Place-based Data Approaches

Data for analysis of spatial inequities in access to services

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Life Course Centre
DATA FOR POLICY
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Computer vision applications to derive a spatial index of access to social services

Place-based approaches

"target specific circumstances of a place"

"can complement the bigger picture of services and infrastructure"

"engage with issues and opportunities that are driven by complex, intersecting local factors and requiring a cross-sectional or long-term response"

Social Service Access Index

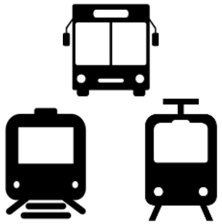
Types of place-based questions that can be answered:

- Where are the service deserts that have the least access to bulk-billed GPs?
  - What are the socio-economic characteristics of these deserts?
- What is the overall access to childcare facilities by young families in Greater Melbourne?
  - How long does it take for the families to reach accessible childcare facilities in the service deserts?

Computer vision applications to derive a spatial index of access to social services

Data

Mixed sources



- Location data of bus stops, train stops, and tram stops (GTFS data—attached with timetables)
- Income by family at SA1 level (2021 Census)
- Number of dwellings without access to a motor vehicle at SA1 level (2021 Census)

- Location data of pharmacies, bulk billing GPs, and public hospitals (National Health Directory data)
- Income by family at SA1 level (2021 Census)
- Young and old populations with long-term health conditions and needs for assistance at SA1 level (2021 Census)

- Location data of childcare facilities (ACECQA national register data)
- Location data of public primary and secondary schools (ACARA national register data)
- Income by family at SA1 level (2021 Census)

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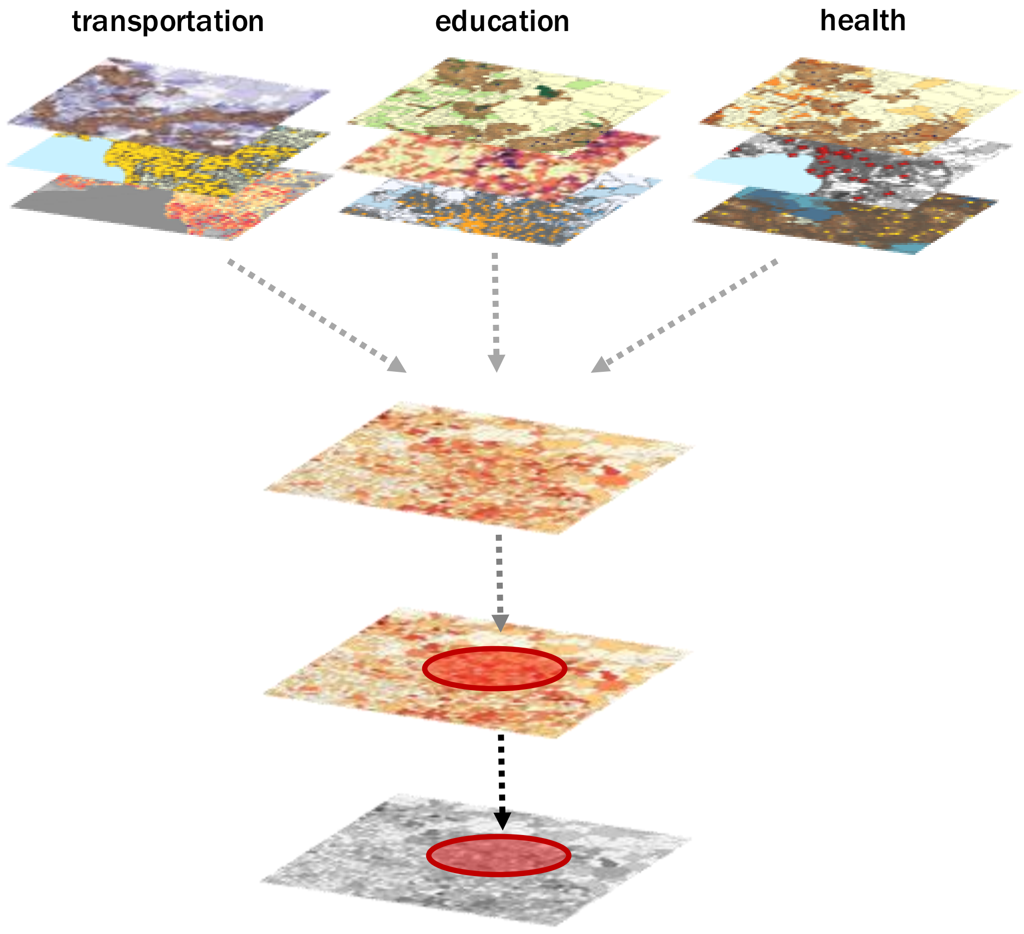
Social Service Access Index

Process



Aggregate access indicators for each domain at SA1 level

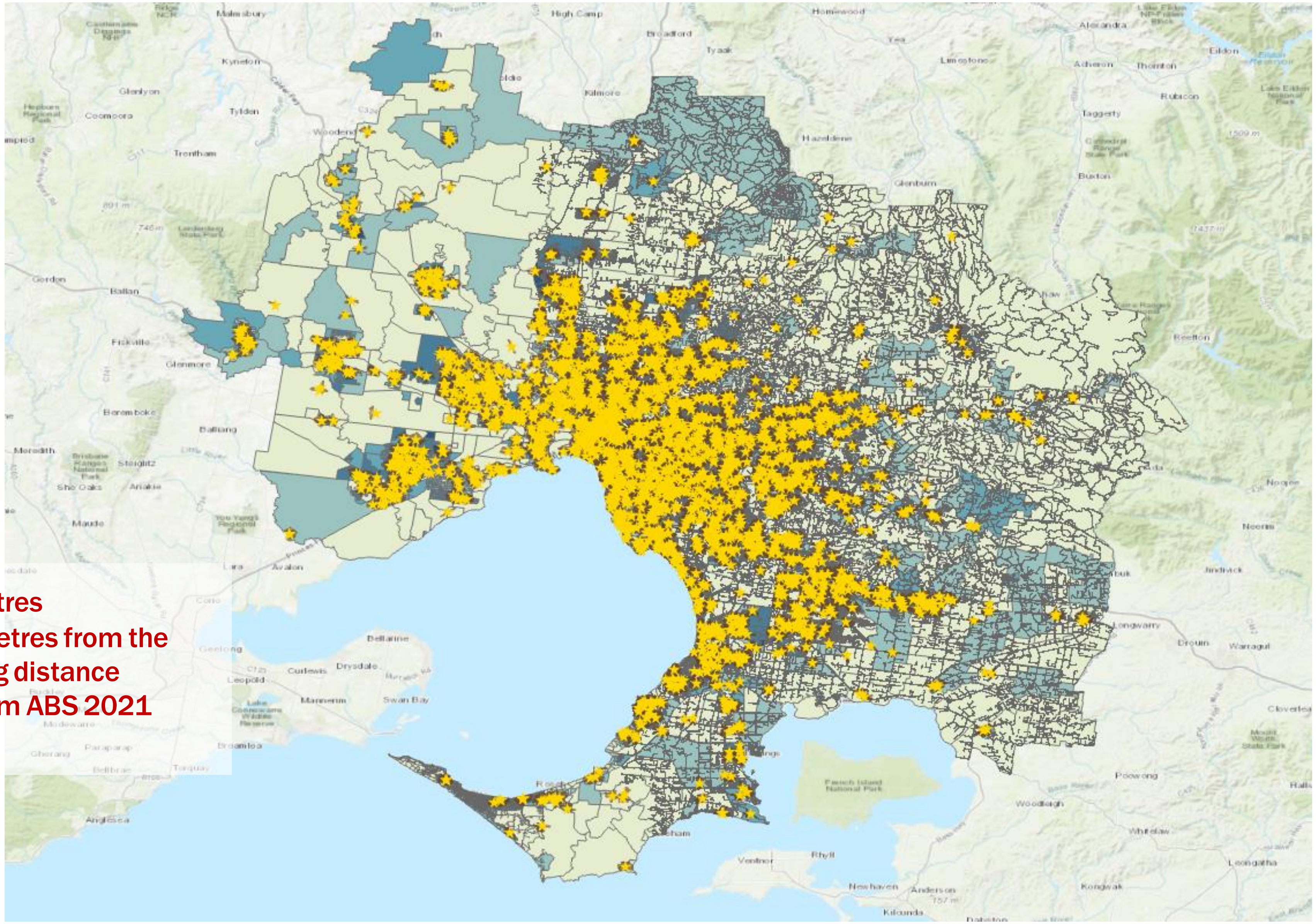
Calculate SSAI at SA1 level using different weights to create indexes

