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Spatial variations in contributors to life satisfaction: An Australian case study

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Abstract

What people consider important, and how these factors contribute to their self-reported life satisfaction (LS), varies significantly across regions. Here, we analyse for the first time how LS varies across space and what factors best explain LS at different locations. Geographically weighted regressions (GWR) were used to analyse the relationship between LS and seventeen objective variables across Australia. We find that contributors to LS vary considerably but individuals living in relative proximity to each other share similar perspectives. Taking into account the spatially explicit heterogeneity of a population allows for the assessment of federal policies at local or regional levels, increasing the likelihood that their impacts will be consistent with the original intent. It also enables the perspectives of the diversity of cultures within a nation to be better understood.

Introduction

Every individual perceives the world in a slightly different way. These perceptions change our behaviour and our relationships; they inform how we interact with the world. They also determine our values. The values we hold—the things we consider important—and how we see the world influences our wellbeing and satisfaction with our own lives. This makes measuring wellbeing a challenge.

In the past few decades, dozens of indicators have been used to try to measure human wellbeing (Dolan et al. 2008; Smith et al. 2013). However, no consensus exists around which indicator is ideal, nor what structure this indicator should take. Until now, indicators have been structured in one of three ways: (1) those that adjust economic indicators to include social and environmental aspects, (2) those that measure quality of life or life satisfaction directly through surveys, and (3) those that are composite indicators bringing together a multitude of aspects (Costanza et al. 2014).

Indicators with structure (2) are solely dependent on subjective variables. Subjective variables use people's own evaluation of their satisfaction with their lives - a cognitive evaluation of their entire lives (Myers and Diener 1995). Subjective life satisfaction (LS), or quality of life, assumes that a person can assess how they feel about their life in context of their own relative standards (Diener and Suh 1997). It implies that a person correctly identifies which aspects of their lives contribute to their wellbeing and the importance of that contribution. However, this also means that an individual's subjective LS is completely dependent on their personal perception of the world, which may not be concurrent with reality as perceived by others, or as measured by objective means (Tyler and Boeckmann 1997; King and Maruna 2009; Ambrey et al. 2014).

Indicators with structure (1), and most with structure (3), use objective variables. Objective indicators are based on observable and quantitative factors that are relatively easy to measure across a large population and provide data with minimal subjectivity (D'Acci 2011). They can also directly target policy interventions at regional or national levels, especially those aspects that contribute to wellbeing but are not perceived by individuals (e.g. ecosystem services and inequality) (Wilkinson and Pickett 2009; Costanza et al. 2017). However, ensuring consistent boundaries and standards around measuring of these indicators is critical for comparison purposes (Dolan and Metcalfe 2012; Kubiszewski et al. 2013).

Objective variables also have their limitations. The biggest is that they do not always represent the reality that individuals perceive, as discussed above (Duffy et al. 2008; Kahneman 2011; Ambrey et al. 2014; Kubiszewski et al. 2018).

Objective indicators represent the conditions and assets that allow people to meet their needs and experience subjective wellbeing (Costanza et al. 2007). These assets, which overlap and interact in complex ways, can be categorized into four broad groups (Costanza et al. 2013):

- **Built capital:** Human built infrastructure that includes buildings, transportation and communication infrastructure, and all other human artifacts and services that fulfil basic human needs — in this paper we include the variables of household income and home ownership.
- **Human capital:** Human beings and their personal attributes, including physical and mental health, knowledge, and other capacities that enable people to be productive

members of society — in this paper we include the variables of age, gender, health, fitness, work life balance, employment, education level, and indigenous heritage.

