Applied Spatial Analysis and Policy (2025) 18:43
https://doi.org/10.1007/s12061-025-09643-9

The Auckland Urban Liveability Index: A Mechanism for Quantifying and Evaluating Modern Urban Densification

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Received: 26 April 2024 / Accepted: 19 January 2025

Abstract
We present the Auckland Urban Liveability Index (AULI), an indicator that quantifies modern liveability at the neighbourhood level in Auckland. The index comprises 29 variables spanning several components of liveability: social infrastructure, green space, transportation, safety and diversity. Each is documented transparently with accompanying data and code. We find that neighbourhoods with the highest liveability scores have comparatively good public transport provision and are amenable to active travel, reflecting the principles of modern urban densification. Through local modelling frameworks, we provide useful context on the generalisability of index components that supports the transfer of our index to other cities in New Zealand and re-evaluation of our index in light of new data.

Keywords Urban Liveability in Auckland · Geospatial Analysis · Spatial Composite Indicator · Urban Densification

Introduction

The concept of urban liveability has long underpinned modern planning theory and practice. Popularised by the idea of a *15-minute city* (Moreno et al., 2021), urban liveability can be characterised as consisting of high-density, walkable neighbourhoods, with high quality public and active transport facilities (Yang, 2008), where work and

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Published online: 01 March 2025

amenities, such as retail, education, leisure and healthcare can be easily accessed (Pozoukidou & Chatziyiannaki, 2021). The concept has clear links to the Sustainable Development Goals of creating sustainable communities and improving the health, well-being and safety of urban-dwellers (Macmillan et al., 2020).

Given this background, the cities of Aotearoa New Zealand, occupy an interesting position. Whilst they are ranked very highly amongst global city liveability rankings (Meares et al., 2015), they are typical of a 20th-century low-density, car-oriented urban planning model. For Auckland, Aotearoa's largest city, this mismatch and the need to move towards reduced car dependency and high-density living has been recognised in the city's urban planning agenda (Faherty & Morrissey, 2014). The 2012 Auckland Plan (Imran & Pearce, 2015), the 2016 Auckland Unitary Plan (Auckland Council, 2016) and the Auckland Plan 2050 (Auckland Council, 2022) focus on reducing car dependency and moving towards high-quality densification of urban spaces.

Several academic studies have explored how liveability can be achieved via strategic spatial planning in Auckland (Imran & Pearce, 2015); investigating the relationship between urban densification and urban liveability (Allen et al., 2018; Haarhoff et al., 2016); and the effects of Auckland's current planning regulations on liveability (Beattie & Haarhoff, 2018). A recent study by Jiang et al. (2024) evaluates two Auckland neighbourhoods in terms of the 15-minute city criteria, describing their liveability. There has, though, been little work quantitatively measuring urban liveability patterns across Auckland or any New Zealand city beyond the macro-level measures, such as The Economist Intelligence Unit's (EIU) world city rankings (Paul & Sen, 2020). The need for a comprehensive spatial measure of urban liveability has been identified by Auckland City Council itself: "[A] comprehensive framework [...] should be populated with data that is aligned to concepts that are valued by residents and policy-makers" (Meares et al., 2015, p. 17).

This study presents and implements such a framework, named the Auckland Urban Liveability Index (AULI). The index characterises liveability using 29 variables organised into five themes or components – social infrastructure, transportation, green space, safety and culture – and aggregates to neighbourhood-level spatial units (Statistical Area 1, $n = 8047$). Data are collected from official governmental data portals as well as user-generated sources, such as OpenStreetMap (OSM), enabling us to capture aspects of liveability relevant to modern, urban densification (Beattie & Haarhoff, 2018).

Through analysis of our index, we demonstrate its empirical value: neighbourhoods with higher liveability scores show greater use of public and active transport, while our local modeling frameworks provide insights into how index components may be adapted for different urban contexts. The key contribution is the index itself and its reproducibility. This is the first time that modern liveability has been estimated in a large-scale way for a city in New Zealand. The index is presented transparently, with an accompanying code repository containing full reproduction materials and an interactive web-map for exploring outputs, which we hope will encourage the transfer of AULI to other cities, supporting useful comparative work.

Materials and Methods

Data

In order to capture detailed neighbourhood-level variations in urban liveability, we used Statistical Area 1 (SA1) units (n = 8047). We chose this scale because it provides consistent small areas containing 100-200 residents, making it ideal for analysing local accessibility and living conditions.

The spatial extent used to collect data is confined to the boundaries of urban areas of Auckland, and Waiheke Island, as per the Urban Rural land classification by Stats NZ Tatauranga Aotearoa (2023). For certain point-of-interest and street network features, we needed to search beyond these borders to mitigate potential leakage or edge effects, where peripheral areas are not modelled as correctly as central ones (Mori & Christodoulou, 2012).

The secondary data used for all indicators were collected from official data portals from the relevant organisations, as well as from OSM using the R package osmdata (Padgham et al., 2017). For census data with missing values, we used spatial interpolation - taking the average value from neighbouring areas - as this preserves local patterns while filling gaps. All data cleaning, spatial analysis and calculations were performed locally using three main software tools – R, Python and QGIS.

Distance Calculations

Out of the 29 variables, 21 were based on network distance calculations. This metric, as opposed to Euclidean distance, was chosen due to Auckland's high geographic irregularity, including bays and islands. The network data for the broader region surrounding the study area were acquired using the OSMnx Python package, which compiles all roads and paths data from OSM into walking, biking or driving networks (Boeing, 2017). In most cases, walking network distances were used - from each SA1 centroid to the nearest point-of-interest (PoI), calculated as origin-destination (OD) pairs (Marshall et al., 2018). The shortest distance calculation was performed using the *sfnetworks* library in R, which snaps points to the nearest edge of the network and calculates the shortest distance for all OD pairs. For each SA1, the distance to the nearest PoI was recorded as the final measure – an approach frequently used to assess accessibility in cities (Apparicio & Séguin, 2006). Where distances could not be calculated, for example due to the disconnect of Waiheke Island from the mainland, erroneous values were manually replaced with values corresponding to the minimum accessibility score of the final indicator.

Transforming Variables Into Indicators

Figure 1 contains a flow chart summarising the data transformation activities underpinning the index.

