**Is there a correlation between housing prices and living standards in different parts of Victoria?**

Authors:

Un Leng Kam 1178863

Ron (Lang) Chen 1181506

Sean (Aoxiang) Xiao 1174270

This project investigated *whether house prices in Victoria are correlated to living standards*. Specifically, we looked at the relationship between the Median House Price (MHP) and living standard using data from each of the 79 LGAs of Victoria. As 'living standard' is a difficult index to measure, with its definition and method of calculation subjective and varying significantly between different sources, one challenge in this project was deriving a function for calculating the living standard that is as objective as possible given the data we could source. We defined living standards by a liveability score: a weighted sum of five different attributes found in each area; its derivation is discussed and justified later. The outcome of our analysis was a scatter plot of MHP to liveability, with linear regression performed as we assumed for such an important investment one would theoretically only pay more for a linear return for their money. Analysis of the regression returned an $r^2$ value of 0.232, which suggests the existence of a positive correlation between MHP and liveability.

Our research question is related to the themes of liveability and sustainability of communities in Victoria, where communities are represented by LGA areas. Through investigating the correlation between housing prices and living standards, we hypothesised that our results would give insights on the liveability in areas with certain MHPs, and by including open spaces in our living standard calculation, sustainability was also explored - open space area is a typically accepted indicator of how sustainable an area is.

Six datasets in the form of csv and .xlsx were used in this project, sourced from multiple databases (Aurin, Discover Data Victoria[1]), of which we extracted the MHP, Crime Rate per 100,000 (CR), Tally of number of Facilities (FT), total Open Area (OA), average ambulance Response Times (RT) and Tally of number of Schools (ST) in each LGA. These five attributes were chosen because we believed they are among the fundamental aspects that homebuyers consider before purchasing a property, and hence the more/better they are in a certain LGA the more demand there would be for a local property and thus the higher its MHP. In our selection process data such as tally of number of open spaces were discarded because they would likely be highly correlated with GA and thus double weigh the impact of sustainability when liveability was calculated.

Major python modules used in the data wrangling and analysis process includes 'Pandas', 're', 'matplotlib', 'Statistics', 'sklearn' and 'NumPy' as well as native datatypes and functions. Excel was used to inspect raw data.

The first wrangling step was creating a csv to map all suburbs to their LGA, and another with an alphabetical order of LGAs so all tallies initiated by it would maintain a unified order that simplified aggregation later. In Victoria, one LGA may consist multiple suburbs, and as most raw datasets came with only LGA or suburbs, the first csv was created to allow them to be tallied by LGA. It is because of this one-to-many relationship that made suburbs an undesirable choice for partitioning Victoria compared to LGAs. Both were created by wrangling and aggregating the 'School.csv' dataset, which for each school provided its suburb, postcode, LGA and LGA code. 're' was used to clean up names (in 'School.csv' all LGA names had a '(*)' after the name which denoted its type) and for a special case the hyphen in 'Otway-Colac' was removed because some data presented 'Otway Colac', and deleting from the dictionary was easier than adding '-' when wrangling the other

[1] See bibliography for full list

data sets.

All other datasets then followed a similar process of importing into a DataFrame and creating a frequency tally of the attribute by LGAs. In some cases, tally inclusion of a row (object) was also based on values in other columns of the raw dataset, because not every single row represented objects that were sought (i.e. in 'VPA_Open_Space.csv' some rows were schools and thus discarded because it would double-weigh schools later). In some files the LGA name had noise and were cleaned up by 're'. When wrangling MHP, we found that our csv which mapped suburbs to LGAs did not include all the Victorian suburbs, likely because in 'School.csv' not every suburb had a school. These were filled in manually in Excel from internet searches as no other 'dictionaries' that had the full set of suburbs-to-LGA could be found. In cases where data of multiple suburbs were merged into one LGA, the median of each merging suburb's values were taken rather than the mean of values because some LGAs had up to 30 suburbs so there was a high chance that the mean would be distorted by high outlier values. The MHP and 5 attributes were then aggregated into one DataFrame.

