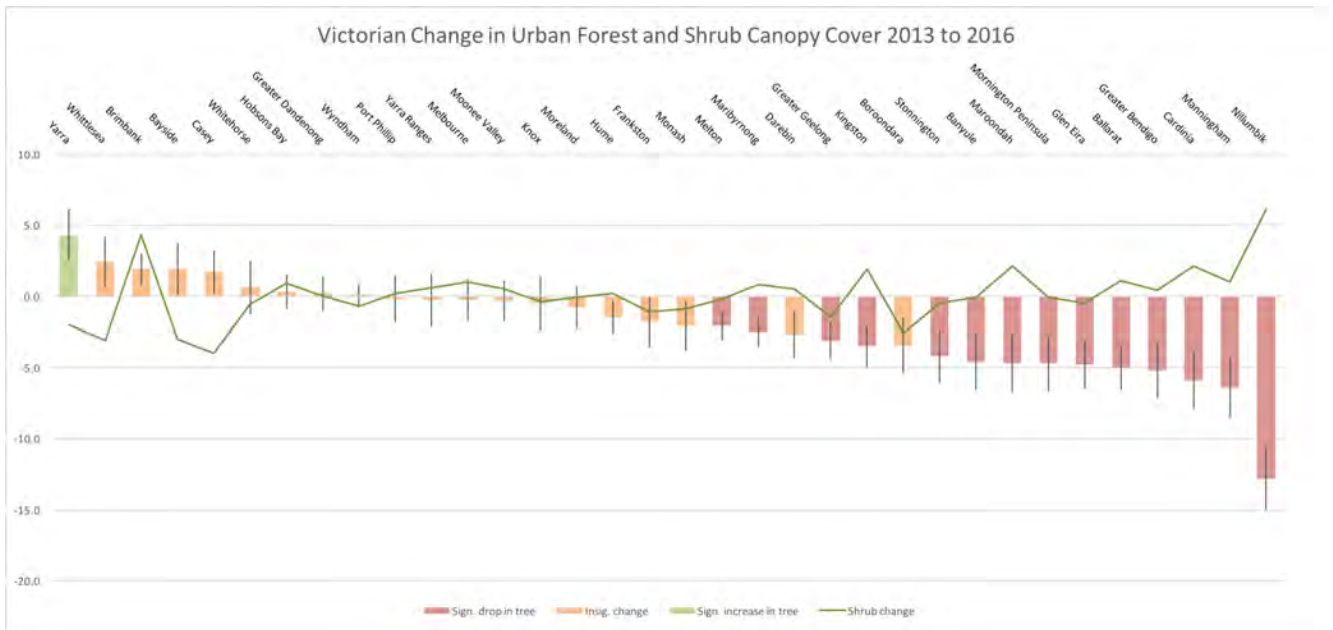


Figure 29: Changes in total green cover for Tasmania 2008-2016



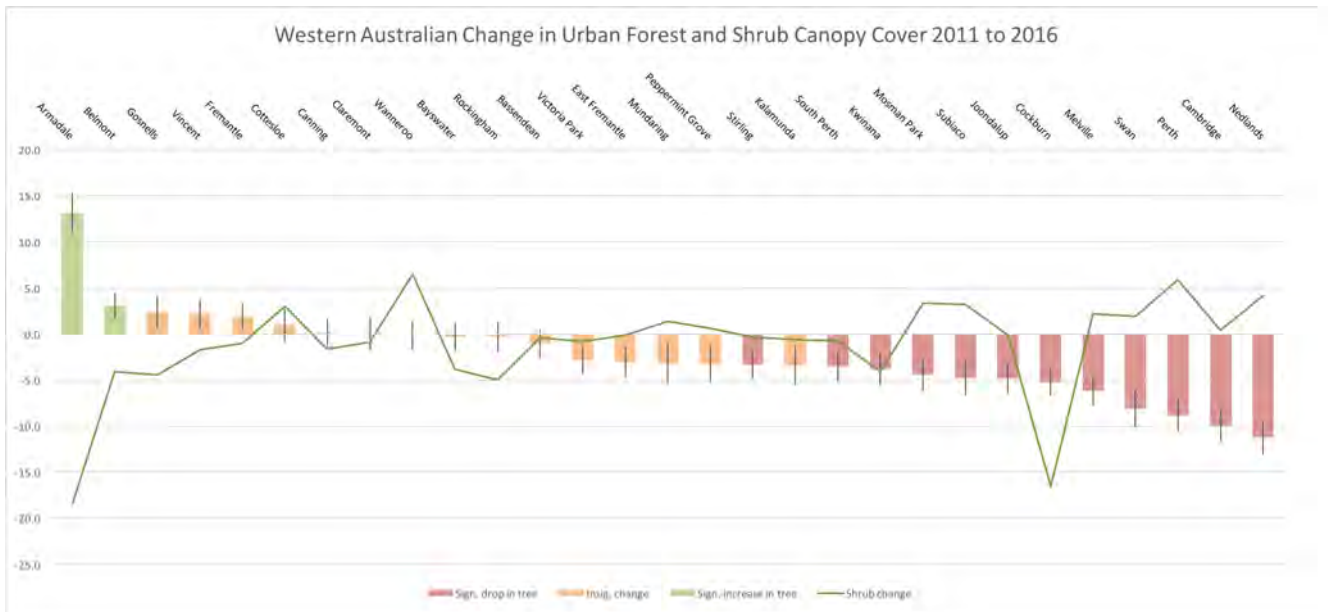
Prepared by Marco Amati

Figure 30: Changes in Canopy and Shrubs for Victoria 2013-2016



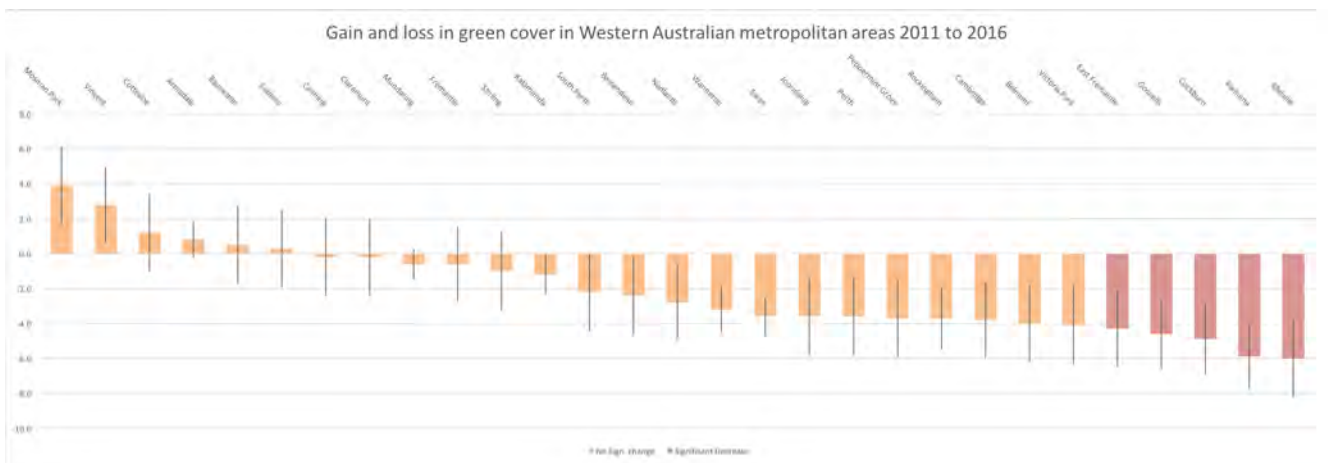
Prepared by Marco Amati

Figure 31: Changes in total green cover for Victoria 2013-2016



Prepared by Marco Amati

Figure 32: Changes in Canopy and Shrubs for WA 2011-2016



Prepared by Marco Amati

Figure 33: Changes in total green cover for WA 2011-2016

2 Urban Heat Island Results for Australian Cities

2.1 Introduction

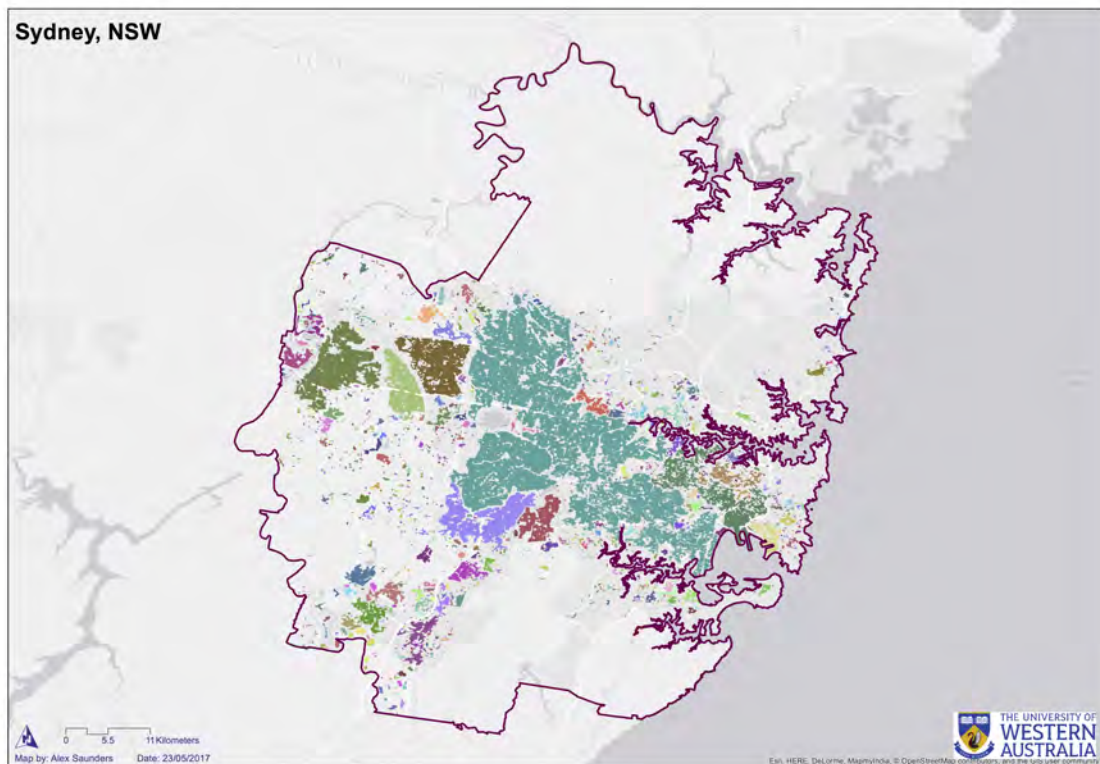
Because of the size of the full set of results from this part of the research (3 sets of 148 maps, total file size 1.5 GB) it was decided to only display a selection of the data for this part of the project.

2.2 Metro wide areas of heat

The following includes the maps produced at the metro level with hot spots individually determined at the mean of temperature plus one, two and three standard deviations.