- **Social and cultural capital:** The web of interpersonal connections, social networks, cultural heritage, traditional knowledge, trust, and the institutional arrangements, rules, norms, and values that facilitate human interactions and cooperation between people. These contribute to social cohesion within strong, vibrant, and secure communities, and to good governance, and help fulfil basic human needs such as participation, affection, and a sense of belonging — in this paper we include the variables of relationship status, having children, and volunteering.
- **Natural capital:** The natural environment and its biodiversity, which, in combination with the other three types of capital, provide ecosystem goods and services: the benefits humans derive from ecosystems. These goods and services are essential to basic needs such as survival, climate regulation, habitat for other species, water supply, food, fibre, fuel, recreation, cultural amenities, and the raw materials required for all economic production — in this paper use normalised difference vegetation index (NDVI) as a proxy variable indicating the level of natural capital in different locations.

Regardless of the structure or type of variables used, many indicators are frequently aggregated to the national level. This allows for comparison between nations and benchmarking a nations' overall progress. However, aggregation to a national, or sub-national, level overlooks critical information about a population. Those that are the most at risk, with the lowest life satisfactions, are averaged out and overlooked (Andreasson 2018; Kubiszewski et al. 2019). National aggregation also assumes homogeneity of perspectives within the entire population. It ignores variations in age, gender, and values held by different segments of the population. It ignores the diversity in cultures and ethnicities that a nation, like Australia, contains, including immigrants and indigenous people, among other minorities (Graham and Markowitz 2011; Diener 2012; Andreasson 2018).

In this paper, we analyse the relationship between objective (reality) and subjective (perception) variables at the local scale within Australia, examining individual communities to identify spatial variations. Such an analysis is an attempt to understand the needs of a diverse population rather than prioritising the average or elite individual (Bache et al. 2016; Cairney et al. 2017).

To do this, we use geographically weighted regressions (GWR) to understand the variations in the relationship between subjective life satisfaction and objective variables, allowing for spatial differences (Fotheringham et al. 2002; Wheeler and Calder 2007). We analyse the variables to determine those having the greatest positive and negative impacts on the Australian population in different geographic locations and to identify where those impacts are most pronounced.

Methods

We estimate the impact of a range of objective variables on the spatial variations in life satisfaction across Australia. To do this, we use individual level data from waves 1-16 (collected in 2001-2016) of the Household, Income and Labour Dynamics in Australia (HILDA) Survey[1].

One of the variables in the HILDA Survey, which we used as the dependent variable in this analysis, is overall life satisfaction. Life satisfaction (LS) at an individual level is taken from responses to the question, "All things considered, how satisfied are you with your life?" Responses are given on an 11-point Likert scale where 0 means totally dissatisfied and 10 stands for totally satisfied. We acknowledge that calculating the mean of Likert items can be problematic, especially not knowing whether increments in scale correspond to equal increments in the underlying latent variable. Treating life satisfaction as ordinal versus interpersonally cardinally comparable is a contentious issue in the literature. Justifications for cardinality include empirical research demonstrating that treating life satisfaction data as cardinal yields similar results to treating it as ordinal, and both assumptions are compatible with life satisfaction scores (Ferrer-i-Carbonell and Frijters 2004; Blanchflower and Oswald 2011; Kristoffersen 2017). Further, Kristoffersen shows that life satisfaction scores are equidistant (Kristoffersen 2017). The purpose of this paper does not require us to take a strong stand in this debate.

The objective variables, or the independent variables from the HILDA Survey, used in this study are also aggregated from individuals living within a given geographic area. We aggregated continuous variables by calculating the mean value per given area. For example, the mean household disposable income for a given area was calculated. Categorical variables were aggregated by obtaining the proportion of individuals of a specific category out of the total individuals within each respective area; for example, the proportion of men, the proportion of university graduates, and proportion of those with a long-term health condition within each area. The variables used in this study were identified based on outcomes from previously published literature, including similar studies done on the individual scale (Kubiszewski et al. 2018) and at aggregated regional scales (Kubiszewski et al. 2019).

Because the HILDA Survey does not include any natural capital variables, we also incorporated the Normalised Difference Vegetation Index (NDVI) as a proxy variable (discussed below) for natural capital. Natural capital has a significant impact on life satisfaction, although it is often omitted from wellbeing studies (Ambrey and Fleming 2014a; Tsurumi and Managi 2015; Fleming et al. 2016; Larson et al. 2016).

