



UNIVERSITY OF TASMANIA | NATIONAL DISASTER RISK REDUCTION GRANT

Greater Hobart and Launceston Community Heatwave Risk

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1 INTRODUCTION

Heatwaves pose significant risks to human health, infrastructure, and ecosystems, particularly in urban environments where high population density and impervious surfaces can exacerbate temperature extremes. As climate change progresses, the frequency, duration, and intensity of heatwaves are expected to increase, underscoring the importance of understanding, and addressing heatwave risks in our communities.

This report presents a detailed analysis of heatwave community risk in selected suburbs across five Local Government Associations (LGAs) in Tasmania: Clarence, Glenorchy, Hobart, Kingborough, and Launceston. The study, a collaboration between the University of Tasmania and local authorities, is funded by the National Disaster Risk Reduction Grant. It aims to identify areas of higher vulnerability to heatwaves by considering factors such as tree canopy cover, land surface temperature, and social vulnerability. A key component of this report is the correlation analysis between tree canopy cover and land surface temperature, which provides valuable insights into the potential benefits of increasing green infrastructure in urban areas to reduce heat-related risks. This comprehensive assessment will help inform targeted interventions and investments to enhance community resilience and support vulnerable populations during extreme heat events.

In addition to mapping heatwave risk, this report also identifies and maps outdoor refuges - areas where temperatures are expected to be lower during extreme heat days. These refuges can provide valuable insights for future heatwave mitigation and adaptation planning.

By enhancing our understanding of heatwave risks and identifying areas of higher vulnerability, this study aims to support the development of more resilient communities and protect the health and well-being of our most vulnerable populations.

2 AREA OF INTEREST

The area of interest for this study includes selected suburbs within five Local Government Associations (LGAs) in Tasmania: Clarence, Glenorchy, Hobart, Kingborough, and Launceston. These suburbs were chosen to represent a diverse range of urban environments and community characteristics. The selected suburbs within each LGA are presented in alphabetical order in the lists below.

2.1 Clarence

Table 1 and **Figure 1** illustrate the selected suburbs within Clarence that were considered in this study.

Table 1: List of selected suburbs in the Clarence LGA.

SUBURB
BELLERIVE
CLARENDON VALE
HOWRAH
LINDISFARNE
MONTAGU BAY
MORNINGTON
OAKDOWNS
ROKEBY
ROSNY
ROSNY PARK
ROSE BAY
TRANMERE
WARRANE

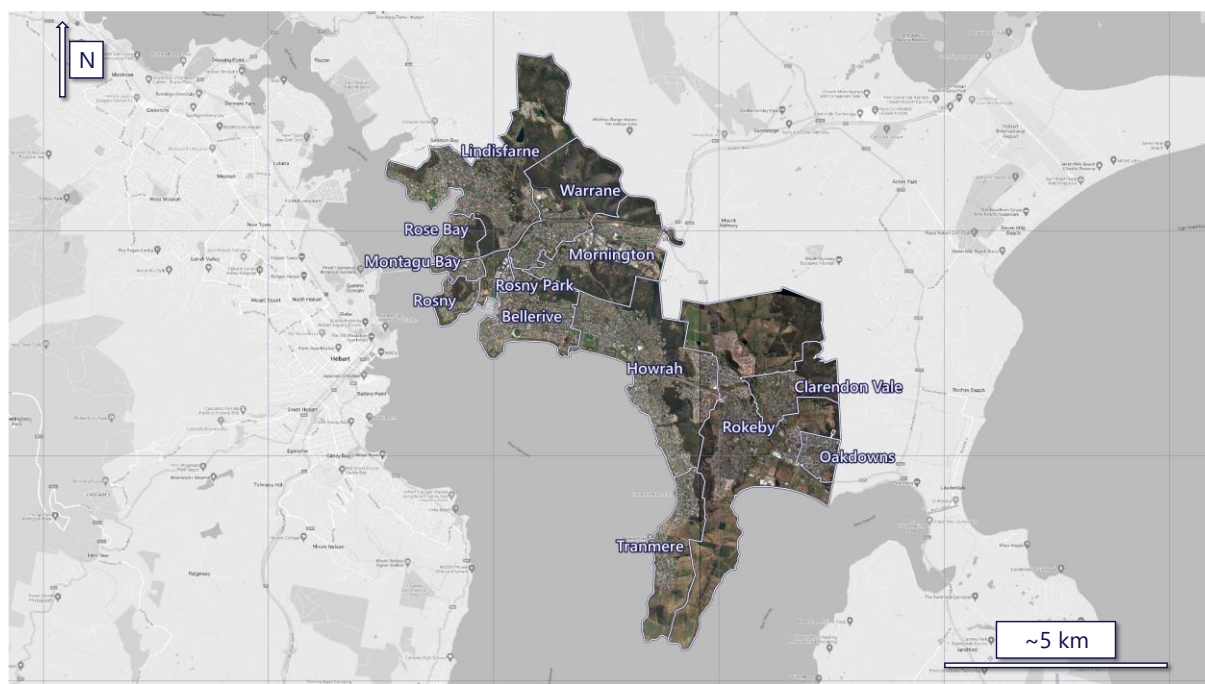


Figure 1: Map of selected suburbs in the Clarence LGA.

2.2 Glenorchy

Refer to [Table 2](#) and [Figure 2](#) for the selected suburbs in Glenorchy analysed in this study.

Table 2: List of selected suburbs in the Glenorchy LGA.

SUBURB
AUSTINS FERRY
BERRIEDALE
CHIGWELL
CLAREMONT
DERWENT PARK
DOWSING POINT
GLENORCHY
GOODWOOD
LUTANA
MONTROSE
MOONAH
ROSETTA
WEST MOONAH