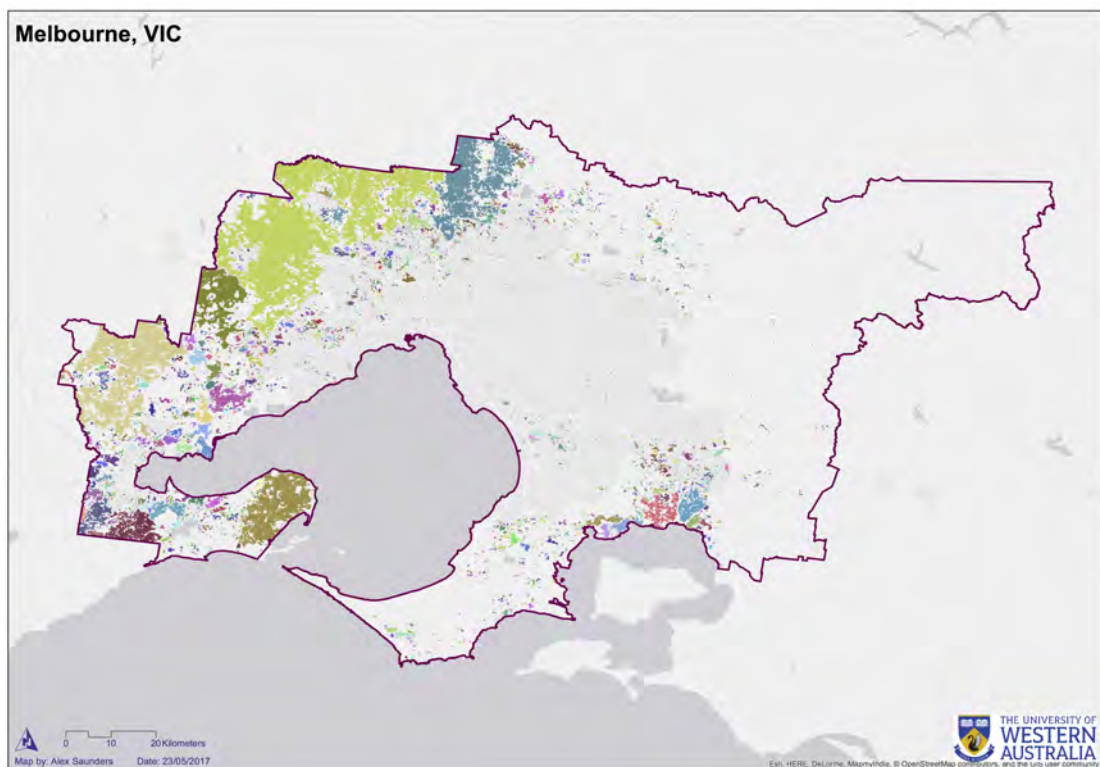
Section 2.4 page 37 shows the maps at State level. Overall some clear trends can be discerned through these.

- *Inside out heat islands* The heat islands for Australian cities is generally lower than that for rural areas. This is because of the latter's inland location and the lack of irrigation on farmland. This is particularly evident in the case of Bendigo and Townsville.
- *A strong link between the affluent areas of towns and a lack of heat* In some of the larger cities such as Melbourne and Sydney, the influence of national parks and also affluence can be seen. Melbourne's areas to the east are generally cooler than those to the West. In Sydney the upper North Shore is cooler compared to areas to the South and West.
- *The impact of infrastructure* Large areas of infrastructure are particularly evident in, Newcastle, Darwin and Sydney for example with the impact of asphalted areas being seen.
- *Heat continents not heat islands* Figure 34 on page 34 and Figure 35 on page 34 shows the lowest temperature for hotspots but coloured by contiguity of heat patches. The maps show that in Australian cities a single patch of heat island (or 'continent') can occupy large areas of the city. These large patches would form a stable area of heat in the city and may resist changes in wind and temperature more than smaller patches. A key task for strategic planning of green infrastructure would be to invest resources in planting corridors to break up these large areas.



Prepared by Alex Saunders. Hot spot defined as 1 standard deviation above the mean.

Figure 34: Contiguous areas of Urban Heat Island in Sydney coloured differently for each contiguous area.



Prepared by Alex Saunders. A hot spot is defined as 1 standard deviation above the mean.

Figure 35: Contiguous areas of Urban Heat Island in Melbourne coloured differently for each contiguous area.

Finally, the relationship overall between heat and the different kinds of land cover also bear out these findings. Figure 36 shows that tree canopy has the most significant impact on % hot spot. Shrub and total green have less of an impact. Surprisingly, grass results in an increase in % hot spot. This is possibly due to the inside-out nature of heat islands in Australia with unirrigated pasture resulting in hot areas.

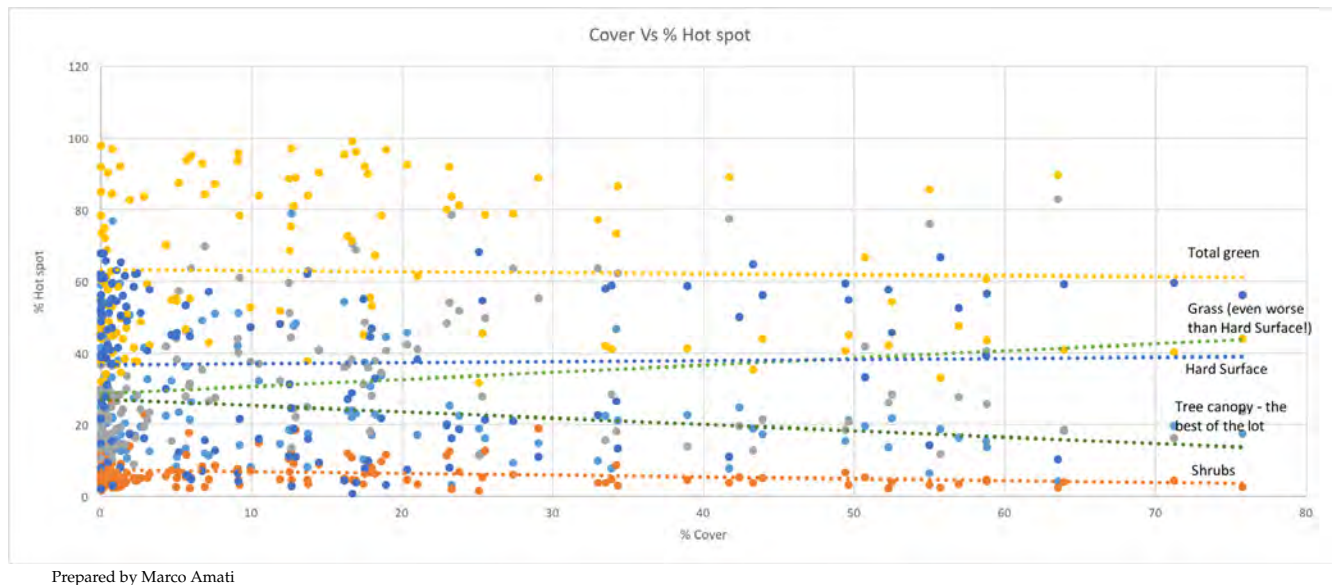


Figure 36: Trendlines displaying the relationship between the different % land covers and % hot spot for each LGA.

2.3 LGA level hot spots

For the maps at LGA level (Section 2.5, page 51) different and varied trends are evident compared to the maps at State level. For example the map focused on Strathfield, NSW in inner Sydney displays a variety of features that are commonly borne out in many of the LGA scale maps.

- *The impact of large areas of infrastructure* The maps show the impact of railway yards and certain roofs of warehouses in the inner west. In all cases these hotspots that are more than 13 degrees hotter than equivalent native vegetation have an orbital impact on the surroundings.
- *The important impact of corridors of native bush* Even in this highly urbanised context, the maps show the often assumed but rarely displayed impact of river corridors and areas of green space such as golf courses on the heat patterns.
- *The impact of the coast* Although, obvious, the limited amount of coastline to the north-east in the neighbouring LGA of Canada Bay also shows the cooling ambient effect of the coastline that can have an impact of two or three houses deep.

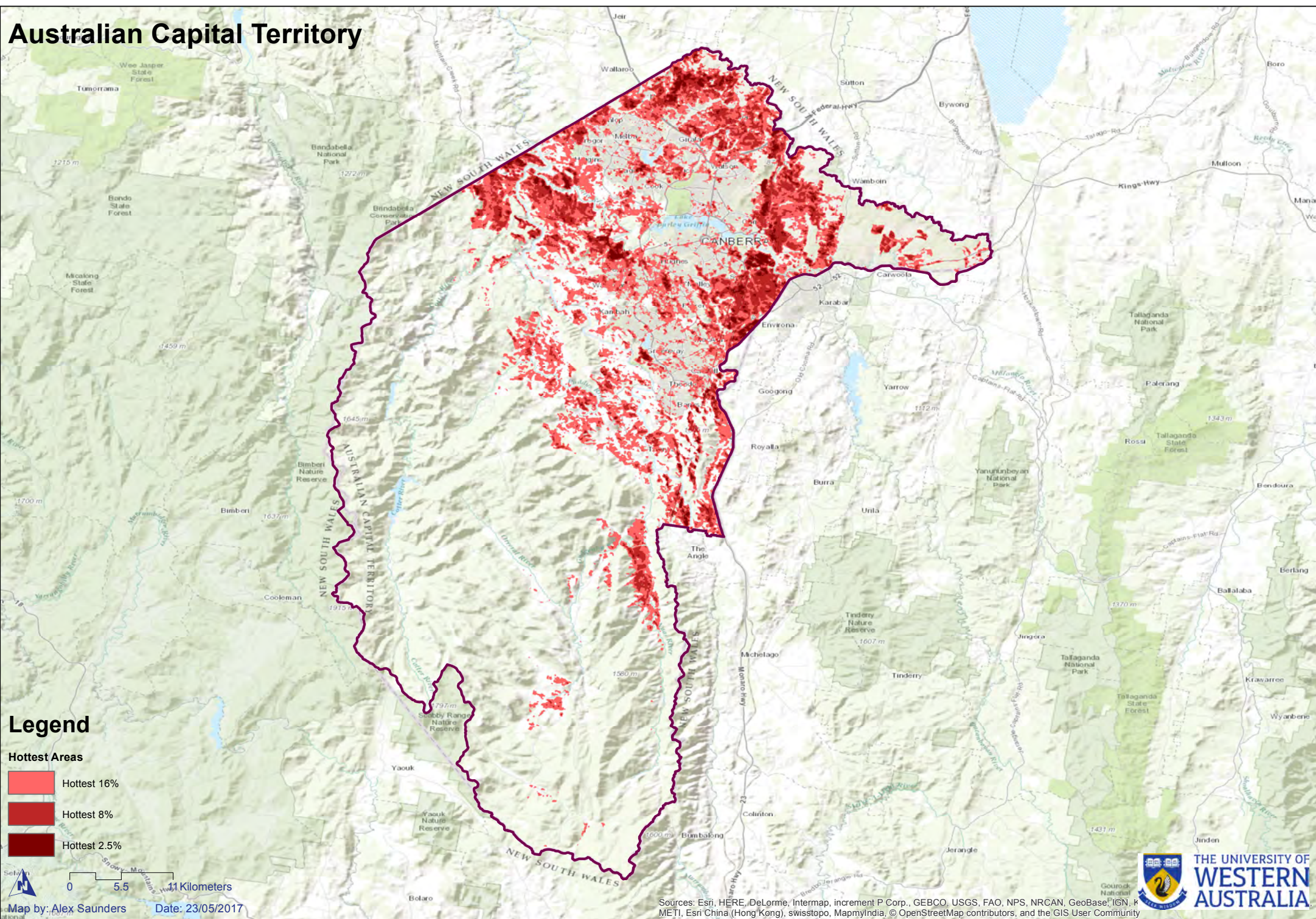
When overlaying the heat maps of LGAs in other areas of Western Sydney the strategic implications of this data become clearer.

