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Modeling Quality of Urban Life Using a Geospatial Approach

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Abstract: The rapid global urbanization of the past century poses several challenges for planners and policy makers. In particular, the conflation of social and urban issues must be understood to create sustainable and livable urban places. In this regard, it was our aim to model and understand the relationship between urban characteristics and peoples' perceived quality of urban life (QoUL) using statistical analysis and geospatial modeling. We selected objective variables representing urban characteristics based on literature and used principal components analysis to develop uncorrelated components. These components served as the independent variables in a multiple linear regression analysis. The subjective, dependent variables were extracted from a QoUL survey. Results indicated that only the Education/Income component is related to QoUL (R^2 of 0.46). Using only single independent variables in a linear model explained 46% of the total variance—over 10% higher than any previously determined relationship between objective variables and subjective QoUL. Furthermore, we found that subjective high QoUL and subjective low QoUL were not strongly correlated, indicating that they are affected by different objective variables, respectively. This suggests that future efforts of increasing QoUL need to define their goals more precisely, as measures for increasing perceptions of high QoUL are likely different from measures for decreasing perceptions of low QoUL.

Keywords: quality of life; quality of urban life; GIS; GIScience; indicators; modeling

1. Introduction

The rapid global urbanization of the past century poses implications and challenges for planners and policy makers. Necessary measures of urban densification have led to the conflation of social and urban issues, which must be understood and considered for sustainable urban planning. In this regard, quality of urban life studies have drawn much attention in political and academic debate in recent decades. The idea behind quality of urban life (QoUL) studies is to measure and assess the relationship between the social and urban characteristics of a place and its perceived quality of life. Many QoUL scholars support the notion that quality, regardless of what entity is being measured, consists of both subjective perceptions and objective reality [1]. Thus, it is necessary to consider both the objective and subjective dimensions—and the relationships between them—to understand the human quality of urban life experience [2,3].

Numerous QoUL studies measuring cause and effect between objective and subjective indicators have been conducted [4–12], and various models representing the relationship between objective reality and subjective experience have been proposed, for example [2,13,14]. These models generally include several variables that are considered to play a role in the overall QoUL perspective at different geographic scales [15]. However, Marans [1] noted that empirical studies were necessary to investigate the relationships suggested in such conceptual models.

To this end, several empirical studies attempting to link subjective and objective QoUL have been conducted in the last decade [5–12]. Many of these studies found direct or indirect (using proxies) statistical relationships between indicator pairs at certain spatial scales (Table 1). However, a recurring issue seems to be the availability and quality of subjective datasets used for such analyses, since these tend to be expensive and time-consuming to elicit, and comprehensive spatial coverage is oftentimes not given. Objective data, on the other hand, such as demographic census data, geometry data, community data, economic data, and so on, are generally openly available at moderately fine spatial resolutions. A comprehensive, spatially transferable measure for QoUL based on objective data alone is elusive. But why? Are we measuring the appropriate characteristics? Does spatial aggregation mask the relationship between objective and subjective data? Previous research has used various spatial scales for observational data (e.g., through a survey of individuals) and aggregated data for the analysis (e.g., census units of mean/median values). We agree, based on the ecological fallacy principle, that a model for one spatial scale might not be appropriate for another spatial scale. A model based on objective data that accurately reflects the subjective dimension would, therefore, be of great scientific value, as it would allow the QoUL of regions not covered by subjective surveys to be predicted, albeit at the same spatial scale. This would provide valuable insight into the population's perceptions of and satisfaction with urban landscapes, which is crucial for planners and policy makers in a time of unprecedented urban growth and demand. The purpose of this study was to investigate the relationship between objective measures and subjective perception of QoUL using multivariate linear and non-linear models at a moderate spatial aggregate level. Both raw data and principal component analysis (PCA) were used to conceptually model the QoUL perception in selected urbanized study areas in New Zealand.

Table 1. Quality of urban life (QoUL) indicators studied in previous research.

Place-Based QoL Study	Spatial Scale	Statistical Analysis Method	Indicators Significantly Correlating with Subjective QoUL
Türksever & Atalik (2001)	District	Multiple linear regression model	*Health* * Climate Crowding *Sporting* * Housing conditions *Travel to work* * *Pollution* **
McCrea et al. (2005)	Housing Neighborhood Metropolitan Area	Path analysis	*Housing age* ** *Temperature* ** Home ownership Govt. service provision Cost of living
McCrea et al. (2006)	Region	Structural equation modeling	Population density Cost of housing
McCrea (2007)	Region	Bivariate analysis	Access to facilities Household composition
McCrea (2007)	Region	Generalized linear modeling	Household composition Socioeconomic environment
Liao (2009)	Cities Counties	Nonparametric correlation coefficients	Environmental quality Education
Keul & Prinz (2011)	District	Grid-based correlation analysis	Housing Greenery *Neighbors* * *Safety* ** Population density
Oswald & Wu (2010)	State	Multiple linear regression	Income Sociodemographic variables Education Employment *Marital Status* *
von Wirth et al. (2014)	Municipalities	Structural equation modeling	Access to facilities

* Indicators omitted from the present study due to high personal and temporal variability. ** Indicators omitted from the present study due to lack of data availability.

The areas studied in this research comprise the wider Auckland, Wellington, and Christchurch regions. These regions were selected as they house most of the country's key functions related to the government, tertiary education system, and business enterprises. The growing commercial interests in these key areas, accompanied by rapid population growth, have led to a number of social issues including soaring house prices and the displacement of marginalized population groups to certain districts, which are now facing poverty, overcrowding and ill health. Such regional disparities need to be addressed by planners and policy makers so that sustainable measures can be implemented, and that deprivation can be reduced in New Zealand's key urban areas. Thus, it is important to identify, if possible, the objective urban and demographic attributes as proxies for subjective QoUL. Subsequently, regions with low modeled QoUL can be identified, and measures can be taken to increase the QoUL of deprived areas. To be clear, we are suggesting the aggregate levels of QoUL can be targeted by governmental or non-governmental urban measures, and individual QoUL improved indirectly (as the models in this research are constructed with aggregated data, as most other models are).

To this end, we sought to develop a model for predicting QoUL in New Zealand, based on the analysis of openly available objective indicators. Subjective QoL data from the 2014 New Zealand Quality of Life Survey were used at the moderate aggregate level to develop the model. The underlying hypothesis for our model is that the subjective QoL per region is a product of the objective economic, community, and environmental aspects present in the respective region. Our metrics, thereby, represent a landscape context and modeling perspective. A noted assumption is the empirical modeled relationship, built on data for the key greater urban centers in New Zealand, is transferable to other geographic areas with similar characteristics (in terms of economic, community and environmental aspects) and at a similar spatial scale. These aims and hypotheses are preceded by an initial literature review, to identify objective indicators likely to predict subjective satisfaction, followed by a correlation and PCA to determine which of these variables predict QoUL in New Zealand. Multiple and simple linear regressions were used to assess the strength and form of models for predicting QoUL.