In seeking a method to derive liveability from the five wrangled attributes, we decided to use a linear function to calculate a liveability score:

$$liveability\ score = a(x_1) + b(x_2) + c(x_3) + d(x_4) + e(x_5)$$

with the $x_i$ values being the normalised scores of each attribute from each LGA and the coefficients being the weighting constants, which were derived by calculating the Normalised Mutual Information (NMI) between the MHP and each attribute. The module 'sklearn.normalized_mutual_info_score' was employed to give NMI scores:

| **Attribute** | **NMI scores** |
|---|---|
| CR | 0.9919028123572338 |
| FT | 0.969466990039968 |
| GA | 0.6447755861424472 |
| RT | 0.9857433425019687 |
| ST | 0.9072602417922371 |

hence the liveability equation is:

$$livability\ score = 0.9919028123572338(x_1) + 0.969466990039968(x_2) + 0.6447755861424472(x_3) + 0.9857433425019687(x_4) + 0.9072602417922371(x_5),$$

$$\text{where } x_1, x_2, x_3, x_4, x_5 \text{ are the normalised values of CR, FT, GA, RT and ST}$$

This was applied to every LGA to get their liveability score[2], where attributes were each normalised with respect to their entire column. The FT, GA and ST columns were normalised by $(x - min)/(max - min)$ while CR and RT columns were normalised by $(max - x)/(max - min)$. The latter was done differently because for these attributes lower values represented better performances, and it was essential that post-normalisation all attributes had values where higher numbers represented better performance in order for the liveability equation to be effective. Normalisation was critical because some attributes had values that were overall much higher than others and thus would have undermined the weighting system and hence produced inaccurate liveability scores (note performing NMI on MHP and attribute values gives same results as NMI on MHP and normalised attribute values).

Whilst using Pearson Correlation or $r^2$ of linear regression on the MHP for each of the five attributes to give the weighting coefficients for the liveability equation was considered, NMI was ultimately chosen because upon inspecting the scatter plots (produced by 'matplotlib.pyplot') of MHP to each attribute, none of the five

[2] See Appendix A for Table of LGA, MHP and Liveability Score

showed a linear relationship, and thus the precondition for using either Pearson or $r^2$ were not satisfied. Principle Component Analysis was also considered but we believed the data was too complexly related to be reduced to a one-dimensional liveability score.

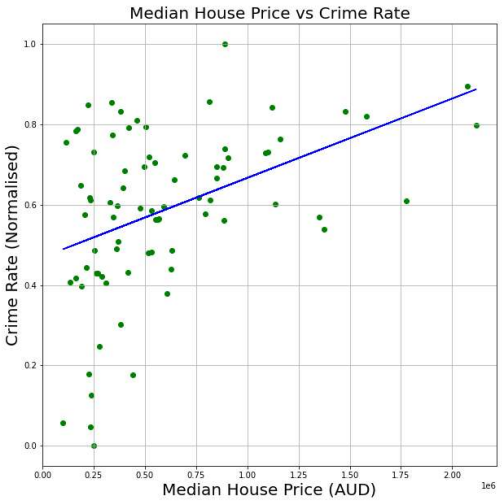


*Figure 1 MHP to Normalised CR – looks logarithmic*


*Figure 2 MHP to Normalised FT – looks logarithmic*


*Figure 3 MHP to Normalised OA*


*Figure 4 MHP to Normalised RT – looks logarithmic*

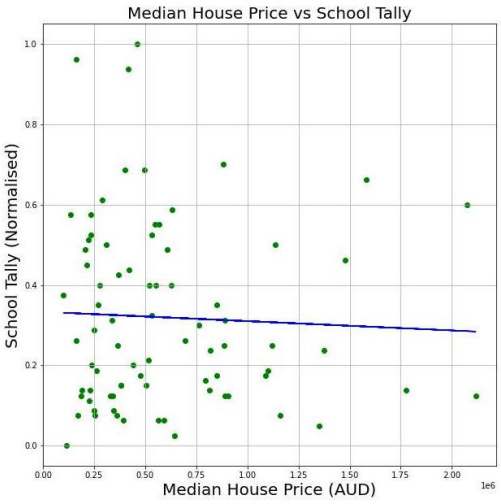


*Figure 5 MHP to Normalised ST – looks like hyperbole*

Linear regression was performed on the MHP to liveability scatter plot using 'sklearn' and 'NumPy' to give the regression function $y = 0.0000005x + 1.6341$, with $r^2$ value 0.232.