Spatial scale

The spatial scale used in this paper is based on the Australian Statistical Geography Standard (ASGS) hierarchical scales. The Australian Bureau of Statistics (ABS) designed the Statistical Areas (SAs) geographic structure specifically for the release of statistical information[2]. Their sizes are based on population, not area. In this paper, we aggregate individual level data to Statistical Area Level 2 (SA2). SA2s have average populations of about 10,000 (between 3,000 and 25,000) people and were designed to represent communities that interact economically and socially.

[1] This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS), and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the author and should not be attributed to either DSS or the Melbourne Institute.

[2] tp://www.abs.gov.au/websitedbs/D3310114.nsf/home/geography

The SA2 scale is used in this paper because it allows us to meaningfully analyse variations across the areas. Larger areas (SA3 and SA4) were not used because as the population and area size of the regions increases, the number of comparable regions decreased significantly. For example, there are approximately 1509 (Standard Deviation (SD) 301) SA2s in each wave of the HILDA Survey, while there are only 317 (SD 12) SA3s in each wave, and 87 (SD 0) SA4s in each wave. Smaller statistical areas (SA1) were not used because although there are a larger number of these across Australia, the average number of HILDA Survey respondents within each SA1 is 3.2 (SD 3.99), as apposed to 10 (SD 10) in each SA2. When analysing the model at multiple scales, SA1 had a significantly lower explanatory power (adjusted R2) then SA2.

Natural capital data – NDVI

We use the Normalised Difference Vegetation Index (NDVI) as a proxy for natural capital. Natural capital is the stock of natural assets from which humans derive services (Costanza et al. 1997b; Millennium Ecosystem Assessment (MEA) 2005). NDVI measures the amount of live green vegetation present. The source of the NDVI data is the Australian Government Bureau of Meteorology (BOM)[3], derived from satellite observations.

NDVI is an index measuring the difference between visible light absorbed and infrared radiation reflected by vegetation. This measure changes due to vegetation density and greenness. The index value lies between -1 and +1. Higher values are associated with greater density and greenness, decreasing as vegetation comes under water stress, becomes diseased, or dies. Bare soil and snow values are close to zero, while water bodies have negative values.

For this analysis, we use NDVI values from January of each year of the HILDA Survey to ensure the data reflects variations year to year. January was selected as being in the middle of the growing season, thus being likely to reflect the period of maximum greenness. NDVI is primarily used as a means of comparison from year to year and between scales. In this study, it is not used for its absolute value.

Each years' January data was intersected with files containing the boundaries of the statistical geographic scales used in this paper. The average NDVI score per geographic region, weighted by spatial area, were calculated using the proportion of each region's area represented by different NDVI scores. These scores per region were calculated at each scale in turn, providing the data for inclusion within the regression described above.

Although NDVI is not directly perceived, it provides an appropriate proxy for vegetation and natural capital (Bai et al. 2008; Sutton et al. 2016), and has been previously found to be a significant predictor of LS (Kubiszewski et al. 2019)

Preparing the variables

Firstly, variables negatively framed were reversed to ensure that all that variables had a positive framing. For example, the question "long term health" was inverted to indicate the proportion of the population in each region that did not have a long-term health problem.

[3] http://www.bom.gov.au/jsp/awap/ndvi/archive.jsp?colour=colour&map=ndviave&period=month&area=nat

Secondly, variables depicting the number of children were combined before being reversed. Rather than separate variables showing one child and multiple children, these were combined into a single variable representing the proportion of the population in each SA2 having children. This variable was then reversed to present the proportion of the population in each region that did not have children.

Finally, we averaged each variable over the 16 years of the HILDA Survey for each of the SA2 regions. This provided us with a single average value for each variable and location (i.e. simplifying panel data to cross sectional data) suitable for use in GWR.