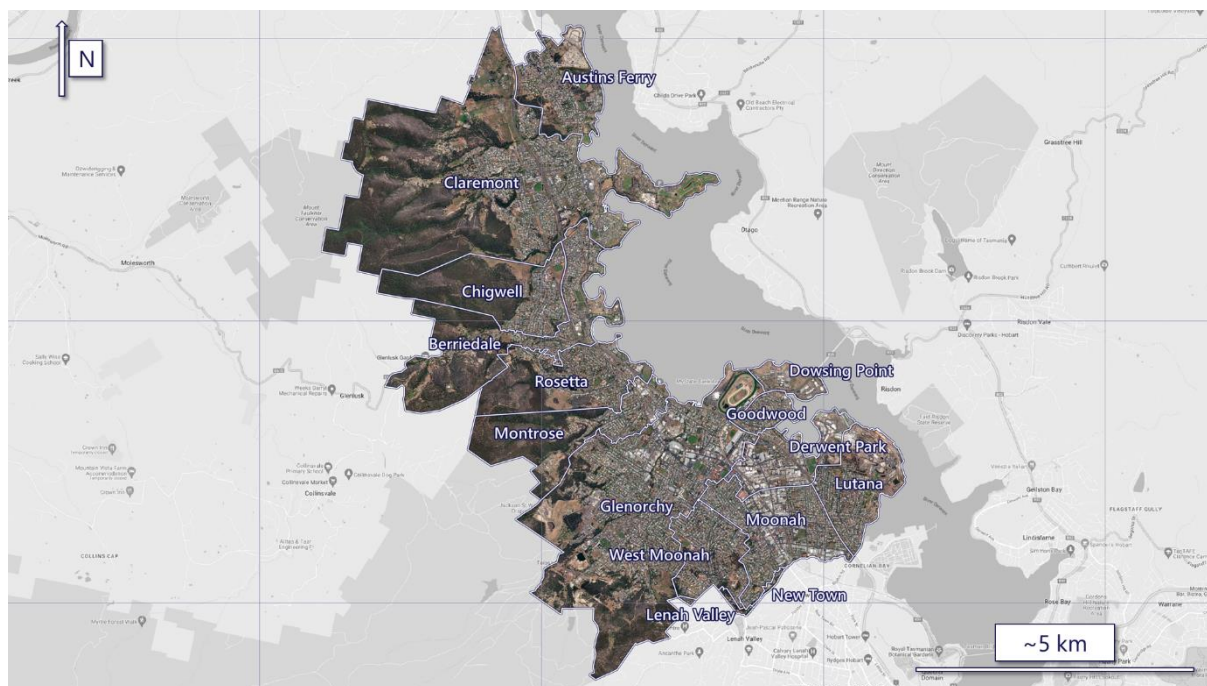


Figure 2: Map of selected suburbs in the Glenorchy LGA.

2.3 Hobart

The chosen suburbs within Hobart for this study can be found in [Table 3](#) and [Figure 3](#).

Table 3: List of selected suburbs in the Hobart LGA.

SUBURB
BATTERY POINT
DYNNYRNE
GLEBE
HOBART
LENAH VALLEY
MOUNT STUART
NEW TOWN
NORTH HOBART
QUEENS DOMAIN
SANDY BAY
SOUTH HOBART
WEST HOBART

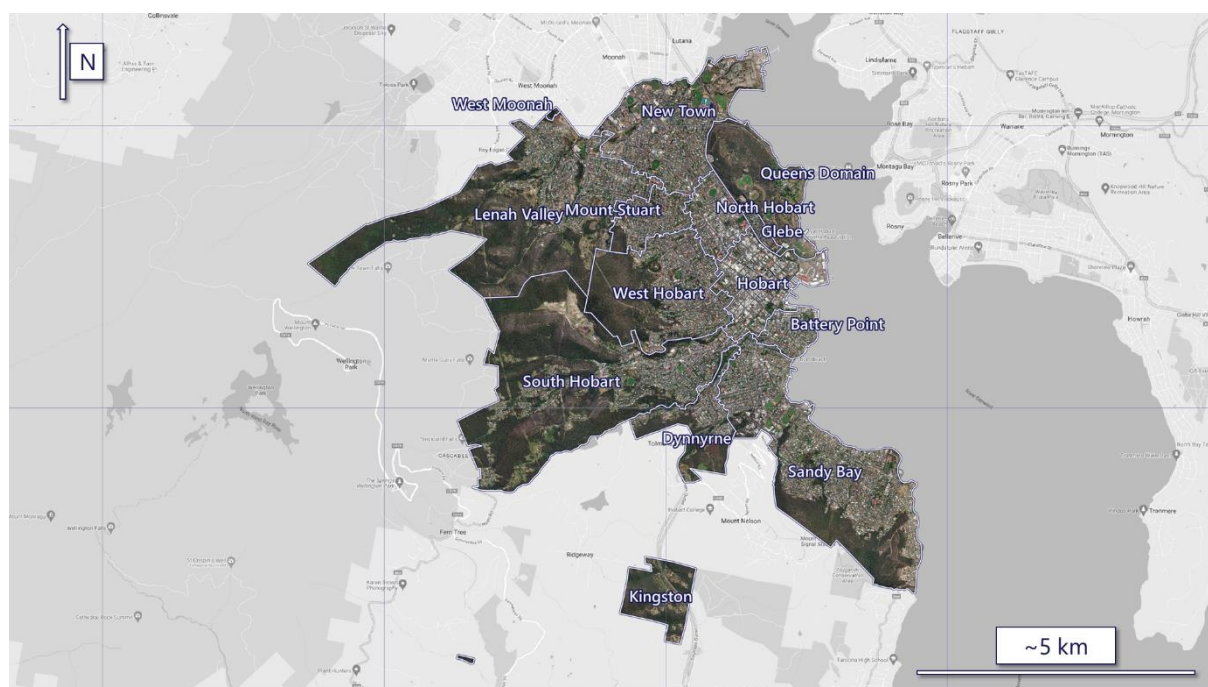


Figure 3: Map of selected suburbs in the Hobart LGA.

2.4 Kingborough

Table 4 and Figure 4 display the selected suburbs in Kingborough considered in this study.

Table 4: List of selected suburbs in the Kingborough LGA.

SUBURB
BLACKMANS BAY
KINGSTON
KINGSTON BEACH
TAROONA

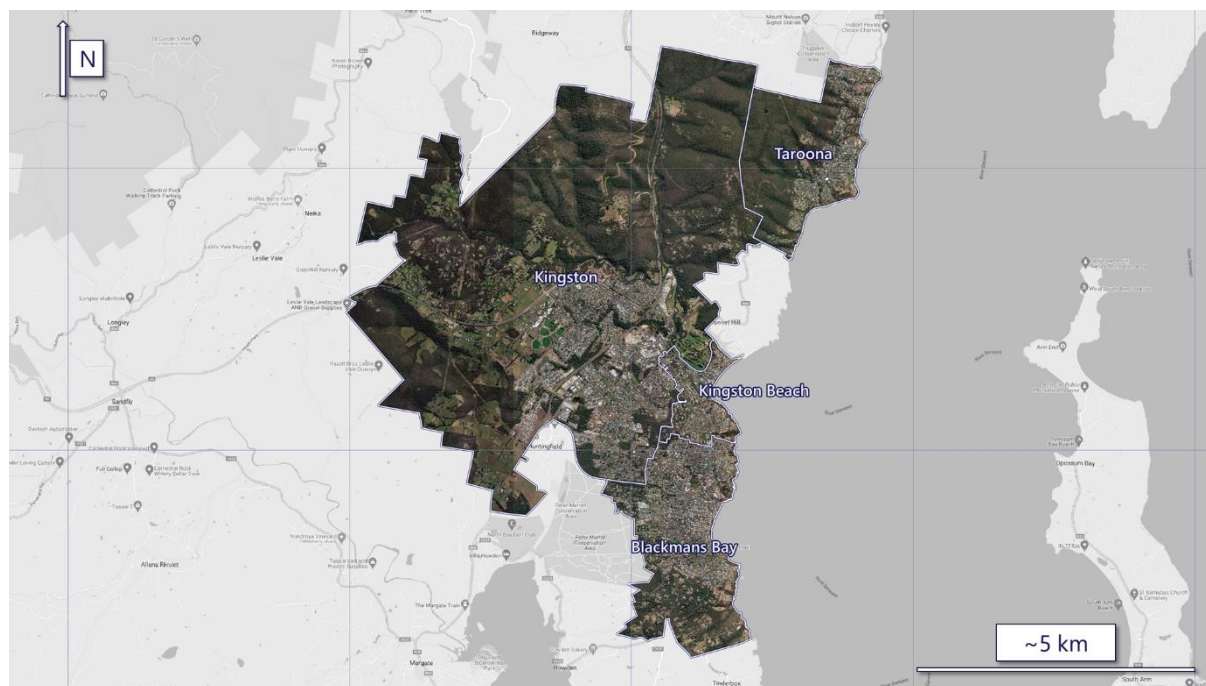


Figure 4: Map of selected suburbs in the Kingborough LGA.