Since raw variables are of differing units, ranges and distributions, data transformation is a crucial step in constructing a composite indicator (Mazziotta & Pareto,

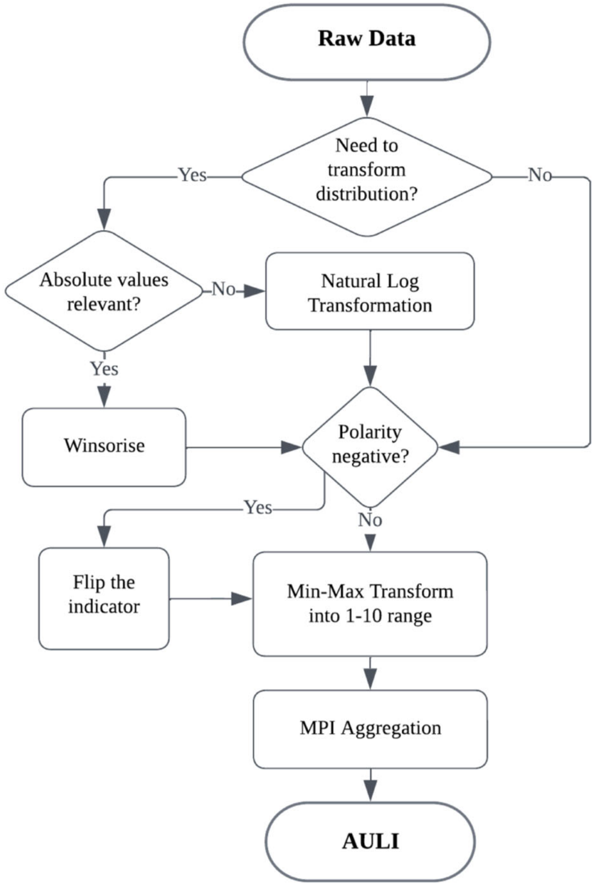


Fig. 1 Schematic diagram of constructing the AULI

2013). Reducing the skewness of an indicator's distribution is a key objective, especially given distance-based variables (Gilthorpe, 1995). To help guide this process, a simple heuristic was employed, aiming to lower the skewness, while also examining the indicator's spatial distribution. Two main methods, described below, were used to transform the raw data into indicators.

Winsorisation This transformation caps extreme values by reassigning any negative values to zero and setting a maximum threshold at the 90th percentile, limiting the top 10% of the distribution.

Log Transformation Where the distributions were severely skewed and absolute values of indicators were not interpretable e.g. (crash risk), a logarithmic transformation was used to normalise the distributions.

The polarity of variables was subsequently standardized to ensure consistent directional relationships with liveability. Distance variables, which predominantly exhibited negative relationships with liveability (greater distance indicating reduced accessibility), were systematically inverted. In the final preprocessing step, all the variables were standardised into the same range (1-10) using min-max standardisation. Maps of all indicators are provided in Fig. 8, and the detailed methodology for their construction, with histograms of their pre-and post-transformation distributions can be found in Table 2, in the Appendix.

Components

The 29 variables on which the index is based are organised into five main components, as presented in Fig. 2.

Each can be justified as contributing in a different way to urban liveability under densification criteria. Social Infrastructure describes access to educational and medical facilities, quality and affordable housing (Cullen, 2005), as well as features of

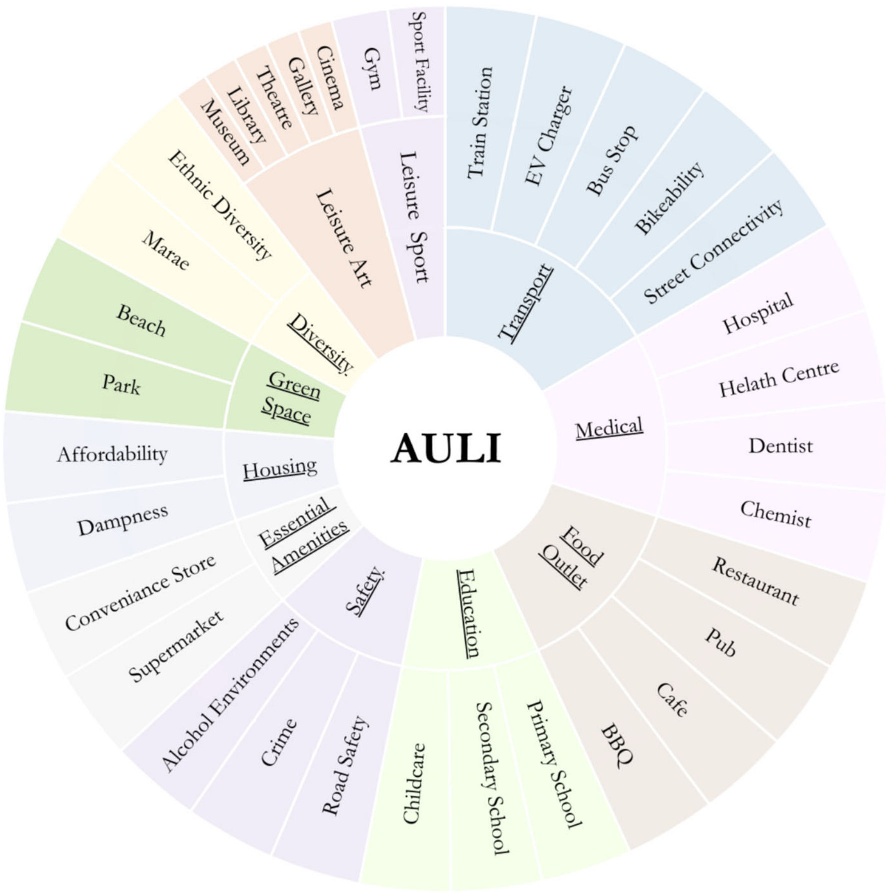


Fig. 2 Indicators and themes of the AULI

perceived liveability – provision of cafés, pubs, and restaurants (Allen et al., 2018). Transportation is a component crucial to the *15-minute city* living and reducing the negative consequences of densification, such as congestion and emissions (Lowe et al., 2015). Green Space was included based on extensive evidence linking urban green space access to health and wellbeing outcomes (Kondo et al., 2018). The Safety component extends beyond typical crime metrics to incorporate locally relevant measures of risk exposure, particularly to road accidents and alcohol-related harm. The Diversity component acknowledges both the cultural significance of Māori heritage and Auckland's multicultural character as integral elements of local liveability.

Social Infrastructure

The Social Infrastructure component integrates six strategically selected subthemes that capture both essential services and quality-of-life amenities: educational and medical facilities, essential amenities, food outlets, leisure and housing.

