Assessing Climate Vulnerability Under Future Changes to Climate, Demographics and Infrastructure: A Case Study for the Chapel Street Precinct, Melbourne

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ABSTRACT

The Chapel Street Precinct is a busy commercial and residential corridor in the City of Stonnington Local Government Area (LGA) located in metropolitan Melbourne, Australia. Authorities and planners in the LGA are interested in understanding how the changing climate affects the socioeconomic environment of the region. By considering existing climate hazards (such as extreme heat, flood and water availability), infrastructure, and demographic information in the region together with future projections of climate change and demographic changes, a Socioeconomic Vulnerability Index (SVI) was created at a Mesh Block scale to better identify relatively high-risk Mesh Blocks in the region. The climate projections under medium and high future emission scenarios (i.e., representative concentration pathways (RCP)) as per IPCC (Intergovernmental Panel on Climate Change) fifth assessment report (AR5), RCP4.5 and RCP8.5 respectively for 30-year epochs around 2030, 2050 and 2070 were used in the SVI development. The current-day scenario is considered under Baseline conditions for demographic and asset information representing present-day conditions, whereas the baseline climate dataset considers the climate for the 30 year period 1991-2020 to best represent the present-day climate. The multi-model mean of the future climate projections from 6 different climate models were obtained from the Victoria's Future Climate tool (https://vicfutureclimatetool.indraweb.io), developed by CSIRO (Commonwealth Scientific and Industrial Research Organisation) Data61 together with the Department of Environment, Land, Water and Planning (DELWP) under Data61's INDRA framework (https://research.csiro.au/indra/). A version of INDRA is currently under development to allow map-based interactivity, experimentation and scrutiny of the vulnerability indices and their subcomponents across the study region.

The SVI was created using a weighted indicator approach utilising a range of indicators belonging to 3 categories, exposure, susceptibility, and baseline adaptive capacity. The indicators were first normalised and the final SVI was given a score between 0-1 for each Mesh Block. The worst levels of vulnerability were observed to be for the RCP8.5 2070 scenario. In general, the RCP8.5 scenarios indicated a worse outcome compared to the RCP4.5 scenario. The area along Chapel Street within the precinct which is a densely built-up area high in population was found to be the most vulnerable area in the study region. It is foreseen that decision makers will be able to use the holistic data-driven outcomes of this study to make better informed decisions whilst adapting to climate change.

Keywords

Climate change, heat, flood, vulnerability, risk, demographics

INTRODUCTION

The City of Stonnington, referred to as the city henceforth is a Local Government Area (LGA) located in the south-eastern suburbs of metropolitan Melbourne, Victoria, Australia which covers an area of 25.6 km^2 and is home to a population of 125,000 people. This population is expected to grow by 14.5% to over 143,000 people by 2036 (.id, 2022). Significant landmarks in Melbourne such as the Prahran Market and Jam Factory are located in the City of Stonington, particularly in the Chapel Street Precinct. The Chapel Street Precinct is a busy retail, entertainment, business and residential region consisting of the suburbs of South Yarra, Windsor and Prahran along Chapel Street that runs north to south (Figure 1). Given the high population density and the built-up nature of the region, it is important to understand how future climate change and changes in demographics could impact the precinct and prepare for additional climate risks that are involved. The purpose of this study is to develop an approach that can be applied to any geographical area to identify regions that are susceptible to both the combined and individual effects of climate hazards such as extreme heat and floods. Another key outcome of this work is that planners will be able to allocate limited resources in a prioritized manner at a granular scale to optimise climate change adaptation outcomes.

INDRA is a Climate and Hazard Risk Analytics and Visualisation Platform developed by CSIRO Data61 that integrates a range of climate, infrastructure, and demographic datasets (https://research.csiro.au/indra/). The platform improves accessibility to curated, relevant and actionable climate data for many end-users. INDRA also supports local governments, urban planners, and other interested parties in planning and to understand and develop climate adaptations for vulnerable regions. The outcomes of this study will be presented on an instance of INDRA termed INDRA Stonnington so that decision makers from the city will have the output datasets in an easily accessible web-based platform which integrates other geospatial analytics capabilities for more meaningful interpretation of the results whilst presenting the background data to better understand the climate and demographic inputs.