2.5 Launceston

See [Table 5](#) and [Figure 5](#) for the specific suburbs within Launceston examined in this study.

Table 5: List of selected suburbs in the Launceston LGA.

SUBURB
EAST LAUNCESTON
INVERMAY
KINGS MEADOWS
LAUNCESTON
MAYFIELD
MOWBRAY
NEWNHAM
NEWSTEAD
NORWOOD
PUNCHBOWL
SOUTH LAUNCESTON
TREVALLYN
WEST LAUNCESTON

SUBURB
YOUNGTOWN

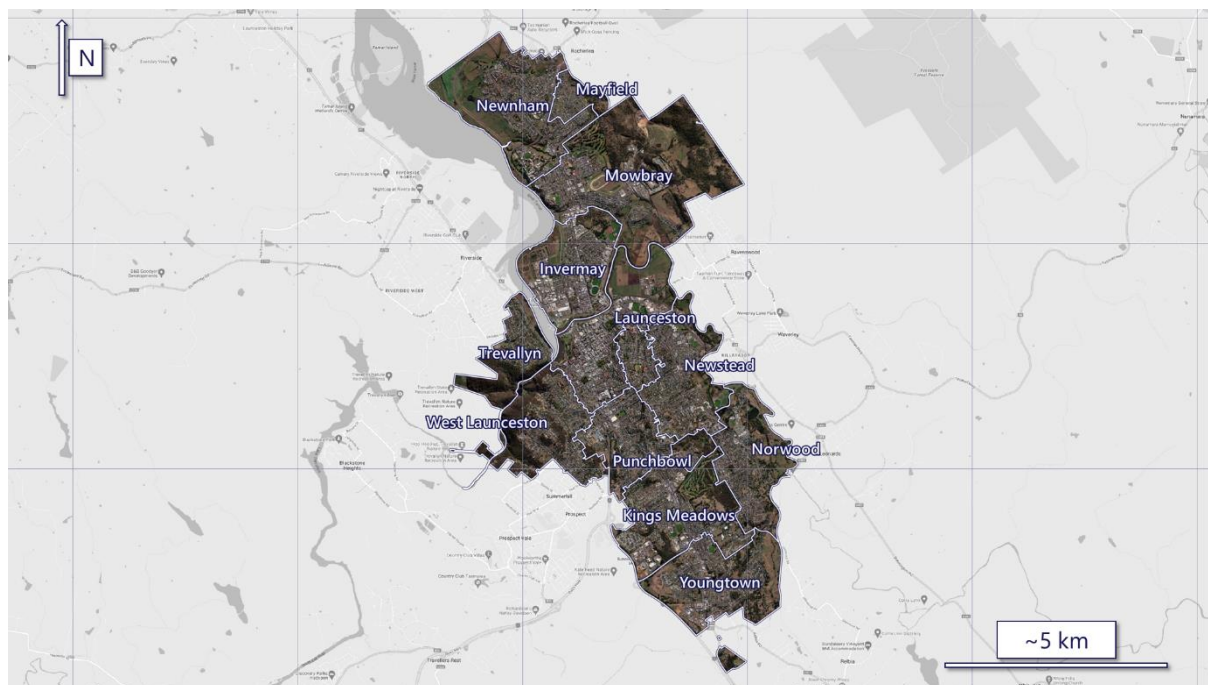


Figure 5: Map of selected suburbs in the Launceston LGA.

3 DATA

In this section, we describe the various datasets used in the study and their characteristics. The data sources included the LIST, MAXAR WorldView satellite imagery, Landsat 8 imagery, and Australian Bureau of Statistics (ABS) census data. These datasets were employed to analyse tree canopy cover, buildings, land surface temperature, and social vulnerability in the study area.

3.1 The LIST Data

The Land Information System Tasmania (LIST) is a comprehensive geospatial data platform maintained by the Tasmanian Government. The LIST provides access to a wide range of spatial datasets and mapping services related to land administration, environmental management, and other areas of interest in Tasmania.

For this study, we utilised the LIST data to obtain accurate Local Government Association (LGA) and suburb boundaries. These boundaries were essential for delineating the area of interest and ensuring that our analysis was focused on the selected suburbs within each LGA.

3.2 WorldView Data

WorldView satellite data was sourced to cover the entire area of interest ([Table 6](#)). WorldView data is characterised by high-resolution multispectral imagery, with a spatial resolution of approximately 0.3 to 0.5 meters for the panchromatic band and 1.2 to 2 meters for the multispectral bands. This high-resolution imagery enables detailed analysis of various land cover types, including tree canopy and buildings.

The WorldView data was utilised to map tree canopy cover and building footprints within the study area. By leveraging the high-resolution imagery, we were able to identify and classify these features with greater accuracy compared to coarser resolution datasets.

Table 6: WorldView Data Acquisition Dates.

AREA	ACQUISITION DATE 1	ACQUISITION DATE 2
CLARENCE	2022-01-22	---
GLENORCHY	2022-02-08	---
HOBART	2022-01-22	---
KINGBOROUGH	2022-01-20	2022-03-12
LAUNCESTON	2021-04-17	---

3.3 Landsat Data

We sourced Landsat 8 satellite data to analyse land surface temperature (LST) within the study area. Landsat 8 data offers moderate spatial resolution (30 meters) and includes multiple spectral bands

suitable for various remote sensing applications, including the thermal infrared bands necessary for LST analysis.

Landsat data was processed to derive land surface temperature for the study area. The data was acquired for two periods: December 2020 to March 2021 and December 2021 to March 2022. This allowed us to assess the temporal variability in LST during the hottest months of the year and its relationship with other factors such as tree canopy cover and social vulnerability.

3.4 Australian Bureau of Statistics (ABS) Data

To assess social vulnerability, we utilised census data from the Australian Bureau of Statistics (ABS). The ABS provides comprehensive demographic, social, and economic data from the Australian Census, which is conducted every five years. For this study, we used the 2021 Census data for the population ages and the 2016 Census data for the socio-economic metrics, as the 2021 socio-economic data was not available at the time of analysis.