Page 53 shows the map for Fairfield, NSW overlaid on a SEIFA map of Index of Relative Socio-Economic Disadvantage. The area to the East is hotter than the West. A key piece of green infrastructure are the Western Sydney Parklands and the Fairfield Golf Course in the Centre of the urban area. While the area to the East is relatively homogeneous from the point of view of socio-economic disadvantage to the north, in the industrial area extreme hotspots coincide with areas of disadvantage. On the other side of the Western Sydney Parklands to the West, a large area with a lack of socio-economic disadvantage coincides with almost no hotspots. However some extreme patches of heat exist in areas of socio-economic disadvantage.

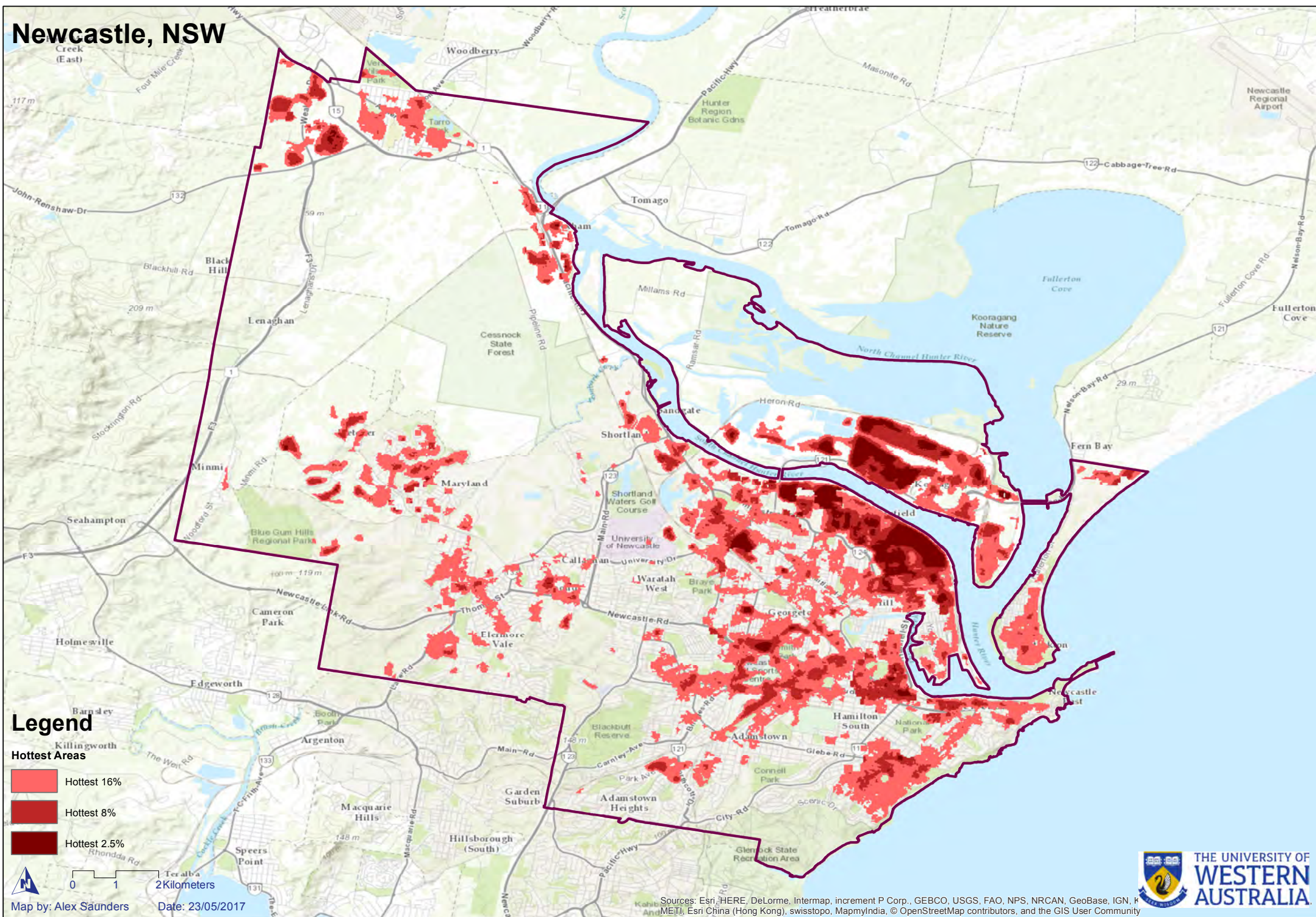
Section 2.5.3 page 54 shows the same information allowing easy identification of the above areas, i.e. Bossley Park around Victoria Street and north Horsley Park.