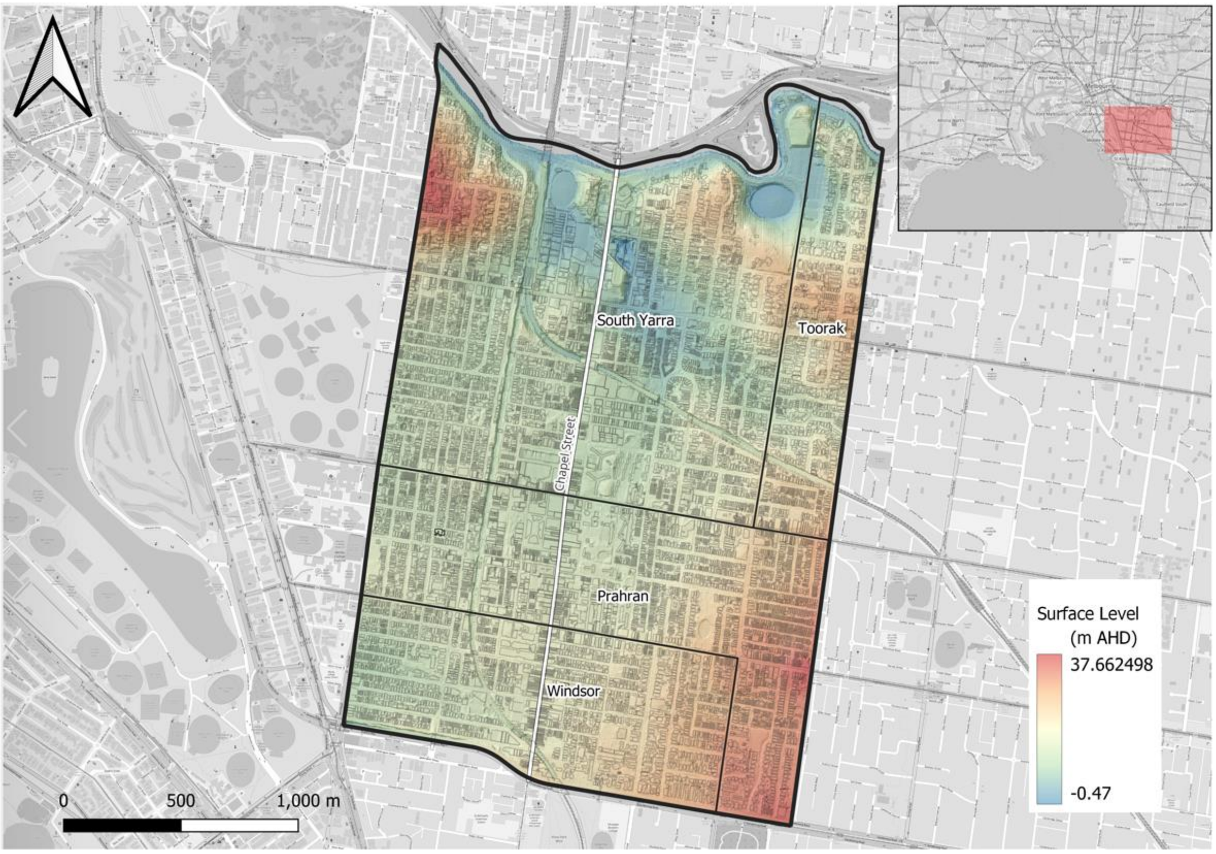


Figure 1 The Chapel Street Precinct with internal suburbs indicated and building footprints outlined in black. The coloured pattern indicates the surface level of the region (in m AHD). The inset map shows the relative location with respect to Melbourne

LITERATURE REVIEW AND LIMITATIONS OF PRESENT APPROACHES

A recent study done by Deakin University (Roös et al., 2020) attempted to identify highly sensitive and vulnerable populations prone to risk caused by heatwaves for the City of Greater Geelong in Victoria. The study explored the concept of Urban Heat Island (UHI), an indicator that represents the subsequent increase in surface and air temperature in urban environments due to the entrapment of heat in impervious surfaces (roads and buildings surfaces including roofs contribute to imperviousness). Upon modelling UHI over the years, the increase in the impervious surface ratio was identified as the key indicator. The study assumed that UHI does not change with future climate projections, where UHI represents the temperature difference between urban and rural zones. It was assumed that both urban and rural environments will equally rise in temperature, the temperature difference may remain the same (Roös et al., 2020). However, this assumption needs to be further investigated.

A study done by Sun et al. (2018) for DELWP presented a Heat Vulnerability Index (HVI) considering the 3 heat vulnerability components: heat exposure, sensitivity to heat and adaptive capability at an Australian Bureau of Statistics (ABS) Statistical Area Level 1 (SA1) scale. The HVI assessment combined nine demographic and geographic indicators to identify areas with high vulnerability to heat waves. A quintile approach was followed to give each SA1 area a HVI score between 1-5, where 1 indicated a low vulnerability and 5 indicated a high vulnerability. Most SA1 regions in the Chapel Street precinct have a low HVI score of 1, except for two SA1 regions that have a high SVI score of 4 and 5 respectively. The study recommends that the percentage of built-up area needs to be integrated into the index development, though was not included due to the lack of data.

For present-day conditions, Heat Vulnerability Indices for various cities have been proposed in Johnson et al. (2012), Wolf et al. (2013) and Rathi et al. (2022) whilst considering data for Land Surface Temperature (LST) and population to provide an overall idea of vulnerable areas and communities in their respective study region.

METHODOLOGY

The existing approaches mentioned earlier quantify the risk based on current day information and data. Though, the effects of extreme heat on the community are explored in detail, the effects of floods and water availability have not been explored. The City of Stonnington is keen to understand the vulnerability imposed by all aspects of heat, flood, and water availability in the socio-economic context. To identify the level of heat vulnerability at a local scale, a Socioeconomic Vulnerability Index (SVI) is developed at the Mesh Block scale, the finest statistical level described by the ABS (ABS, 2022) using a cohort of climate, demographic and infrastructure indicators. This scale was chosen to balance providing adequate spatial granularity to identify vulnerable communities whilst not singling out individual people or infrastructure. The first iteration of the study utilises diverse sources of data that includes climate data from the INDRA tool, publicly available data (Mesh Blocks and short-term demographic forecasts) and the data provided by the city (road data, building footprints, flood maps, etc.). The SVI is created for current day or "Baseline" and 3 future time periods centred on 2030, 2050 and 2070.