The ABS data offers various indicators related to population characteristics, such as age, income, education, and employment status, which can be used to assess social vulnerability. In our analysis, we specifically focused on population age data to estimate the number of children under 5 years old and people aged 65 years or older. These age groups are generally considered more vulnerable to heat-related health risks. Additionally, we used the Socio-Economic Indexes for Areas (SEIFA) Index of Relative Socio-economic Advantage and Disadvantage (IRSAD) to assess the overall socio-economic vulnerability of the study area.

By integrating ABS data with our spatial analysis, we were able to identify areas with higher social vulnerability, accounting for both age distribution and socio-economic factors. This allowed us to examine the relationship between social vulnerability and heatwave impacts and develop targeted strategies for mitigating heatwave community risk.

4 DEEP LEARNING SEGMENTATION

In this study, deep learning segmentation techniques were employed to identify and map tree canopy and buildings within the selected suburbs. Deep learning segmentation is a process that leverages advanced neural networks to classify and delineate features within high-resolution satellite imagery.

The use of deep learning segmentation techniques enabled us to accurately identify and map tree canopy and buildings within our study area. These detailed maps provided essential inputs for our spatial analysis, allowing us to examine the relationship between urban environments, heatwave impacts, and community vulnerability.

4.1 Tree Canopy Segmentation

To identify and segment tree canopy, we used a deep learning model specifically designed to recognise vegetation within high-resolution WorldView satellite imagery. The model was trained on a large dataset of labelled images, where tree canopy areas were annotated to provide the model with examples to learn from. By analysing patterns and features within these training images, the model was able to generalise and recognise tree canopy areas in the imagery.

The deep learning model was applied to the WorldView data for each suburb within our area of interest. As a result, we obtained detailed tree canopy maps (**Figure 6**), which enabled us to analyse the distribution of tree canopy cover across the selected suburbs and assess its relationship with land surface temperature. This layer can also be used to target mitigation measures.



Figure 6: Example of tree canopy segmentation results using deep learning techniques.

4.2 Building Segmentation

For building segmentation, we employed a deep learning model specifically tailored to identify and delineate building footprints within high-resolution WorldView satellite imagery. The model was trained on a large dataset of labelled images, where building footprints were annotated to provide the model with examples to learn from. By analysing patterns and features within these training images, the model was able to generalise and recognise buildings in the imagery.

The deep learning model was applied to the WorldView data for each suburb within our area of interest. The resulting building maps (Figure 7) allowed us to analyse the distribution of residential buildings and assess their relationship with land surface temperature and social vulnerability.



Figure 7: Example of building segmentation results using deep learning techniques.

5 INDICES

In our study, we generated and mapped four indices to assess and visualize the relationships between urban heat, social vulnerability, and community risk. These indices include:

1. Social Vulnerability Index.
2. Heat Susceptibility Index.
3. Community Heat Exposure Index.
4. Community Heat Risk Index.

By generating and mapping these four indices, we can better understand the relationships between urban heat, social vulnerability, and community risk, and inform policy development, resource allocation, and research for mitigating heat-related hazards.

5.1 Social Vulnerability Index

The Social Vulnerability Index was calculated using Geoneon's Social Vulnerability Index formula, which combines the Index of Relative Socio-economic Advantage and Disadvantage (IRSAD) and our Vulnerable Population Index where the number of people living in a dwelling aged less than 5 years old or more than 65 years old are sorted into classes from 1 to 10 using the Jenks natural breaks algorithm. (Figure 8). The formula assigns higher scores to dwellings with lower IRSAD scores, more children under 5, and more adults over 65. The resulting score can be used to identify dwellings that may be more vulnerable to natural disasters. The result of the below equation is then sorted into sorted into 10 classes using natural breaks to give a final Social Vulnerability Index from 1 to 10.

$$\text{Social Vulnerability Index} = 11 - \text{IRSAD} + \text{Vulnerable Population Index}$$

This formula assigns higher scores to dwellings with lower IRSAD scores, more children under 5, and more adults over 65, which are all factors that may increase the vulnerability of a dwelling to natural disasters. The resulting score can be used to identify dwellings that may be more vulnerable to natural disasters and prioritize resources for disaster preparedness and response.

It is important to note that this is just one possible formula for calculating social vulnerability to natural disasters per parcel, and there may be other factors or variables that could be included in the calculation depending on the specific context and goals of the analysis.



Figure 8: Social Vulnerability Index - A map showcasing the distribution of social vulnerability in the study area, with purple colour indicating higher vulnerability due to socio-economic factors and population age.

5.2 Heat Susceptibility Index

The Heat Susceptibility Index was generated using Landsat 8 data and various LST (Land Surface Temperature) calculation methods from different papers (Avdan & Jovanovska, 2016; Wang et al., 2015) (Figure 9). The calculation process involved three main steps:

1. Calculating brightness temperature, calculating emissivity, and calculating LST.
2. We then clipped each LST image to the area of interest, split the images into seasons, and produced a new median image for each season.
3. The resulting images were split into five classes based on percentiles.

The two attributes used for this study are:

- **Median Temperature:** The observed median land surface temperature across the region during summer months, measured in degrees Celsius (°C).
- **Heat Susceptibility Index:** An index ranging from low to high (1 to 5), representing the degree to which an area is susceptible to heat-related events based on the observed median temperature.

It is important to note the limitations of using Landsat 8 data for LST analysis, such as the sun-synchronous orbit causing each image to be taken at the same time of day and the effect of highly reflective surfaces on LST measurements. In the studied areas of Tasmania, this corresponds to 10 am/11 am – i.e., in standard/daylight savings time, respectively. As a result, we do not obtain a comprehensive understanding of temperature fluctuations throughout the day but do gain valuable

insights into relative morning temperatures across the year. The timing of the images can lead to certain areas where the landscape's topography influences temperature readings. For instance, this is noticeable in East Launceston, where the temperature gradient between the warmer east-facing slopes and the cooler west-facing slopes to the west distinctly aligns with the hill's topography. This is likely due to the sun's eastward rise, which warms the east-facing slopes earlier in the day.

Despite these limitations, LST measurements are still useful for assessing temperatures at city-wide scales.