2.4 State based Heat Maps

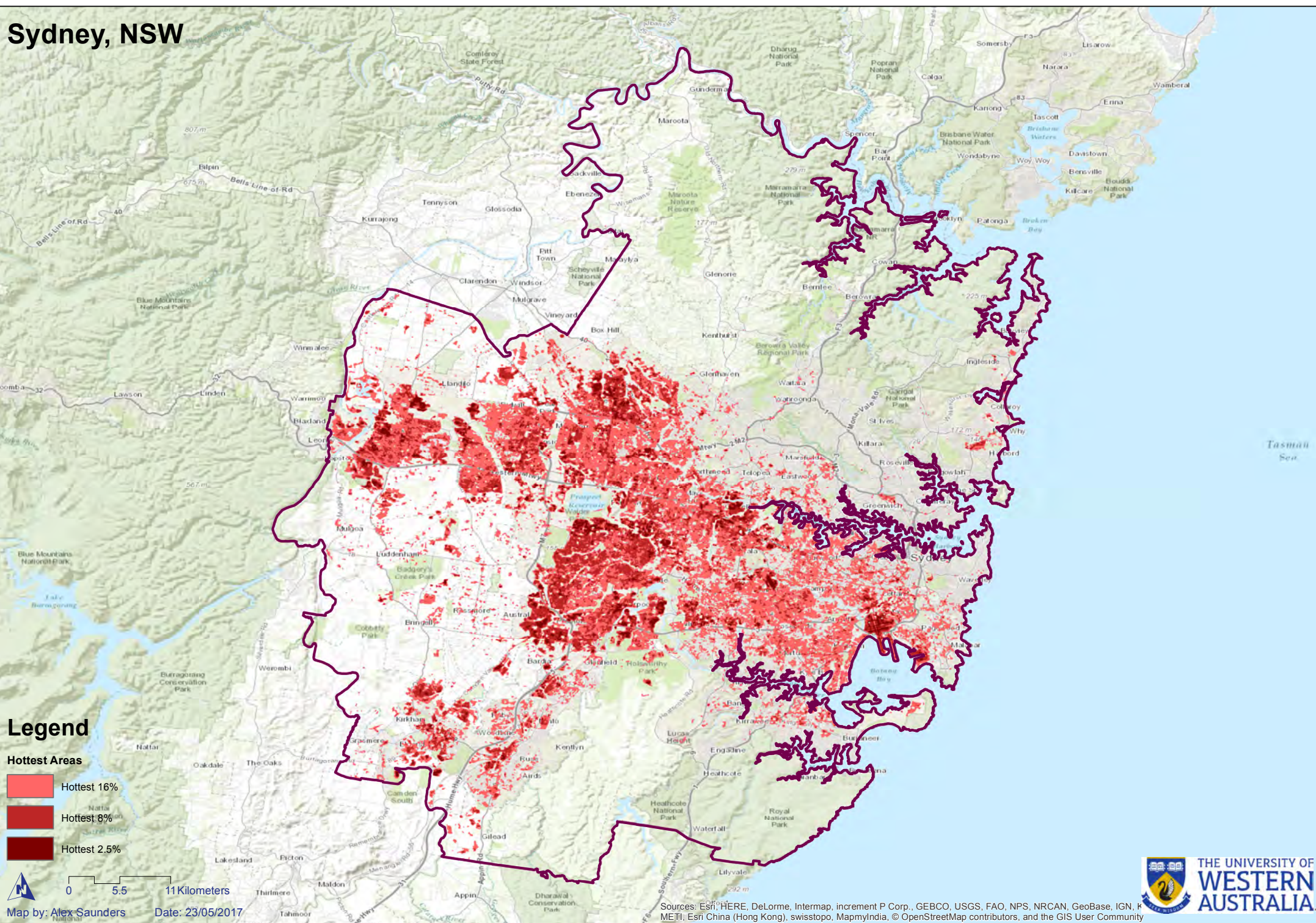
Australian Capital Territory



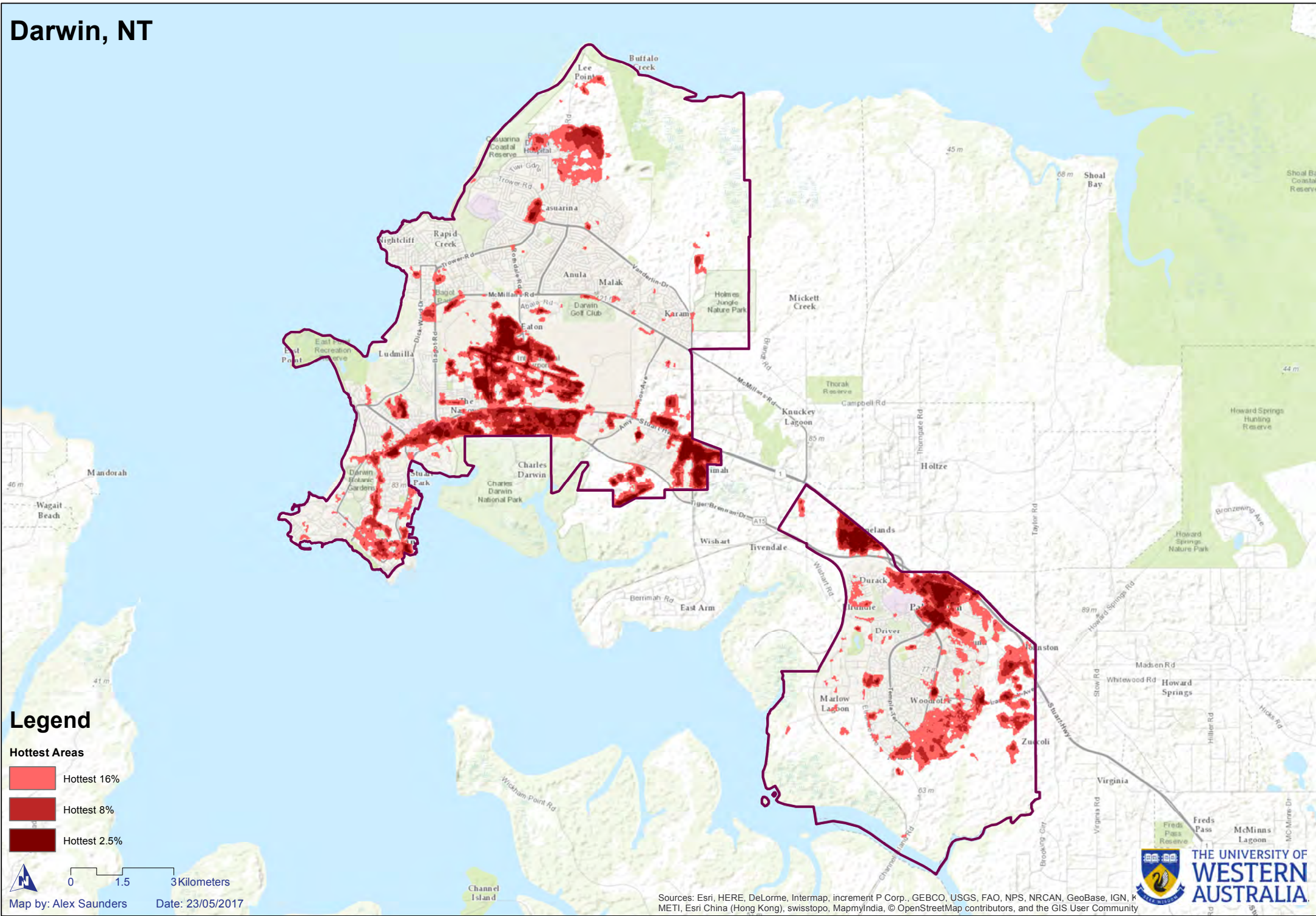
Newcastle, NSW



Sydney, NSW



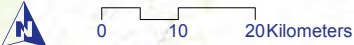
Darwin, NT



Cairns, QLD

Legend

- Hottest Areas
- Hottest 16%
 - Hottest 8%
 - Hottest 2.5%

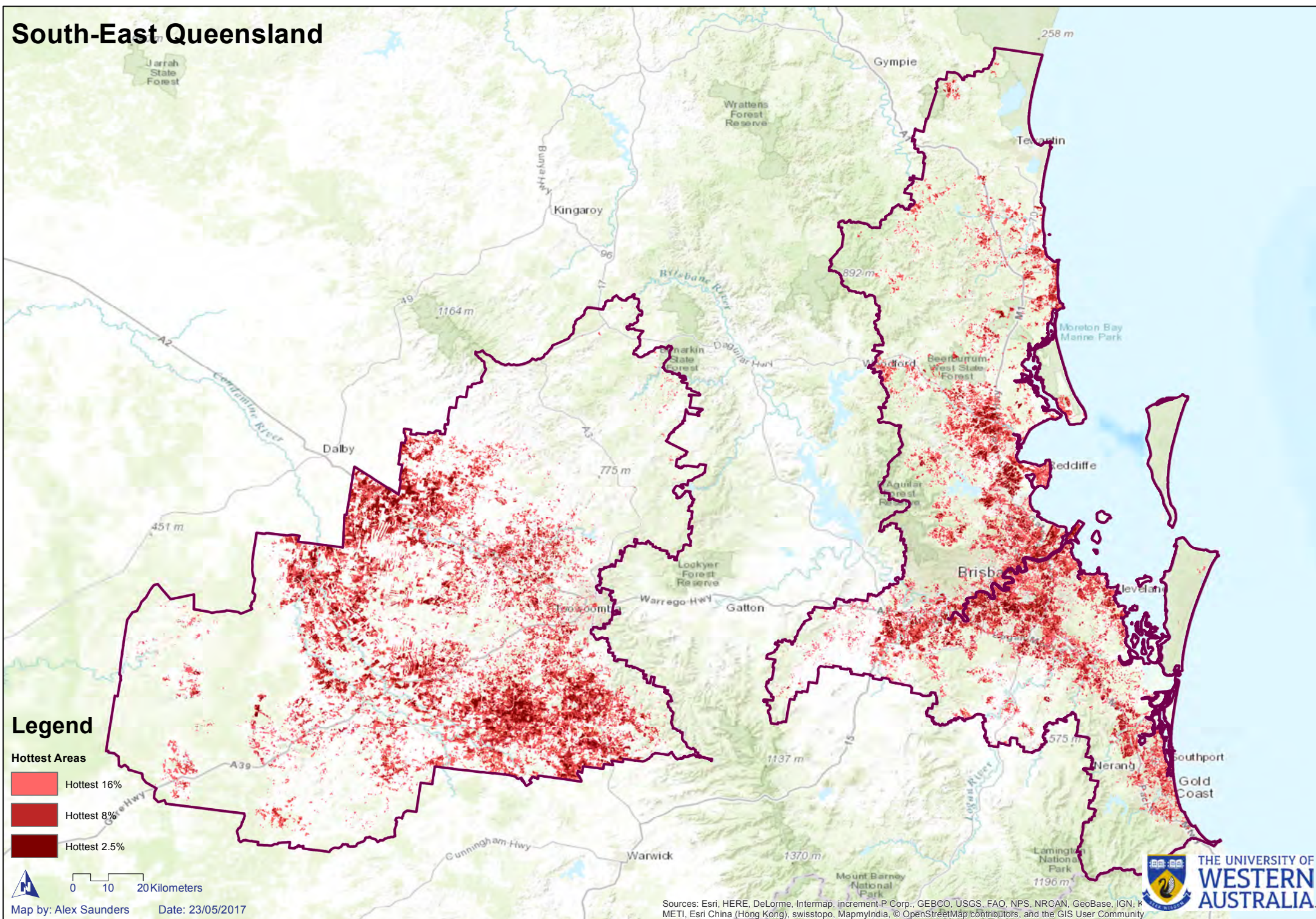


Map by: Alex Saunders Date: 23/05/2017

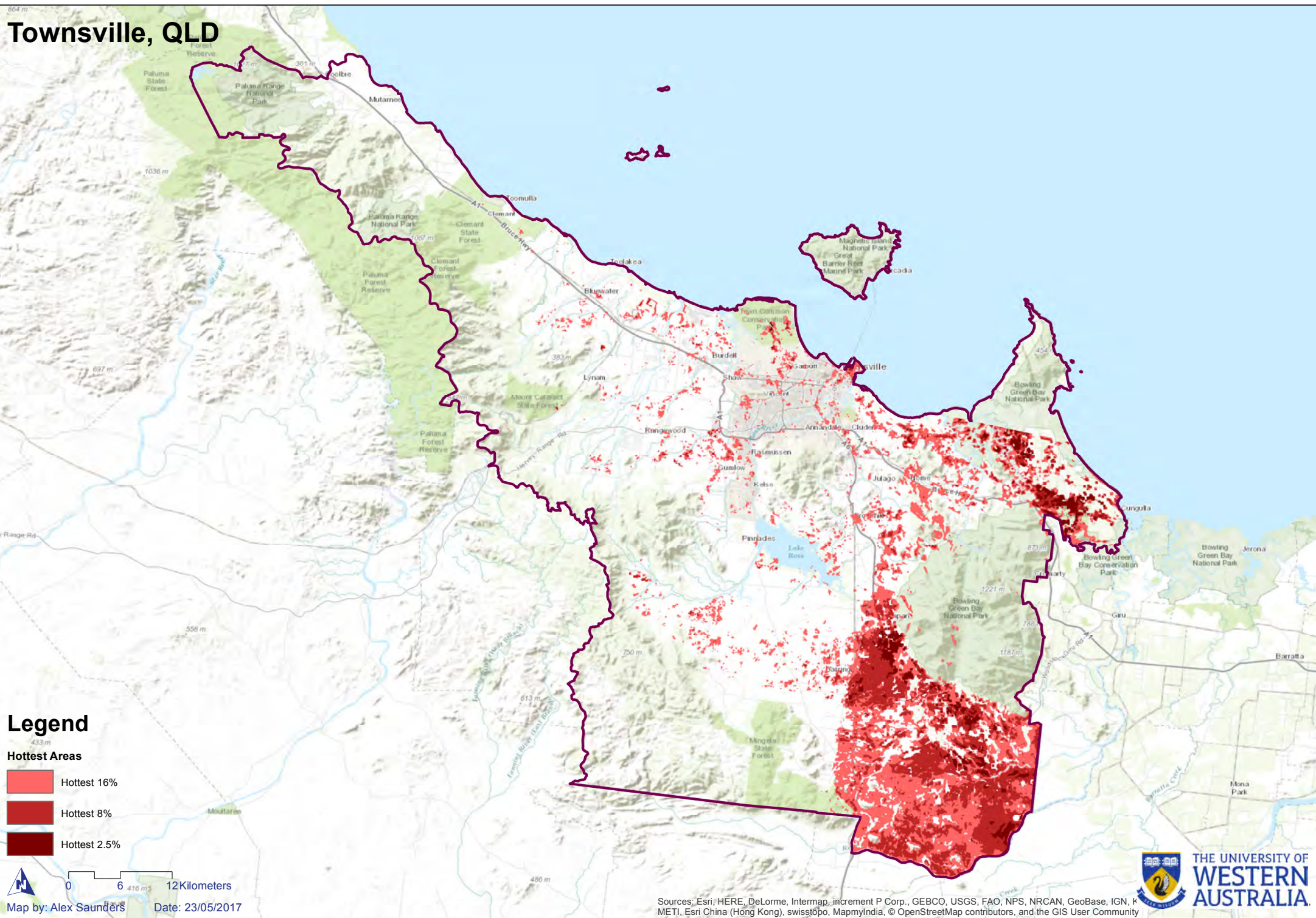
Sources: Esri, HERE, DeLorme, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, KMEITI, Esri China (Hong Kong), swiss topo, MapmyIndia, © OpenStreetMap contributors, and the GIS User Community