GWR and the Empirical model

This paper estimates a geographically weighted regression (GWR), a refinement to the OLS regression that enables us to explore variations between different SA2 regions. GWR is a technique to analyse spatial non-stationarity, this is when the relationship between variable changes from area to area (Mennis 2006). A standard ordinary least squares regression (OLS) analyses the relationship between variables with the assumption that the relationship is uniform over the entire study area. For example, the relationship between life satisfaction and objective variables has been analysed in Australia, determining a single average correlation for the entire country (Boreham et al. 2013; Ambrey and Fleming 2014b; Kubiszewski et al. 2018; Kubiszewski et al. 2019). Such analyses, although important, ignore regional heterogeneity. GWR allows us to estimate the relationship between variables, such as life satisfaction and contributing objective variables, at local scales separately using a single modelling framework. Basically, GWR estimates regression coefficients for each location, whereas OLS estimates 'global' coefficients fixed across the whole region (Wheeler and Páez 2010). GWR thus allows the identification of spatial variations within the population, reflecting the sample's heterogeneity. A failure to address spatial relationships may result in biased or invalid estimation results (Bateman et al. 2002; Stanca 2010).

GWR is a critical tool in understanding spatial heterogeneity in a population. However, GWR also has its weaknesses (Ali et al. 2007). For example, the sample size is reduced significantly at local levels from what it is at a regional or national level. A smaller sample size provides lower statistical power. GWR also requires running dozens, potentially thousands, of regressions. Depending on the number of observations and variables being analysed, this can be computationally very intensive and produce a massive amount of results.

GWR has been used in many other fields, including ecology (Foody 2003; Kumar et al. 2012), environmental equity (Mennis and Jordan 2005), ecosystem services valuation (Jarvis et al. 2017), ecological influences on voting (Calvo and Escolar 2003), poverty analysis (Longley and Tobón 2004; Benson et al. 2005; Partridge and Rickman 2005), housing markets (Yu et al. 2007), and regional development (Huang and Leung 2002; Yu 2006), amongst others.

The use of GWR provides local and regional benefits. Federal policies can be assessed at local or regional levels, ensuring that their impacts are consistent with the original intent (Matthews and Yang 2012). Local and regional policies can be formulated to target specific populations, ensuring maximum positive impact. Furthermore, this method can highlight those variables which are explicitly important when considered at local scales amongst diverse population, but whose importance is eliminated at national level due to offsetting impacts that may mitigate against each other at a larger scale (Ali et al. 2007).

Whilst the use of GWR adds practical value in many circumstances, conventional 'global' correlations are useful for general understanding and benchmarking. Comparison between countries or states requires an aggregation of averaged results. Also, federal policy development necessitates an understanding at the national or international level. Such aggregation is also likely to provide a higher statistical power within the model. Thus, adopting a 'global' method versus a spatially distributed method, such as GWR, depends on whether the objective is to understand the average situation or to understand the regional variations that exist around that average. If a population is fairly homogenous then the two methods will not provide dissimilar results; the use of GWR for developing local/regional policies becomes more important in countries where the population displays notable levels of spatial heterogeneity.

In this paper, the empirical model run using GWR can be defined by:

$$\mathrm{Y}_i = \beta_0\,(u_i, v_i) + \Sigma_k\, \beta_k\,(u_i, v_i)\ \mathrm{X}_{ik} + \varepsilon_i$$

Where

- Y_i is the dependent variable (in our case self reported life satisfaction from the HILDA Survey),
- X_i is the corresponding covariate vector of variables (in our case the objective variables described in further detail below),
- (u_i, v_i) denotes the coordinates of the i^{th} point in space, and
- $\beta_k\,(u_i, v_i)$ is a realisation of the continuous function $\beta_k\,(u_i, v_i)$ at point i.