*Figure 6 MHP to Liveability Score (with Linear Regression)*


*Figure 7 MHP to Liveability Score (With Linear Regression and highlighted outliers)*

While 0.232 is typically considered a weak correlation, without domain knowledge (e.g. comparisons to results from this analysis performed on other Australian states) at minimum a positive correlation between MHP and liveability can be concluded; this means generally as house prices goes up the living standard also increases.

The majority of points in Figure 6 are clustered in the lower region of MHPs, with their liveability scores varying between 0.5-2.8 whereas in the higher values (>1,250,000) the points are sparser, varying between 1.7-2.8. The clustering of points in the low MHP region is caused because there are few LGAs in Victoria with high MHPs – most are between 250,000-1,250,000; this is one primary insight from the result. Boroondara is an LGA that fits the trend line well, with MHP 2,075,000 and Liveability Score 2.837; it is observed that it has normalised values over 0.5 for all attributes except 0.0042 for OA[3], which is actually rather high for this attribute because OA has a few very high outliers so the majority of normalised scores are below 0.005. This shows that communities with higher MHP have better liveability and sustainability – the latter as the presence of open spaces in the area suggests that over-development is being guarded against by keeping some land 'construction-less'. Ballarat, Greater Geelong and Yarra Ranges were outliers according to the upper/lower fence outlier analysis performed on residuals. The reason for these outliers is because they have at least two high weighting attributes with very high normalised scores -Ballarat had RT and ST scores at 0.93 and 0.94 which were weighted 0.99 and 0.90 respectively. Ballarat's high score combined with its comparatively low MHP thus made it an outlier. Stonnington has the highest MHP, but a liveability score of 2.1 which is around the median of all scores. This indicates that at higher MHPs more money does not necessarily return proportionate liveability and sustainability: Stonnington's normalised value for OS is quite low at 0.0014; it also has limited facilities (0.29) and schools (0.125). This may also suggest that the MHP-liveability relationship may not be linear for all MHP ranges.

Possible beneficiaries of the result and insights are the government and real estate investors. The latter could use it to assist their analysis of whether a property's value has potential for sharp growth because of the planned improvements related to our five liveability attributes, while the government could use it to understand what the people value having near their homes and improve attributes in areas that are currently under-performing to increase the overall welfare of society. The low OA weighting compared to other attributes may also suggest to the government that sustainability is not a priority to buyers and by inference the public; this may influence their future policymaking. For general homebuyers, the result may help them recognise that the return in liveability for highly priced properties may not be linear.

One limitation of this analysis was we couldn't find data on other representative attributes such as tally of public transport - including these may have given a better liveability equation as e.g. here buyers would likely favour areas with good access to public transport. Another was that the raw data of OA had 'missing at random': many country LGAs had no records (0 on tally)[4]. Mean imputation was not performed as it would have imputed metropolitan data onto country, and the many 0's likely lowered OA's weighting. The final model could perhaps be analysed by logarithmic regression, because most points are clustered in the lower MHPs and 16 of them have high liveability scores of >2.25, providing the sharp increase at low values of log functions. Trialling this in Excel returned a higher $r^2$ at 0.3076. This suggests that at higher MHPs, the current liveability equation either hasn't captured all attributes that have an impact on property value (i.e. distance from Melbourne CBD) or that the relationship was never linear and our initial belief of linear return for money is incorrect. Nonetheless these limitations do not challenge our primary result of the existence of positive correlation.