2. Background

To determine the relative importance of various objective characteristics for the subjective perception of QoUL, it is necessary to contextualize objective indicators with subjective assessments using models that investigate the (statistical) relationships between both dimensions [15]. Geographic information systems (GISs) possess the integrative capability of contextualizing survey data, census data, community data, and environmental data based on location, and thus, providing a common denominator for a subsequent relationship-analysis. As such, various aspects of geocoded subjective survey data and contextualized urban attributes can be quantified by means of bivariate and multivariate statistical analyses [15]. This notion was first proposed by Marans [1], who highlighted analysis possibilities for planning and policy making, but has since been applied by a number of scholars, e.g., [5,7–9,12], all of whom determined some, albeit weak, statistical relationships between objective and subjective indicators mapped to areal units. Similar findings were obtained by other QoUL studies, which determined statistical links between objective and subjective QoUL based on suburbs, districts, cities, or regions, e.g., [6,10,11].

One early such district-based QoUL study was conducted in 2001 by Türksever and Atalik [11], who utilized multiple linear regression modeling to determine independent (objective) variables predicting life satisfaction in the metropolitan area of Istanbul, based on districts. The authors determined that objective health, climate, crowding, sporting, housing conditions, travel to work, and environmental pollution are the major determinants of subjective satisfaction in Istanbul (generalized from all districts).

Going beyond the spatial scale of districts, McCrea et al. [7] conducted path analyses to determine links between objective urban and demographic characteristics and subjective satisfaction on three spatial levels (in their analysis termed “domains”): housing level, neighborhood level, and wider metropolitan area level in the study area of South East Queensland. They further analyzed the impact of satisfaction in each respective domain on overall life satisfaction. Interestingly, neighborhood satisfaction was shown to be far less important in predicting overall life satisfaction than the other two domains, although nonetheless indirectly impacting life satisfaction through the other domain levels [7].

To further explore the relationship between objective and subjective QoUL indicators, McCrea et al. [8] spatially contextualized subjective QoUL perceptions and objective urban indicators using a GIS. They subsequently applied structural equation modeling to determine and quantify statistical relationships between the respective objective and subjective indicators in regard to services, facilities, and overcrowding [8]. They determined that overall subjective QoUL is correlated with both subjective access and subjective overcrowding, together accounting for 34% of the total variation. In the second step of the analysis, the relationship between objective latent variables and perceived QoUL was tested, where the authors determined that the relationship between objective access and subjective QoUL was completely mediated by subjective access [8]. Objective density and objective cost of housing, on the other hand, were only partially mediated by subjective overcrowding regarding overall subjective QoUL.

Furthermore, McCrea [9] conducted a multivariate analysis using generalized linear modeling to test the relationship between objective indicators and subjective QoUL, and, again, found that only some of the examined objective factors significantly predicted subjective QoUL. These factors were the coastal environment, household environment, and socioeconomic environment, while objective characteristics of the built environment were merely weak predictors of subjective QoUL [9].

Another study that found only weak links between objective and subjective QoUL variables was conducted by Liao [6], who analyzed the QoUL in cities and counties of Taiwan. The investigated variables included medical services, domestic finances, work, education, leisure, public safety, and environmental quality [6]. Liao applied nonparametric correlation analyses (Kendall’s tau-b and Spearman’s rho) and determined significant correlations between subjective satisfaction with the residential environment and the objective indicators of environmental quality and education. For all other variables, however, no significant correlations with overall satisfaction were found.

In contrast to Liao [6], Keul and Prinz [5] determined several correlations between subjective and objective measures in their indicator-based QoUL study in Salzburg, Austria. The authors determined population density, housing, greenery, neighbors, and safety correlate positively and highly with overall perceived QoUL [5].

Similarly to McCrea et al. [8], von Wirth et al. [12] also utilized structural equation modeling to test the direct and indirect (mediated) impacts of objective indicators on subjective QoL in the Limmattal area of Switzerland. The authors found a significant relationship ($R -0.61$) between objective access and perceived access, and between objective safety and perceived safety. They subsequently investigated the degree to which objective latent variables are mediated through their subjectively perceived counterparts and determined that objective access was only partially mediated by subjective access and, thus, still weakly associated with perceived QoUL [12].

The findings of the strength of a statistical relationship between objective and subjective indicators must be couched in the spatial aggregation scale of the data in the analysis. The relationship between the scale of observation/analysis and the statistical correlation has long been conjectured and demonstrated in different disciplines, such as statistics [16], geography [17], and cartography [18]. Based on the different spatial scales and cultural settings of the study areas, and on the different range of selected indicators, data elicitation techniques, and various statistical methods, the findings of these studies are neither fully comparable nor spatially transferrable. Most notably, a strong statistical relationship between objective variables and subjective QoUL seems elusive. The generally weak correlation found between subjective and objective QoUL indicators can be partially attributed to the issue of scale discordance, which recognizes that "the territorial base of an individual's subjective evaluation may not coincide with the boundaries of the units used for the collection of objective data" [19] (p. 1). Even using multiple objective variables to predict QoUL has resulted in "statistically significant" relationships, albeit with very low (e.g., 36%) explanatory power. This notion is underpinned by the seemingly parallel study designs of McCrea et al. [8] and von Wirth et al. [12], both of whom analyzed measures of access by means of structural equation modeling, yet obtained differing results. While McCrea et al. merely determined a weak link between objective and subjective access, von Wirth et al. found the same relationship to be relatively strong [12]. The authors of the latter study postulate that this discrepancy may be attributed to the different nature of the two study areas (compact vs. vast), whereby they quote Angur [20] (p. 51) in that "congruence among objective and subjective indicators was stronger when the neighborhoods in question were small". This, in turn, contradicts the findings of Oswald and Wu [10], who determined a significant and strong state-by-state correlation (R = 0.6 or 36% explanatory power) between objective QoUL variables and the subjective QoUL dimension in a large-scale U.S.-wide study. Their prestigious study, published in *Science Magazine*, incorporated an unprecedented number (1.3 million) of subjective QoUL perceptions by U.S. citizens, that were found to be significantly predicted by seven banded objective variables, including household income, and sociodemographic variables such as age, gender, ethnicity, education, marital status, and employment type [10].

This ongoing discordance between findings of studies investigating the relationships between objective and subjective quality of life, together with the agreement among scholars that understanding this complex relationship is of utmost importance for planners and policy makers [6,8,15,21] is what drives the need for further empirical investigations into the matter. To this end, the present study seeks to develop a QoUL prediction model, to predict the district-based spatial distribution of average QoUL based solely on objective variables, but subsequently validated with subjective QoUL survey data. We, therefore, used the case study area of the three main metropolitan regions of New Zealand: Auckland, Wellington, and Christchurch.

3. Methodology

3.1. Aim and Hypothesis

The aim of this study is to develop a model for predicting the quality of urban life in New Zealand's urban areas, based on the analysis of objective indicators, and subsequently validated with subjective QoUL survey data. The underlying hypothesis for the model is that the subjectively perceived QoUL per region is a product of the objective economic, community, and environmental aspects present in the respective region [1]. A further assumption is that a model based on a few urban centers is transferable to other geographic areas with similar characteristics and at a similar spatial scale (in terms of economic, community and environmental aspects).

3.2. Objective Indicator Selection and Data Preparation

This study builds on the findings of the previous GIS-based QoUL studies outlined in the previous section. Thus, we utilize the objective indicators that have previously been empirically demonstrated to predict subjective QoUL as a whole, or certain aspects of it (such as housing satisfaction, neighborhood satisfaction, etc.). Table 1 provides an overview of the location-based QoUL studies that examined possible correlations between objective and subjective aspects of QoUL, together with the respective statistical method implemented and the indicators found to be significant. Six of the eight studies (McCrea [9] is one dissertation thesis, however, outlining several investigations) identified aspects of housing as a predictor of subjective QoUL, while three studies identified population density (although termed as "crowding" in the study by Türksever and Atalik [11]), and two identified objective access to facilities as significant predictors. All other indicators were only identified in one of the studies.