Identify potential service deserts in the target areas

Assess access level by different population groups (i.e., young families, elderly, etc.) in potential service deserts

Scenario example

Access to childcare in Greater Melbourne area

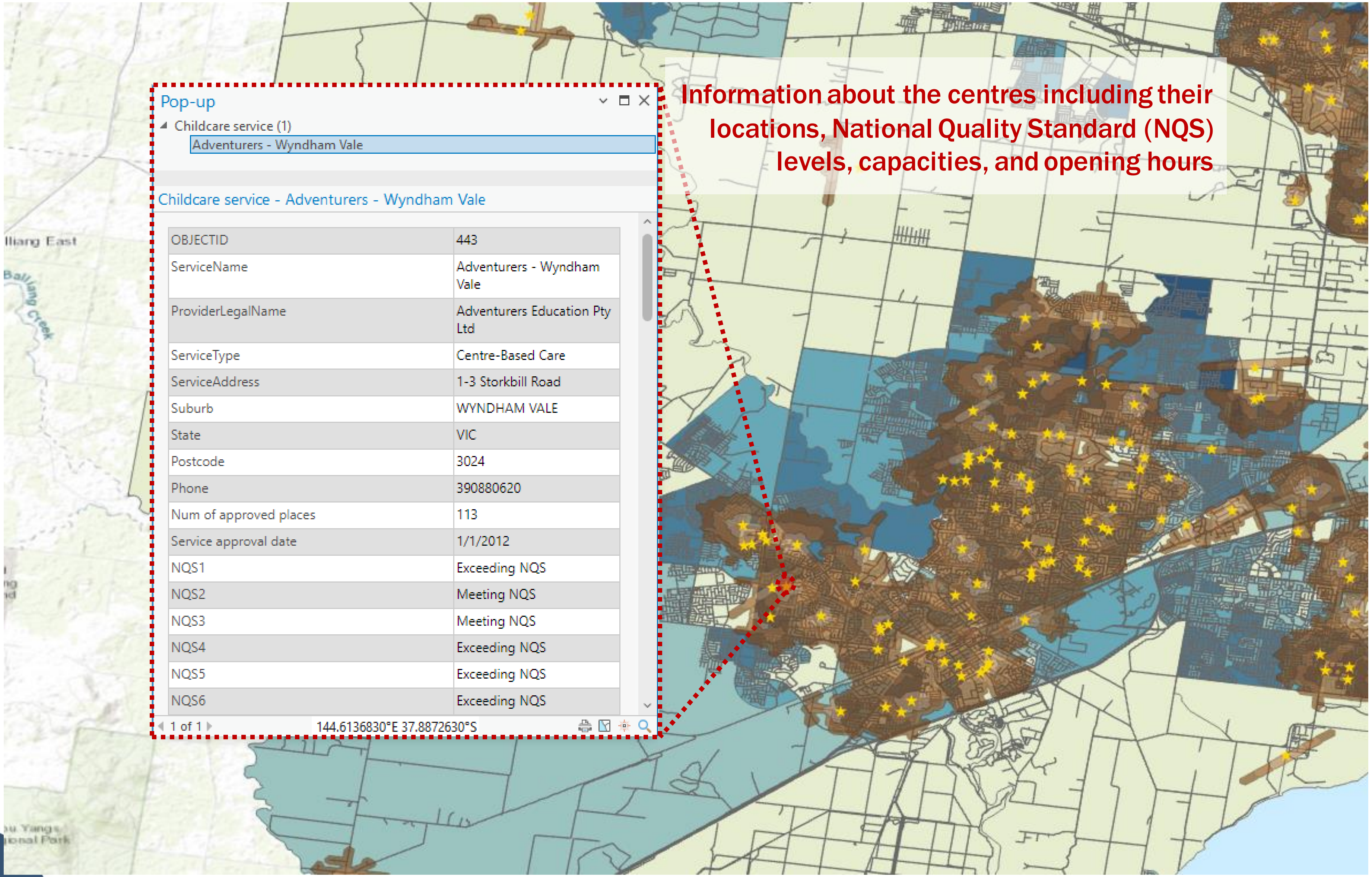


- Yellow stars: locations of childcare centres
- Service areas: 400, 800, and 1,000 metres from the centres (5-, 10-, and 15-minute walking distance
- SA1 areas: selected characteristics from ABS 2021 population census

Source: A framework for place-based approaches (2020). Department of Premier and Cabinet, Victorian Government. Available at: https://www.vic.gov.au/framework-place-based-approaches/print-all