The three main types of spatio-temporally varying indicators are,

1. Exposure (Baseline, 2030, 2050, 2070) – climate hazards such as heat, flood and water availability
2. Susceptibility (Baseline, 2030, 2050, 2070) – components of the socioeconomic environment that are susceptible to the effects of climate change and climate hazards
3. Baseline adaptive capacity – the existing ability of the built environment to alleviate climate hazards and adapt to climate variability

Indicators

The indicators were chosen from an extensive literature search to assimilate various indicators that contribute to overall climate vulnerability. Additionally, local expertise from city officers was sought in integrating the various vulnerability indicators. It should be noted that certain indicators will have a higher contribution towards the overall vulnerability whilst others will not contribute much towards the vulnerability. To account for this, weights (low, moderate, and high) are assigned to the indicators. Finally, the availability of data dictated the final selection of indicators although extensive research was carried out to assimilate a vast collection of data relevant to the region. Indicators used to develop the SVI and the assigned weightings of the indicators are summarised in Table 1.

Exposure Indicators

To consider the combined vulnerability of Mesh Blocks to climate hazards, the exposure category of vulnerability combines heat, flood and water availability related datasets. Variables have been selected such that some variables provide spatial granularity regarding the climate hazards and the other variables provide temporal granularity into the future. For instance, climate projections on a 5 km spatial grid provide the temporal granularity in developing the indices. Application-ready gridded datasets for climate projections from an ensemble of climate models were obtained from the Victoria's future climate tool which sits within the INDRA framework developed by CSIRO's Data61 together with DELWP (https://vicfutureclimatetool.indraweb.io) (DELWP, 2021). The platform combines six future climate models ACCESS 1-0, CNRM-CM5, GFDL-ESM2M, HadGEM2-CC, MIROC5 and NorESM1-M to produce a multi-model mean climate dataset. The tool provides future projections for four 30-year epochs centred on 2030, 2050, 2070 and 2090, and for two representative concentrations pathways RCP4.5 (medium emissions) and RCP8.5 (high emissions). The platform also includes baseline historical data for the period 1986-2005, however, in this study, an updated baseline dataset for the period between 1991-2020 was developed to get a better representation of the current climate. The raw values for climate variables including maximum and minimum temperatures and rainfall volumes were utilised to produce processed climate extreme layers including projections of heatwaves, annual number of days above certain temperature thresholds, extreme value analysis of extreme rainfall (1 in 20-year daily rainfall volume) and the annual number of days above certain rainfall thresholds which are directly integrated as the relevant indicators.

The Urban Heat Island 2018 dataset published by DELWP (2019) has UHI data for metropolitan Melbourne at a fine Mesh Block scale based on remote-sensed Land Surface Temperature (LST) values. The difference in LST values with a standard rural temperature value provides the urban UHI value for each Mesh Block. The intensity of the UHI is the temperature difference expressed at a given time between the hottest sector of the city and the non-urban space surrounding this (Martin-Vide et al., 2015). The DELWP UHI dataset is used to provide spatial granularity for the heat variables. Furthermore, the number of days above 30, 35 and 40 C° are assigned low, moderate, and high weightings respectively to provide the temporal granularity to the heat vulnerability component in the exposure index. The total number of annual heatwaves are also considered in the indices and are assigned a high weighting as heatwaves are a severe climate hazard projected to increase into the future, moreover, extreme heatwaves have claimed more lives than any other natural hazard in Australia (Coates et al., 2014).

Table 1. Indicators used to derive the Socioeconomic Vulnerability Index (SVI) with low (L), moderate (M) and high (H) weightings indicated.

Exposure (Baseline, 2030, 2050, 2070)	Susceptibility (Baseline, 2030, 2050, 2070)	Baseline Adaptive Capacity
Heat Variables	Population density (M)	Street trees (H)
UHI 2018 map (H)		
Days above 30 deg C (L)	Elderly (older than 75 years) (H)	Green (permeable) spaces (M)
Days above 35 deg C (M)		
Days above 40 deg C (H)		
Number of Heatwaves (consecutive days of above 35 deg C for 3 days) (H)	Young children (0-4 years old) (H)	Drainage capability (pits and pipes) (M)
Flood Variables		
Flood maps (H)	Homeless (H)	Building footprints which negatively impacts adaptive capacity (H)
Increases in flood intensity due to climate change represented by change in 1 in 20-year rainfall volume (H)	People with disabilities (H)	Roads which negatively impacts adaptive capacity (M)
Terrain elevation range within a Mesh Block (L)	People with medical conditions (H)	
Water availability Variables	Low-income households (H)	
Decrease in water availability due to climate change (represented by reduction in days with rainfall above 10 and 20 mm) (M)		