The list of indicators suggested from previous research was reduced to include only economical, community, and environmental aspects (as suggested by Marans [1]), while disregarding factors with high personal and temporal variance such as health, sporting, travel to work, and neighbors—indicators identified as significant predictors of life satisfaction by Türksever and Atalik [11] and Keul and Prinz [5]. Furthermore, the indicators of housing age, indoor temperature, crime, and pollution had to be disregarded in this present study, as no reliable, comprehensive datasets with this information were available for the study area. Climatic indicators, such as winter and summer low/high temperatures do not vary substantially across New Zealand and were therefore not included.

The remaining indicators were grouped into economic, environmental, and community aspects (including urban aspects such as housing, access to facilities, population density, etc.), and respective indicators were selected for each aspect (Table 2). Indicator data were obtained at the ward level (New Zealand administrative districts) from various official sources, including the 2013 New Zealand census, official council reports and websites, Statistics New Zealand, and national GIS datasets. These indicators provided the basis for a PCA.

Table 2. QoUL indicators selected for the present study based on previous research.

Indicator Type	Composite Indicator (Literature Based)	Separate Indicators
Economic	Socioeconomic	Employment status Personal income Household income No. of motor vehicles per HH
	Education	Percent of population with university degree Percent of population with no formal qualifications
Community	Population density	Population density
	Housing conditions	Home ownership Cost of living Household composition
	Government service provision	Expenditure on Community
	Access to facilities	Schools Libraries Supermarkets Historic places
Environmental	Climate	Average annual sunshine hours Average annual rain Average temperature
	Greenery	Area of parks

Before a PCA was conducted, some of the objective indicators were standardized, since many of them were measured on different scales. For example, absolute values, such as the number of facilities, are often proportional to the area of the ward and were therefore converted to relative values before being used in the PCA (outlined in Section 3.4).

3.3. Subjective Validation Data

The New Zealand Quality of Life Project (NZQOLP) was initiated in 1999 and focused on collecting the subjective views of New Zealand residents on social, economic, and environmental indicators that are not available from official sources (Quality of Life Survey 2014—Technical Report). The project was founded in response to the concern of increasing urbanization in New Zealand, with the key goal of informing and aiding planners and decision-makers in the optimization of QoUL in New Zealand's urban areas (NZQOLP Website). Although the wider NZQOLP was discontinued in 2007, a quality of life survey continued to be administered on a two-year basis by participating councils. According to the Quality of Life Survey 2014—Technical Report: "the objective of the survey is to measure residents' perceptions of aspects of living in large urban areas, including contact with neighbors, transport and safety", with the aim of providing data to both councils and the general public.

In this study, the perceptions of respondents on the two extremes of the QoUL scale—those who indicated their QoL was "Extremely Good" and "Poor"/"Extremely Poor"—were studied. The categories of "Poor" and "Extremely Poor" were summarized as one variable indicating the lowest QoUL scores due to the small number of respondents indicating an "Extremely Poor" QoUL. The exact proxy for these groups was the percentage of respondents per ward indicating that they have an "Extremely Good", or "Poor"/"Extremely Poor" overall QoUL. This QoUL percentage was the dependent variable in subsequent analyses relating to the objective influences. Overall, the percentage of respondents indicating an "Extremely Good" or "Poor"/"Extremely Poor" QoUL was 19% and 3%, respectively, for Auckland, 17% and 4%, respectively, for Christchurch, and 26% and 1%, respectively, for Wellington. The spatial distribution of respondents in these two independent variables for the three study areas is illustrated in Figure 1. For brevity we use the term "Excellent QoUL" rather than "Extremely Good QoUL" throughout the article.

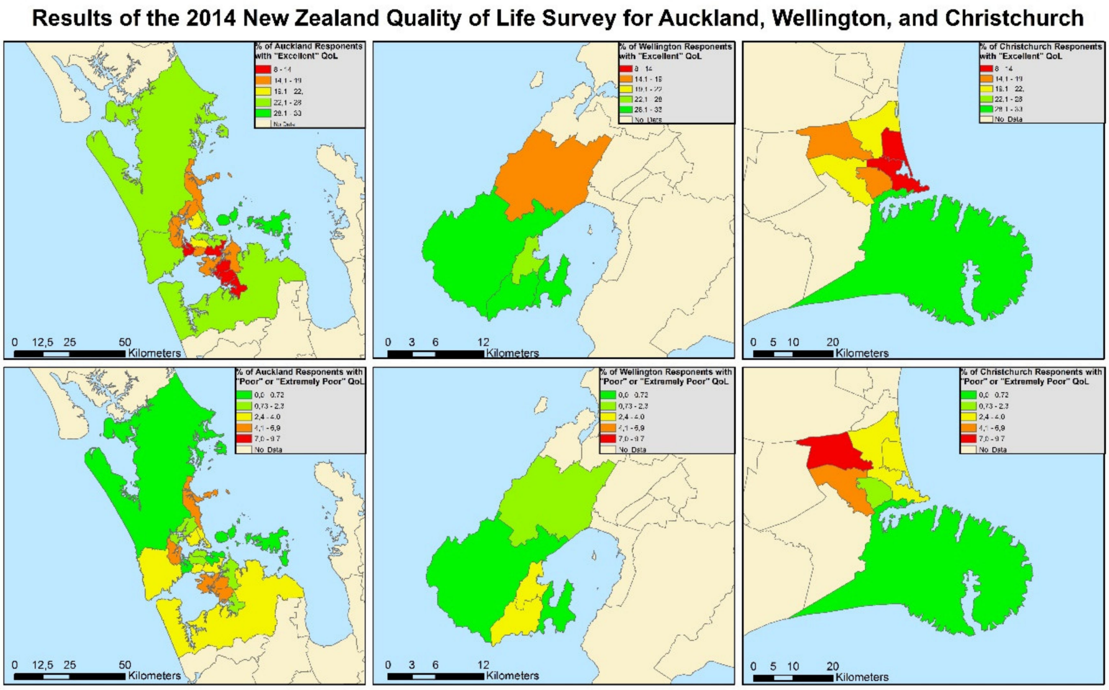


Figure 1. Excellent (top) and poor (bottom) subjective quality of life for Auckland (left), Wellington (center) and Christchurch (right). Source: Authors' own depiction based on the results of the 2014 NZ Quality of Life Survey.

3.4. Principal Components Analysis and Multiple Linear Regression Modeling

The development of an explanatory model for relating factors influencing quality of life has taken many forms. The purpose of most models is first to identify important variables and, subsequently, the relative importance of each variable. Most commonly used models are multiple regression or path analysis (often through structural equation modeling). The advantage of a multiple regression form is that the relative influence of each variable (sometimes referred to as the partial derivative) on the QoUL variable can be empirically derived. Such an approach is commonly used with a hedonic model form, for instance. A disadvantage of a regression model is each variable is expected to be of a functional form (e.g., linear or specific non-linear type) and, most importantly, of an independent nature (uncorrelated). It is rare for the variables to be uncorrelated and attempts to include such correlation (e.g., multiplicative) have strong seldom-known assumptions. Path models attempt to discretize the factors and sub-variables that influence each other and, ultimately, the QoUL factor.