[3] See Appendix B for all normalised attribute values of each LGA

[4] From inspection and domain knowledge of being a Victorian resident

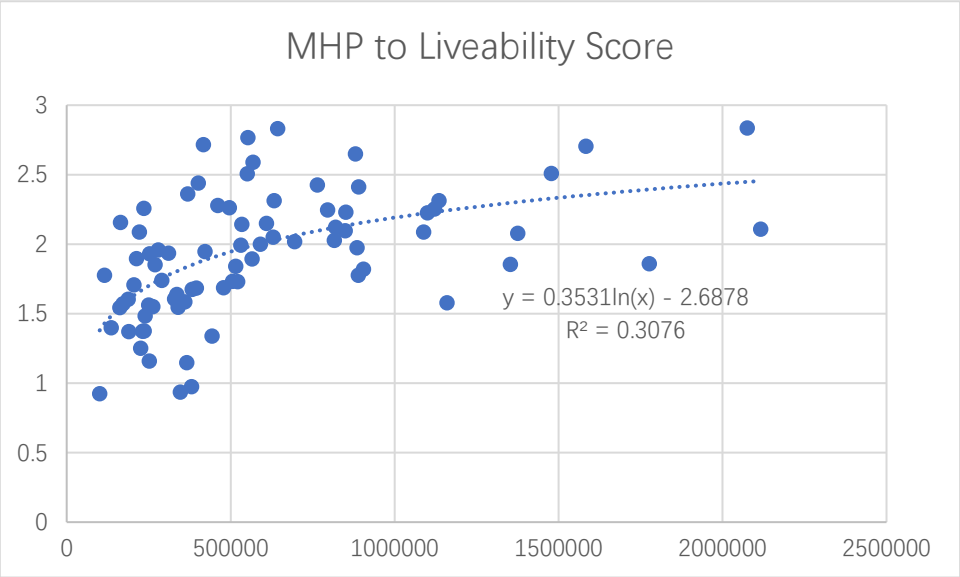


*Figure 8 MHP to Liveability Score (Logarithmic Regression) - produced by Excel*

An extension/modification to this project is to treat liveability scores as a model and use a method similar to k-fold cross validation but on different combinations of attributes to build and test for the best model of liveability. However, this is more prediction-related and while better serves the purposes of the aforementioned beneficiaries does not answer our research question.

**Bibliography**

Raw Datasets (italicised filenames as found in the .zip on LMS and on github – may not be same as when first downloaded)

1. Median House Price: discover.data.vic.gov.au/dataset/victoria-property-sales-report-median-by-suburb-time-series1
   *"Suburb_House_final.csv"*

2. Crime Rates: https://www.crimestatistics.vic.gov.au/family-violence-data-portal/download-data-tables - Table 3
   *"Ambulance Victoria Data Tables - 2019-20.xlsx"*

3. Sporting and Recreational Facilities: Government of Victoria - Department of Environment Land Water and Planning, 2019, VIC DELWP - Vicmap Features of Interest - Sporting Facilities (Polygons), Retrieved from https://portal.aurin.org.au on 2021-04-05
   *"Sport_and_recreation.csv"*

4. Open Space: https://discover.data.vic.gov.au/dataset/open-space
   *"VPA_Open_Space.csv"*

5. Ambulance Response Time: https://discover.data.vic.gov.au/dataset/ambulance-victoria-lga-response-time-performance
   *"LGA-Response-Time-Performance-FY-2019.csv"*

6. Schools: Government of Victoria - Department of Education and Training, 2018, VIC DET - School Locations for Victoria 01/02/2018, Retrieved from https://portal.aurin.org.au on 2021-04-05
   *"School.csv"*

Libraries/modules

***For the use of libraries and modules please see the README file submitted on LMS or github***

**Appendix A**

| **LGA Name** | **Median House Price** | **Liveability Score** |
|---|---|---|
| **ALPINE** | 460000 | 2.279017856451208 |
| **ARARAT** | 163250 | 2.156227507844175 |
| **BALLARAT** | 416000 | 2.715337431545911 |
| **BANYULE** | 880500 | 2.650137192237664 |
| **BASS COAST** | 495500 | 2.2624904920603903 |
| **BAW BAW** | 401250 | 2.4392453058358505 |
| **BAYSIDE** | 1582500 | 2.7040439085699037 |
| **BENALLA** | 290000 | 1.739107387612497 |
| **BOROONDARA** | 2075000 | 2.8368436256478136 |
| **BRIMBANK** | 632500 | 2.3126065593780973 |
| **BULOKE** | 135500 | 1.399155772145344 |
| **CAMPASPE** | 234500 | 2.2574981381775667 |
| **CARDINIA** | 550000 | 2.507555786556805 |
| **CASEY** | 567500 | 2.5903105680780767 |