Thus, the equation recognises that spatial variations in the relationships exist and allows for obtaining localised parameters estimates for any point in space (Fotheringham et al. 2002). Local standard errors are also calculated, based on the normalised residual sum of squares from the local regression equations (Fotheringham et al. 2002).

When appropriately used, this method provides powerful and useful information for examining relationships that vary across space. Before using the approach, it is important to test for the presence of spatial autocorrelation (such as the Global Moran's I Index)[4] and spatial non-stationarity (such as the Koenker (BP))[5].

Thus our approach involved the following steps. First, we used aggregated LS scores and objective variables in each SA2 to run an ordinary least squares (OLS) model (eliminating variables insignificant at 10% level). Secondly, we used principal components analysis (PCA) to reduce the dimensions within our model. Thirdly, we estimated the LS model using GWR.

Step 1. Aggregation

Aggregating the life satisfaction (LS) scores and individual variables for each of the SA2s, across the 16 years, reduced our data from 22,745 to 2002 observations. To ensure no anomalies occurred as a result of aggregation, we compared the results from the OLS models estimated on the aggregated and pre-aggregated datasets with the same variables controlling

[4] If no spatial autocorrelation is found in the residuals, then the model reflects the inherent spatial nature of the data with no important spatial variables having been omitted.
[5] In the presence of spatial non-stationarity, global models are unreliable (unless it is controlled for). In these circumstances, GWR successfully analyses the spatially varying relationships.

for fixed effects by year. The two models had similar results. All the variable coefficients had the expected signs and the majority of significant variables remained significant, apart from the variables indicating age and the proportion of people who spoke English well within the region. The age-squared coefficient, however, remained significant and positive. Previous studies found both age and age-squared as significant influences on LS (Di Tella et al. 2003; Ferrer-i-Carbonell and Gowdy 2007; Murray et al. 2013; Schwandt 2016). However, others found age insignificant when age-squared was included (Jarvis et al. 2017). Thus, this is not inconsistent with the literature. Furthermore, the explanatory power of the model, as measured by adjusted R^2, improved from 0.174 to 0.197.

Step 2. Reduction of variable dimensions

The comparison of these models shows that the variables selected were sufficiently robust to further reduce the dimensions by using principal components analysis (PCA)[6]. We grouped the variables into four 'capital' groupings (built, natural, human, social) (Costanza et al. 1997a) using PCA, which applied varimax rotation with Kaiser normalisation. Each of the grouped variables were standardised to ensure comparability of relative impacts on LS. The variables used to develop our composite variables representing the different capitals can be seen in Appendix Table 1.

The factors resulting from the PCA and the standardisation process were used in our models to explain variations in LS within each of the SA2 regions, forming the basis of the results and analysis presented here.

Step 3. GWR estimation tests

The variables developed in step 2 were used to estimate their relationship with LS using OLS. We then tested the appropriateness of GWR compared to OLS. The Koenker (BP) statistic was significant, indicating that spatial relationships may be present, whilst the Global Moran I Index test indicated that spatial autocorrelation was not present. Therefore, GWR could be used to estimate the spatially varying relationships between LS and the variables developed from step 2.

In addition, we compared the GWR model with the standard OLS model, finding that the Akaike information criterion (AICc) statistic indicates the GWR model to be the better model and the explanatory power of the GWR model to be stronger as indicated by the higher adjusted R^2 statistic.

Variables included within the final model

The final model was based on nine independent variables (derived from step 2 described above) for each SA2 region. These include:

- **AgeSq:** the squared value of the average age of the sample.
- **Male:** the proportion of males in the sample.
- **Built:** the composite variable representing the impact of both the natural log of household incomes for the sample and the proportion of the sample owning their own homes.
- **Human_1:** a composite variable representing the impact relating to long-term health, fitness, work-life balance, and education level. This factor mainly reflects the proportion

[6] Both the Kaiser-Meyer-Olkin measure of sampling adequacy and the Bartletts's test of sphericity indicated that factor analysis would be useful with our data, and we checked for separability between dimensions by looking at correlation coefficients.

of the sample engaged in physical exercise, the proportion not having a long-term health problem, and the average number of hours worked by the sample.