Such models assume explicit independence between some variables and direct correlation between others. The issue with all such empirical models is the explicit assumptions of cause-effect variable relations and functional form (linear or other) of the relations.

In this research, a multiple regression model is used to test for correlation between logical groups of independent variables identified through factor analysis and previous QoUL studies. A selected set of indicator variables that others have argued influence perceived QoUL were incorporated in a PCA to eliminate the autocorrelation between variables. A resulting four-component set of factors was then incorporated in a multiple regression model to test for the dominating factors influencing QoUL. A strong correlation with QoUL was determined between only one factor. A partial correlation analysis was subsequently used to untangle the underlying variables in this component that indeed correlate with QoUL.

A partial correlation indicates the strength of the correlation (and significance) between two variables while holding one or more variables constant (in effect, removing the other variables' influence). A partial correlation analysis is a test of the correlation between the remaining residuals from a primary correlation (in this case, education and QoUL). A multiple regression examines the semi-partial correlations while a partial correlation examines the first-order correlations.

The workflow of the PCA and multiple linear regression analysis was as follows. In the first stage, we analyzed the raw variables for correlations using Pearson correlations and scatterplots to determine collinearity in objective variables and the relative linearity in the relationship between the QoUL variables and objective variables. Next, we applied PCA to extract non-correlated indicators of the important variables identified by previous researchers for explaining QoUL, and the components were not rotated. We also examined scatterplots between each QoUL indicator and the components to evaluate the possibility of a non-linear relationship.

Subsequent to the PCA, we employed multiple linear regression to model the importance of each PCA component in predicting subjective quality of life. We conducted the regression analysis with the same components for each of the two QoUL variables (i.e., excellent QoUL and the poor/very poor QoUL). We also conducted the analysis at each step of adding a variable into the equation by examining the possible non-linear correlation between residuals and independent components. In all cases, the relationships were either linear or non-existent. We then used a simple linear regression model for the two statistically significant variables to develop a predictive quality of life model for New Zealand based on objective indicators. Finally, we applied two empirically based predictive models to the subjective data for predicting quality of life for all of New Zealand. We produced maps to spatially illustrate the predicted quality of life.

4. Results

From the correlation matrix it was clear that many of the variables were correlated (e.g., number of supermarkets, libraries, and stores; personal income and education; ownership of motor vehicles and the number of families in the home) and using them together in a multivariate regression would violate statistical assumptions in a subsequent multivariate analysis.

The objective indicators were subject to a PCA, where four components were extracted, jointly accounting for 84% explained variance (Table 3). All independent variables loaded high (over 68% explained variance by the factor) on at least one factor (with most only loading high on one factor) (Table 4). Based on the raw variables that loaded strongly on the different components, the components were labeled as Urbanization and Population (1), Education and Income (2), Household and Community (3), and Public Green Spaces (4). The relationships between these four components and the dependent variables of "Excellent QoUL" and "Poor QoUL" were subsequently analyzed in a multiple regression analysis.

Component 1 (Urbanization and Population) is positively correlated with population density and number of motor vehicles per population while negatively correlated with one-family and ownership of dwelling. Component 2 (Education and Income) represents income and education (often correlated in any study). The second component is also negatively correlated with employment status (i.e., the percentage of unemployed). Household and Community (Component 3) is negatively correlated with the expenditures on community services and positively correlated with the number of one-family households. The final component (4) has a strong positive correlation with the relative area of parks in the ward. No other variable loads on this fourth component.

Table 3. Total variance explained by the four extracted components.

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	**Total**	**% Variance**	**Cumulative %**	**Total**	**% Variance**	**Cumulative %**
1	6.158	43.984	43.984	6.158	43.984	43.984
2	2.885	20.606	64.590	2.885	20.606	64.590
3	1.750	12.497	77.087	1.750	12.497	77.087
4	0.990	7.074	84.161	0.990	7.074	84.161

Table 4. The four extracted components (C1 through C4) and the variable loadings.

Initial Eigenvalues	C1	C2	C3	C4
% European Pop	−0.494	0.682	−0.396	−0.053
% Uni. Degree	0.409	0.824	0.087	−0.049
Median Income	−0.079	0.903	0.141	0.107
One-Family Household	−0.651	−0.077	0.698	0.139
Owned Dwelling	−0.881	0.053	0.049	0.107
Median Weekly Rent	−0.365	0.582	0.558	0.098
% Unemployed Population	0.548	−0.723	0.191	0.053
% Pop. Without Motor Vehicle	0.809	0.098	−0.427	−0.074
Population Density	0.901	0.016	0.194	0.104
Relative Area of Parks	−0.134	−0.041	−0.219	0.943
Community Expenditure	−0.353	0.016	−0.658	0.050

The resulting multiple linear regression model for the excellent QoUL indicator using all four components indicates a relatively strong relationship (Table 5, R^2 of 0.494). However, only Component 2 was statistically related to the excellent QoUL indicator (as judged by the T-score and 0.000 significance level). Component 2 represents education, income, and employment status. The household/community (Component 3) was statistically significant at only the 0.066 level but with a relatively low coefficient (compared to coefficient 2). Thus, only the education/income component is a good predictor of excellent quality of life. All other components, representing proxies for objective indicators found by previous works as important, were not statistically related to excellent QoUL.

Table 5. Results of the multiple linear regression predicting excellent quality of QoUL life using PCA components.

	Model R^2	***F***	**Significance-*F***
Regression Model	0.494	6.596	0.001
Parameter	**Coefficient**	***T***	***p*- Value**
Intercept	0.206	22.625	0.000
Component 1 (Urban/Population)	0.006	0.635	0.531
Component 2 (Education/Income)	0.043	4.686	0.000
Component 3 (Household/Community)	−0.018	−1.914	0.066
Component 4 (Public Green Spaces)	−0.006	−0.596	0.556

The multiple linear regression analysis for the poor QoUL variable resulted in a lesser R^2 value of 0.243 and, again, only Component 2 was significantly related (at the 0.031 significance level). While it was expected that causations for a poor QoUL would be somewhat different, the very weak correlations with subjective variables (as PCA components) were surprising. The causal factors for poor quality of life appear to involve other indicators, in addition to education and income.

The relationships between expected objective indicators (urbanization/population, household/community, access to parks) and subjective excellent or poor QoUL responses were not found. This is a similar finding to the non-existent or weak relationships previously noted by other scholars. However, the relationship between the education/income PCA component (number 2) and excellent QoUL was very strong in this analysis. We explored further the individual variables represented by Component 2 (i.e., Education and Income) for a better interpretation. We used a simple linear regression model to predict excellent QoUL by each individual variable (Table 6a). The percentage of the ward's population with a university degree and median personal income were strong predictors (R^2 of 0.46 and 0.37 respectively). The interpretation of how changes in the percentage of university degrees in a ward results in a percentage change of excellent QoUL in that ward is from the regression coefficient (0.0043). A one percent change in the percentage of university degrees results in a 0.43% change in respondents indicating an excellent QoUL.

Table 6. Single linear models for excellent QoUL. (**a**) Results of the linear regression predicting excellent QoUL using university degree as a subjective variable. (**b**) Results of the linear regression predicting excellent QoUL using median income as a subjective variable.