Flood hazard is included in the exposure index by using flood extents maps to provide the spatial granularity for exposure index. The flood maps for 1 in 100, 1 in 50 and 1 in 20-year return period scenarios were modelled by

Melbourne Water and provided by the city. In the study region, the flood maps show detailed flood extents from the combined effects of extreme rainfall and subsequent catchment flooding. Furthermore, the terrain elevation range for each Mesh Block is derived from the 2.5-metre-high resolution Victorian Coastal Digital Elevation Model (DEM) (CRCSI, 2017). The terrain elevation range within a Mesh Block was calculated simply as the difference between the maximum elevation in a Mesh Block and the minimum elevation within each Mesh Block ($\boldsymbol{Terrain\ elevation\ range\ within\ a\ meshblock = elevation_{max} - elevation_{min}}$ Equation 1). If a Mesh Block has a larger terrain elevation range (proxy for steeper slope), flood water will tend to flow and drain out of the Mesh Block instead of stagnating. On the other, hand, flatter Mesh Blocks (smaller terrain elevation range) are assumed to entrap water without providing the elevation difference to water to flow, thus, pooling the water in that Mesh Block increasing the flood vulnerability. However, it should be noted that this approach only considers the potential depth of pooled water as an indicator of vulnerability and does not consider the added hazards of high velocity flood waters. Given the availability of hydrodynamic data, the combined effects of flood depth flood velocity can be incorporated into the methodology in future versions of the SVI.

$$\boldsymbol{Terrain\ elevation\ range\ within\ a\ meshblock = elevation_{max} - elevation_{min}} \quad \textbf{Equation 1}$$

The change in water availability into the future is a crucial aspect that would expose vulnerable populations to complex health related issues. The water requirements for Stonnington are served from Victoria’s potable water system (10,831 ML/yr) for potable water, and rainwater (185 ML/yr) is mainly utilised for non-potable uses. Water consumption is further supplemented by the river water extracted (75 ML/yr) from the Yarra River and groundwater use (28 ML/yr) (E2DesignLab, 2022). Looking at the rainfall extremes data presented in the Victoria’s future climate tool, the number of days with rainfall above 10 mm and 20 mm reduces into the future together with a reduction of annual rainfall volume indicating a hotter drier future. Since the overall rainfall is an indicator of the availability of potable water, a reduction of overall rainfall volume indicates an increase in vulnerability.

Susceptibility Indicators

Population and household forecasts for the City of Stonnington were prepared by informed decisions (id) (2022) and are available at suburb scale. These are based on 2016 census data and are spaced every 5 years up until 2036, thus giving data 5 different points in time (2016, 2021, 2026, 2031 and 2036) between 2016-2036. Present day population data and demographic breakdowns were available at a Statistical Area 1 (SA1) level which consists of multiple Mesh Blocks. This data was disaggregated further down to individual Mesh Blocks. To project the growth of population into the future, the suburb level growth forecasts were used for each Mesh Block. It is worth appreciating that population growth is dependent on a vast suite of complex factors which are specific in time and space for each region. However, identifying the complexities of population growth for the region was not the purpose of this study. Here, a logarithmic equation was fitted to the projections of population growth, and the fitted model was then used to predict the growth up to the year 2070. It was found that the change in population could be well represented by an exponentially decaying function. To account for differences in Mesh Block sizes, population density values were used in the susceptibility indices. Finally, high weightings were assigned to indicators that represented vulnerable communities such as the elderly, young children, people with disabilities and people from low socioeconomic backgrounds.