To account for access to education, spatial data on both primary and secondary schools (from the Education Counts data portal (Ministry of Education, 2014)), and day care centres (from OSM). Next, for access to medical facilities, point data on hospitals, health centres, dentists and pharmacies were acquired from OSM. Food and beverage establishments were included based on empirical evidence from Auckland resident interviews, which identified cafés, pubs, and restaurants as key contributors to perceived neighbourhood liveability (Allen et al., 2018). Furthermore, accessibility to public barbecues has also been accommodated in the index. Data on all four of these amenities were accessed from OSM.

Lastly, cultural and leisure facilities also contribute positively to urban liveability by facilitating social interaction and entertainment. Thus, point data of museums, galleries, libraries, cinemas, theatres and gyms were collected from OSM, and sport facilities from Sport New Zealand (2023). These were aggregated additively to form two indicators: *LeisureArt* and *LeisureSport*.

Affordability is approximated by the median rent, aiming to capture the broad variations in living cost throughout the city. Another indicator - *dampness* - reflects one particularly problematic aspect of housing quality in Auckland (Dupuis & Dixon, 2002). Both metrics were derived from the 2018 Census data (Stats NZ Tatauranga Aotearoa, 2020).

Transportation

Spatial point data for the two main modes of public transport in Auckland, train stations and bus stops, were accessed from the Transport for Auckland data portal (Auckland Transport, 2022a). In addition, to account for bus frequency, data from the General Transport Feed Specification (GTFS) for Auckland buses were used to select bus stops with a 'frequent' bus service (Auckland Transport, 2022b). These were identified as stops with an average bus departure of every 10 minutes or more, for simplicity discounting the irregularities in scheduling throughout the day.

While our framework primarily emphasizes sustainable transportation modes, we included driving distance to electric vehicle charging stations. This methodological choice acknowledges both the car-dependent reality of New Zealand's urban form and the transition towards low-emission mobility. Rather than entirely dismissing automobile infrastructure, which would ignore current mobility patterns, this metric captures the provision of infrastructure supporting a shift towards more sustainable personal transportation.

Another metric – bikeability, was approximated by calculating the total length of bikeable paths and roads from the bikeable network per SA1 area.

Somewhat related to Transportation is Walkability, which was quantified separately due to the weight of evidence in support of walkability as a key aspect of urban liveability both globally (Shamsuddin et al., 2012), and in Auckland (Allen et al., 2018). Walkability in AULI is approximated with *streetConnectivity*, measured by counting intersections of three or more roads within the walking network selected for its established relationship with active transport patterns (Badland et al., 2017).

It should be noted that our measures of walkability and bikeability are high-level approximations. Other measures exist, for example, that take into account detailed information on infrastructure provision (Beecham et al., 2023), urban form and streetscape quality (Lee et al., 2022), and exposure-adjusted crash risk (Ferster et al., 2021).

Green Space

Spatial data on parks were accessed from OSM and filtered to those with an area larger than 1.5 ha. This threshold, also employed in Melbourne's urban liveability index (Higgs et al., 2019), was selected to ensure the captured spaces provide meaningful recreational opportunities. To calculate walking distances, access points around the park boundaries were generated every 250 m, and together with park centroids were used as the destination points in walking distance calculations, following the methodology employed by Koohsari et al. (2015). This method more accurately reflects how residents access parks, particularly larger spaces with multiple entry points.

Safety

The Safety component integrates three distinct dimensions selected to capture both perceived and actual safety risks in urban environments: crime patterns, road safety, and alcohol-related risks. The *crime* indicator was constructed using reported crime statistics from the New Zealand Police (New Zealand Police, 2018), denominated by area of Aerial Unit, and extrapolated to SA1s. This method does not directly retain the relevance of crime rates, but conveys the level of crime risk in SA1s. The next measure, *roadSafety*, is the number of crashes divided by total road length in each SA1, denominated by population counts (Waka Kotahi NZ Transport Agency, 2023). To smooth the metric, a geographically weighted mean with an adaptive bandwidth of 15 neighbours was used. The final indicator is a binary variable based on alcohol prohibition zones, reflecting areas with high alcohol-related safety risks (Auckland Council, 2022)

Diversity

The indigenous Māori culture is an important aspect of perceived liveability in Aotearoa's cities, which is why the index includes an accessibility measure to Marae, traditional meeting places of the Māori people (from Te Puni Kōkiri Data, 2018).

The high diversity of Aotearoa is mentioned in the Auckland Plan 2050 (Auckland Council, 2022) as a feature that positively affects urban liveability. For this reason, a measure of diversity is included in the index in the form of an entropy function - Shannon Diversity Index (Shannon, 1948):

$$diversity_j = -\sum_{e=1}^{E} p_{ej} * \ln(p_{ej}) \tag{1}$$

Where p_{ej} is the percentage of the population of ethnicity e in location j. SA1s with no population were assigned the minimum value for this indicator.

Figure 3 displays the relationships between all indicators and the AULI.