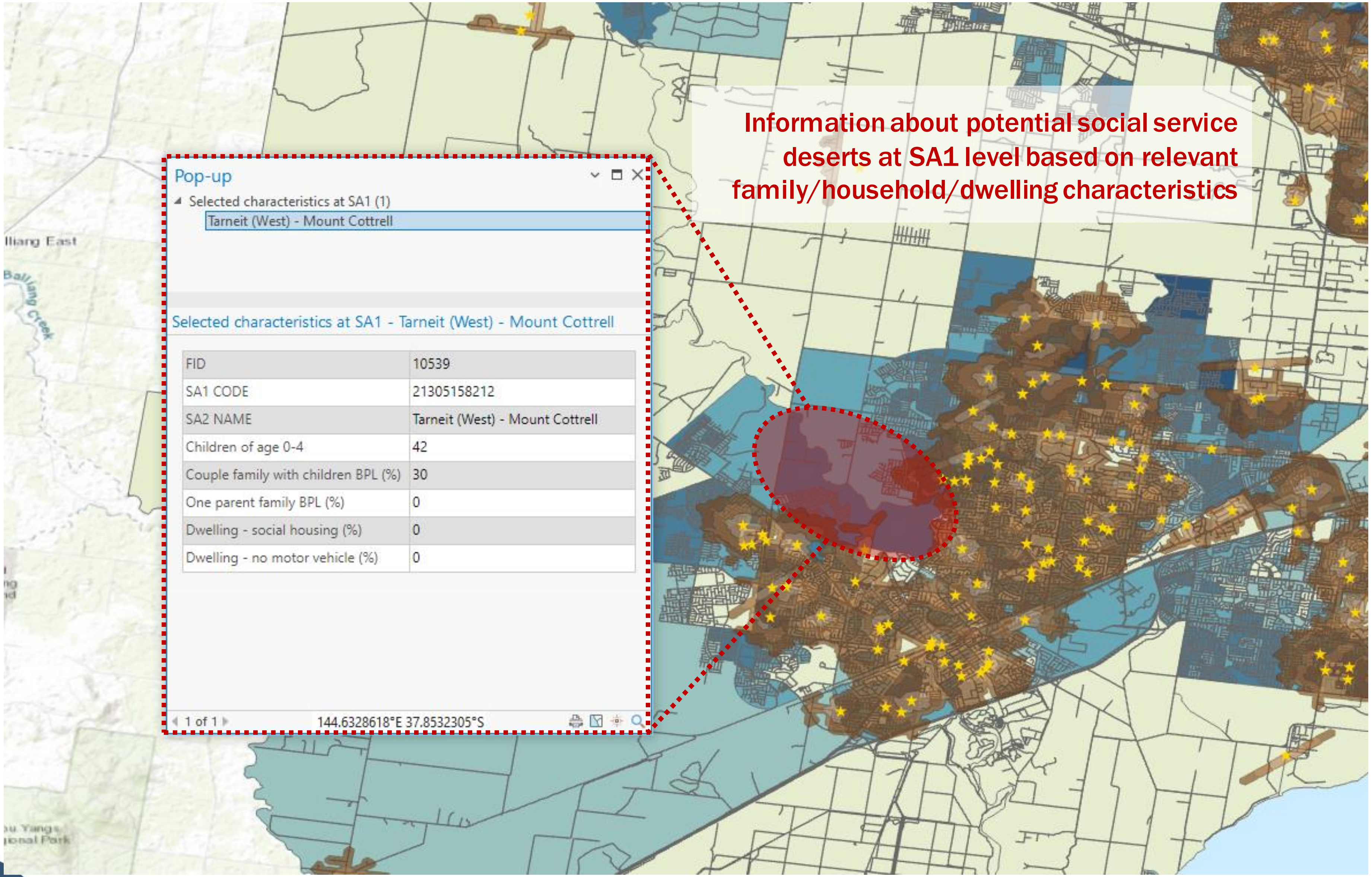
Web map example

Access to childcare in Greater Melbourne area: provider details



Web map example

Access to childcare in Greater Melbourne area: SA1 demographics details



Social Service Access Index

Indicator and weighting example

Factor	Factor weight	Indicator	Indicator weight
Transportation	0.3	Walking distance (within 15-minute)	0.5
		Weekly frequency	0.5
Education	0.35	Walking distance (within 15-minute)	0.3
		Holiday/afterschool availability	0.3
		Seat availability	0.2
		Quality standard	0.2
Health	0.35	Walking distance (within 15-minute)	0.35
		Opening hour/after hour availability	0.35
		Billing type	0.3

Scenarios can include different weightings and different sets of parameters for different groups such as:

- Elderly or disabled
- Young families with children
- Single parent households

Limitations

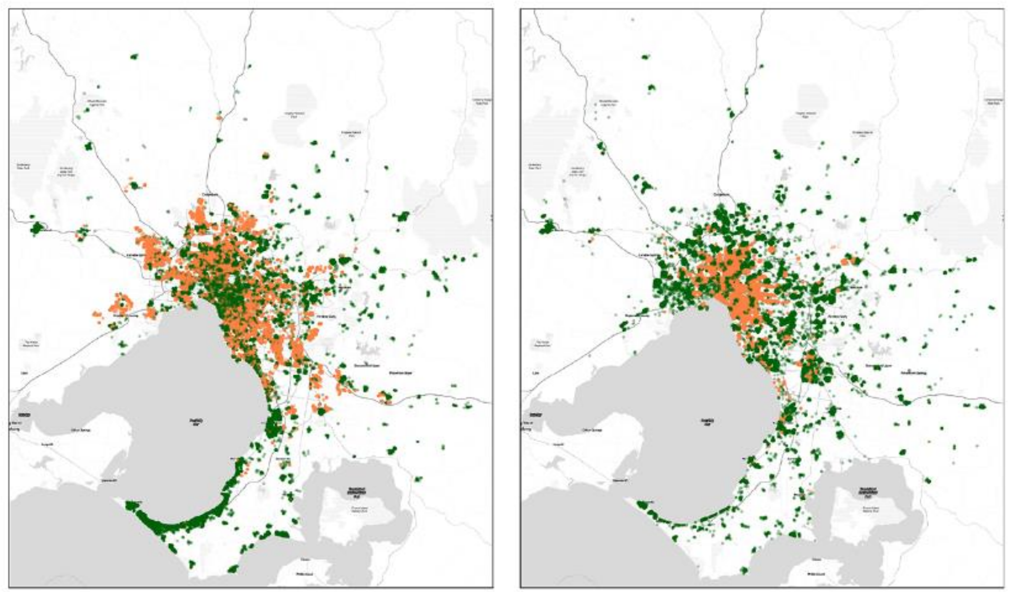
- Data not always available for all areas
- Inconsistent/incomplete data
- Out of date data
- Authoritative data might not tell the entire story

Potential enhancements

- Dynamic data
- Temporal aspects: longitudinal over many years
- Qualitative enhancements
- Augmented analysis insights through machine learning

Augmented analysis through computer vision

- Use of generative computer vision models (GANs) to highlight characteristics of areas with good vs. bad outcomes.