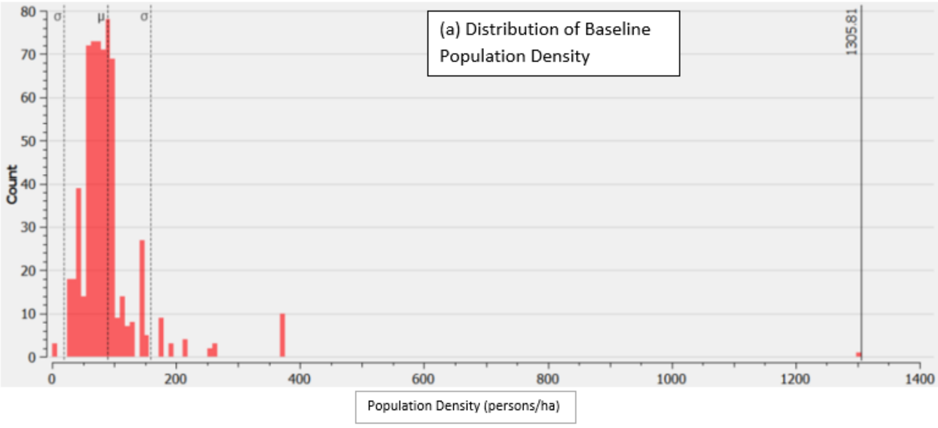
Baseline Adaptive Capacity Indicators

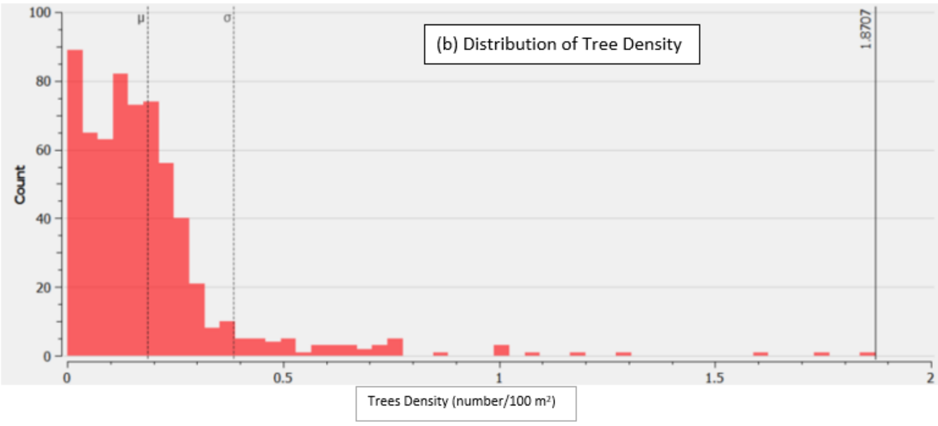
To engage the decision makers and subject experts in the city, the baseline adaptive capacity is considered using the present-day scenario of the built and natural environment. The changes in the built environment factors which support climate adaptation is entirely dependent on development standards that are introduced with the use of tools such as the one being developed in this study. Future phases of this study include steps such as workshops to engage with representatives in the city to discuss how future adaptive capacity indicators can be integrated into the methodology. The indicators included in the adaptive capacity category consist of elements in the physical environment that may have either a positive or negative impact in adapting to climatic hazards. Trees in urban environments are proven to provide benefits in reducing ambient air temperatures and to cool urban environments through evapotranspiration and shade (Kalkstein et al., 2022; Rahman et al.,2020 and DELWP, 2019). Furthermore, green spaces which include parks and sporting fields with permeable surfaces encourage infiltration of stormwater through ground infiltration. Additionally, evapotranspiration from grass may contribute to cooling the air temperature as well. To get an idea about a region’s hydrodynamic drainage potential in present conditions which help manage stormwater, the quantities of pipe volumes and the number of volumes per unit area was included in the adaptive capacity indicators. Although, the inclusion of drainage assets might not be the best indicator of flood adaptive capacity as during heavy rainfall events these systems tend to get saturated, the assumption provides a basis for considering the existing adaptive ability of a region. Hard impervious surfaces in urban environments consist of roads and buildings. It is understood that impervious surfaces tend to entrap heat and exacerbate the impacts of heatwaves (Zhang et al., 2012). Furthermore, impervious surfaces cause water to run-off (rather than infiltrate) without leaving much moisture in the ground which reduces evaporative cooling. Moreover, high-density developments can have height and form that can trap heat at night. The existence of green infrastructure and vegetation reduces UHI (AECOM, 2013). Therefore, the area fractions of roads and building footprints are included in the adaptive capacity column as these factors act negatively and reduces the overall adaptive capacity.

Combination of Indicators

Vulnerability indices are inherently somewhat different from mathematical expressions of a conceptual model of vulnerability if they are not compared with observational data and tested (Bao et al., 2015). The approach undertaken in the study is summarised below.

1. Normalise each indicator to a value between 0-1 ($\boldsymbol{normalised\ indicator} = \frac{\boldsymbol{value - range_{min}}}{\boldsymbol{range_{max} - range_{min}}}$ Equation 2) by scaling to a range. When normalizing, for indicators which have temporal data from baseline until 2070, normalise based on the entire range including future values. It was found that each indicator exhibits a different form of distribution of values, with a common occurrence that included outliers on the maximum end of the range. As an example, there were a couple of Mesh Blocks with an extremely high population density due to the presence of high-rise apartment buildings. Additionally, certain Mesh Blocks representing parks had an unusually high number of trees compared to other Mesh Blocks. Since almost all of the indicators suggested a positive skew (a couple of examples of these distributions are shown in





2. Figure 2), the maximum of the range was clipped to two standard deviations from the mean. Since the actual minimum value did not extend too far beyond the mean implying an outlier for all indicators, the actual minimum value of the range is used as the lower limit.

$$\boldsymbol{normalised\ indicator} = \frac{\boldsymbol{value - range_{min}}}{\boldsymbol{range_{max} - range_{min}}} \quad \textbf{Equation 2}$$