South-East Queensland



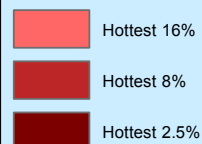
Townsville, QLD



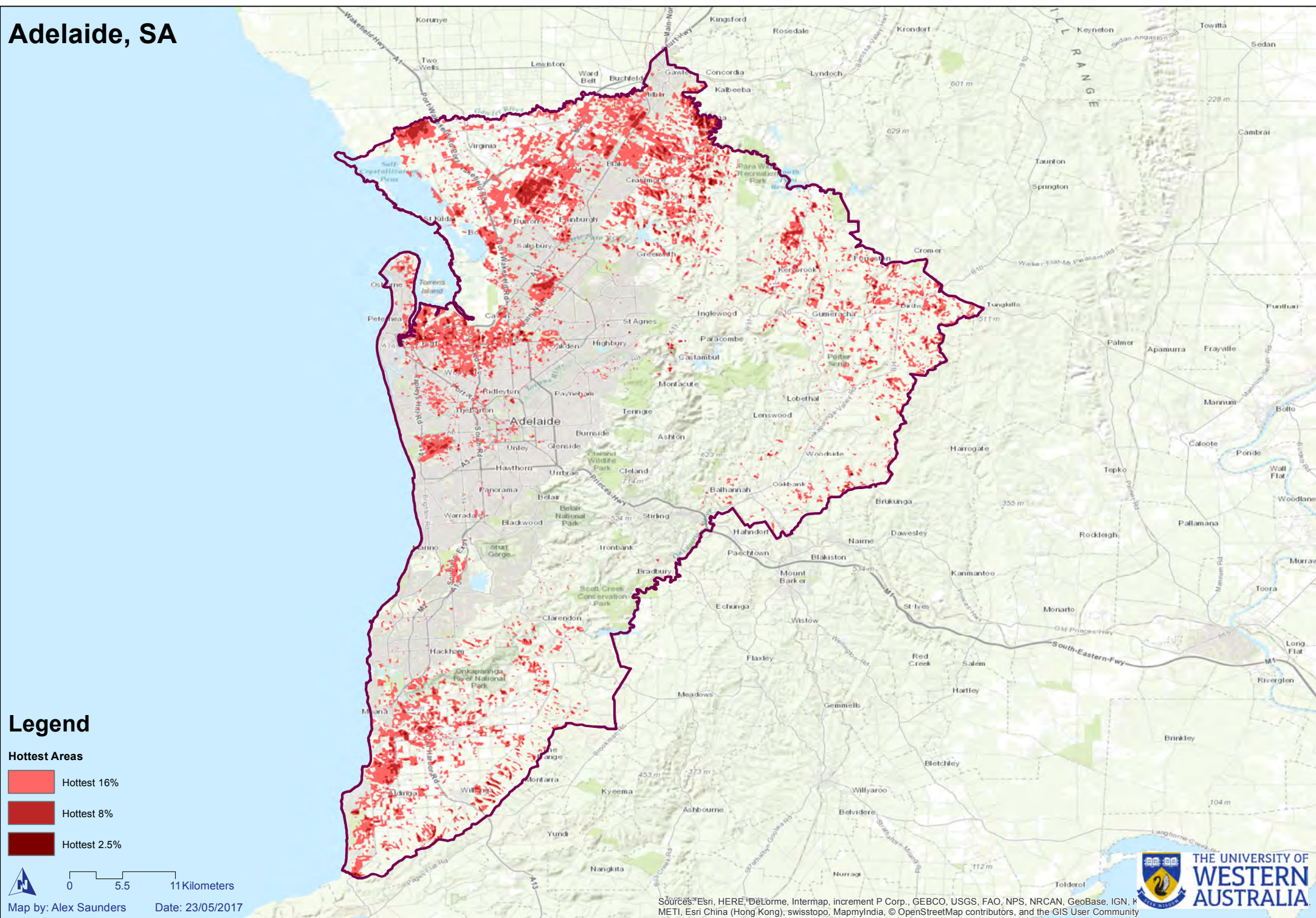
Adelaide, SA

Legend

Hottest Areas



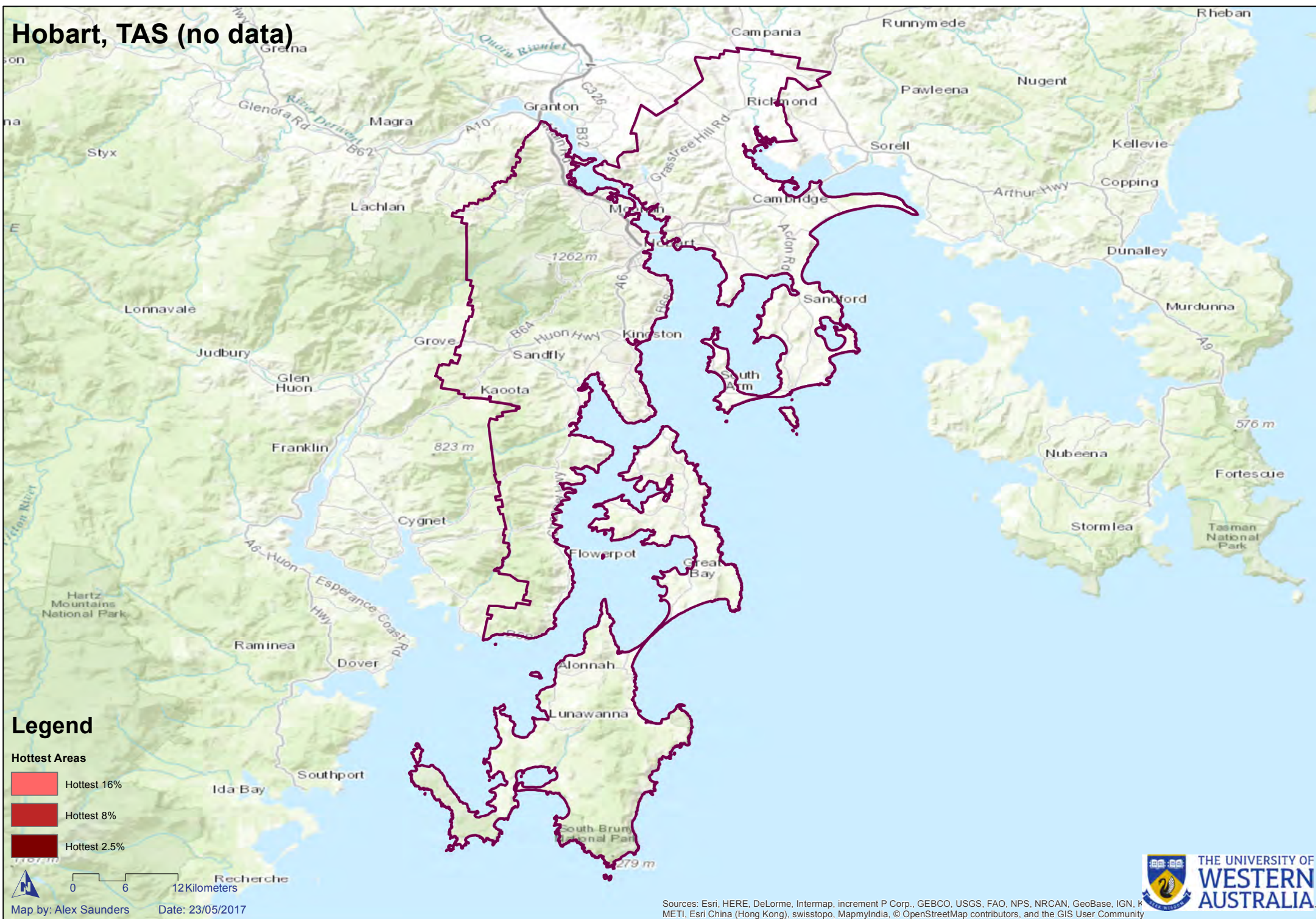
Map by: Alex Saunders Date: 23/05/2017



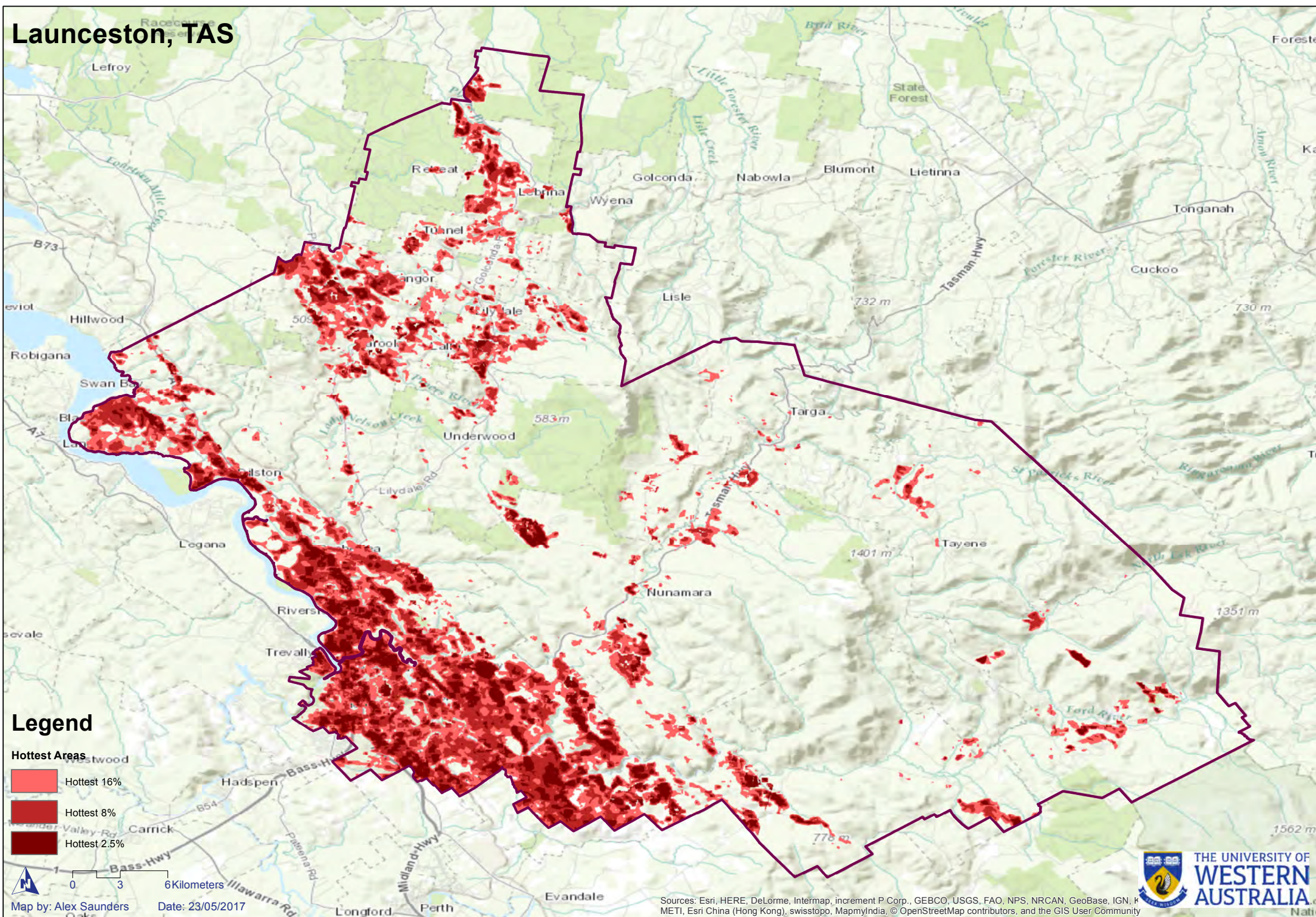
Sources: Esri, HERE, DeLorme, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, METI, Esri China (Hong Kong), swisstopo, MapmyIndia, © OpenStreetMap contributors, and the GIS User Community



Hobart, TAS (no data)