| | | |
|---|---|---|
| **CENTRAL GOLDFIELDS** | 235500 | 1.3763201587999694 |
| **COLAC OTWAY** | 530250 | 1.993244858979771 |
| **CORANGAMITE** | 221500 | 2.0881095462474115 |
| **DAREBIN** | 1135000 | 2.312900073883726 |
| **EAST GIPPSLAND** | 310000 | 1.9351826044607967 |
| **FRANKSTON** | 608750 | 2.149084342082875 |
| **GANNAWARRA** | 205000 | 1.7065373023940116 |
| **GLEN EIRA** | 1477750 | 2.508541533252486 |
| **GLENELG** | 212750 | 1.8950754089430983 |
| **GOLDEN PLAINS** | 421500 | 1.9468128633004147 |
| **GREATER BENDIGO** | 368750 | 2.362089981610652 |
| **GREATER DANDENONG** | 629000 | 2.050355371724189 |
| **GREATER GEELONG** | 552500 | 2.766546728484037 |
| **GREATER SHEPPARTON** | 279250 | 1.9589742822693 |
| **HEPBURN** | 521250 | 1.731252297553474 |
| **HINDMARSH** | 100500 | 0.9232552798950614 |
| **HOBSONS BAY** | 850750 | 2.229605965690888 |
| **HORSHAM** | 269000 | 1.8523082802029143 |
| **HUME** | 533500 | 2.1422621159216613 |
| **INDIGO** | 335500 | 1.6371074508014265 |
| **KINGSTON** | 890250 | 2.411518603017613 |
| **KNOX** | 763500 | 2.424973980723895 |
| **LATROBE** | 250000 | 1.5630712337383574 |
| **LODDON** | 161750 | 1.5432433202421507 |
| **MACEDON RANGES** | 695000 | 2.018901742491153 |
| **MANNINGHAM** | 1121000 | 2.2519375032496507 |
| **MANSFIELD** | 365750 | 1.1485055580864514 |
| **MARIBYRNONG** | 885000 | 1.9751810758665256 |
| **MAROONDAH** | 819250 | 2.121887851495286 |
| **MELBOURNE** | 1375000 | 2.0784089943949478 |
| **MELTON** | 515000 | 1.8407566888554507 |
| **MILDURA** | 239000 | 1.4848009921631191 |
| **MITCHELL** | 442500 | 1.3381691157435764 |
| **MOIRA** | 262500 | 1.5513108842527197 |
| **MONASH** | 1100000 | 2.2247534602091124 |
| **MOONEE VALLEY** | 1088500 | 2.0871231817153233 |
| **MOORABOOL** | 477500 | 1.687042963304442 |
| **MORELAND** | 849250 | 2.097552124204076 |
| **MORNINGTON PENINSULA** | 795000 | 2.2465036008755965 |
| **MOUNT ALEXANDER** | 505000 | 1.7321940038389902 |
| **MOYNE** | 382000 | 1.675348363714706 |
| **MURRINDINDI** | 380500 | 0.97557993491256 |
| **NILLUMBIK** | 815500 | 2.0263814069655566 |
| **NORTHERN GRAMPIANS** | 189000 | 1.3712036614723058 |
| **PORT PHILLIP** | 1776250 | 1.8599249784535532 |
| **PYRENEES** | 231000 | 1.3739751945208492 |
| **QUEENSCLIFFE** | 888750 | 1.7762092395683893 |
| **SOUTH GIPPSLAND** | 328750 | 1.6068044229687402 |
| **SOUTHERN GRAMPIANS** | 186750 | 1.6030831375529997 |