	(**a**)		
	Model R^2	***F***	**Significance-*F***
Regression Model	0.4629	25.8539	0.0000
Parameter	**Coefficient**	***T***	***p*- Value**
Intercept	0.0948	3.9976	0.0000
Percentage with Degrees	0.0043	5.0847	0.0000
	(**b**)		
	Model R^2	***F***	**Significance-*F***
Regression Model	0.3693	17.5634	0.0002
Parameter	**Coefficient**	***T***	***p*- Value**
Intercept	−0.0206634	−0.3753	0.7101
Median Personal Income	0.0000073	4.1909	0.0002

Simple linear regressions were also conducted with poor/very poor QoUL responses as the dependent variable. Using the percentage of university degrees as the independent variable resulted in an R^2 of 0.17. The relationship with median personal income was even lower. As noted earlier, the causes of a poor QoUL response is likely related to objective variables not evaluated in this study.

To help interpret the relative contributions of each of the factors while holding the other factors constant, we used a partial correlation analysis (Tables 7b and 8b for predicting excellent and poor QoUL, respectively). Relatively speaking, the education/income factor explains 45% (R = 0.66974) of the variance, while household/community explains 12% (R = −0.3456) of the variance holding the other factors constant. Clearly, the ward-level averages of the excellent QoUL perception are mostly controlled by education and income related measures.

The overall regression model for predicting the percentage of respondents in a ward that indicated a poor QoUL was not as strong (R^2 = 0.2434) as for excellent QoUL but still statistically significant at the 0.10 probability level. Similar to the model for excellent QoUL, only one parameter estimate was statistically significant at the 0.10 level—factor 2 (education/income). Also consistent is the functional relationship between the education/income factor and poor QoUL, a negative relationship as compared to the positive relationship with excellent QoUL. The partial correlations clearly indicate that only education/income is a significant variable in predicting poor QoUL. The education/income factor explains 16% of the variance when holding all other factor effects constant.

Table 7. Multiple Regression and Partial Correlations for QoUL. (**a**) Results of the multiple regression analysis predicting excellent QoUL from the four factor components. (**b**) Results of the partial correlation analysis predicting excellent QoUL from the four factor components.

(**a**)

	Model R^2	***N/df***	***F***	***p*- Value**
Regression Model	0.4942	32/27	6.596	0.000773
Parameter	**Estimate**	**Std. Error**	***T*- Value**	***p*- Value**
Intercept	0.206496	0.009127	22.625	$<2 \times 10^{-16}$
Factor 1 (Urban/Population)	0.005885	0.009273	0.635	0.5310
Factor 2 (Education/Income)	0.043457	0.009273	4.686	< 0.00001
Factor 3 (Household/Community)	−0.01774	0.009273	−1.914	0.0663
Factor 4 (Public Green Spaces)	−0.005525	0.009273	−0.596	0.5562

(**b**)

Parameter	**Excellent QoUL (Pearson Correlation)**	***T*- Value**	***p*- Value**
Factor 1 (Urban/Population)	0.12124	0.635	0.5309900
Factor 2 (Education/Income)	0.66974	4.686	0.0000707
Factor 3 (Household/Community)	−0.34560	−1.914	0.0663111
Factor 4 (Public Green Spaces)	−0.11392	−0.596	0.5562441

Five variables loaded strongly on Factor 2 in the factor analysis. Using these five raw variables and the three factors, a new multiple regression was used to examine the dominant variables in Factor 2 that correlated with excellent and poor QoUL (Table 9). The new model was highly significant (R^2 = 0.5909). Only one variable (percent of the population with a degree), other than the intercept, was statistically significant. Interpreting the coefficient (i.e., first derivative) for this variable, it can be said that a 1% change in the percentage of the population with a degree would result in a 0.50% change in the percentage of population claiming excellent QoUL. The partial correlations also substantiate this strong relationship (R = 0.41) between population with a degree and excellent QoUL (Table 10). This is the only statistically significant variable.

Table 8. Multiple Regression and Partial Correlations for Poor QoUL. (**a**) Results of the multiple regression analysis predicting poor QoUL from the four factor components. (**b**) Results of the partial correlation analysis predicting poor QoUL from the four factor components.

(**a**)

	Model R^2	*N/df*	*F*	*p*- Value
Regression Model	0.2434	32/27	2.172	0.09918
Parameter	**Estimate**	**Std. Error**	***T*- Value**	***p*- Value**
Intercept	0.02925	0.003819	7.659	3.08×10^{-8}
Factor 1 (Urban/Population)	−0.00318	0.003880	−0.821	0.4191
Factor 2 (Education/Income)	−0.00881	0.003880	−2.270	0.0314
Factor 3 (Household/Community)	0.00362	0.003880	0.933	0.3590
Factor 4 (Public Green Spaces)	0.00548	0.003880	1.411	0.1695

(**b**)

Parameter	Poor QoUL (Pearson Correlation)	*T*- Value	*p*- Value
Factor 1 (Urban/Population)	−0.155989	−0.821	0.4190684
Factor 2 (Education/Income)	−0.400299	−2.270	0.0314171
Factor 3 (Household/Community)	0.176753	0.933	0.3590247
Factor 4 (Public Green Spaces)	0.262133	1.411	0.1695354

Table 9. Results of the multiple regression analysis predicting excellent QoUL from the five Factor 2 variables and three factors.

	Model R^2	*N/df*	*F*	*p*-Value
Regression Model	0.5909	32/23	4.152	0.003425
Parameter	**Estimate**	**Std. Error**	***T*- Value**	***p*- Value**
Intercept	−0.1397	1.880×10^{-1}	−0.743	3.08×10^{-8}
Factor 1 (Urban/Population)	0.03431	3.580×10^{-2}	0.958	0.3479
Percent European	0.00088	2.181×10^{-3}	0.406	0.6883
Median Household Income	<−0.00001	1.840×10^{-6}	−0.007	0.9941
Median Weekly Rent	0.00014	5.962×10^{-4}	0.234	0.8167
% of Population with Degree	0.00507	2.328×10^{-3}	2.176	0.0401
Percent Unemployed	0.02189	1.529×10^{-2}	1.432	0.1657
Factor 3 (Household/Community)	−0.01667	4.459×10^{-2}	−0.374	0.7119
Factor 4 (Public Green Spaces)	−0.00785	1.121×10^{-2}	−0.701	0.4905

Table 10. Results of the partial regression analysis predicting excellent QoUL from the five Factor 2 variables and three factors.