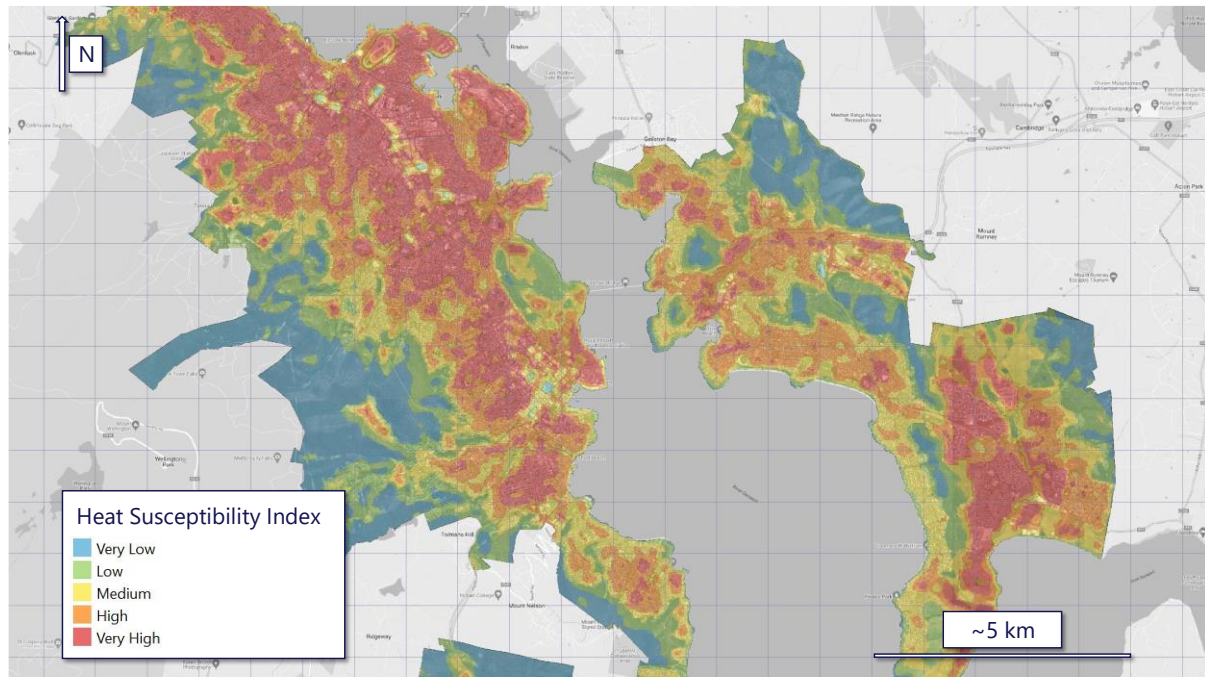


Figure 9: Heat Susceptibility Index - A visual representation of the land surface temperature distribution in the study area, illustrating areas with higher and lower heat susceptibility.

5.3 Community Heat Exposure Index

The Community Heat Exposure Index represents the intersection of the Heat Susceptibility Index and residential, aged care, and health facility buildings (Figure 10). This index provides insight into the relative temperature levels that may be experienced in these buildings, which are crucial for understanding heat-related hazards within a community.

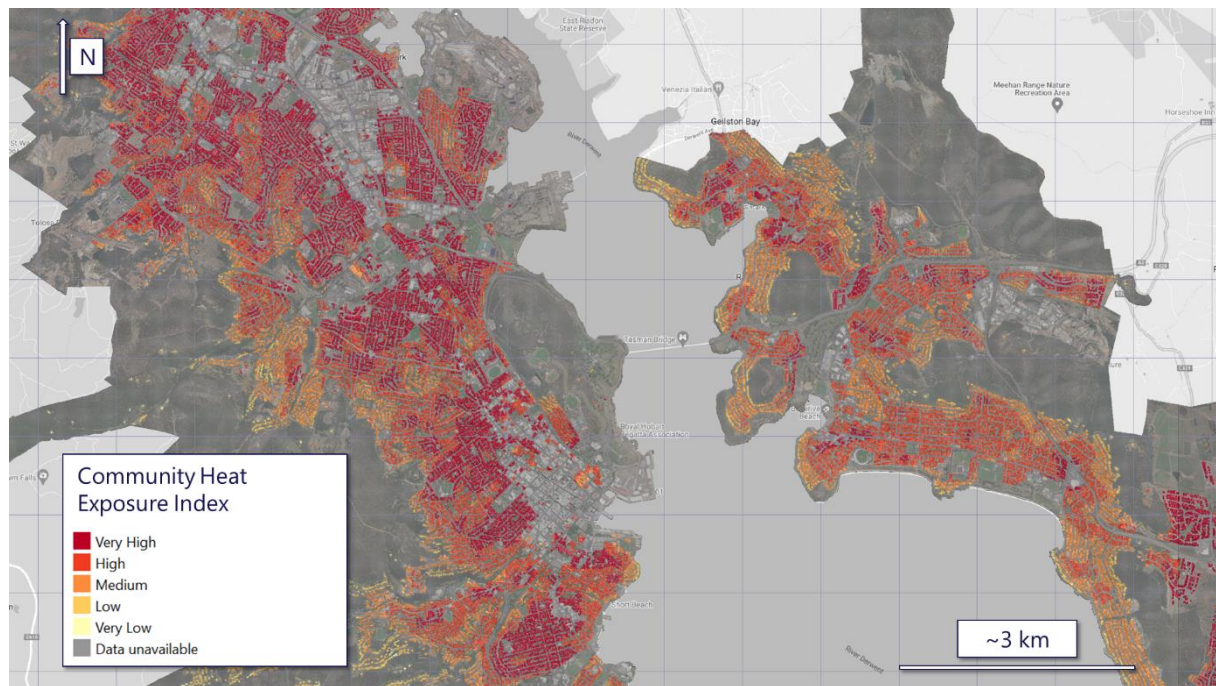


Figure 10: Community Heat Exposure Index - A spatial representation of the potential heat exposure in residential, aged care, and health facility buildings within the study area, highlighting areas with higher exposure to extreme heat.

5.4 Community Heat Risk Index

We employed the Jenks natural breaks method to create the Community Heat Risk Index, which combines the Community Heat Exposure Index with vulnerable population data and IRSAD data to map areas where more vulnerable communities face heat-related hazards (Figure 11). The index is created using a combination of the Vulnerable Population Index, IRSAD Index, and LST Index. The resulting index ranges from 1 to 10, where higher scores indicate higher risk.

It is essential to consider the limitations of these indices, such as potential missing or misclassified buildings and the use of natural breaks algorithm that may affect the comparability of classes between different areas or time periods. Another important limitation to consider is the varying resolutions of each input dataset. Different spatial resolutions can influence the level of detail captured and the precision of the results.

By generating and mapping these four indices, we can better understand the relationships between urban heat, social vulnerability, and community risk, and inform policy development, resource allocation, and research for mitigating heat-related hazards.