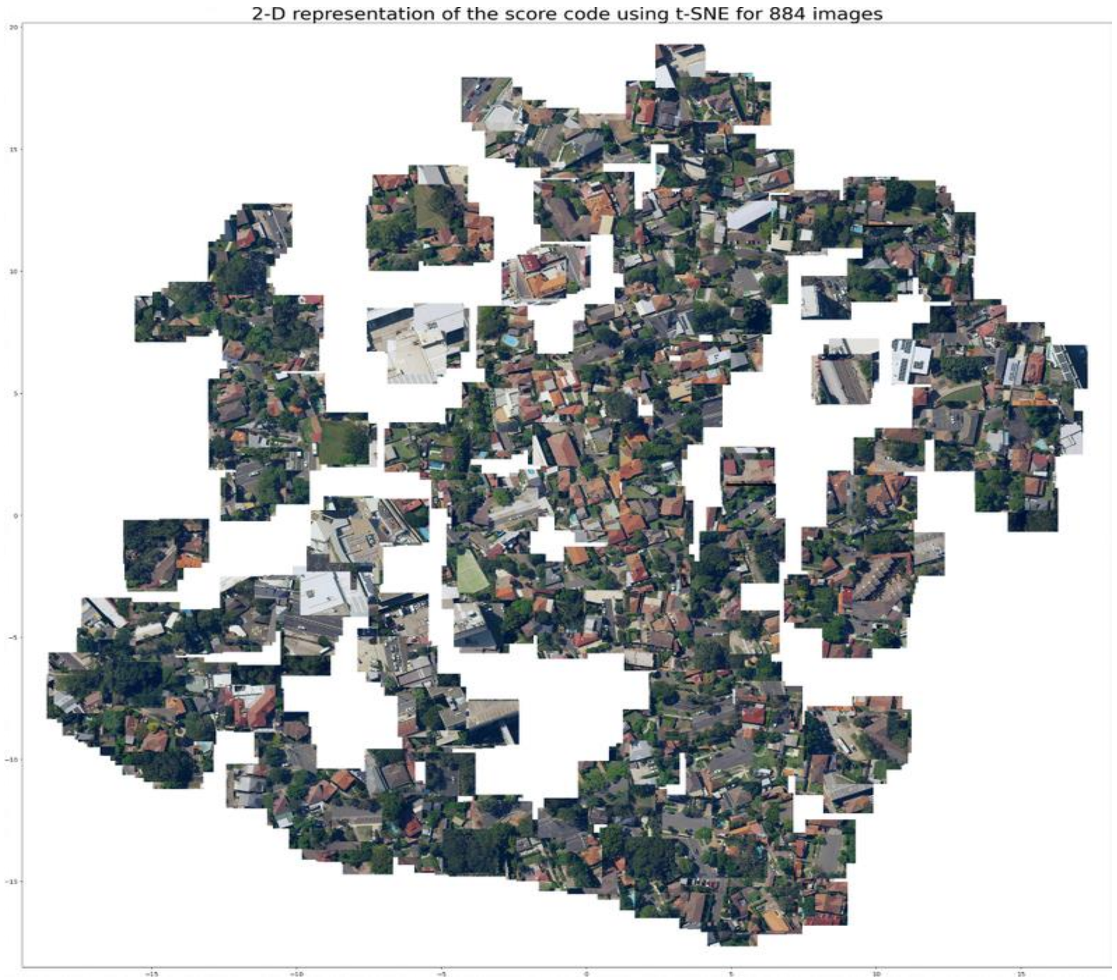


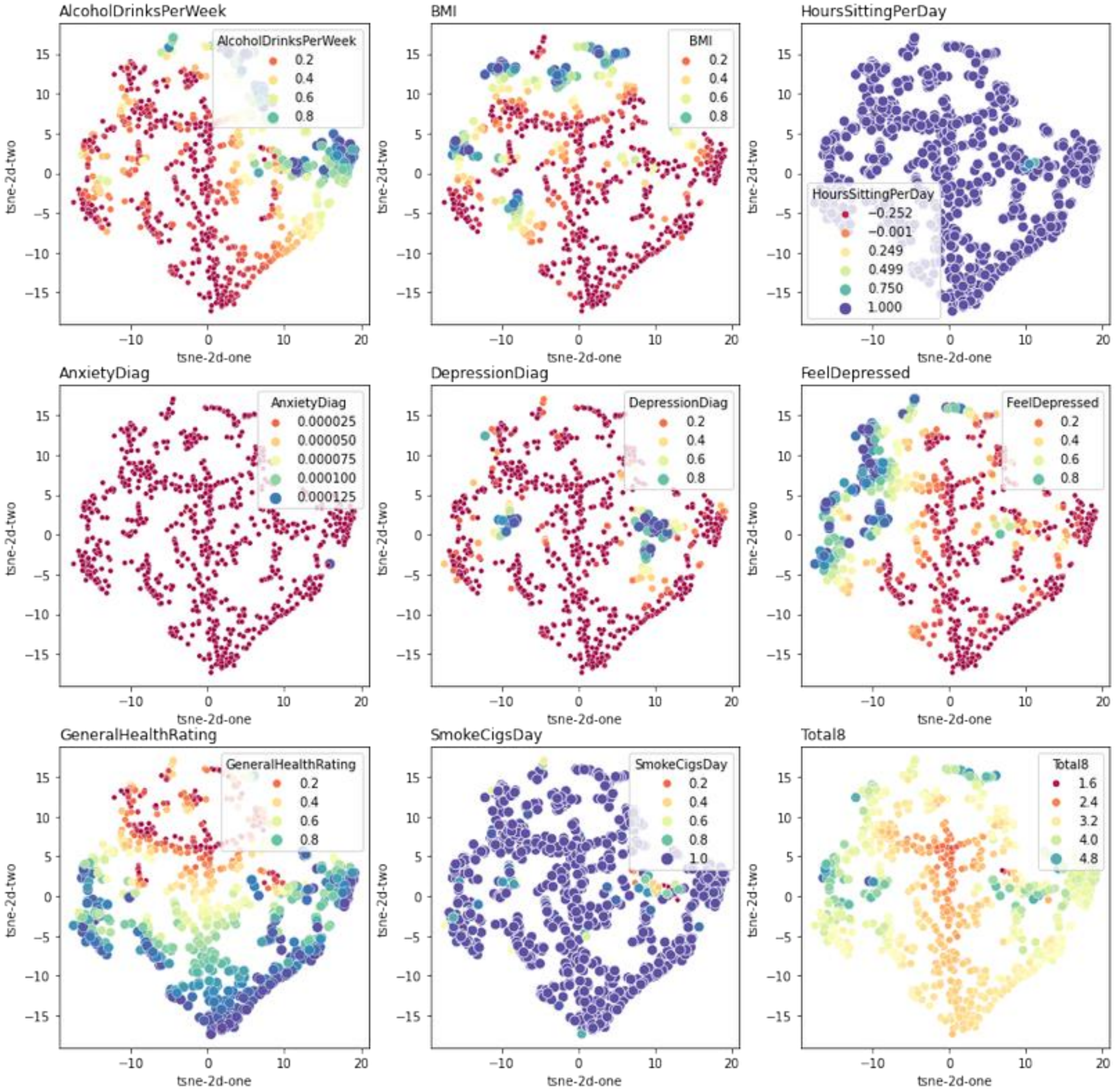
(a) General health (b) Social capital

Good general health to bad

J. Wijnands, K. Nice, J. Thompson, H. Zhao, and M. Stevenson, Streetscape augmentation using generative adversarial networks: optimising health and wellbeing., Sustainable Cities and Society, 2019

Analysing self-reported health indicators with GANs





Zhao et al, in preparation.