| | | |
|---|---|---|
| **STONNINGTON** | 2116250 | 2.108344659706451 |
| **STRATHBOGIE** | 339500 | 1.5453839892393293 |
| **SURF COAST** | 905000 | 1.8195476444503096 |
| **SWAN HILL** | 225000 | 1.2500399183520183 |
| **TOWONG** | 251500 | 1.1583313255658538 |
| **WANGARATTA** | 345750 | 0.9361798788937388 |
| **WARRNAMBOOL** | 360000 | 1.5858065426312844 |
| **WELLINGTON** | 252500 | 1.9316711048384558 |
| **WEST WIMMERA** | 171250 | 1.570497748249457 |
| **WHITEHORSE** | 1159500 | 1.5783227537831162 |
| **WHITTLESEA** | 590500 | 2.0008594549663754 |
| **WODONGA** | 395000 | 1.6839158235564338 |
| **WYNDHAM** | 565000 | 1.89392751574602 |
| **YARRA** | 1352500 | 1.855080142348744 |
| **YARRA RANGES** | 642500 | 2.831952643734072 |
| **YARRIAMBIACK** | 114500 | 1.7755305119836042 |

**Appendix B**

| **LGA Name** | **CR** | **FT** | **OA** | **RT** | **ST** |
|---|---|---|---|---|---|
| **ALPINE** | 0.809079854 | 0.156976744 | 0.0 | 0.423076923 | 1.0 |
| **ARARAT** | 0.416700446 | 0.174418605 | 0.0 | 0.710702341 | 0.9625 |
| **BALLARAT** | 0.431698419 | 0.540697674 | 0.0 | 0.925585284000 0001 | 0.9375 |
| **BANYULE** | 0.693149574000 0001 | 0.404069767 | 0.0056071830 00000001 | 0.945652174 | 0.7 |
| **BASS COAST** | 0.693960276 | 0.22965116300 000002 | 0.0 | 0.738294314 | 0.6875 |
| **BAW BAW** | 0.684637211 | 0.42151162799 999997 | 0.0 | 0.738294314 | 0.6875 |
| **BAYSIDE** | 0.820429672 | 0.395348837 | 0.005305291 | 0.915551839 | 0.6625 |
| **BENALLA** | 0.421970004 | 0.09011627900 000001 | 0.0 | 0.68729097 | 0.6125 |
| **BOROONDARA** | 0.895419538 | 0.502906977 | 0.00423198 | 0.927257525 | 0.6 |
| **BRIMBANK** | 0.485610053 | 0.38662790700 000005 | 0.0102045809 99999999 | 0.929765886 | 0.5875 |
| **BULOKE** | 0.40656668 | 0.203488372 | 0.0 | 0.280936455 | 0.575 |
| **CAMPASPE** | 0.612079449 | 0.398255814 | 0.0 | 0.753344482 | 0.575 |
| **CARDINIA** | 0.704499392 | 0.39244186 | 0.183467522 | 0.822742475 | 0.55 |
| **CASEY** | 0.565058776 | 0.630813953 | 0.0260270570 00000003 | 0.915551839 | 0.55 |
| **CENTRAL GOLDFIELDS** | 0.047426024000 000004 | 0.16569767400 000002 | 0.0 | 0.702341137 | 0.525 |
| **COLAC OTWAY** | 0.585731657999 9999 | 0.26744186 | 0.0 | 0.686454849000 0001 | 0.525 |
| **CORANGAMITE** | 0.848804215999 9999 | 0.276162791 | 0.0 | 0.52090301 | 0.5125 |
| **DAREBIN** | 0.601134982 | 0.328488372 | 0.005129389 | 0.954849498 | 0.5 |
| **EAST GIPPSLAND** | 0.404945277999 99996 | 0.424418605 | 0.0 | 0.678093645 | 0.5 |