- **Human_3:** a composite variable representing the impact of employment status (proportion of the sample that are employed) and the proportion of the sample that are indigenous.
- **Social_1:** a composite variable representing the impact focused on relationship status and whether another adult was there when answered survey.
- **Social_2:** a composite variable representing the impact focused on volunteering and having children.
- **NDVI:** representing the natural capital of the region.
- **Dsat:** the standard deviation in life satisfaction within each SA2 region.

The 'Human 2' variable was dropped from the analysis due to being insignificant. It was a composite variable representing the impact of the nationality dimension of human capital. Further information regarding these variables can be found in Appendix Table 1.

Results

We ran an OLS model using the variables described above to estimate the impact of each variable on variations in LS across Australia. This provided an adjusted R^2 of 0.161.

We then estimated the same variables using a geographically weighted regression (GWR). This produced a higher overall adjusted R^2 of 0.232. However, the GWR technique estimates the relationships within each SA2 region and shows varying degrees of explanatory power between different SA2 regions across the country (Figure 1).

The GWR generated maps showing the impact of each of the variables on each of the SA2 regions. Figures 2 and 3 show the variables that have the highest and lowest coefficients (indicating the level of impact of the variable on LS) in each SA, respectively. The variables that have the greatest positive impact on parts of Australia include age, built capital, human capitals 1 and 3, gender, and social capital 1 (see Figure 2). The variables that have the most negative impacts on different parts of Australia include gender, NDVI, social capitals 1 and 2, and dsat (see Figure 3).

Figure 4 shows the variables that have the greatest impact on LS by mapping the coefficients with the highest absolute values (ignoring whether this impact is negative or positive) in each of the SAs. All the variables appear on the map in at least one location, demonstrating the spatial heterogeneity of variables with the greatest impact on LS.

A comparison of all the coefficients and their range can be seen in Figure 5. Because each of the variables was standardized, a comparison of their impacts on LS is possible. We see that most of them are clustered in a normal distribution, with minor exceptions. Table 1 shows the extent of the range of each of these variables and mean and standard deviation. Age-squared has the greatest mean, followed by Social_1 and dstat. Human_1, on the other hand, has the highest standard deviation, followed by Human_3 and age-squared.

Appendix Figure A1 shows the magnitude of the impact of each variable on each of the SA2s. All the variables range from negative to positive in some locations around Australia. Built capital shows the most positive impact and proportion of males shows as having the most negative impact on regions around Australia.

Discussion

Life satisfaction (LS) varies significantly around Australia. For individuals, it ranges from 0 to 10, averaging around 7.9 with a standard deviation of ±1.4 to ±1.7. When aggregated to SA2, as we did in this paper, LS ranges from 3 to 10, averaging around 7.836 (±0.604). Looking at the distribution of LS in Australia (Figure 6), no discernable pattern appears. However, we do find that the lowest average LS (between 3 and 4.99) occurs in the middle of the Northern Territory. Interestingly, the highest LS (between 9 and 10) occurs directly north of that SA2, along the coast. The biggest differences between these two areas (Appendix Figure A1) show that in the coastal SA, both NDVI and the built variable have a positive impact on LS, while in the inner SA, the SA with the lower LS, both NDVI and the built variable have a negative impact.

The population of both these area includes a significant portion of individuals identifying as aboriginal, who have a unique relationship with the natural environment (Rose 1996) and the world. The SA closer to the coast will have a lusher environment, allowing that population more opportunity to live off the natural resources that the land provides. The inner SA, with a more arid environment, makes it more difficult to live off the land.