Parameter	Excellent QoUL (Pearson Correlation)	*T*-Value	*p*-Value
Factor 1 (Urban/Population)	0.195945	0.9583	0.348
Percent European	0.084406	0.4062	0.688
Median Household Income	−0.001552	0.0074	0.994
Median Weekly Rent	0.048837	0.2345	0.817
% of Population with Degree	0.413179	2.1759	0.040
Percent Unemployed	0.286029	1.4316	0.166
Factor 3 (Household/Community)	0.077729	−0.3739	0.712
Factor 4 (Public Green Spaces)	−0.144586	−0.7008	0.490

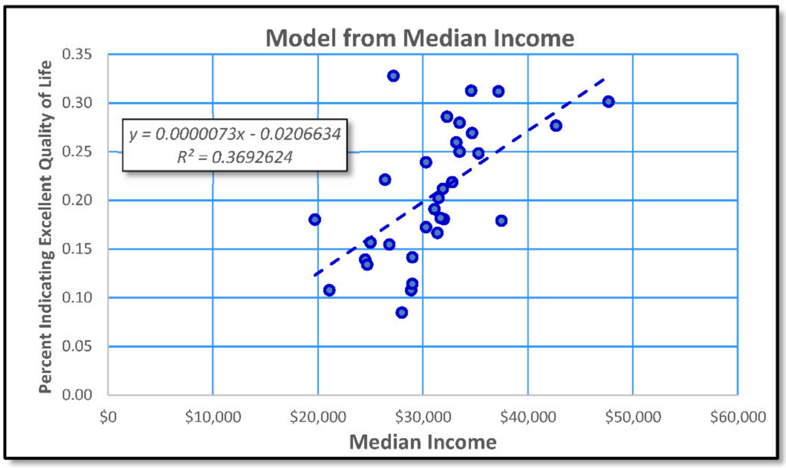
Assume for the moment that education and income are the only variables important in predicting excellent or poor QoUL. Are both contributing to changes in QoUL or is one the controlling variable to QoUL while the other is merely influenced by the controlling variable (and thus, autocorrelated)? We specifically examine the hypothesis that education was the dominant influence on QoUL while income was not (Table 11).

Table 11. Results of the partial correlation analysis predicting excellent and poor QoUL from the hypothesized dominant education/income variables.

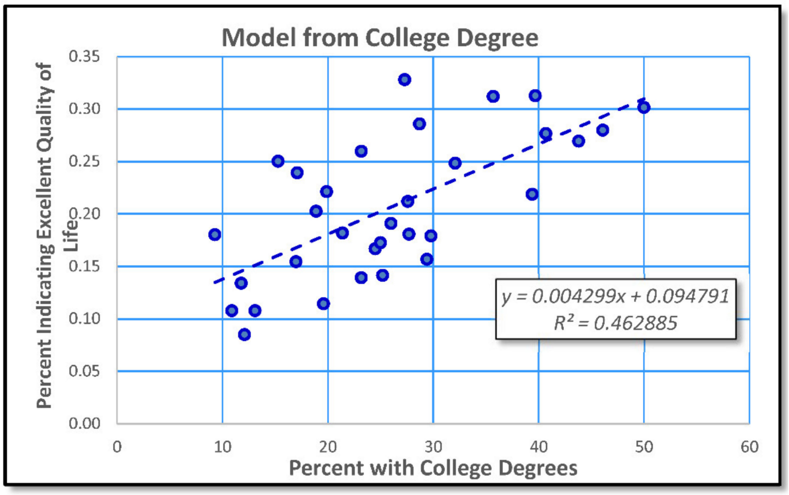
	Excellent QoUL		
Parameter	**Excellent QoUL (Pearson Correlation)**	***T*- Value**	***p*- Value**
Median Household Income	−0.034177	−0.184	0.855
Percent Population with Degree	0.555579	3.598	0.001
	Poor QoUL		
Parameter	**Poor QoUL (Pearson Correlation)**	***T*- Value**	***p*- Value**
Median Household Income	0.046506	0.251	0.804
Percent Population with Degree	−0.316541	−1.797	0.083

Only one variable was significantly correlated with QoUL—percentage of population with a degree. The partial correlation (Pearson) between the percentage with a degree and excellent QoUL while controlling for median household income was 0.555. The correlation of percentage with a degree and poor QoUL was −0.316. Both were statistically significant at the 0.10 probability level. On the other hand, the partial correlation between median household income and excellent QoUL, while controlling for the population with a degree, was only −0.03 and not statistically significant. Median household income was also not significantly correlated with poor QoUL. These results strongly suggest the dominant factor in predicting either excellent or poor QoUL perception was education level rather than household income. One might argue that other variables should be included in the analysis, such as those used in the factor analysis. However, none of the other factors were significantly correlated with either QoUL measure. This partial correlation analysis precludes the apparently small influences of other variables on predicting QoUL.

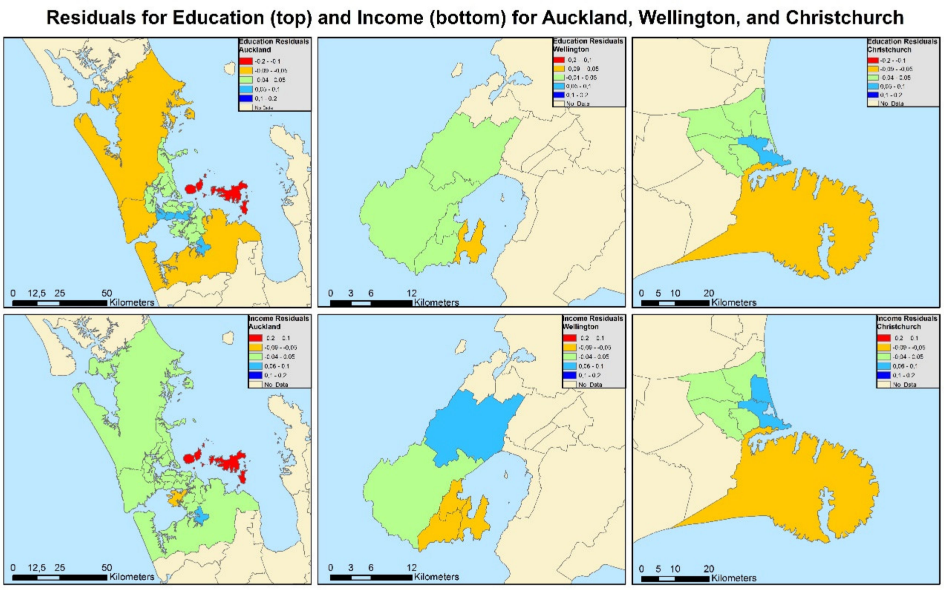
We further plotted and mapped the residuals for perceived excellent QoUL and income (Figure 2a) and perceived excellent QoUL and education (Figure 2b). For both variables, the QoUL of the Waiheke ward was the most under-predicted ward, indicating that the prediction model does not fit well for this area. One may speculate that the high QoUL in Waiheke can be attributed to the socially and culturally diverse nature of the island, with a flourishing creative sector, or to the beautiful natural setting of the island. Perhaps the integration of more community and environmental variables would help to provide a comprehensive understanding of factors influencing high QoUL in Waiheke. In contrast to the QoUL under-prediction in Waiheke, QoUL was most over-predicted for the Papakura ward with the income-based prediction model. This too may be attributed to the distinct social nature of the ward, which constitutes the heart of issue-plagued South Auckland. The area is characterized by the country's highest rate of overcrowding and above average numbers of unqualified and unemployed youths. More social and community variables would need to be analyzed to improve the QoUL prediction for Papakura. Figure 2c indicates that the education-based QoUL model works best in smaller, central wards, while generally under-predicting QoUL for larger, semi-rural, outskirt wards. The mapped residuals for quality of life and income (Figure 2c) show a less distinct pattern, with only slight spatial autocorrelation in central Wellington and Auckland.



(**a**)



(**b**)



(**c**)

Figure 2. Regression results between excellent QoUL and predictive variables of education and degree (**a**) Observed values for perceived excellent QoUL and annual median income. (**b**) Observed values for perceived QoUL and percent with university degree. (**c**) Mapped residuals for education and income for Auckland, Wellington, and Christchurch.