$$\boldsymbol{range_{max}} = mean + 2\ standard\ deviations$$

$$\boldsymbol{range_{min}} = minimum(value\ range)$$

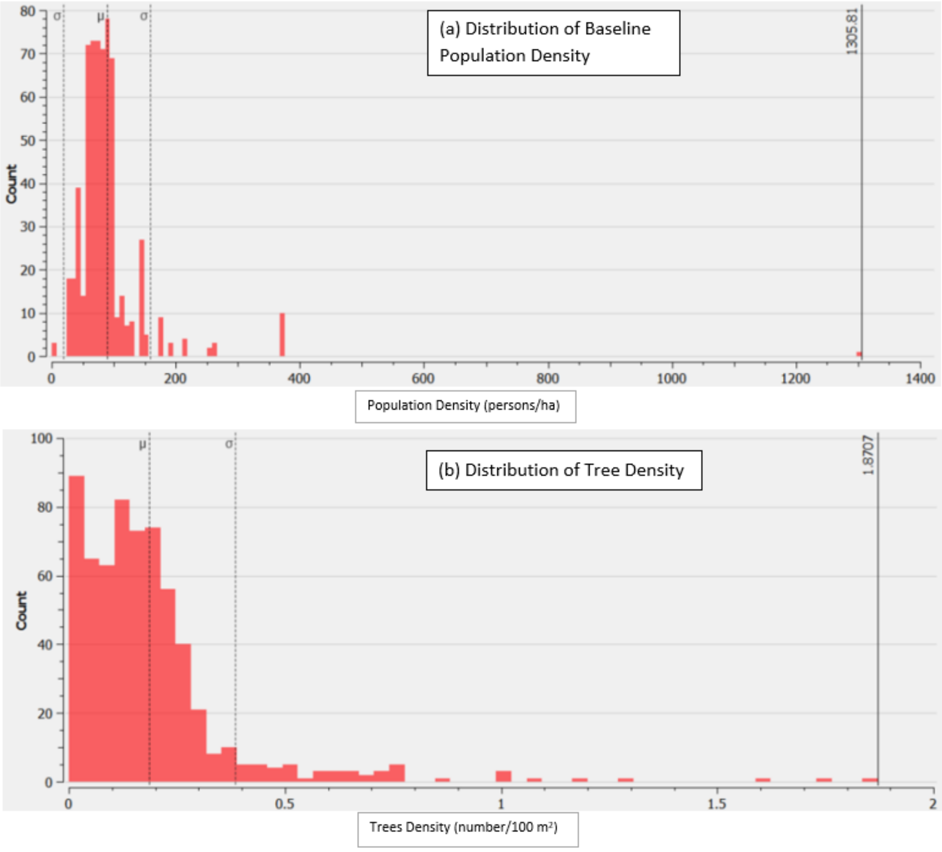


Figure 2 Distribution of values for Mesh Blocks highlighting the positive skew with outliers for the value distributions for (a) population density and (a) number of trees per 100 m^2. The standard deviation and mean of the distributions are marked with dotted lines

3. Calculate the indices for each vulnerability component –
    a. For the Exposure category, the temporally varying indicators for heat, flood, and water availability such as days above a certain temperature threshold are normalised and the weighted average for each hazard type is multiplied by the normalised spatially varying indicators, UHI for heat and flood maps for floods considering the weights.
    b. For Susceptibility, the weighted average of the normalised indicators.
    c. For Adaptive Capacity, the weighted average of the normalised indicators.
4. The final Socioeconomic Vulnerability Index is calculated using $\boldsymbol{SVI} = \frac{\boldsymbol{Exposure\ Index + Susceptibility\ Index + (1 - Adaptive\ Capacity\ Index)}}{\boldsymbol{3}}$ Equation 3

$$\boldsymbol{SVI} = \frac{\boldsymbol{Exposure\ Index + Susceptibility\ Index + (1 - Adaptive\ Capacity\ Index)}}{\boldsymbol{3}} \quad \textbf{Equation 3}$$

RESULTS AND DISCUSSION

The SVI was produced for 7 different scenarios including baseline (present-day) vulnerability and 6 future climate scenarios; for the years 2030, 2050 and 2070 under the future emission scenarios of RCP4.5 and RCP8.5. The SVI results and the individual indicators are presented on an instance of CSIRO Data61's geospatial visualization and analytics platform INDRA, INDRA Stonnington which is created for this study. Figure 3 includes the SVI results for four different climate scenarios; Baseline, 2030, 2050 and 2070 under the RCP8.5 future climate emissions scenario as presented on INDRA Stonnington. The figure shows all 630 Mesh Blocks in the study region coloured by the SVI which ranges between 0-1 with red colour indicating a high vulnerability and the lighter green and yellow colours indicate areas with a lower overall vulnerability. The baseline condition in Figure 3(a) shows higher vulnerability along Chapel Street (along the centre of the study region from north to south). As expected, densely built-up areas with high populations indicate a higher vulnerability while parks and other open space areas demonstrate a lower overall vulnerability. From Figure 3, it can be clearly seen that the overall SVI increases into the future, moreover, the Mesh Blocks which indicate a relatively higher socioeconomic vulnerability can be identified from the results.