| | | | | | |
|---|---|---|---|---|---|
| **FRANKSTON** | 0.378597487 | 0.39244186 | 0.01739442 | 0.953177258 | 0.4875 |
| **GANNAWARRA** | 0.575597892 | 0.209302326 | 0.0 | 0.497491639 | 0.4875 |
| **GLEN EIRA** | 0.832590191 | 0.33430232600000004 | 0.0029072359999999997 | 0.9506688959999999 | 0.4625 |
| **GLENELG** | 0.44345358700000004 | 0.27906976699999997 | 0.0 | 0.787625418 | 0.45 |
| **GOLDEN PLAINS** | 0.792055128 | 0.27906976699999997 | 0.0 | 0.50083612 | 0.4375 |
| **GREATER BENDIGO** | 0.508309688 | 0.6540697670000001 | 0.0 | 0.850334448 | 0.425 |
| **GREATER DANDENONG** | 0.43899473 | 0.313953488 | 0.006102104000000006 | 0.95735786 | 0.4 |
| **GREATER GEELONG** | 0.563437373 | 1.0 | 0.0 | 0.887959866 | 0.4 |
| **GREATER SHEPPARTON** | 0.24726388300000002 | 0.470930233 | 0.0 | 0.907190635 | 0.4 |
| **HEPBURN** | 0.719092015 | 0.151162791 | 0.0 | 0.5158862879999999 | 0.4 |
| **HINDMARSH** | 0.056749087999999996 | 0.104651163 | 0.0 | 0.431438127 | 0.375 |
| **HOBSONS BAY** | 0.665585732 | 0.36046511600000003 | 0.004974073 | 0.912207358 | 0.35 |
| **HORSHAM** | 0.429671666 | 0.215116279 | 0.0 | 0.913043478 | 0.35 |
| **HUME** | 0.48236724799999997 | 0.470930233 | 0.011504873999999998 | 0.918060201 | 0.325 |
| **INDIGO** | 0.8540737740000001 | 0.127906977 | 0.0 | 0.38795986600000004 | 0.3125 |
| **KINGSTON** | 0.738548845 | 0.470930233 | 0.010405871 | 0.945652174 | 0.3125 |
| **KNOX** | 0.618565059 | 0.60755814 | 0.008838097 | 0.95819398 | 0.3 |
| **LATROBE** | 0.0 | 0.450581395 | 0.0 | 0.877926421 | 0.2875 |
| **LODDON** | 0.783948115 | 0.18023255800000001 | 0.0 | 0.35785953200000004 | 0.2625 |
| **MACEDON RANGES** | 0.723145521 | 0.313953488 | 0.0 | 0.77006689 | 0.2625 |
| **MANNINGHAM** | 0.843129307 | 0.34011627899999997 | 0.01192645 | 0.863712375 | 0.25 |
| **MANSFIELD** | 0.597486826 | 0.063953488 | 0.0 | 0.27090301 | 0.25 |
| **MARIBYRNONG** | 0.561815971 | 0.261627907 | 0.001811823 | 0.9498327759999999 | 0.25 |
| **MAROONDAH** | 0.612079449 | 0.331395349 | 0.005907211 | 0.988294314 | 0.2375 |
| **MELBOURNE** | 0.538710985 | 0.354651163 | 0.003592891 | 0.996655518 | 0.2375 |
| **MELTON** | 0.479935144 | 0.28488372100000003 | 0.022735937999999997 | 0.8938127090000001 | 0.2125 |
| **MILDURA** | 0.12525334400000002 | 0.302325581 | 0.0 | 0.8988294309999999 | 0.2 |
| **MITCHELL** | 0.17673287399999998 | 0.244186047 | 0.004505155 | 0.752508361 | 0.2 |
| **MOIRA** | 0.429671666 | 0.316860465 | 0.0 | 0.657190635 | 0.1875 |
| **MONASH** | 0.7316578840000001 | 0.447674419 | 0.006114921 | 0.903846154 | 0.1875 |