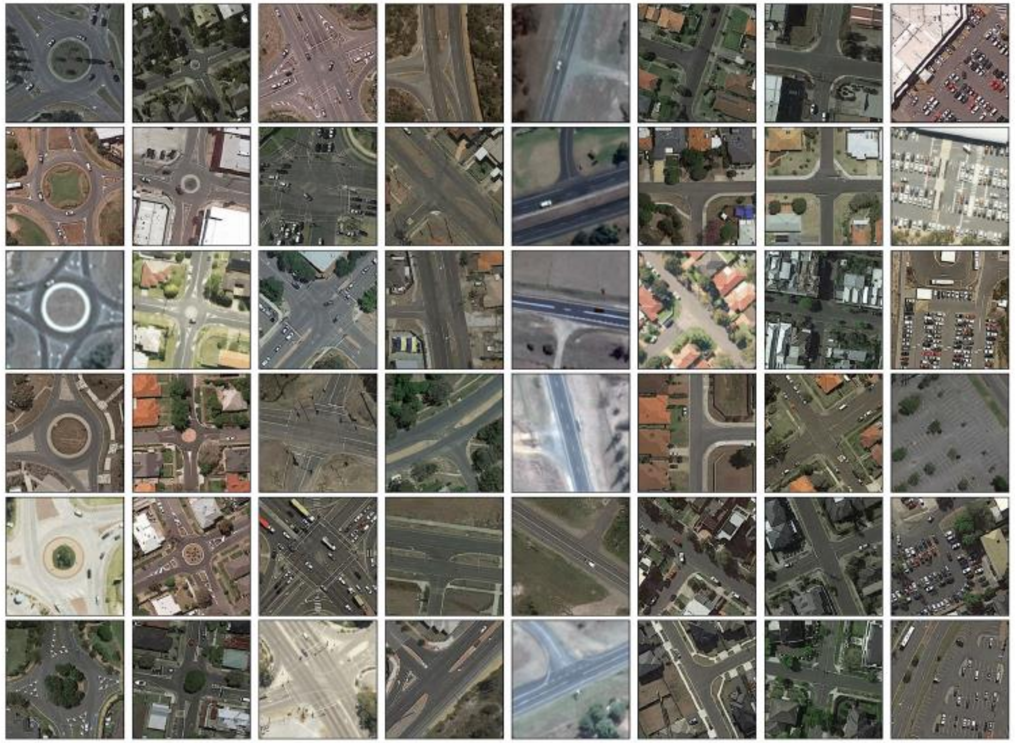
Analysing self-reported health indicators with GANs: Insights from large imagery datasets

Examples of GANs Image Translations

BMI			
Original Image	Translated to High	Translated to Low	Observations:
			Red roof buildings are more likely to appear in Low BMI areas, while grey roof buildings are likely to appear in High BMI areas.

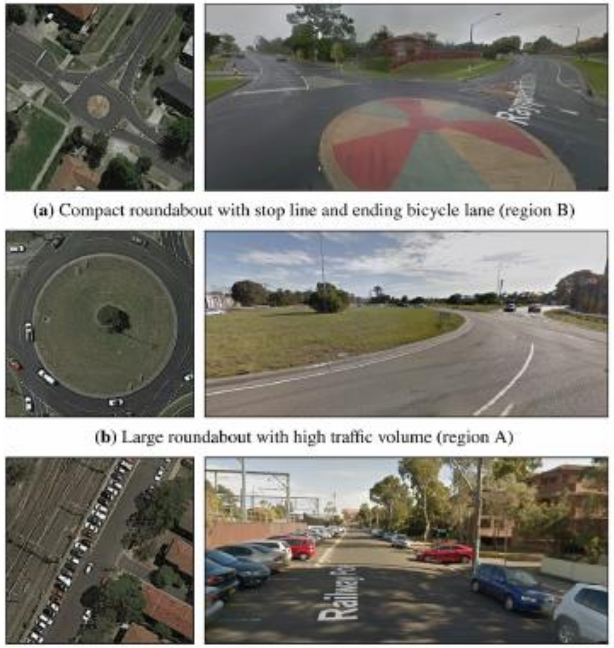
Infrastructure detection through computer vision

- Use of computer vision to quickly generate infrastructure inventories extracted from urban imagery across all of Australia
- How are different types of infrastructure used and what the public health outcomes



(a) Region A (b) Region B (c) Region C (d) Region D (e) Region E (f) Region F_1/F_2 (g) Region G (h) Region H

FIGURE 6 Each column provides sample images for the corresponding region in Figure 5. (a) Region A, (b) Region B, (c) Region C, (d) Region D, (e) Region E, (f) Region F_1/F_2, (g) Region G, and (h) Region H



(a) Compact roundabout with stop line and ending bicycle lane (region B)

(b) Large roundabout with high traffic volume (region A)

(c) Parking spots along T-intersection (region F)

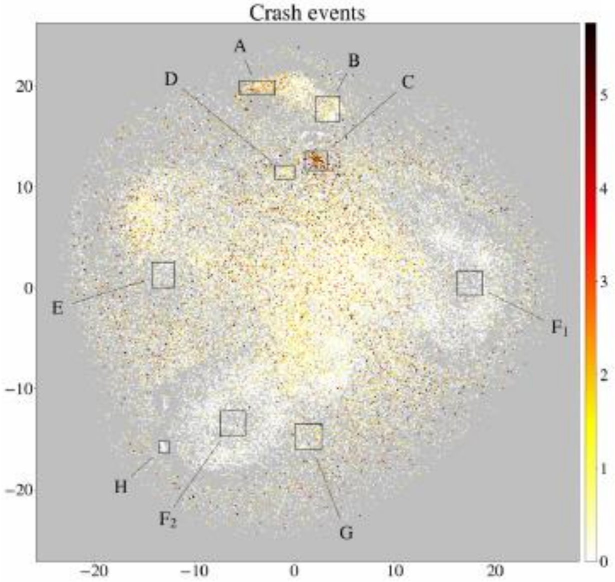


FIGURE 9 t-SNE clusters with matched crash events

900,000 intersections in Australia clustered by their design and relationships to safety outcomes (crashes) and unsafe driving behaviours (hard acceleration/braking)

Source: Jasper S. Wijnands, Haifeng Zhao, Kerry A. Nice, Jason Thompson, Katherine Scully, Jingqiu Guo, Mark Stevenson, Identifying safe intersection design through unsupervised feature extraction from satellite imagery, Computer-Aided Civil and Infrastructure Engineering, 2020

Generative design and urban visualisations

"A street which is ideal for walking in"

Converts noise into an image.
Generates images with desirable properties:
Wide walkable area, pleasant experience.