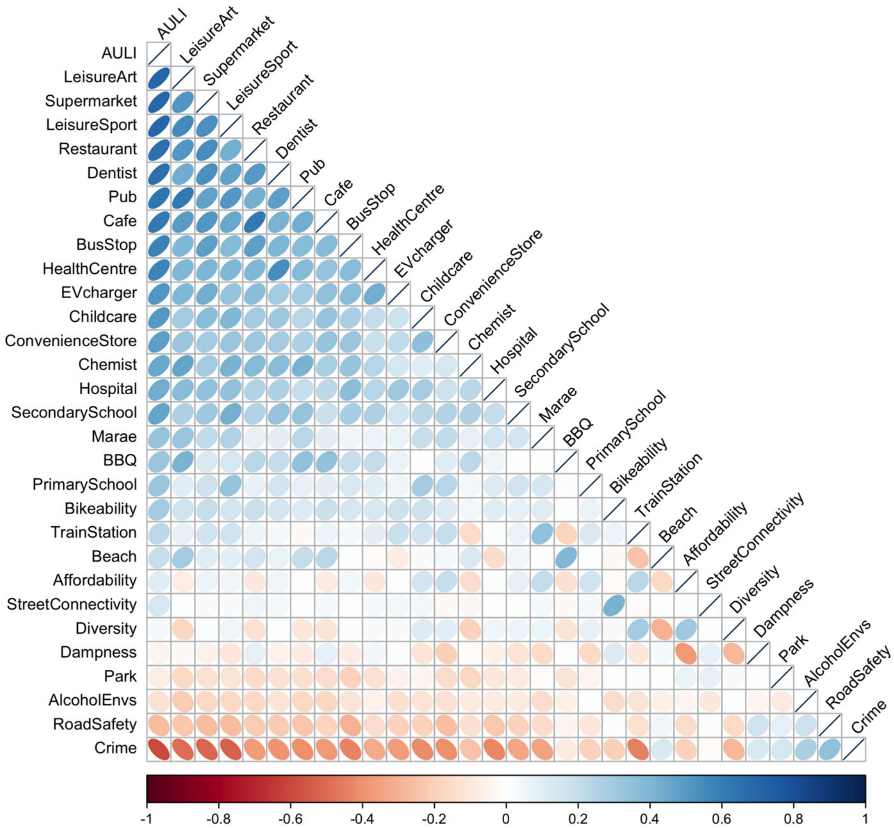


Fig. 3 Correlation Matrix of Indicators and the AULI

Aggregation and Analysis

For aggregation, we use the Mazziotta-Pareto Index (MPI) (De Muro et al., 2011), a non-compensatory technique specifically developed for indices of multifaceted social phenomena. The MPI was selected over simpler methods like arithmetic or geometric means because it addresses two key challenges in measuring urban liveability: the need to account for balance among indicators and to avoid complete compensation between variables. It calculates an arithmetic mean that penalises locations where variable values are unbalanced, according to the coefficient of variation. This penalisation is particularly important for liveability measurement, as good performance in one aspect (e.g., green space) should not completely offset poor performance in another (e.g., safety). This produces a final score that better reflects the multidimensional nature of urban liveability by rewarding consistent performance across all variables. Lastly, no individual weights were assigned to the variables, however by aggregating certain variables before the final composite (e.g. leisure components), we downgrade the individual importance of specific amenities.

Since the AULI is an original and newly constructed measure, there is no ground truth against which to validate it. In our analysis (Section "Validating AULI Using Regression Frameworks"), we therefore use spatial statistics to describe variation in the index and to suggest at its usefulness. To partially validate that AULI is capturing liveability, we develop regression models that explore variation in the index against variation in area-level socioeconomic and demographic variables that were omitted from the index itself. To investigate the generalisability, or stability, of the index against these candidate explanatory variables we use a multiscale geographically weighted regression (MGWR) model (Comber et al., 2023; Fotheringham et al., 2017).

Code and data used to generate the index and its analysis are presented on a public code repository. Additionally, the index and its components can be explored visually via an interactive web-map.

Results

Spatial Variation in AULI

A choropleth map of the AULI with areas of higher liveability represented by more saturated colours is presented in Fig. 4.

The map shows a clear pattern of high liveability present in and around the Auckland CBD, as well as the main metropolitan centres, often on the main transit nodes, including Avondale, Papakura, and Onehunga. This reflects the high urban densification measured by AULI, which can be characterised as Transit Oriented Developments (TOD) (Ibraeva et al., 2020). Conversely, the lowest liveability is recorded in low-density residential and industrial neighbourhoods, areas on the peripheries of the city, often of large area, such as around Auckland Airport.

As can be expected, the global Moran's I statistic of 0.73 indicates a high level of spatial autocorrelation in AULI. This is due to the intrinsically autocorrelated distance-based accessibility indicators on which the AULI is largely based. The Local Moran's

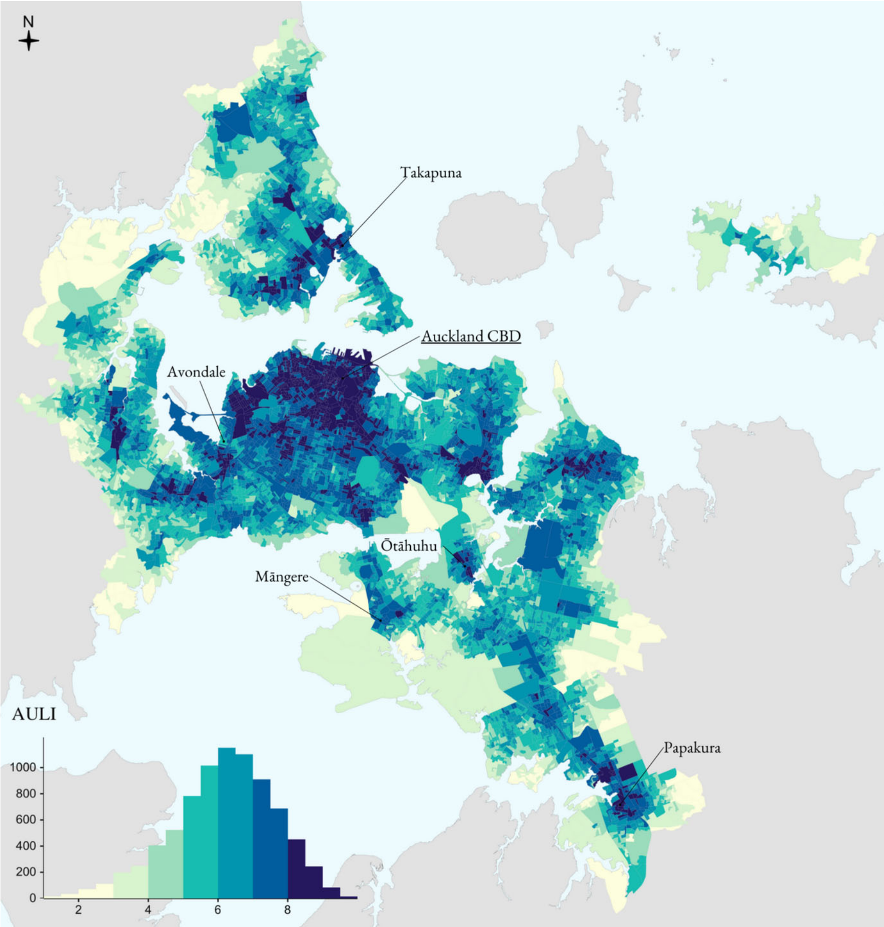


Fig. 4 Auckland Urban Liveability Index

I statistic for every SA1 is presented in Fig. 5 a). The highly autocorrelated regions tend to be close to the CBD and close to the boundary of the study area, whereas areas of low autocorrelation are present in west Auckland, the North Shore, or the largely industrial areas in South-East Auckland. The Moran's I clusters map in Fig. 5 b) emphasises areas of consistently high and low liveability, revealing a large area of high liveability extending from the south edge of the CBD west to New Lynn, as well as in several other town centres, and low liveability in peripheral districts like Albany.