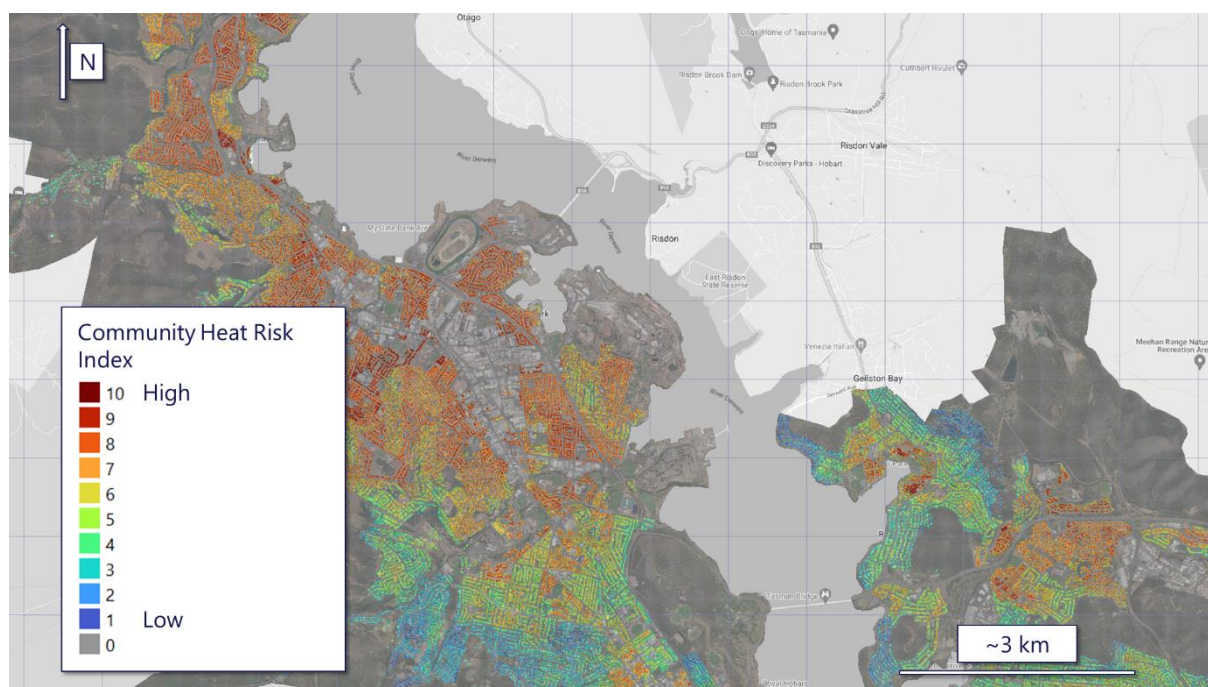


Figure 11: Community Risk Index - A comprehensive map depicting the combined risk of heat exposure and social vulnerability in the study area, with darker colours representing areas with a higher risk of heat-related hazards.

6 ANALYTICS

This section presents an analysis of the data collected, focusing on the residential building areas and their distribution across the different risk index classes, as well as the correlation between tree canopy cover and land surface temperature (LST). The results are visualised in three ways:

- Correlation between tree canopy cover and LST.
- Absolute area in square kilometres of residential building area in each suburb.
- Relative area as a percentage of the total residential building area in each suburb.

6.1 Correlation Analysis: Tree Canopy and Land Surface Temperature

A critical aspect of our study is to understand the relationship between tree canopy cover and land surface temperature (LST) across the study area. To investigate this relationship, we conducted a correlation analysis using the 30-metre resolution LST image and tree canopy coverage. In the graph, the x-axis represents the percentage of tree canopy cover per 30 metre LST pixel, while the y-axis shows the actual temperature of that pixel ([Figure 12](#)).

We employed a simple linear regression model to quantify the relationship between tree canopy cover and LST. Our analysis revealed a strong and statistically significant negative correlation between tree canopy cover and land surface temperature. As the percentage of tree canopy cover per pixel increases, the LST of that pixel tends to decrease, indicating that areas with higher tree canopy coverage have cooler surface temperatures.

Based on the linear regression fit, starting at approximately 26 degrees Celsius, every 1% increase in tree cover results in a ~0.06 degree decrease in temperature. This translates to a 6.22 degree decrease in temperature between 0% and 100% tree cover.

This correlation underscores the importance of incorporating green infrastructure and tree planting initiatives in urban planning and development. Such measures can contribute to reducing heat exposure in communities and improving their overall resilience to heatwaves. By understanding the relationship between tree canopy and LST, we can better inform strategies for mitigating heat-related risks and enhancing the overall well-being of residents in the studied suburbs.

6.2 Risk Class per Absolute Area of Residential Buildings

[Figure 13](#) displays the absolute area of residential buildings in square kilometres for each risk index class. The y-axis represents the suburbs, and the x-axis indicates the number of square kilometres. Suburbs are ranked by the greatest area (in square kilometres) in the highest risk class.

This analysis highlights the distribution of residential building areas in each suburb and their respective risk index classes. By comparing the absolute areas, we can identify which suburbs have the largest areas of high-risk residential buildings, which may require prioritised attention for heatwave mitigation efforts.

6.3 Risk Class per Relative Area of Residential Buildings

Figure 14 presents the relative area of residential buildings in percentage for each risk index class, considering only residential buildings. Each column ranges from 0% to 100%, illustrating the percentage of the residential building area in each risk index class. The suburbs are ranked by the greatest percentage area in the highest risk class.

This visualisation offers a different perspective on the distribution of residential building areas across risk index classes. By examining the relative proportions, we can better understand the overall risk profile of each suburb, as well as identify suburbs with a higher concentration of high-risk residential buildings. This information can be valuable for targeted heatwave adaptation and mitigation strategies in each area.