S. Seneviratne, D. Senanayake, S. Rasnayaka, R. Vidanaarachchi, and J. Thompson. "DALLE-URBAN: Capturing the urban design expertise of large text to image transformers." In 2022 International Conference on Digital Image Computing: Techniques and Applications (DICTA

Possible Policy Implications

Link to and support existing policy initiatives by the State Government agencies such as:

- “20-minute neighbourhoods” initiative that supports Plan Melbourne 2017-2050 by the Victorian Government
- Digital Twin Victoria
- Department of Transport and Planning’s effort on ingesting OpenStreetMap road data

Support the local governments and relevant NGOs in the target areas for prioritising resource distribution

Support mapping unmapped areas in regional and rural Australia and beyond for international communities

Conclusions

Place-based data analysis provides important insight to understand the target communities and supports the decision-making process.

Place-based data that are generated through alternative methods could supplement authoritative data.

Thank you

Research Team:

Kerry Nice: Urban climates/computer vision/software engineering
Sachith Seneviratne: Computer vision/artificial intelligence
Youjin Choe: Human-centred design/public policy analysis/geomatics
Mark Stevenson: Transport systems/epidemiology

Examples of previous THUS research lab's projects of urban modelling and urban analysis utilising large datasets and machine learning

Machine learning using 1.6 million maps to cluster 1600 cities into city typologies to analyse the impacts of urban design types on road injuries

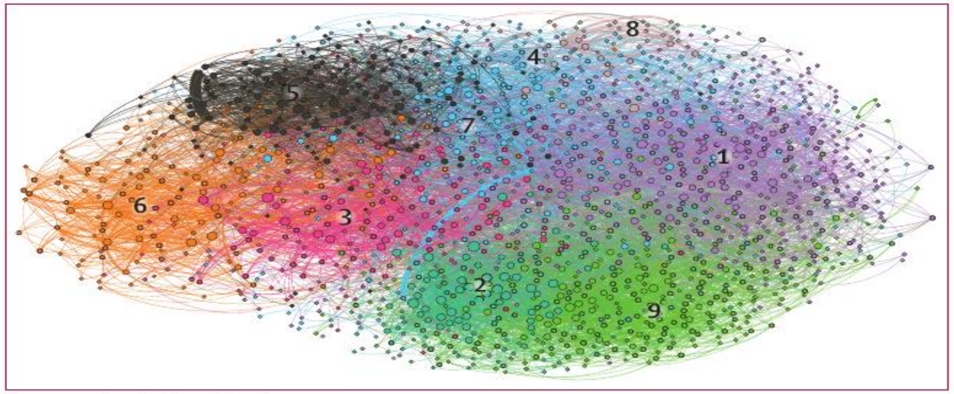


Figure 3: Network graph of the model's confusion matrix
Featuring all 1632 cities and identified city types identified by colour with approximate locations from one to nine (1=informal, 2=irregular, 3=large block, 4=cul de sac, 5=high transit, 6=motor city, 7=chequerboard, 8=intense, 9=sparse); a searchable version of the chart containing city names is available in the appendix (p 1).