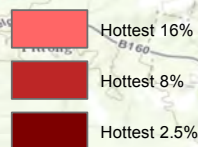
Launceston, TAS



Ballarat, VIC

Legend

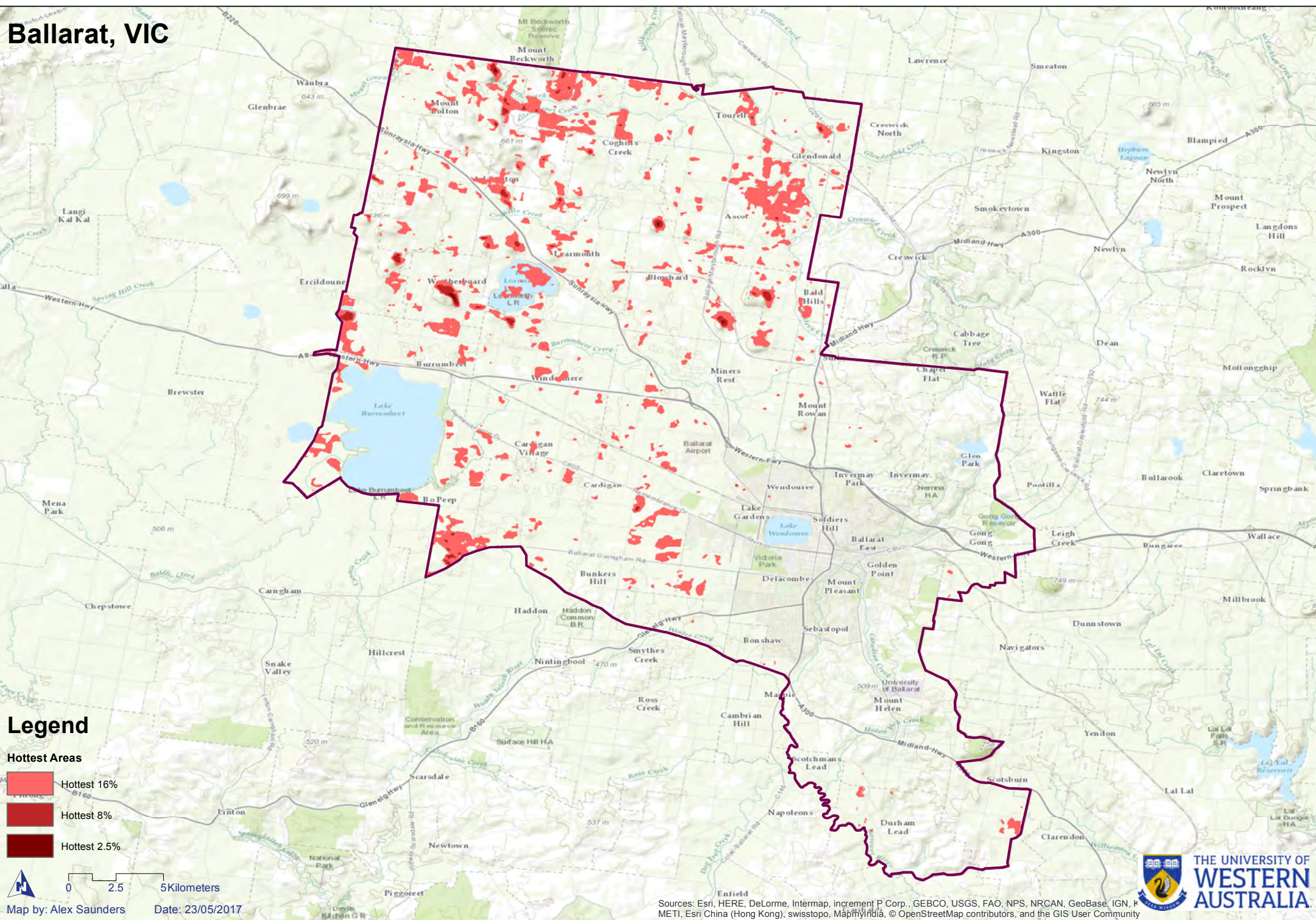
Hottest Areas



Map by: Alex Saunders

Date: 23/05/2017

0 2.5 5 Kilometers

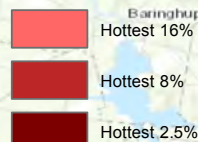


Sources: Esri, HERE, DeLorme, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, K
METI, Esri China (Hong Kong), swisstopo, MapmyIndia, © OpenStreetMap contributors, and the GIS User Community

Bendigo, VIC

Legend

Hottest Areas



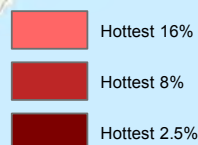
Map by: Alex Saunders Date: 23/05/2017

Sources: Esri, HERE, DeLorme, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, METI, Esri China (Hong Kong), swisstopo, MapmyIndia, © OpenStreetMap contributors, and the GIS User Community

Melbourne, VIC

Legend

Hottest Areas



0 10 20 Kilometers

Map by: Alex Saunders

Date: 23/05/2017

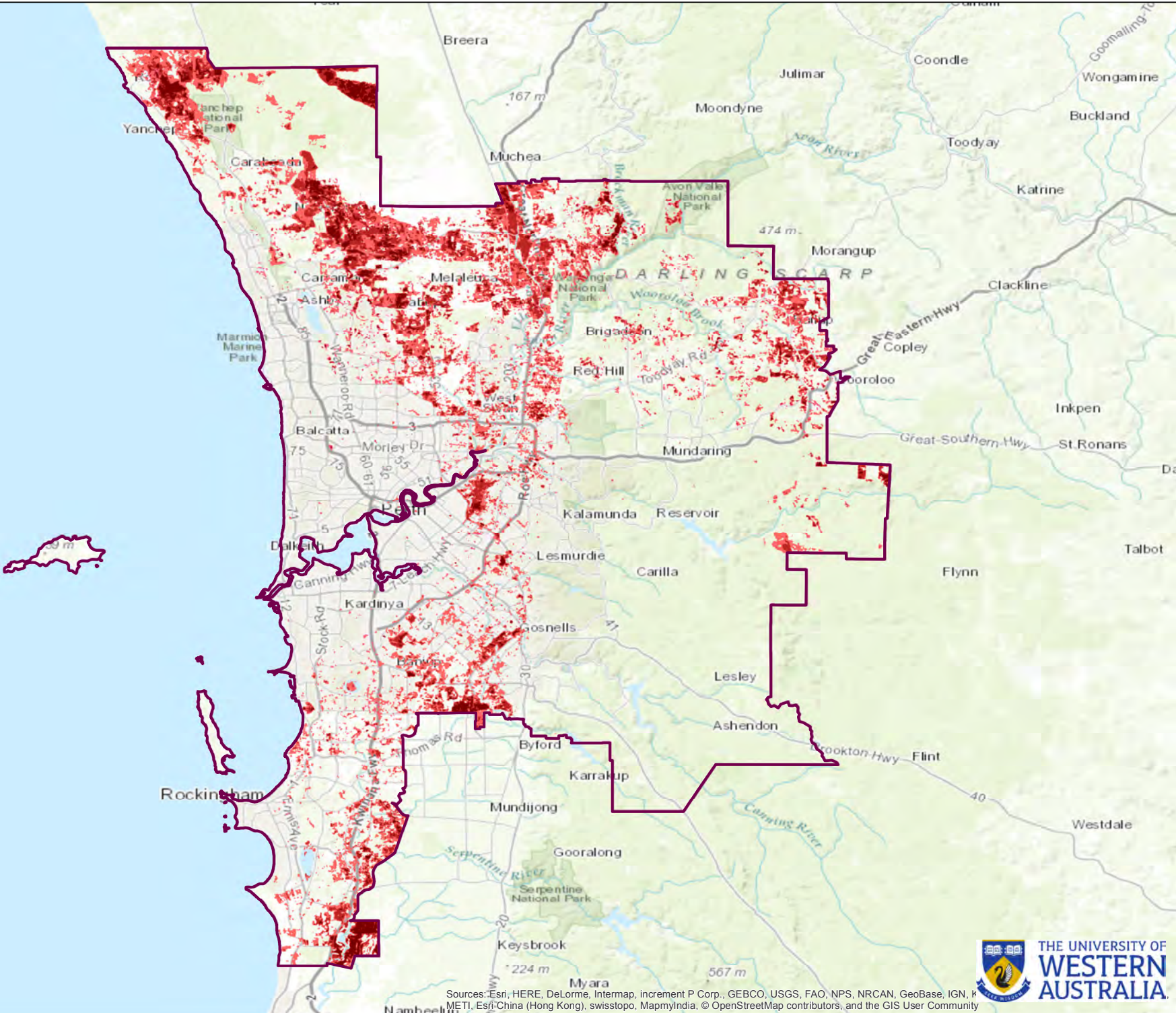
Sources: Esri, HERE, DeLorme, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, METI, Esri China (Hong Kong), swisstopo, MapmyIndia, © OpenStreetMap contributors, and the GIS User Community

Perth, WA

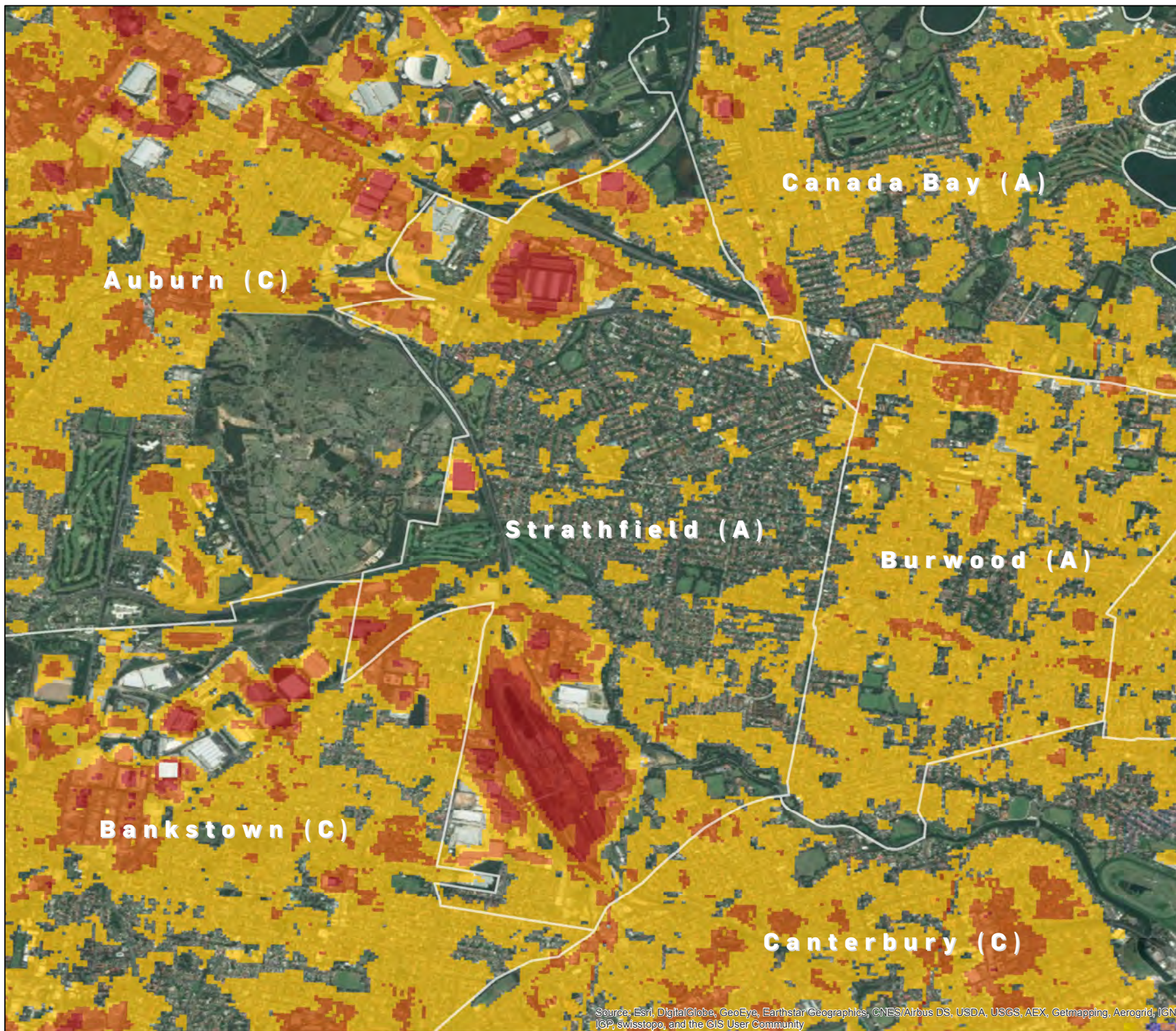
Legend

- Hottest Areas
- Hottest 16%
 - Hottest 8%
 - Hottest 2.5%

Map by: Alex Saunders Date: 23/05/2017



2.5 LGA based Heat Maps



Legend

Strathfield New South Wales

Key Statistics

Tree Cover: 15.4%
Change in Proportion: -3%

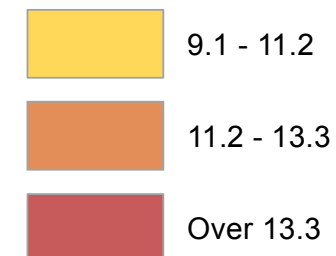
Shrub Cover: 6.7%
Change in Proportion: 3.2%