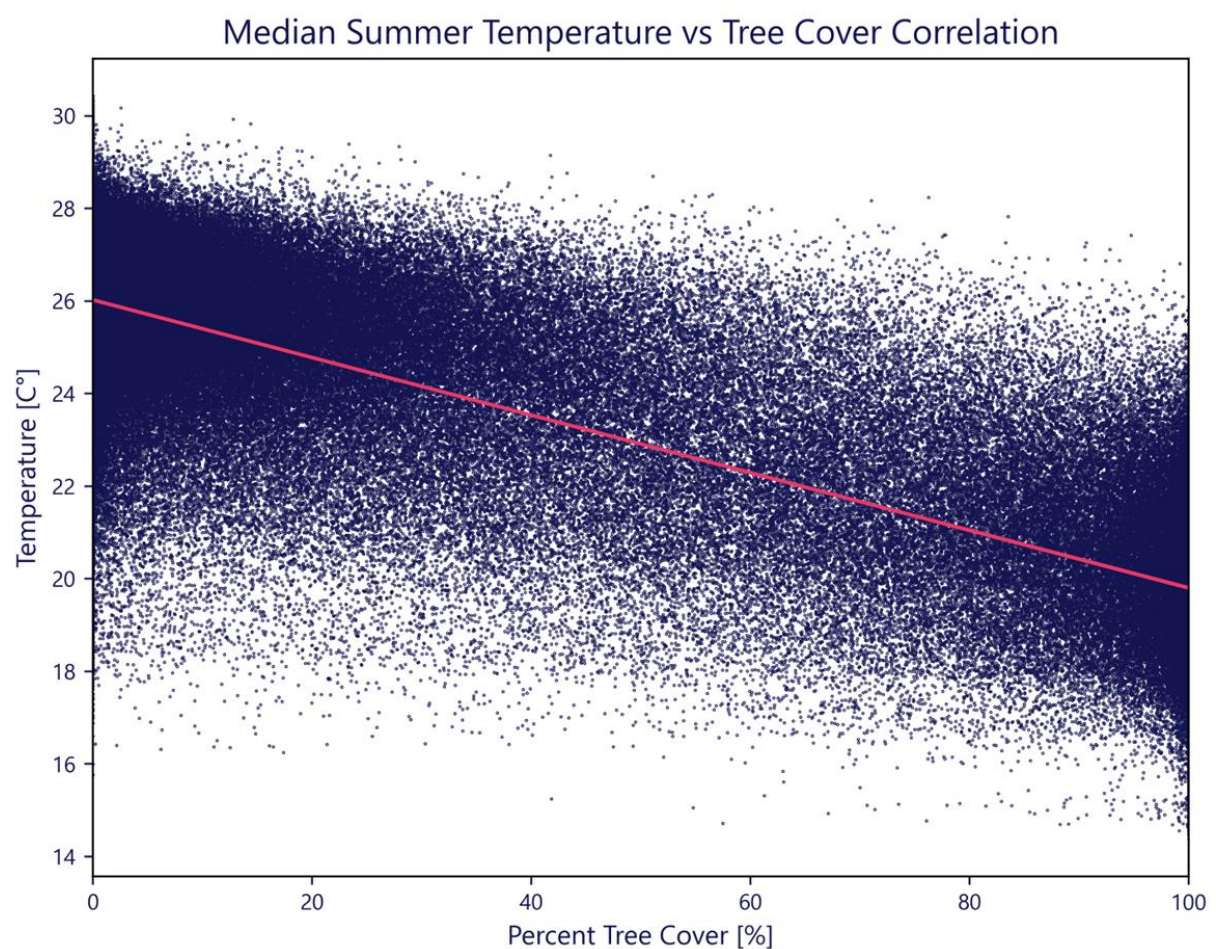


Figure 12: Scatterplot illustrating the correlation between tree canopy cover (%) and land surface temperature (°C) for each 30mx30m pixel in the study area. The linear regression line is overlaid on the scatterplot, showing the negative relationship between tree canopy cover and land surface temperature. This graph demonstrates that as tree canopy cover increases, the land surface temperature tends to decrease, highlighting the potential benefits of increasing green infrastructure in urban areas to mitigate heat-related risks.

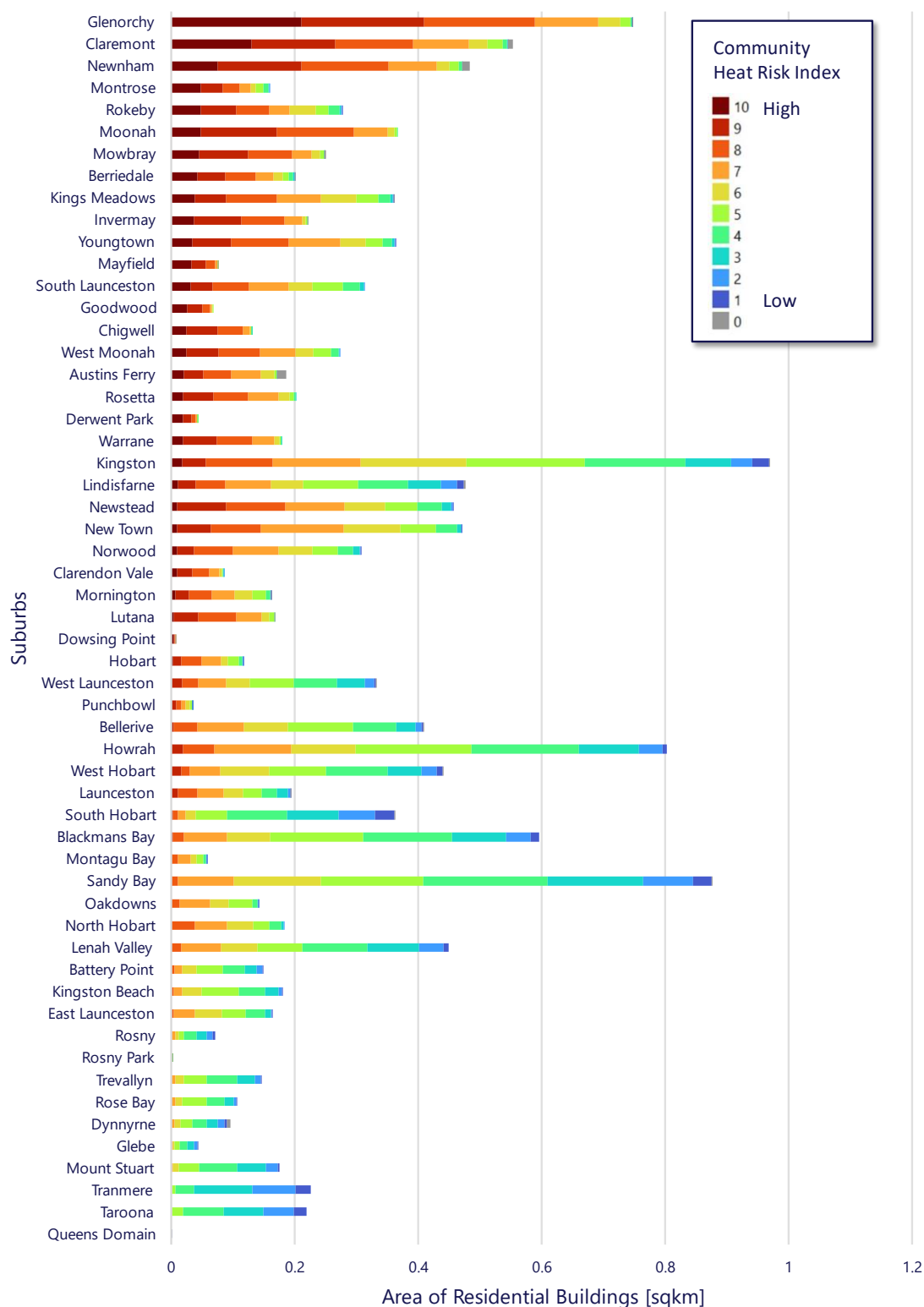


Figure 13: Absolute area of residential buildings in square kilometres for each risk index class.