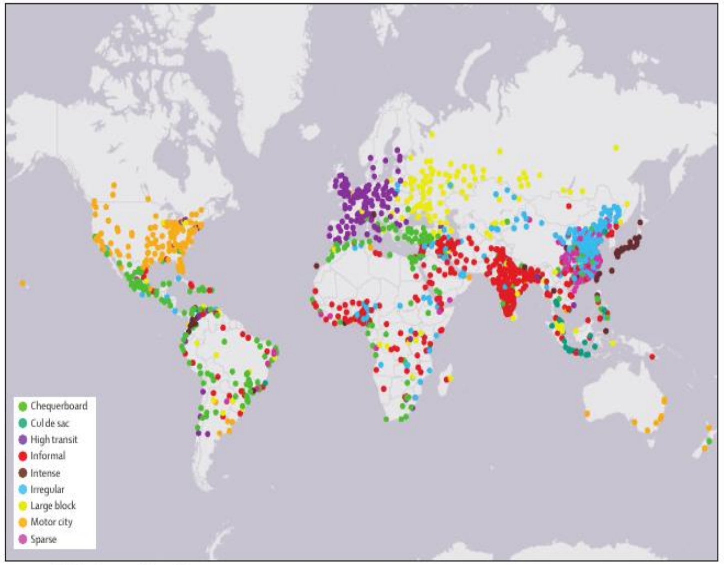


Figure 4: Global distribution of identified city types

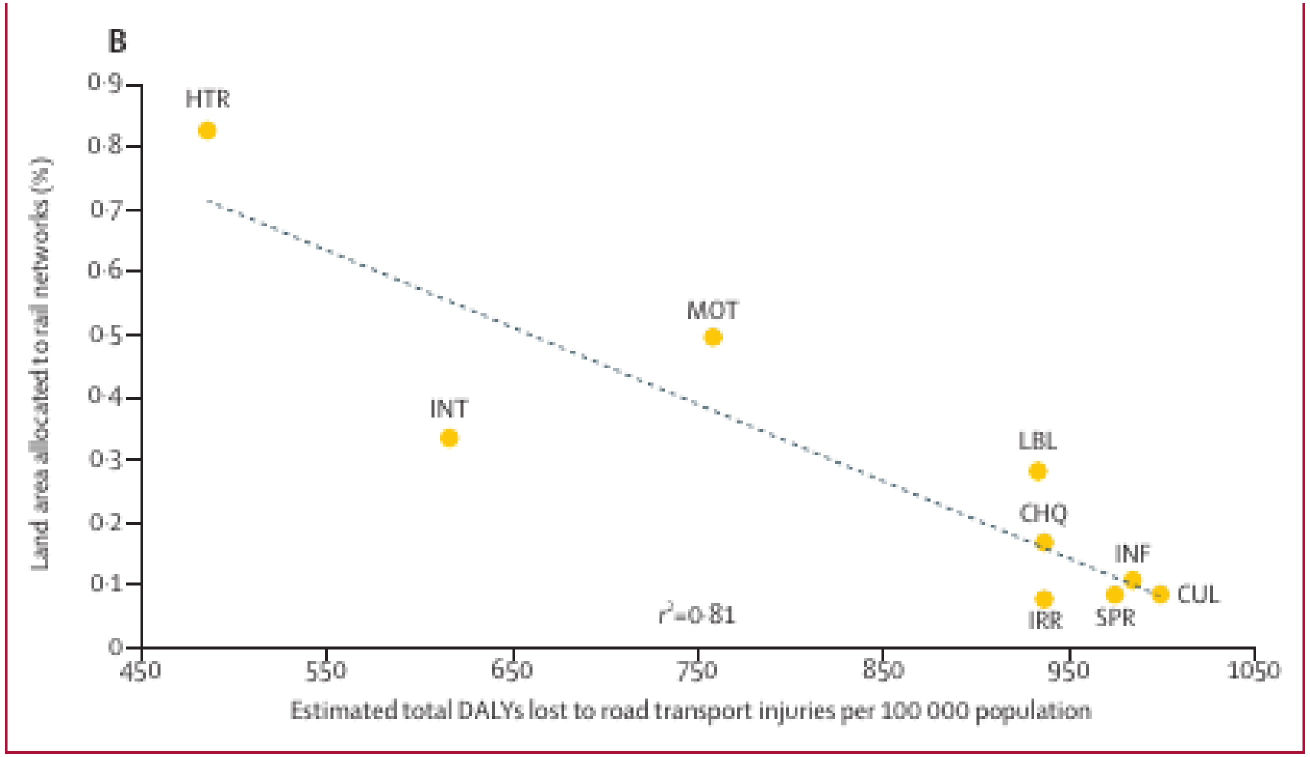


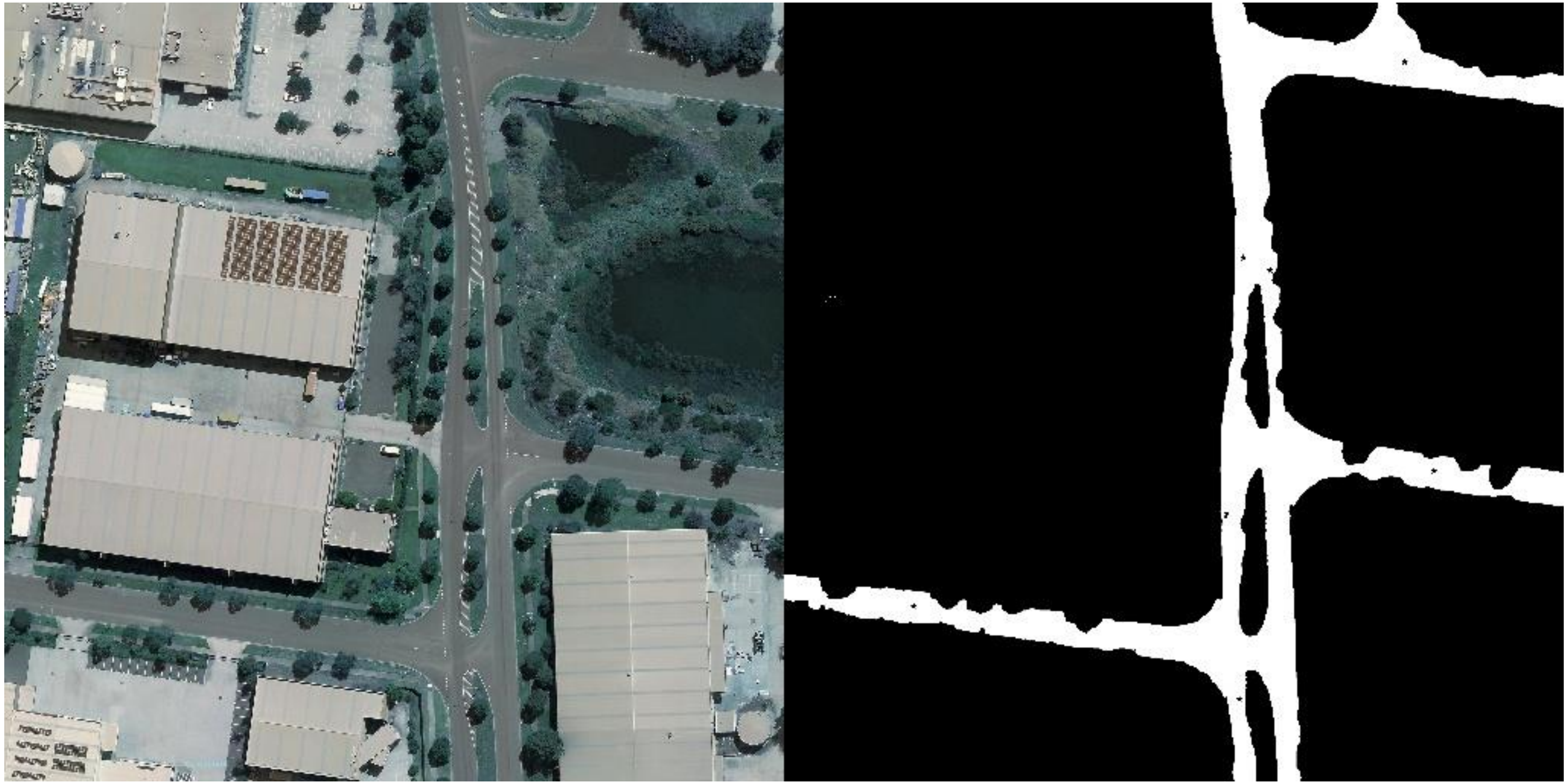
Figure 5: Association between city types dedicated to road (A) and rail (B) networks and DALYs lost to road transport injury per 100 000 population
HTR=high transit. MOT=motor cities. INT=intense. CUL=cul de sac. CHQ=Chequerboard. INF=informal. IRR=irregular. LBL=large block. SPR=sparse. DALYs=disability-adjusted life-years.

Thompson J, Stevenson M, Wijnands J, Nice K, Aschwanden G, Silver J, Nieuwenhuijsen M, Rayner P, Schofield R, Hariharan R, Morrison C. A global analysis of urban design types and road transport injury: an image processing study. The Lancet Planetary Health, 2020

Example 3

Infrastructure detection through computer vision

Spatial layer generation



Example 3

Infrastructure detection through computer vision

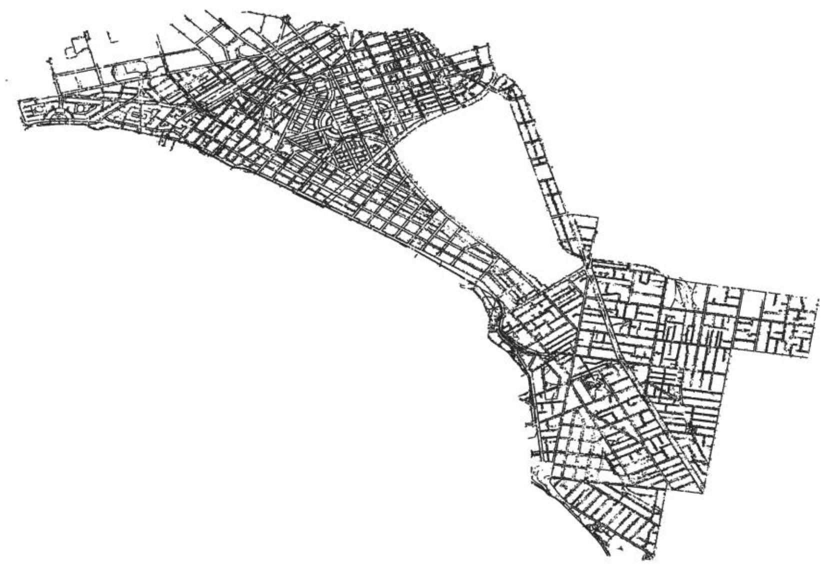
Works through obstructions

Example 3

Infrastructure detection through computer vision

Accuracy

Footpath data (left) vs GIS layer generated using only computer vision and aerial imagery