Validating AULI Using Regression Frameworks

Firstly, a simple OLS multiple linear regression model is fitted, as a baseline model to show the relations between the AULI and the selected variables. To account for the high spatial autocorrelation in the AULI, which is also present in the OLS model's

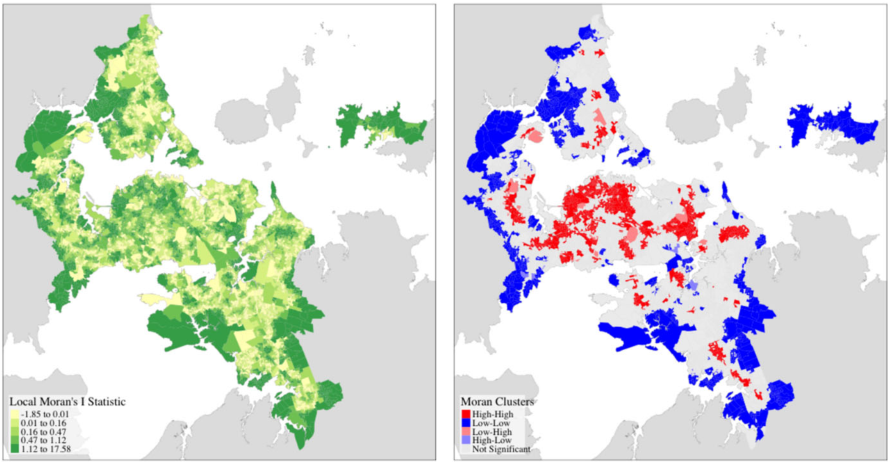


Fig. 5 a) Local Moran's I map; b) Local Moran's I Clusters Map

residuals, a Spatial Lag model is also fitted. Lastly, an MGWR model is fitted with an adaptive bandwidth and using the bisquare kernel function, on the same data aggregated to the level of Statistical Areas 2 (SA2) ($n = 509$). This model allows us to examine spatial variations in relationships and, paying attention to the bandwidths estimated for individual coefficients, the *scale* at which associations between the candidate explanatory variables and our AULI measure operate (e.g. Li et al., 2020). Table 1 shows a summary of the results from this analysis.

Table 1 Regression Coefficients for the analysis with AULI

	OLS	Spatial Lag	Median MGWR (bw.)
privateTransportToWork	−0.367***	−0.011	−0.009 (69)
cycleToWork	0.105***	0.010	−0.190 (170)
noCar	0.189***	0.063***	0.780 (71)
EuropeanDesc	−0.130***	−0.024**	−0.208 (29)
deprivation	0.196***	0.019	−0.105 (508)
degreeEducated	0.390***	0.041***	−0.717 (182)
logPopDensity	0.229***	0.087***	0.137 (82)
Constant	6.09***	1.15***	7.616 (13)
ρ	–	0.826***	–
Observations	8, 047	8, 047	509
R^2	0.295	–	0.632
AICc	25593	18355	1635

*p<0.1; **p<0.05; ***p<0.01
bw. – bandwidth

The identified coefficients uncover a number of interesting insights. Firstly, some of the observed relationships are consistent with expectation, specifically negative relations between the AULI and *privateTransportToWork*, or positive relations with *noCar* and *cycleToWork*. This is in accordance with Higgs et al. (2019) who also found positive associations between liveability and use of public transport in Melbourne – high liveability neighbourhoods are served by more frequent public transport and have better provision of infrastructure for active transport modes. After controlling for the spatial lag, which produces a rather high ρ coefficient, the significance of several other coefficients drops below 95%. This may suggest that some of the relationships identified in the OLS model may have been artificially inflated due to the spatial dependence of the variables.

Since AULI is not based on sociodemographic variables, an evaluation of the relationship between population characteristics and the liveability of the built urban environment can be made. Firstly, we find that the OLS model shows a strong positive relationship between deprivation and livability, while the MGWR results reveal this relationship to be negative or close to 0 across Auckland, exhibiting a global pattern of association with AULI, as indicated by its large estimated bandwidth (508). This highlights the importance of controlling for spatial effects when modelling these associations.

Another relevant finding that helps validate AULI is that in suburban areas the index is strongly positively associated with the *NoCar* variable, indicating that low-density

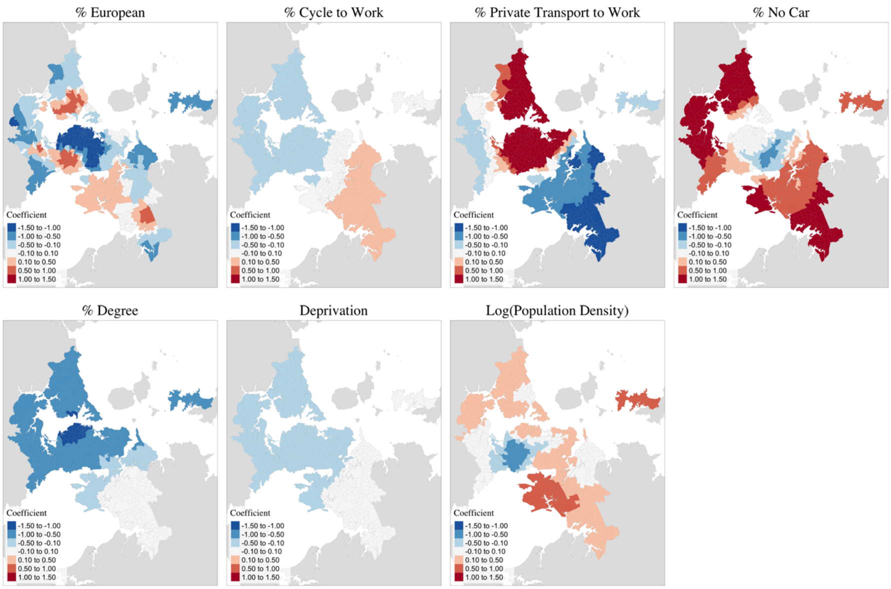


Fig. 6 Maps of MGWR coefficients

areas where more households do not own an automobile are naturally more indicative of liveability than in central Auckland.

The estimated MGWR coefficients for the *EuropeanDescent* variable are somewhat curious: while the OLS model indicated a strong negative association with *EuropeanDescent*, in our MGWR the coefficient estimate is strongly negative in central Auckland and distinctly high in areas like Takapuna and Mount Roskill (Fig. 6).