Grass Cover: 18.5%
Change in Proportion: -6.8%

Hard Surface Cover: 59.4%
Change in Proportion: 6.6%

Hot Spots: 49.4%

Degrees Above Mean



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AUSTRALIA

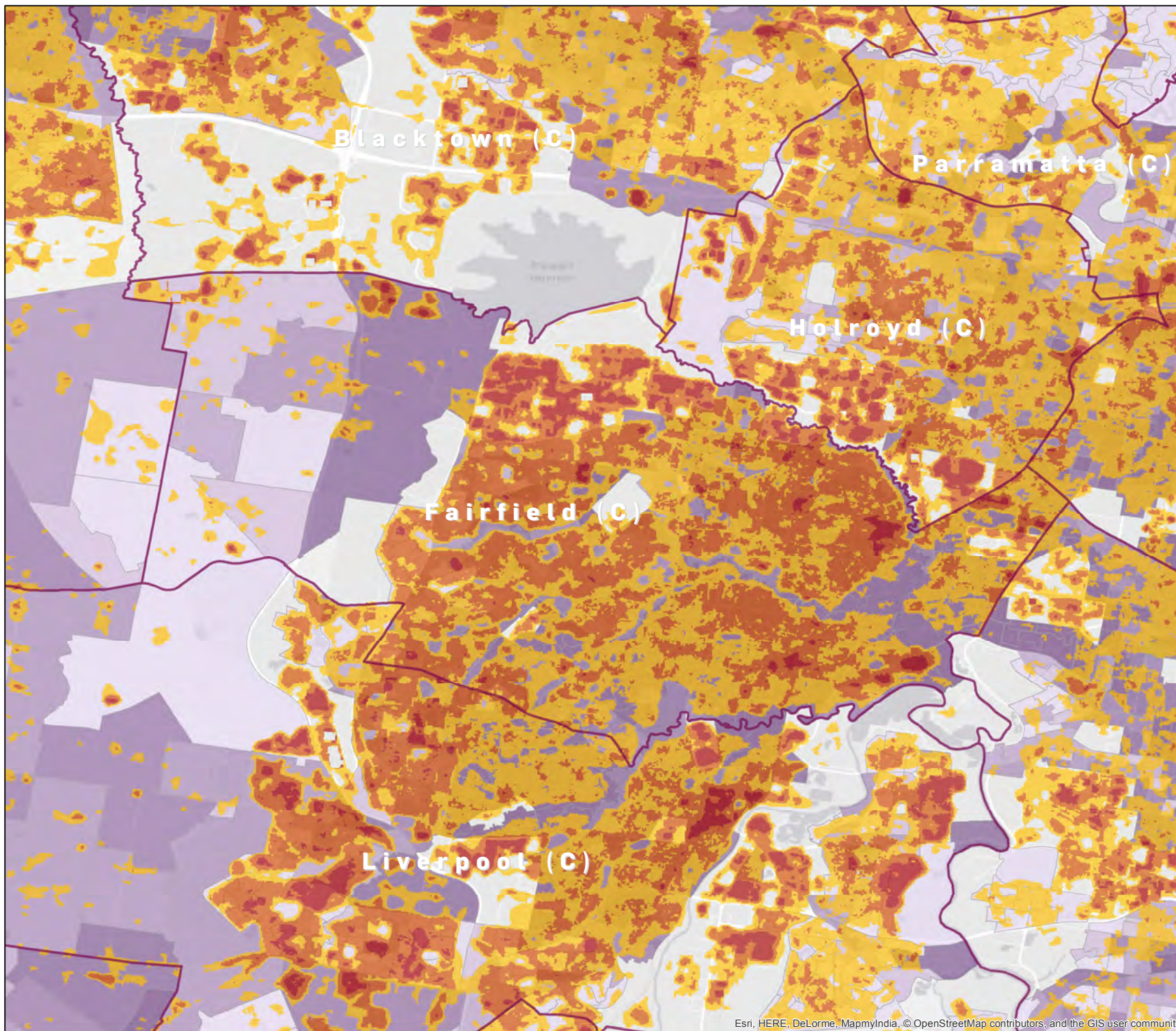


0 0.55 1.1 Kilometers

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Date: 11/05/2017

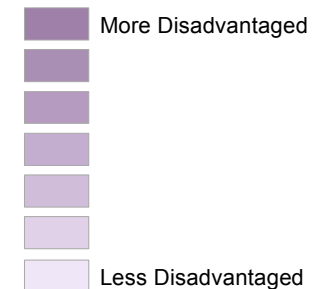
Source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community



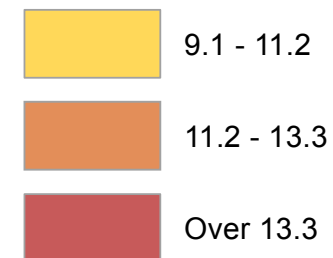
Legend

Fairfield New South Wales

Index of Relative Socio-economic Disadvantage



Degrees Above Mean



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WESTERN
AUSTRALIA

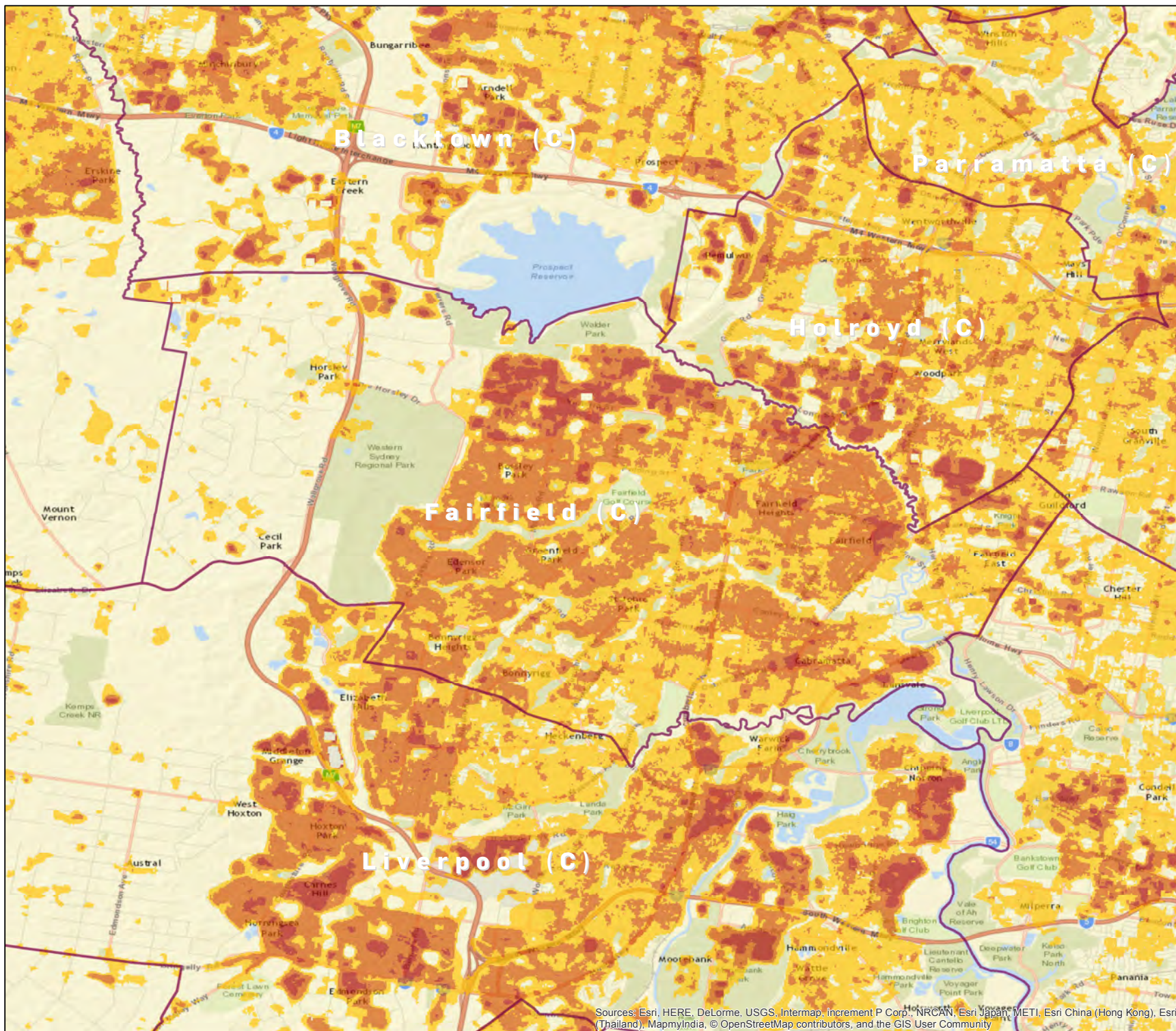


0 1 2 Kilometers

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Date: 11/05/2017

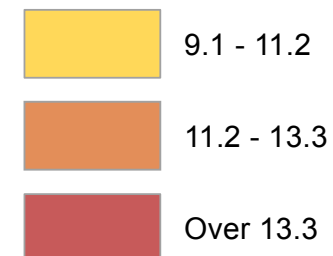
Esri, HERE, DeLorme, MapmyIndia, © OpenStreetMap contributors, and the GIS user community



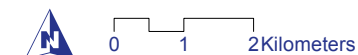
Legend

Fairfield
New South Wales

Degrees Above Mean



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Sources: Esri, HERE, DeLorme, USGS, Intermap, increment P Corp., NRCAN, Esri Japan, METI, Esri China (Hong Kong), Esri (Thailand), MapmyIndia, © OpenStreetMap contributors, and the GIS User Community

3 Measuring risk from multiple variables

Section 3.1 page 56 shows the risk profiles of the different LGAs ordered by risk levels according to the methodology in section 6, page 16. At one extreme of the scale are those LGAs that have a combination of above median levels of heat, low canopy, poor human health and socio-economic outcomes and below median levels of growth in greening.

The growth in greening plays an important part in the LGAs in NSW in reducing their risk profiles. However, it should be re-emphasised that these LGAs may in fact be losing green cover but this will be at a lower than median rate compared to the rest of country.

The following is an explanation of the columns:

- Canopy heat = % hotspot in each LGA by % canopy cover (Figure 11).
- Health = Self-Assessed Health by ASR100 for each LGA by Prevalence of diabetes by ASR100 (Figure 12).
- Economic = SEIFA Index of Relative Socio-Economic Disadvantage in each LGA by SEIFA Index of Economic Resources (Figure 13).
- Green gain = rate of total green loss in each LGA by canopy cover loss (Figure 14)
- Vulnerable pop = rate of % population under 5 in each LGA versus % population over 65 and living alone (Figure 15)