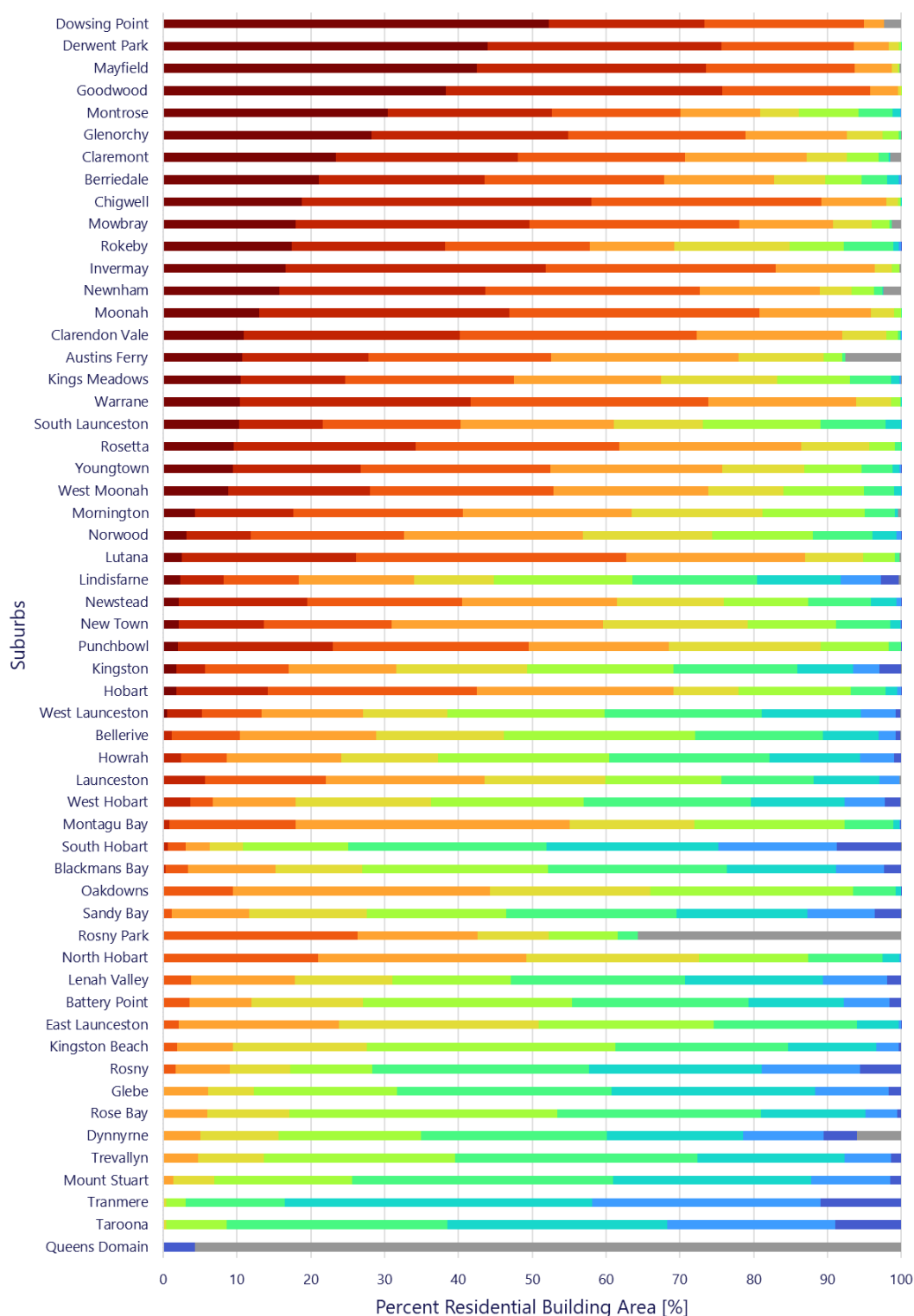


Figure 14: Relative area of residential buildings as a percentage for each risk index class (same legend than Figure 13).

7 MAPPING OUTDOOR REFUGES

Outdoor refuges are essential spaces that can provide relief during extreme heat days. These areas typically have lower temperatures compared to their surroundings, offering a safe haven for individuals, particularly vulnerable populations, to escape the heat. In this study, we have identified and mapped outdoor refuges using an algorithm that focuses on parks and nature reserves with low to moderately low heat susceptibility.

7.1 Mapping Outdoor Refuges

The algorithm used for mapping outdoor refuges (Figure 15) considers factors such as heat susceptibility and land use to determine areas with lower heat susceptibility. By focusing on parks and nature reserves, the algorithm prioritises green spaces that are generally accessible to the public and provide natural cooling effects.

It is essential to note that the map presented below is a preliminary representation of outdoor refuges in the study area. Further detailed analysis could improve the accuracy and comprehensiveness of the refuge identification process, as well as incorporate additional factors that contribute to cooler outdoor spaces.



Figure 15: Preliminary map of outdoor refuges in the study area.

7.2 Expanding Refuge Identification

While this study focuses on outdoor refuges, it is crucial to consider indoor spaces as well, such as libraries, shopping malls, and community centres, where vulnerable populations can take refuge during heatwaves. Incorporating indoor refuges into the analysis would provide a more

comprehensive understanding of the available resources for heatwave mitigation and support the development of targeted strategies to protect vulnerable individuals and communities.

Future studies could expand the refuge identification process by incorporating additional datasets, refining the algorithm, and exploring partnerships with local organisations and businesses to develop a more extensive network of safe spaces for heatwave relief. By doing so, we can enhance the resilience of our communities in the face of extreme heat events and protect those most vulnerable to their impacts.

8 CONCLUSION

This report presents a comprehensive analysis of heatwave community risk in selected suburbs across five Local Government Associations (LGAs) in Tasmania. By considering factors such as tree canopy cover, land surface temperature, and social vulnerability, we have developed a heatwave risk index to assess the potential impacts of extreme heat events on these communities. Our correlation analysis between tree canopy cover and land surface temperature highlights the critical role of green infrastructure in mitigating heat-related risks. The study has also identified and mapped outdoor refuges that can provide respite during heatwaves, offering valuable insights for future heatwave mitigation and adaptation planning.

Our findings emphasize the importance of understanding and addressing the complex interplay of environmental and social factors that contribute to heatwave risk. By identifying areas with higher vulnerability, this study can help inform targeted interventions and investments to enhance community resilience, such as increasing tree canopy cover, improving access to green spaces, and supporting vulnerable populations.

While the maps and data presented in this report provide valuable insights, it is crucial to continue refining and expanding the analysis. Future studies could explore additional datasets, refine the heatwave risk index methodology, and incorporate indoor refuges to develop a more comprehensive understanding of heatwave risks and resources.

In conclusion, this study highlights the urgent need for proactive planning and investment in heatwave mitigation and adaptation measures, particularly in the face of climate change and increasing urbanisation. By working together to understand and address heatwave risks, we can build more resilient communities and protect the health and well-being of our most vulnerable populations.

9 REFERENCES

- Avdan, U. and Jovanovska, G. (2016) "Algorithm for automated mapping of land surface temperature using Landsat 8 satellite data," *Journal of Sensors*, 2016, pp. 1–8. Available at: <https://doi.org/10.1155/2016/1480307>.
- Wang, F. et al. (2015) "An improved mono-window algorithm for land surface temperature retrieval from Landsat 8 Thermal Infrared sensor data," *Remote Sensing*, 7(4), pp. 4268–4289. Available at: <https://doi.org/10.3390/rs70404268>.