Access to Liveability

As a further method of evaluating AULI, we investigate how it relates to the population in Auckland. All locations were first grouped by AULI percentiles, and then the percentage of the cumulative sums of populations of different ethnicities, in each was calculated. The results are visualised through the empirical cumulative distribution functions (ECDF) plot, in Fig. 7. The left-hand side of this plot corresponds to the most liveable areas, with liveability decreasing towards the right. The analysis reveals that populations of different ethnicities across Auckland are relatively evenly distributed across neighbourhoods with varying levels of livability. Notably, while previous research has identified structural inequalities affecting Māori and Pasifika communities in various aspects of urban living including deprivation (Terruhn, 2020), our analysis suggests that access to liveable environments, as defined by our densification-focused metrics, is more equitably distributed.

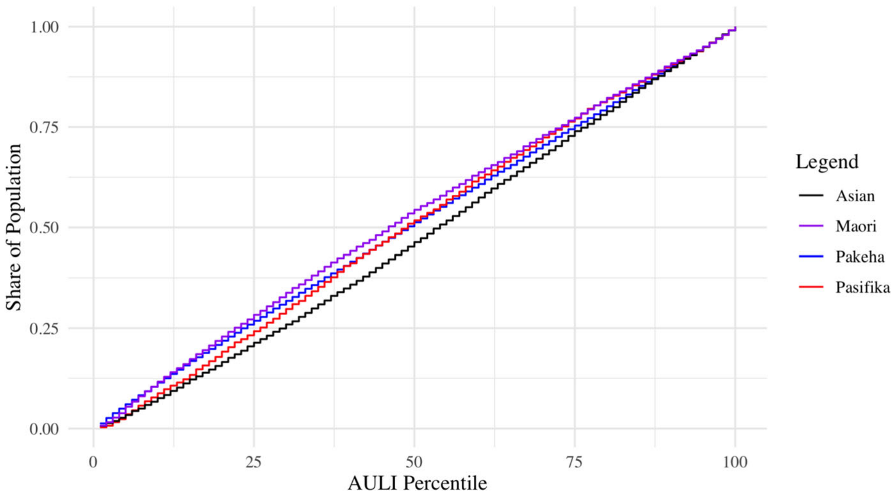


Fig. 7 Percentage of population by ethnicity at AULI percentiles

Discussion

The Auckland Urban Liveability Index (AULI) is the first attempt to systematically and quantitatively describe all neighbourhoods in Auckland using criteria relevant to contemporary urban densification and the concept of the *15-minute city*. Our analysis of AULI suggests the index does indeed confer greater liveability to neighbourhoods that support high-density living. Net of socio-demographics and population density (a proxy for rurality), neighbourhoods with greater use and provision of public and active transport modes were associated with higher liveability. This is consistent with expectations and, for instance, Higgs et al. (2019)'s study of liveability in Melbourne. Whilst there does not appear to be a strong association between neighbourhood-level deprivation and liveability, it is interesting that net of other factors (use of active travel, ethnicity and population density), neighbourhoods with comparatively higher shares of *degreeEducated* residents are associated with higher liveability scores, as shown by the OLS model coefficient.

This variable is perhaps an umbrella for a wider set of cultural and behavioural factors associated with contemporary urbanism. It is interesting, for example, that in recent area-level analysis of populist vote outcomes, and 'left-behind' places, *degreeEducated* consistently appears as a global 'catch-all' type variable (Essletzbichler et al., 2018; Beecham et al., 2020).

The analysis has several data-related limitations. The MGWR models employ Euclidean distance for spatial weighting, which may not accurately reflect real-world connectivity in Auckland's complex urban geography. Using network distances or travel times for the distance decay function, as proposed by Lu et al. (2011), could better model the true spatial relationships. Additionally, temporal misalignment between data sources introduces potential inconsistencies - while OpenStreetMap data reflects up-to-date (2024) conditions, census variables are from 2018, and other sources vary in their reliability. This temporal misalignment may potentially affect the accuracy of relationships identified in our models.

Our analysis also demonstrates difficulties in generating such comprehensive composite indicators. The outputs of our geographically weighted model – the very small bandwidths estimated particularly for transport-behaviour variables – suggest some adjustment may be desirable when applying AULI to city contexts that vary in rurality. Densification is a key component of contemporary urban liveability. Since density of social and cultural services and of sustainable transport provision varies so greatly with rurality, there is an argument that it could be judged or *scaled* differently in an index for suburban and semi-rural settings than very dense urban settings. It could be for this reason that when validating our index we counter-intuitively find little association between neighbourhood-level deprivation and liveability, as defined by AULI.

Relatedly, the transferability of AULI to other urban contexts requires careful consideration, also regarding data availability. Many of the key data sources, specifically OSM and the road network, are easily reproducible across different cities. However, several indicators rely on Auckland-specific datasets, such as crash risk, crime statistics, and alcohol-prohibited zones, which may not be consistently available or relevant in other contexts. To enhance transferability, the index could prioritise indicators derived from universally accessible data sources. For example, crash risk assessment could be derived purely from road network characteristics rather than historical crash data, following approaches developed by Borgoni et al. (2021), and Qiu et al. (2024). The index's modular structure allows for context-specific adaptations - for instance, in cities without rail infrastructure, the transportation component could be reweighted to emphasize other transit modes.

Comparison to Other Indicators

The AULI offers several distinguishing features when compared to existing liveability indices. While most established indicators operate at the city level for international comparison or focus on specific domains like sustainability or health (Lowe et al., 2015), AULI provides granular, neighbourhood-scale measurement specifically oriented toward modern urban densification criteria. The index aligns with common themes identified in Lowe et al. (2015) evaluation of liveability indicators - incorporating metrics of safety, transport, and housing - but deliberately emphasizes characteristics associated with high-density, walkable neighbourhoods. However, this specialization brings certain limitations: the index excludes some traditional liveability components, such as local employment metrics, or environmental quality measures like air pollution and water quality (Newman, 1999), due to data availability constraints at the fine spatial scale (SA1) used.

Urban liveability captured by AULI specialised to densification criteria may not appeal equally to every member of society (c.f. Yang, 2008). For example, younger groups typically express more enthusiasm for particular aspects of high-density living than do older groups (Opit et al., 2020; Hopkins & Stephenson, 2016; Goodwin & Van Dender, 2013). It may be possible to adjust for this heterogeneity of perception by assigning appropriate weights to indicators in specific locations based on the characteristics of the local population (Allam et al., 2022). A crucial consideration in explaining the desirability of places in the New Zealand context is also natural beauty, particularly in coastal areas (Freeman & Cheyne, 2008). Often this factor could outweigh all other measures of a density-based liveability score like the AULI. This could unintuitively affect the findings from models evaluating liveability against measures of affordability or deprivation, further substantiating the need for localised modelling techniques.