LGA_CODE	NAME	LGA_NAME11	STATE	Canopy Heat	Health	Economic	Green gain	Vulnerable pop	Total	Risk Level
20570	Ballarat, City of	Ballarat	VIC	0	1	0	0	0	1	0.5
21890	Darebin, City of	Darebin	VIC	1	0	0	0	0	1	0.5
23270	Hume, City of	Hume	VIC	0	0	0	0	1	1	0.5
41060	Charles Sturt, City of	Charles Sturt (C)	SA	0	0	0	0	1	1	0.5
42030	Gawler, Town of	Gawler (T)	SA	0	0	0	0	1	1	0.5
45680	Playford, City of	Playford (C)	SA	0	0	0	0	1	1	0.5
45890	Port Adelaide Enfield, City of	Port Adelaide Enfield (C)	SA	0	0	0	0	1	1	0.5
48410	West Torrens, City of	West Torrens (C)	SA	0	0	0	0	1	1	0.5
50490	Belmont, City of	Belmont	WA	0	0	0	1	0	1	0.5
10750	Blacktown, City of	Blacktown	NSW	0	0	0	1	1	2	1
11100	Botany Bay, City of	Botany Bay	NSW	0	0	0	2	0	2	1
11550	Canterbury, City of	Canterbury	NSW	0	0	0	1	1	2	1
13950	Holroyd, City of	Holroyd	NSW	0	0	0	1	1	2	1
16650	Rockdale, City	Rockdale	NSW	0	0	0	2	0	2	1
21180	Brimbank, City of	Brimbank	VIC	0	0	0	1	1	2	1
24330	Maribyrnong, City of	Maribyrnong	VIC	1	0	0	0	1	2	1
25250	Moreland, City of	Moreland	VIC	1	0	0	1	0	2	1
44060	Marion, City of	Marion (C)	SA	1	0	0	0	1	2	1
47140	Salisbury, City of	Salisbury (C)	SA	0	0	0	1	1	2	1
54830	Kwinana, City of	Kwinana	WA	0	0	1	0	1	2	1
64010	Launceston, City of	Launceston	TAS	1	0	0	1	0	2	1
10200	Auburn City	Auburn	NSW	0	0	0	2	1	3	1.5
10350	Bankstown, City	Bankstown	NSW	1	0	0	1	1	3	1.5
11500	Campbelltown, City of	Campbelltown (C)	NSW	1	0	0	1	1	3	1.5
12850	Fairfield, City	Fairfield	NSW	0	0	0	2	1	3	1.5
14900	Liverpool, City of	Liverpool	NSW	0	0	1	1	1	3	1.5
22170	Frankston, City of	Frankston	VIC	1	1	0	1	0	3	1.5
22620	Greater Bendigo, City of	Greater Bendigo	VIC	1	1	0	1	0	3	1.5
22670	Greater Dandenong, City of	Greater Dandenong	VIC	1	0	0	1	1	3	1.5
22750	Greater Geelong, City of	Greater Geelong	VIC	0	1	0	1	1	3	1.5
23110	Hobsons Bay, City of	Hobsons Bay	VIC	1	0	1	1	0	3	1.5
24650	Melton, City of	Melton	VIC	0	0	2	0	1	3	1.5
40070	Adelaide Hills Council	Adelaide Hills (DC)	SA	1	0	1	0	1	3	1.5
45340	Onkaparinga, City of	Onkaparinga (C)	SA	0	0	0	2	1	3	1.5
51820	Cockburn, City of	Cockburn	WA	0	0	2	0	1	3	1.5
58510	Victoria Park, Town of	Victoria Park	WA	1	0	1	0	1	3	1.5
61410	Clarence, City of	Clarence	TAS	2	0	0	1	0	3	1.5
62610	Glenorchy, City of	Glenorchy	TAS	2	0	0	1	0	3	1.5
10150	Ashfield, Municipality of	Ashfield	NSW	0	0	1	1	2	4	2
11300	Burwood Council	Burwood	NSW	0	0	0	2	2	4	2
11520	Canada Bay, City of	Canada Bay	NSW	0	1	2	0	1	4	2
15200	Marrickville Council	Marrickville	NSW	0	0	1	2	1	4	2
15900	Newcastle, City of	Newcastle	NSW	1	1	0	1	1	4	2
16250	Parramatta, City of	Parramatta	NSW	1	0	0	2	1	4	2
17100	Strathfield, Municipality of	Strathfield	NSW	0	1	1	0	2	4	2
25060	Moonee Valley, City of	Moonee Valley	VIC	0	1	1	1	1	4	2
27070	Whittlesea, City of	Whittlesea	VIC	1	0	1	1	1	4	2
27260	Wyndham, City of	Wyndham	VIC	0	0	2	1	1	4	2
33960	Ipswich, City of	Ipswich	QLD	1	0	0	2	1	4	2
34590	Logan City	Logan	QLD	1	0	1	1	1	4	2
36910	Toowoomba Regional Council	Toowoomba	QLD	1	1	0	2	0	4	2
40910	Campbelltown, City of	Campbelltown	SA	1	0	1	1	1	4	2
42600	Holdfast Bay, City of	Holdfast Bay (C)	SA	1	1	1	0	1	4	2
50350	Bassendean, Town of	Bassendean	WA	0	1	1	2	0	4	2
58050	Swan, City of	Swan	WA	1	0	2	0	1	4	2
58760	Wanneroo, City of	Wanneroo	WA	0	0	2	1	1	4	2
71000	Darwin, City of	Darwin	NT	1	0	2	0	1	4	2
14150	Hurstville, City of	Hurstville	NSW	1	0	1	1	2	5	2.5
16350	Penrith, City of	Penrith	NSW	1	0	1	2	1	5	2.5
16550	Randwick, City of	Randwick	NSW	0	1	1	2	1	5	2.5
22310	Glen Eira, City of	Glen Eira	VIC	1	2	2	0	0	5	2.5
23430	Kingston, City of	Kingston	VIC	1	2	2	0	0	5	2.5
26350	Stonnington, City of	Stonnington	VIC	1	2	1	0	1	5	2.5
32070	Cairns Regional Council	Cairns	QLD	1	1	0	2	1	5	2.5
45290	Norwood Payneham & St Peters, City of	Norwood Payneham St Peters (C)	SA	1	0	1	2	1	5	2.5
46510	Prospect, City of	Prospect (C)	SA	1	1	1	1	1	5	2.5
50210	Armadale, City of	Armadale	WA	1	0	1	2	1	5	2.5
53430	Fremantle, City of	Fremantle	WA	1	0	1	2	1	5	2.5
53780	Gosnells, City of	Gosnells	WA	1	0	2	1	1	5	2.5
57080	Perth, City of	Perth	WA	1	1	1	0	2	5	2.5
57490	Rockingham, City of	Rockingham	WA	0	1	2	1	1	5	2.5
72800	Palmerston, City of	Palmerston	NT	1	0	2	1	1	5	2.5
11450	Camden Council	Camden	NSW	0	2	2	1	1	6	3
17200	Sydney, City of	Sydney	NSW	0	1	1	2	2	6	3
20660	Banyule, City of	Banyule	VIC	2	2	2	0	0	6	3
21610	Casey, City of	Casey	VIC	0	1	2	2	1	6	3
24410	Maroondah, City of	Maroondah	VIC	2	2	2	0	0	6	3
25900	Port Phillip, City of	Port Phillip	VIC	1	2	1	1	1	6	3
35010	Moreton Bay Region	Moreton Bay	QLD	1	1	2	1	1	6	3
36710	Sunshine Coast	Sunshine Coast	QLD	1	1	2	1	1	6	3
47980	Unley, City of	Unley (C)	SA	2	1	2	0	1	6	3
48260	Walkerville, Town of	Walkerville (M)	SA	2	1	2	0	1	6	3
50420	Bayswater, City of	Bayswater	WA	1	0	2	2	1	6	3
51310	Cambridge, Town of	Cambridge	WA	1	2	2	0	1	6	3
53150	East Fremantle, Town of	East Fremantle	WA	1	2	2	0	1	6	3
55320	Melville, City of	Melville	WA	1	2	2	0	1	6	3
57910	Stirling, City of	Stirling	WA	1	1	2	1	1	6	3
63610	Kingborough Council	Kingborough	TAS	2	1	2	1	0	6	3
14100	Hunter's Hill, Municipality of	Hunters Hill	NSW	2	2	2	0	1	7	3.5
14450	Kogarah, City of	Kogarah	NSW	1	1	2	1	2	7	3.5
15150	Manly Council	Manly	NSW	2	2	2	1	0	7	3.5
16370	Pittwater Council	Pittwater	NSW	2	2	2	1	0	7	3.5
16700	Ryde, City of	Ryde	NSW	1	2	2	1	1	7	3.5
17420	The Hills Shire	The Hills Shire	NSW	1	2	2	1	1	7	3.5
18000	Warringah Council	Warringah	NSW	2	2	2	1	0	7	3.5
18050	Waverley Council	Waverley	NSW	1	2	2	2	0	7	3.5

LGA_CODE1	NAME	LGA_NAME11	STATE	Canopy Heat	Health	Economic	Green gain	Vulnerable pop	Total	Risk Level
21110	Boroondara, City of	Boroondara	VIC	2	2	2	0	1	7	3.5
21450	Cardinia, Shire of	Cardinia	VIC	1	2	2	1	1	7	3.5
24600	Melbourne, City of	Melbourne	VIC	1	2	1	1	2	7	3.5
24970	Monash, City of	Monash	VIC	1	2	2	0	2	7	3.5
25340	Mornington Peninsula, Shire of	Mornington Peninsula	VIC	2	2	2	0	1	7	3.5
33430	Gold Coast City	Gold Coast	QLD	1	1	2	1	2	7	3.5
36250	Redland City	Redland	QLD	1	1	2	1	2	7	3.5
37010	Townsville City Council	Townsville	QLD	1	1	2	2	1	7	3.5
54170	Joondalup, City of	Joondalup	WA	1	2	2	0	2	7	3.5
55740	Mosman Park, Town of	Mosman Park	WA	1	2	2	1	1	7	3.5
56580	Nedlands, City of	Nedlands	WA	1	2	2	1	1	7	3.5
57840	South Perth, City of	South Perth	WA	1	2	2	1	1	7	3.5
57980	Subiaco, City of	Subiaco	WA	2	2	1	1	1	7	3.5
58570	Vincent, City of	Vincent	WA	1	1	2	2	1	7	3.5
62810	Hobart, City of	Hobart	TAS	2	2	1	1	1	7	3.5
89399	ACT	Unincorporated ACT	ACT	1	2	2	1	1	7	3.5
14700	Lane Cove, Municipality of	Lane Cove	NSW	2	2	2	2	0	8	4
14800	Leichhardt, Municipality of	Leichhardt	NSW	1	2	2	2	1	8	4
15950	North Sydney Council	North Sydney	NSW	2	2	2	1	1	8	4
17150	Sutherland Shire	Sutherland Shire	NSW	2	2	2	2	0	8	4
18250	Willoughby, City of	Willoughby	NSW	2	2	2	1	1	8	4
24210	Manningham, City of	Manningham	VIC	2	2	2	0	2	8	4
26980	Whitehorse, City of	Whitehorse	VIC	2	2	2	1	1	8	4
27350	Yarra, City of	Yarra	VIC	2	1	1	2	2	8	4
31000	Brisbane, City of	Brisbane	QLD	1	2	2	1	2	8	4
40700	Burnside, City of	Burnside (C)	SA	2	2	2	1	1	8	4
51330	Canning, City of	Canning	WA	1	1	2	2	2	8	4
52170	Cottesloe, Town of	Cottesloe	WA	1	2	2	2	1	8	4
54200	Kalamunda, Shire of	Kalamunda	WA	2	2	2	1	1	8	4
56090	Mundaring, Shire of	Mundaring	WA	1	2	2	1	2	8	4
56930	Peppermint Grove, Shire of	Peppermint Grove	WA	2	2	2	0	2	8	4
14000	Hornsby Shire	Hornsby	NSW	2	2	2	1	2	9	4.5
14500	Ku-ring-gai Council	Ku-ring-gai	NSW	2	2	2	1	2	9	4.5
15350	Mosman, Municipality of	Mosman	NSW	2	2	2	2	1	9	4.5
18500	Woollahra, Municipality of	Woollahra	NSW	2	2	2	2	1	9	4.5
20910	Bayside, City of	Bayside	VIC	2	2	2	2	1	9	4.5
23670	Knox, City of	Knox	VIC	2	2	2	1	2	9	4.5
25710	Nillumbik, Shire of	Nillumbik	VIC	2	2	2	1	2	9	4.5
27450	Yarra Ranges, Shire of	Yarra Ranges	VIC	2	2	2	2	1	9	4.5
40120	Adelaide, City of	Adelaide (C)	SA	1	2	2	2	2	9	4.5
44340	Mitcham, City of	Mitcham (C)	SA	2	2	2	2	1	9	4.5
47700	Tea Tree Gully, City of	Tea Tree Gully (C)	SA	2	1	2	2	2	9	4.5
51750	Claremont, Town of	Claremont	WA	2	2	2	2	1	9	4.5