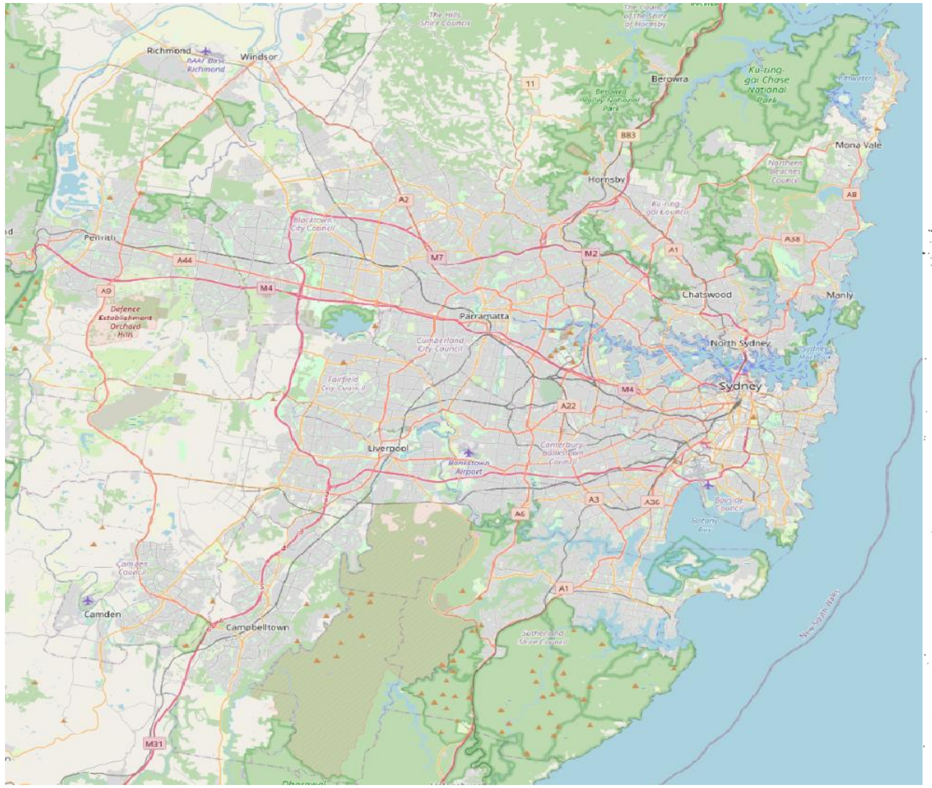


Example 3

Infrastructure detection through computer vision

Speed

Less than 10 minutes to scan all of Sydney and identify cycling lanes into a GIS layer

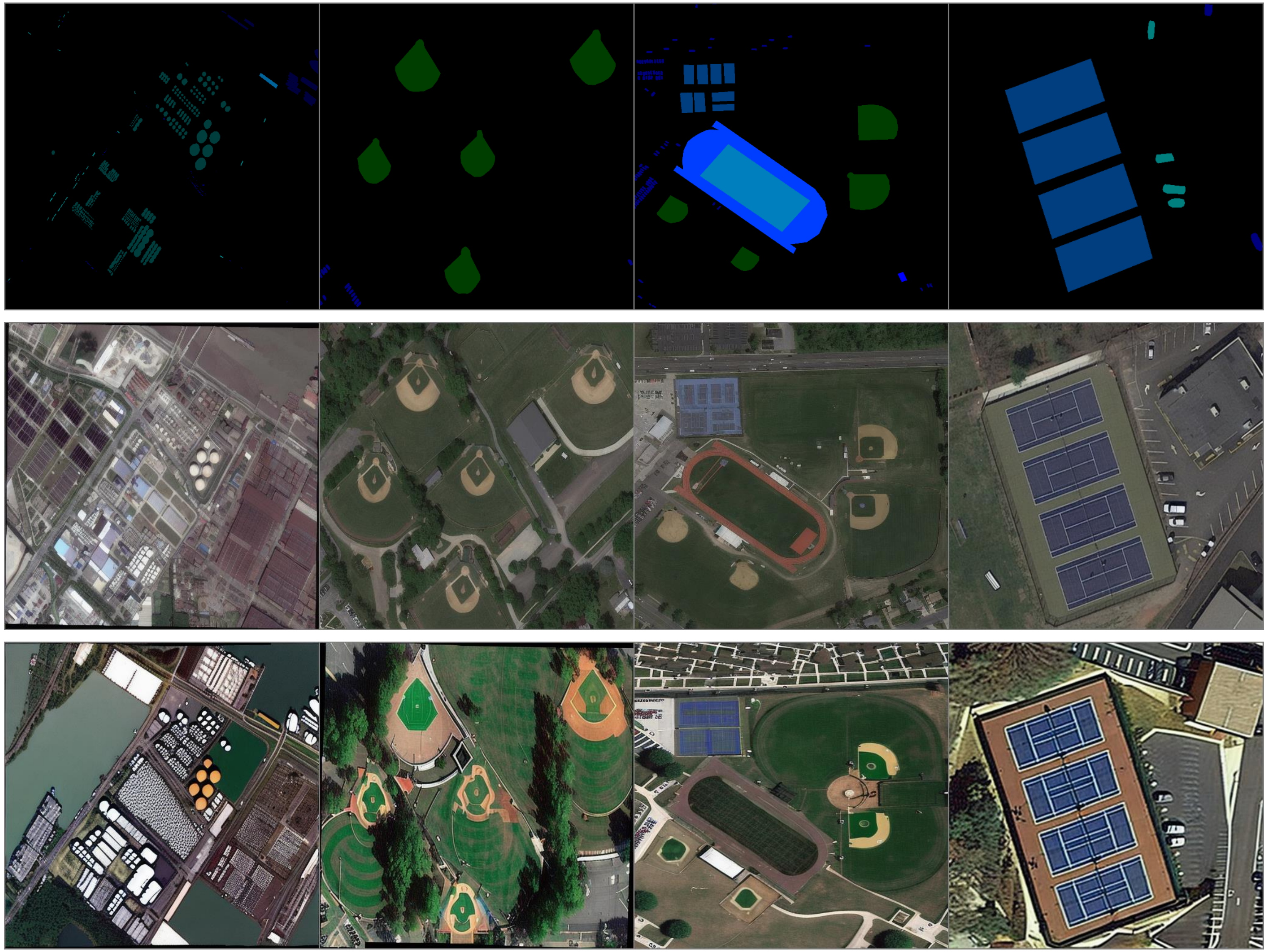


Example 3

Allows generation of realistic spatial content for rare instances for analysis by models

Infrastructure detection through computer vision

Synthetic generation



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