One of our final goals was to map quality of life from objective indicators. As the relationships with education/income and those perceiving an excellent quality of life were strong, we focused on these relationships to build predictive models for all wards in New Zealand (Figure 3). For comparison between models and for comparing to the original subjective responses, we used a Likert scale for displaying the modeled QoUL in the maps (in accordance with the Likert scale QoUL measure used in the NZ Quality of Life Survey).

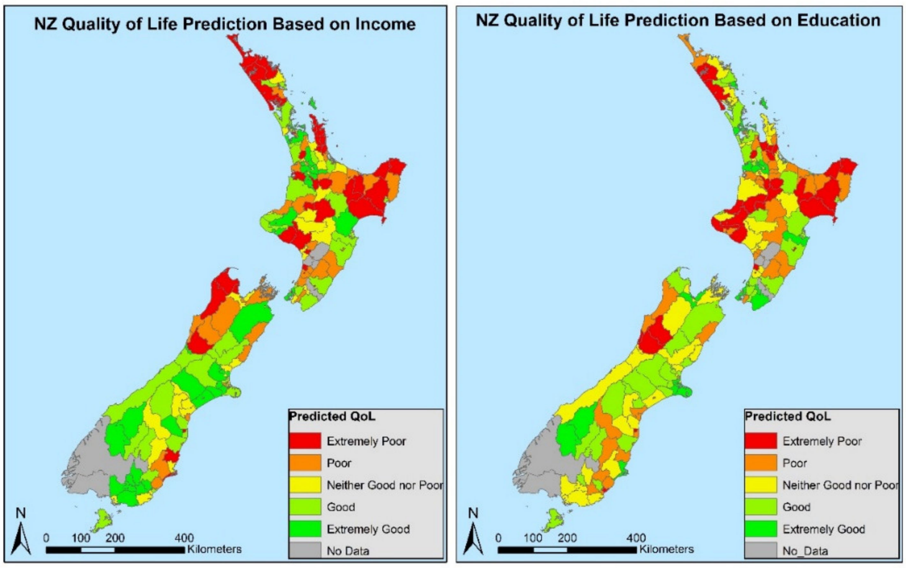


Figure 3. QoL prediction model for New Zealand based on income (left) and education (right). Source: own depiction based on 2013 NZ census data.

5. Discussion and Conclusions

In this study, we determined that 46% of the variation in perceived "Excellent" QoUL can be predicted with either the variable of education or income. In terms of education, these findings align with those of Liao [6], while Pittau et al. [22] also identified income as a predictor of "life satisfaction". The R^2 value of 0.49 obtained in the multiple linear regression between the subjective variable of "Excellent QoUL" and Component 2 (Education & Income) or the single objective variables of education (R^2 = 0.49) or income (R^2 = 0.37) exceed the R^2 values determined in prior studies of aggregate spatial scales utilizing linear regression by up to 10%. For example, Oswald and Wu's [10] empirical study at the state level found a modestly strong relationship (R^2 = 0.36) between objective variables and subjective QoUL. Türksever and Atalik [11] determined an R^2 value of 0.326 between a number of objective variables and the dependent variable of "Satisfaction" for Istanbul). McCrea [8] found the two latent variables of subjective access and subjective overcrowding in his structural equation model explaining 34% of the variance in subjective QoUL. All other objective variables previously identified as predicting subjective QoUL, at least in a minimal way, were found to have no relationship with QoUL. This observation can, to some degree, perhaps be traced back to the spatial scope in which a given study is conducted—a problem well known to geographers as the modifiable areal unit problem [23]. This principle suggests that the higher the level of data aggregation is, the stronger the correlations will be, due to the so-called scale effect [24], making all results conditional to the scale and aggregation level on which they were conducted [25]. However, the present study at ward level found a stronger relationship between objective factors and subjective QoUL than the studies conducted by Türksever and Atalik [11] at city level and Oswald & Wu [10] at the state level, indicating that perhaps different factors, or different functional models, need to be considered at different spatial scales. While variables such as climate or pollution may well play a role between large areas, located far from one another, or in a single study region (such as Istanbul in the study by Türksever and Atalik), they are unlikely to be perceived differently (affecting QoUL) among neighboring wards. On the other end of the spectrum, measures such as accessibility may only make sense in small-scale, individual analyses, since these possibly vary greatly within a ward, the effects of which are entirely lost through generalization. This observation has critical implications for planners and policy makers, as it emphasizes the need for carefully considered indicator selection when examining QoUL on a micro level. Depending on the scale of analysis and the aims of a QoUL study, we recommend probing what may influence subjective QoUL with focus group interviews that ask broader questions to get an understanding of general themes people consider important. For example, these interviews could include open ended questions like "What do you understand quality of urban life to mean?", "What makes you feel something good about [the study area]?", "What makes you feel something bad about [the study area]?". Once recurring themes have been established, these findings can be incorporated into the design of a broader questionnaire designed in a more codable manner (e.g., using the Likert scale) which can be widely administered to capture broad public opinion on pertinent matters.

Another reason for discrepancies between studies lies in the choice of proxies for objective QoUL. While many indicators, such as sociodemographic variables and other census data, are clearly defined and, thus, directly transferable to other study areas, others are not. For instance, the loosely defined variable of "urban green" can either be measured by relative area of parks (as in this study), with the inherent limitation that sharp ward boundaries in the analysis create barriers where there are in fact none (i.e., someone living at the edge of a ward may well utilize the facilities of an adjacent ward), or by using measures such as normalized difference vegetation index (NDVI), which may positively impact the green rating by including green areas that are not accessible (i.e., the neighbor's garden). The same issues hold true for variables such as government service provision (annual expenditure, total facilities, accessibility to facilities), accessibility (which facilities are included, relative number, facility quality), and so on. Naturally, composite indicators can be created to include many variables into any one proxy; however, this again may lead to varying results based on the respective weights assigned to each variable and how these weights were derived (expert opinions, statistical models, etc.). As such, any chosen proxy will have its limitations and lead to varying results between QoUL studies. It should perhaps be a matter of future work to determine appropriate proxies for objective indicators, by further refining QoUL surveys to determine what influences a person's satisfaction with a given life aspect.

Furthermore, we determined that subjective "Excellent QoUL" and subjective "Poor QoUL" are only weakly correlated with each other, indicating that they may, in fact, be explained by different objective factors. We are not aware of others probing the issue of the problem of modeling the extreme classes with the same model. This is also supported in the different magnitude of R^2 between the significant component (Education and Income) and "Excellent" (0.425), respectively, and "Poor" QoUL (0.243) in the multiple regression analyses. This means that a greater number of university degrees/higher median income per ward increases the subjective "Excellent QoUL" to a greater extent than a lesser number of university degrees/a lower median income per ward increases subjective "Poor QoUL". As such, not only indicators measuring high QoUL need to be defined in order to subsequently try to increase the proportion of citizens perceiving high QoUL but indicators explicitly contributing to low QoUL also need to be defined, so that planners and policy makers can explicitly tackle these issues. To this end, the focus group interviews mentioned above could help identify possible explanatory variables. To get a better understanding of each end of the QoUL spectrum, we recommend including open-ended "why" questions in such surveys, so survey participants indicating "Excellent" respectively to "Poor" QoUL can explicitly state their reasons for doing so. This would enable future studies to clearly define their aims (is high or low QoUL being examined) and create targeted indicators, rather than simply assuming that low QoUL is a negative outcome of high QoUL. This is of particular relevance to planners and policy makers, since most planning initiatives are concerned with increasing the QoUL of poorly rated areas (at any given scale) rather than further increasing the QoUL of highly rated areas. Therefore, initiatives with the specific aim of increasing the

QoUL of a given area need to focus on identifying and mitigating the QoUL-limiting factors rather than aiming to replicate or match characteristics of positively rated areas.