| | | | | | |
|---|---|---|---|---|---|
| **MOONEE VALLEY** | 0.729631131 | 0.3343023260000004 | 0.003004257999999997 | 0.891304348 | 0.175 |
| **MOORABOOL** | 0.590595865 | 0.162790698 | 0.0 | 0.795986622 | 0.175 |
| **MORELAND** | 0.694770977 | 0.3401162789999999997 | 0.002707699 | 0.9314381270000001 | 0.175 |
| **MORNINGTON PENINSULA** | 0.576813944 | 0.610465116 | 0.08763875900000001 | 0.891304348 | 0.1625 |
| **MOUNT ALEXANDER** | 0.79327118 | 0.220930233 | 0.0 | 0.60367893 | 0.15 |
| **MOYNE** | 0.832590191 | 0.177325581 | 0.0 | 0.549331104 | 0.15 |
| **MURRINDINDI** | 0.301175517 | 0.1947674419999999999 | 0.0 | 0.357023411 | 0.15 |
| **NILLUMBIK** | 0.856505878 | 0.238372093 | 0.08830227199999999 | 0.775083612 | 0.1375 |
| **NORTHERN GRAMPIANS** | 0.3964329139999999997 | 0.154069767 | 0.0 | 0.714046823 | 0.1375 |
| **PORT PHILLIP** | 0.610052696 | 0.186046512 | 0.002896546 | 0.961538462 | 0.1375 |
| **PYRENEES** | 0.618565059 | 0.09883720900000001 | 0.0 | 0.547658863 | 0.1375 |
| **QUEENSCLIFFE** | 1.0 | 0.0 | 0.0 | 0.6806020070000001 | 0.125 |
| **SOUTH GIPPSLAND** | 0.6047831370000001 | 0.375 | 0.0 | 0.537625418 | 0.125 |
| **SOUTHERN GRAMPIANS** | 0.647750304 | 0.220930233 | 0.0 | 0.642140468 | 0.125 |
| **STONNINGTON** | 0.7985407379999999 | 0.293604651 | 0.001376566 | 0.9306020070000001 | 0.125 |
| **STRATHBOGIE** | 0.772598298 | 0.12209302300000001 | 0.0 | 0.555183946 | 0.125 |
| **SURF COAST** | 0.71625456 | 0.3401162789999999997 | 0.0 | 0.6755852840000001 | 0.125 |
| **SWAN HILL** | 0.177948926 | 0.191860465 | 0.0 | 0.796822742 | 0.1125 |
| **TOWONG** | 0.732063235 | 0.069767442 | 0.0 | 0.289297659 | 0.0875 |
| **WANGARATTA** | 0.5683015810000001 | 0.302325581 | 0.0 | 0.0 | 0.0875 |
| **WARRNAMBOOL** | 0.49047426 | 0.244186047 | 0.0 | 0.8060200670000001 | 0.075 |
| **WELLINGTON** | 0.486420754 | 0.441860465 | 0.0 | 0.9665551840000001 | 0.075 |
| **WEST WIMMERA** | 0.788406972 | 0.104651163 | 0.0 | 0.6279264210000001 | 0.075 |
| **WHITEHORSE** | 0.764085934 | 0.40988372100000003 | 0.003494022000000003 | 0.35785953200000004 | 0.075 |
| **WHITTLESEA** | 0.5954600729999999 | 0.3604651160000003 | 0.06419659700000001 | 0.9765886290000001 | 0.0625 |
| **WODONGA** | 0.641264694 | 0.14244186 | 0.0 | 0.865384615 | 0.0625 |
| **WYNDHAM** | 0.563032023 | 0.3866279070000005 | 0.007328721 | 0.912207358 | 0.0625 |
| **YARRA** | 0.569517633 | 0.348837209 | 0.002563835 | 0.918060201 | 0.05 |
| **YARRA RANGES** | 0.662748277 | 0.537790698 | 1.0 | 1.0 | 0.025 |

| | | | | | |
|---|---|---|---|---|---|
| **YARRIAMBIACK** | 0.7555735709999999 | 0.200581395 | 0.0 | 0.843645485 | 0.0 |

**Appendix c**

*Raw data files, data files created in the intermediate steps and .ipynb used to achieve the results are submitted via the .zip file in the LMS. The order they are to be run to be guaranteed to work and input/output they require/produce are specified in the README file.*