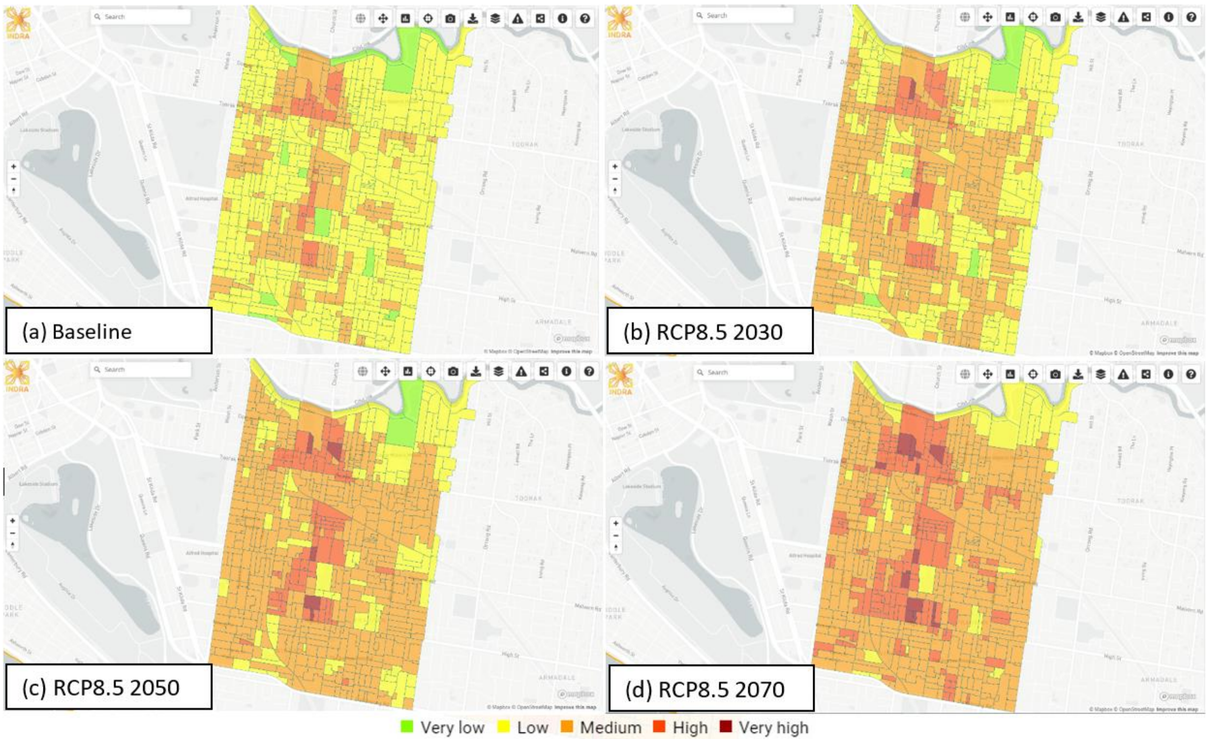


Figure 3. Socioeconomic Vulnerability Index for Mesh Blocks in the Chapel Street Precinct in the City of Stonnington under present and future climate scenarios (a) Baseline (b) RCP8.5 2030 (c) RCP8.5 2050 and (d) RCP8.5 2070. Vulnerability for each Mesh Block is given a value between 0-1, the risk levels based on the score can be interpreted as 0-0.2: very low, 0.2-0.4: low, 0.4-0.6: medium, 0.6-0.8: high and 0.8-1.0: very high

The bar plot in Figure 4 shows the variation of the SVI of all 630 Mesh Blocks in the study region across all 7 climate scenarios. The Baseline scenario shows that over 60% of the Mesh Blocks are in the Low vulnerability category (SVI value between 0.2-0.4) as represented by the yellow bars. Approximately 30% of the Mesh Blocks fall under the medium vulnerability category (SVI score of 0.4-0.6) whereas less than 25 Mesh Blocks fall under each category of Very Low (0-0.2) and High (0.6-0.8) for the baseline case. Looking at the SVI for 2030, under both RCP cases, majority of the Mesh Blocks move into the medium vulnerability category from the low vulnerability category. RCP8.5 in 2030 shows that more Mesh Blocks are in higher vulnerability than for the RCP4.5 2030 case. Moving further into the 2050's, the number of Mesh Blocks in the Very Low vulnerability category tends to go to 0, whereas a few Mesh Blocks in the Very High vulnerability category (0.8-1.0) start to appear. Comparing RCP4.5 and RCP8.5 for the 2050's, the 2050's under a RCP8.5 future demonstrates a scenario with a higher overall vulnerability. The difference between RCP8.5 2050 and RCP4.5 2070 is not significant, each vulnerability category has a similar number of Mesh Block counts. However, a significant difference in vulnerability can be observed between RCP4.5 2070 and RCP8.5 2070. Over double the number of Mesh Blocks fall in to the High and Very High vulnerability levels in the RCP8.5 2070 case compared to the RCP4.5 2070 case.