Furthermore, this study provides a basis for understanding urban ecosystem interactions, since aspects such as equity to park access or the so-called "luxury effect" [26,27] can subsequently be examined in conjunction with social stratification and perceived quality of life. As such, several studies have found a relationship between the variables of education and income and vegetation structure and diversity in urban parkland [28], indicating an unequal "quality" of urban facilities based on demographics, which one could subsequently expect to be reflected in perceived QoUL. Therefore, future studies of urban quality of life should explicitly incorporate not only the presence/absence of certain objective indicators but also the equity of their accessibility to all population groups and their respective "quality".

Much work remains to understand the influences of factors on the subjective quality of life. Importantly, the development of a predictive model that is robust across more than one geographic area is elusive. Further, the problem of the appropriate scale of analysis underlies all studies. Our future work will focus on teasing apart the variables of high QoUL and poor QoUL, and subsequently identifying and constructing meaningful indicators for explaining the remaining 64% of variance currently not explained by linear models.

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References

1. Marans, R.W. Understanding Environmental Quality through Quality of Life Studies: The 2001 DAS and Its Use of Subjective and Objective Indicators. *Landsc. Urban Plan.* **2003**, *65*, 73–83. [CrossRef]
2. Campbell, A.; Converse, P.E.; Rodgers, W.L. *The Quality of American Life: Perceptions, Evaluations, and Satisfactions*; Russell Sage Foundation: New York, NY, USA, 1976.
3. Kahneman, D.; Diener, E.; Schwarz, N. (Eds.) *Well-Being: Foundations of Hedonic Psychology*; Russell Sage Foundation: New York, NY, USA, 1999.
4. Haslauer, E.; Delmelle, E.C.; Keul, A.; Blaschke, T.; Prinz, T. Comparing Subjective and Objective Quality of Life Criteria: A Case Study of Green Space and Public Transport in Vienna, Austria. *Soc. Indic. Res.* **2015**, *124*, 911–927. [CrossRef]
5. Keul, A.G.; Prinz, T. *The Salzburg Quality of Urban Life Study with GIS Support*; Springer: Dordrecht, The Netherlands, 2011.
6. Liao, P.S. Parallels between objective indicators and subjective perceptions of quality of life: A study of metropolitan and county areas in Taiwan. *Soc. Indic. Res.* **2009**, *91*, 99–114. [CrossRef]
7. McCrea, R.; Stimson, R.J.; Western, J. Testing a general model of satisfaction with urban living using data for South East Queensland. Australia. *Soc. Indic. Res.* **2005**, *72*, 121–152. [CrossRef]
8. McCrea, R.; Shyy, T.-K.; Stimson, R. What is the strength of the link between objective and subjective indicator of urban quality of life? *Appl. Res. Qual. Life* **2006**, *1*, 79–96. [CrossRef]
9. McCrea, R. Urban Quality of Life: Linking Objective Dimensions and Subjective Evaluations of the Urban Environment. Ph.D. Thesis, The University of Queensland, Brisbane, Australia, 2007.
10. Oswald, A.J.; Wu, S. Objective Confirmation of Subjective Measures of Human Well-Being: Evidence from the USA. *Science* **2010**. [CrossRef] [PubMed]
11. Türksever, A.N.E.; Atalik, G. Possibilities and limitations for the measurement of the quality of life in urban areas. *Soc. Indic. Res.* **2001**, *53*, 163–187. [CrossRef]

12. Von Wirth, T.; Grêt-Regamey, A.; Stauffacher, M. Mediating Effects between Objective and Subjective Indicators of Urban Quality of Life: Testing Specific Models for Safety and Access. *Soc. Indic. Res.* **2015**, *122*, 189–210. [CrossRef]
13. Marans, R.W.; Mohai, P. Leisure resources, recreation activity, and the quality of life. In *The Benefits of Leisure*; Driver, B.L., Brown, P., Peterson, G.L., Eds.; Venture Publishing: State College, PA, USA, 1991.
14. Marans, R.W.; Rodgers, W. *Toward an Understanding of Community Satisfaction*; Metropolitan America; National Academy of Sciences: Washington, DC, USA, 1974.
15. Marans, R.W.; Stimson, R. *An Overview of Quality of Urban Life*; Springer: Dordrecht, The Netherlands, 2011.
16. Gehlke, C.E.; Biehl, K. Certain Effects of Grouping upon the Size of the Correlation Coefficient in Census Tract Material. *J. Am. Stat. Assoc.* **1934**, *29*, 169–170.
17. Clark, W.A.; Avery, K.L. The Effects of Data Aggregation in Statistical Analysis. *Geogr. Anal.* **1976**, *3*, 428–438. [CrossRef]
18. Mandelbrot, B. How long is the coast of Britain? Statistical self-similarity and fractional dimension. *Science* **1967**, *156*, 636–638. [CrossRef] [PubMed]
19. Lee, T.; Marans, R.W. Objective and subjective indicators: Effects of scale discordance on interrelationships. *Soc. Indic. Res.* **1980**, *8*, 47–64. [CrossRef]
20. Angur, M.G.; Robin, W.; Sudhir, G.A. Congruence among Objective and Subjective Quality-of-Life (QOL) Indicators. *Alliance J. Bus. Res.* **2004**, *5*, 47–52.
21. Cummins, R.A. Objective and subjective quality of life: An interactive model. *Soc. Indic. Res.* **2000**, *52*, 55–72. [CrossRef]
22. Pittau, M.G.; Zelli, R.; Gelman, A. Economic disparities and life satisfaction in European regions. *Soc. Indic. Res.* **2010**, *96*, 339–361. [CrossRef]
23. Openshaw, S.; Taylor, P.J. A million or so correlation coefficients: Three experiments on the modifiable areal unit problem. In *Statistical Applications in the Spatial Sciences*; Pion: London, UK, 1979; Volume 21, pp. 127–144.
24. Wong, D. The Modifiable Areal Unit. In *The SAGE Handbook of Spatial Analysis*; SAGE Publications Ltd: New York, NY, USA, 2008; Volume 105.
25. Manley, D. Scale, Aggregation, and the Modifiable Areal Unit Problem. In *Handbook of Regional Science*; Springer: Berlin/Heidelberg, Germany, 2014.
26. Hope, D.; Gries, C.; Zhu, W.; Fagan, W.F.; Redman, C.L.; Grimm, N.B.; Nelson, A.L.; Martin, C.; Kinzig, A. Socioeconomics Drive Urban Plant Diversity. Available online: https://www.researchgate.net/publication/10673984_Socioeconomics_Drive_Urban_Plant_Diversity (accessed on 15 July 2016).
27. Martin, C.A.; Warren, P.S.; Kinzig, A.P. Neighborhood socioeconomic status is a useful predictor of perennial landscape vegetation in residential neighborhoods and embedded small parks of Phoenix, AZ. *Landsc. Urban Plan.* **2004**, *69*, 355–368. [CrossRef]
28. Conway, T.; Hackworth, J. Urban pattern and land cover variation in the greater Toronto area. *Can. Geogr./Géographe Can.* **2007**, *51*, 43–57. [CrossRef]