Policy Implications

From a policy standpoint, AULI can serve as a practical planning aid to inform urban developments and policy. As a diagnostic tool, it can identify specific deficiencies in neighbourhood liveability - for instance, highlighting areas that lack adequate public transport connections or social infrastructure. The component-based structure enables scenario modelling, allowing simulation of how proposed developments (such as new transit stations or community facilities) might impact local liveability scores. Beyond planning applications, AULI's analysis can inform wider policy initiatives, from affordable housing strategies to transport investment, helping ensure urban intensification efforts do not exacerbate existing disparities (Lowe et al., 2015; Schindler & Dionisio, 2024). This supports evidence-based decision-making, enabling policymakers to plan interventions that improve liveability while ensuring their impact is both sustainable and equitable. Furthermore, the spatially disaggregated nature of AULI makes it a valuable tool for monitoring progress on sustainable development goals like SDG 11.2 and 11.3, which aim to provide equitable access to sustainable transport systems and inclusive and sustainable urbanisation (Giles-Corti et al., 2020).

Conclusion

Evidence-based indices can serve as a valuable tool in urban planning design and evaluation (Lowe et al., 2020). The Auckland Urban Liveability Index (AULI) is one such tool that uses entirely open data to quantitatively describe liveability in Auckland in the context of modern urban densification criteria. The presented index comprises 29 variables organised into five themes that reflect the multidimensional nature of urban liveability – from transportation, through social infrastructure accessibility, to safety. These variables are aggregated over neighbourhood-level spatial units (Statistical Area 1, $n = 8047$). By analysing the created index, this study aims to provide insight into the spatial patterns of liveability in Auckland, and its relations with the sociodemographic characteristics of its population. Introspecting into the index using local, geographically-weighted models, we also provide useful context for the transfer of AULI and liveability indices more generally. Code and data used to generate the index and its analysis is presented via a public code repository, and will be maintained and updated in light of new data.

Appendix

AULI indicators

The figures below present the spatial distributions of each indicator, with polarity already controlled for. Darker values correspond to higher indicator value - higher liveability.

The Table 2, below, details the transformation details of each indicator, with a brief description of the method of calculation, the transformation steps, the indicator polarity, the values of skewness and kurtosis as well as histograms of the indicator distributions, before and after the transformations.

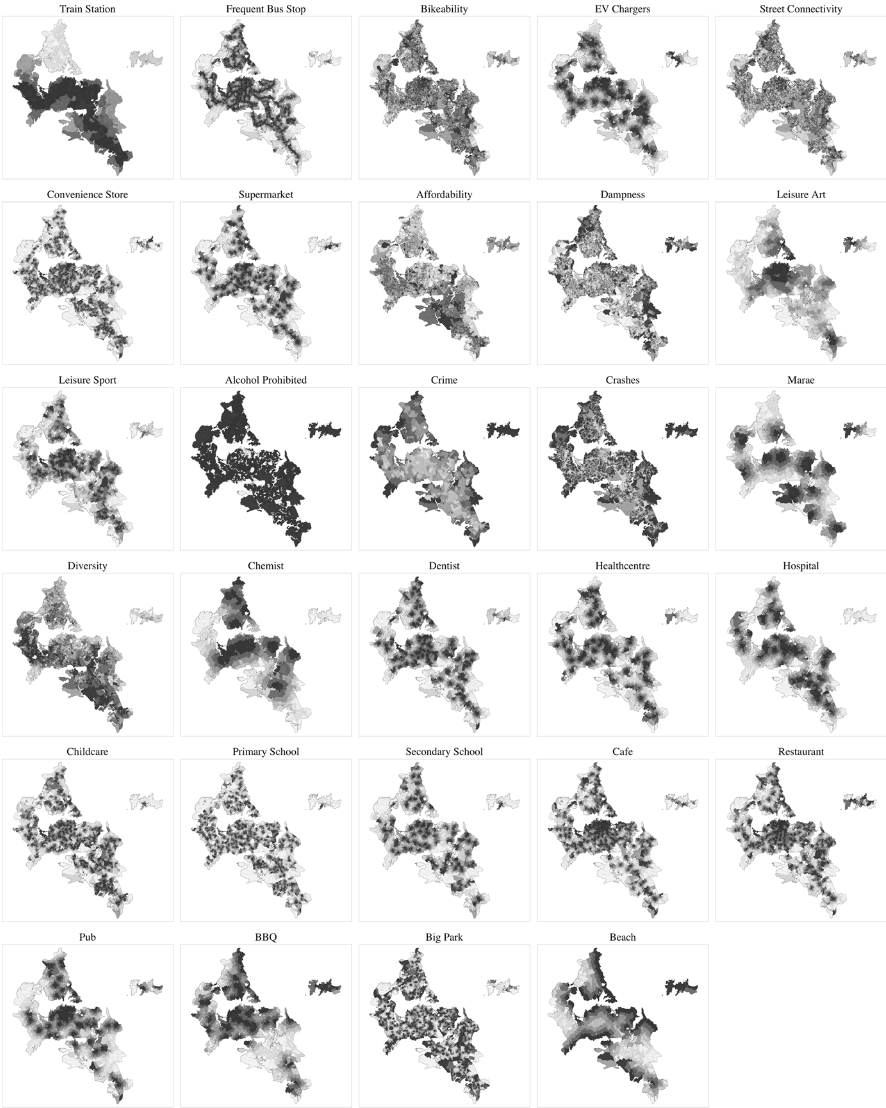


Fig. 8 Maps of all indicators in the AULI

Table 2 Table with transformation details

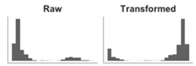
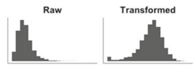
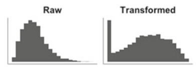
Indicator	Method of Calculation	Transformation	Polarity	Type	Skewness	Kurtosis	Distribution
Theme: Transportation							
Train Station	Walking distance to nearest	Winsorisation (10%)	–	Raw Data	2.398	10.554	
				Transformed	–1.502	3.424	
Bus Stops	Walking distance to nearest bus stop with departures every 10 minutes	Winsorisation (10%)	–	Raw Data	2.817	15.510	
				Transformed	–0.709	2.395	
Bikeability	Total length of bikeable paths/roads, divided by area	Natural Logarithm	+	Raw Data	1.564	7.278	
				Transformed	–0.773	5.334	
EV Chargers	Driving distance to nearest electric vehicle charger	Winsorisation (10%)	–	Raw Data	0.478	2.864	
				Transformed	–0.030	2.070	