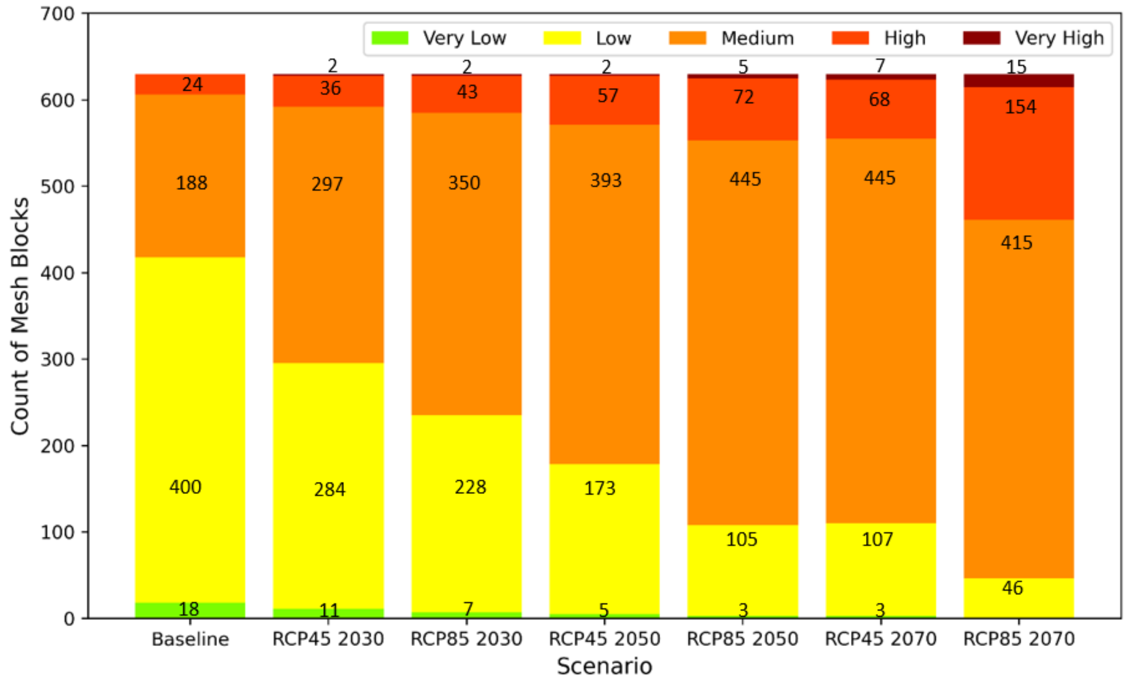


Figure 4. Socioeconomic Vulnerability Index - counts of Mesh Blocks for all modelled climate scenarios. 5 risk levels based on the vulnerability score between 0-1 are considered; 0-0.2: very low, 0.2-0.4: low, 0.4-0.6: medium, 0.6-0.8: high and 0.8-1.0: very high

CONCLUSION

The SVI developed highlights Mesh Blocks in the Chapel Street Precinct which are prone to vulnerability due to the combined effects of climate hazards including heat, floods and water availability also considering the future vulnerability due to climate change and changes in demographics in the socioeconomic context. The relative index for Mesh Blocks provides a basis for the City of Stonnington to start identifying vulnerable areas in the region. Furthermore, the insights from the SVI maps can be used by decision makers for targeted adaptive measures, and to better equip the most vulnerable communities in dealing with the implications of climate change. The weighted indicator-based approach which has been used in other similar studies provides an opportunity to incorporate several factors which may or may not have an inherent scientific relationship with each other but are still perceived to contribute to the overall vulnerability. The consideration of existing climate hazards such as UHI and flood maps at a fine spatial scale together with future climate projections is a first pass attempt to identify the increasing severity of climate hazards with future climate change. The projection of demographics into the future is useful in understanding that in a growing population, the increase in number of vulnerable communities may exacerbate the impacts of climate change. Furthermore, the consideration of current adaptive capacity as "Baseline Adaptive Capacity" will direct decision makers to think in a way that they can plan future development whilst contributing to the overall adaptive capacity in the form of green infrastructure and Water Sensitive Urban Design (WSUD) elements. The adaptive capacity contributor of the SVI can be readjusted to further investigate the best course of action to reduce vulnerability going into the future. From the SVI results obtained, it was clear that the region will become more vulnerable further into the future compared with the Baseline vulnerability, the RCP8.5 future emissions pathway indicated a higher overall vulnerability compared with the RCP4.5 future emissions pathway.

INDRA Stonnington, a tool being built alongside the vulnerability indices will help decision makers analyse the changes in socioeconomic vulnerability and the climate and demographic components in further detail by selecting the required indicators separately to better identify the underlying causes to increasing climate vulnerability. The web-based platform will be deployed such that interested parties will have easy access from any web browser with an internet connection.

In terms of the future development of the project, the city is also interested in understanding the climate vulnerability for physical infrastructure assets in the public and private realms. Infrastructure assets such as buildings, roads and drainage networks undergo accelerated deterioration under the harsh impacts of climate hazards such as extreme heat and floods which reduces the effective lifespan of these assets thereby increasing costs associated with maintenance and replacement. This excess "climate cost" is not currently well understood in a scientific and mathematical context and therefore not considered accurately in design and maintenance standards. Therefore, it is in the city's best interest to identify vulnerable locations so that climate adaptations can be targeted to those assets. The Infrastructure Vulnerability Indices for both private realm and public realm assets are currently being developed considering a suite of infrastructure related indices and further research is being done to develop projections of infrastructure vulnerability into the future which will all be incorporated into the INDRA Stonnington platform. Moreover, the current SVI will be improved further based on inputs from city stakeholders including decision makers and subject specialists and future adaptive capacity improvement scenarios will be included to better inform city decision making. The goal of this project is to develop a scalable framework that can be applied across the country to identify higher vulnerability areas within local government jurisdictions, the present version of the SVI presented in this paper can easily be applied to other LGAs.

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