Table 2 continued

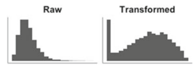
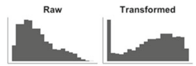
Indicator	Method of Calculation	Transformation	Polarity	Type	Skewness	Kurtosis	Distribution
Theme: Essential Amenities							
Convenience Store	Walking distance to nearest	Winsorisation (10%)	–	Raw Data	2.054	11.078	
				Transformed	–0.485	2.260	
Supermarkets	Walking distance to nearest	Winsorisation (10%)	–	Raw Data	2.125	11.231	
				Transformed	–0.304	2.073	
Theme: Green Space							
Parks	Walking distance to nearest park access point	Winsorisation (10%)	–	Raw Data	3.449	36.953	
				Transformed	–0.213	1.931	
Beaches	Walking distance to nearest	Winsorisation (10%)	–	Raw Data	0.781	2.823	
				Transformed	–0.472	2.104	

Table 2 continued

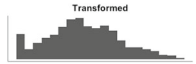
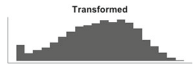
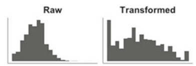
Indicator	Method of Calculation	Transformation	Polarity	Type	Skewness	Kurtosis	Distribution
Theme: Social Infrastructure							
Leisure Art	Aggregate walking distances to nearest cultural amenities	Additive Aggregation	–	Final Indicator	0.225	2.580	
Leisure Sport	Aggregate walking distances to nearest sports facilities	Additive Aggregation	–	Final Indicator	–0.286	2.424	
Theme: Housing							
Affordability	Median Rent from Census 2018	Winsorisation (10%)	+	Raw Data	–0.145	4.344	
				Transformed	0.871	3.548	
Dampness	Dampness Indicator from Census Data 2018	Winsorisation (10%)	–	Raw Data	0.235	3.238	
				Transformed	0.308	2.295	

Table 2 continued

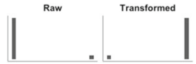
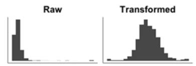
Indicator	Method of Calculation	Transformation	Polarity	Type	Skewness	Kurtosis	Distribution
Theme: Safety							
Alcohol Environments	Binary variable: 1 for areas with alcohol-related crime risk	None	–	Raw Data	3.032	10.191	
				Transformed	–3.032	10.191	
Crime	Crime per area joined to SA1 level	Natural Logarithm and Winsorisation (-11, 10)	–	Raw Data	6.692	54.296	
				Transformed	0.077	4.792	
Road Safety	Crashes per road length and population, geographically weighted	Natural Logarithm and Winsorisation (-10, -1)	+	Raw Data	76.132	6281.605	
				Transformed	0.646	3.931	

Table 2 continued

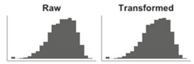
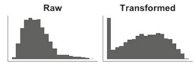
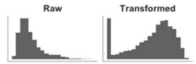
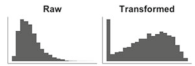
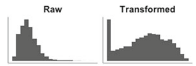
Indicator	Method of Calculation	Transformation	Polarity	Type	Skewness	Kurtosis	Distribution
Theme: Diversity							
Ethnic Diversity	Shannon Diversity Index	None	+	Raw Data	–0.607	3.34	
				Transformed	–0.607	3.34	
Marae	Walking distance to nearest Marae	Winsorisation (10%)	–	Raw Data	1.103	4.545	
				Transformed	–0.143	1.976	
Theme: Medical Infrastructure							
Chemist	Walking distance to nearest	Winsorisation (10%)	–	Raw Data	9.374	104.01	
				Transformed	–0.705	2.44	
Dentist	Walking distance to nearest	Winsorisation (10%)	–	Raw Data	1.187	4.948	
				Transformed	–0.333	2.066	
Health Centre	Walking distance to nearest	Winsorisation (10%)	–	Raw Data	1.296	6.022	
				Transformed	–0.202	2.008	

Table 2 continued

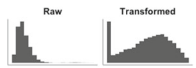
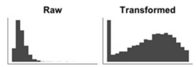
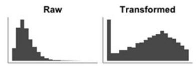
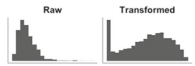
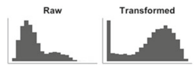
Indicator	Method of Calculation	Transformation	Polarity	Type	Skewness	Kurtosis	Distribution
Hospital	Walking distance to nearest	Winsorisation (10%)	–	Raw Data	11.498	137.588	
				Transformed	–0.302	2.076	
Theme: Education							
Childcare	Walking distance to nearest	Winsorisation (10%)	–	Raw Data	2.330	15.565	
				Transformed	–0.355	2.073	
Primary School	Walking distance to nearest	Winsorisation (10%)	–	Raw Data	2.290	17.224	
				Transformed	–0.073	2.105	
Secondary School	Walking distance to nearest	Winsorisation (10%)	–	Raw Data	1.822	9.67	
				Transformed	–0.208	2.15	
Theme: Food Outlets							
Café	Walking distance to nearest	Winsorisation (10%)	–	Raw Data	1.768	10.511	
				Transformed	–0.275	2.013	

Table 2 continued

Indicator	Method of Calculation	Transformation	Polarity	Type	Skewness	Kurtosis	Distribution
Restaurant	Walking distance to nearest	Winsorisation (10%)	–	Raw Data	1.697	9.229	
				Transformed	–0.352	2.059	
Pub	Walking distance to nearest	Winsorisation (10%)	–	Raw Data	1.764	10.314	
				Transformed	–0.281	2.045	
BBQ	Walking distance to nearest	Winsorisation (10%)	–	Raw Data	1.333	3.882	
				Transformed	–0.918	2.577	

Acknowledgements Not applicable

Data Availability Additional data manually downloaded and cleaned, required to reproduce the index is freely available in a data-sharing repository https://doi.org/10.6084/m9.figshare.27926595.v1. Additional data sources used in this study include publicly available datasets from OpenStreetMap, Statistics New Zealand, Auckland Council, and other government agencies, as detailed in the Methods section. The complete codebase for generating the index and conducting the analyses presented in this paper is available in our public code repository https://github.com/jankomag/uli-nz.

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