The GWR estimates a correlation between variables for every SA individually, determining a R^2 for each of the SAs. Figure 1 shows that there is a significant variation between how well LS correlates with the objective variables, with the R^2 ranging from 0.12 to 0.78. In one region, the regression is able to explain 78% of self-reported life satisfaction, in 9 other SAs it can explain over 70%, with 8 out of these 9 being in the Northern Territory and the 9th in West Australia (WA). In general, SAs showing the higher R^2 are in the northern and western part of the country, while the eastern and southern SAs show lower R^2s. This may be due to a larger representative sample in the southeast as that is where most of the Australian population resides. This portion of the population will be more diverse, including immigrants and a wider range of education levels and held values. Also, most of the population in the southeast lives in an urban setting while those in the northwest parts are more rural, this may also show a difference in values between these two population types. Two regions showing the lowest R^2 of 0.12 are located in Queensland (QLD) and New South Wales (NSW), indicating that key variables are missing from the model within these populations.

While in certain SAs we are able to explain the contributor to LS to different degrees, in all of them we are able to show the variables having the greatest impact on LS, positively or negatively (Figures 2 and 3). A pattern appears when looking at the variables with the greatest positive impact. For example, in much of QLD, Tasmania, and around Melbourne, the greatest positive impact on LS is increased age. As individuals grow older, the more satisfied they become with their lives. Further research is required to determine whether this is due to these areas having policies friendlier to retirees or the physical geography/weather is more suitable.

Within the southern part of Western Australia (WA), Cape York Peninsula, and the southwest corner of QLD, the greatest positive impact on LS is increasing built capital, which focuses on household income and homeownership. Research has shown that the economic situation of an individual is the most important contributor to life satisfaction when the average level of income is low. However, when a certain level of income is achieved, other variables become more important (Easterlin 2008; Becchetti and Rossetti 2009; Kubiszewski et al. 2013). And in most of NSW, South Australia, and Victoria (besides the Melbourne region) the greatest positive impact on LS is increased social capital through variable Social_1 (focusing on relationship status and presence of another adult during survey).

Interestingly, human capital is the most important positive variable in the Northern Territory (NT) and northern WA. The Human_1 variable, focusing on health, fitness, and work-life balance, is seen to be most important in the middle of the NT and WA. While the Human_3 variable, a composite of the employment status and the proportion of the population that identifies itself as indigenous, has the strongest positive impact on LS in northern NT, near Darwin and Arnhem Land, in the southern part of the NT, and the northeast corner of WA. The two variables in Human_3 were very closely but inversely grouped together indicating that the regions with higher proportions of indigenous individuals reported having higher unemployment rates. In the NT, the indigenous population accounts for approximately 27% of the population. Unfortunately, in HILDA, especially in the NT, indigenous people are significantly under represented.

The variables that have the greatest negative impact on LS also display a pattern (Figure 3). For example, in Tasmania, Victoria, southern part of QLD, the eastern part of SA, around Darwin, and western part of WA, the greatest negative impact is due to the standard deviation (dsat) of LS. This shows that as the inequality of life satisfaction increases amongst the population, LS decreases. This is especially true for those unsatisfied with life (Kubiszewski et al. 2019). This is comparable to the impact that inequality in income, wealth, and opportunities has on the population (Oscar H. Gandy and Baron 1998; Wilkinson and Pickett 2006; Boyce et al. 2010; Oshio and Urakawa 2014; Diermeier et al. 2017).

Being male in the southern part of WA shows to have the greatest negative impact on LS. This may be due to a relatively small population and a significant number of mines being worked by male miners in this part of the country, a job that research has found does not promote high LS (Iverson and Maguire 2000; Sharma 2009; Phelan et al. 2017). Interestingly, NDVI has the largest negative impact within central NT. This may be due to the current lack of natural capital in the red centre.

For comparison purposes, Figure 4 shows the primary factors contributing to LS, whether positive or negative. There is no real discernable pattern in this figure. Almost every variable appears on this map, showing that what contributes to human LS is complex and differs significantly even within one country.

In many instances on these maps (Figure 1-6), the outline of the states is visible, even though no boundaries are drawn. This implies that policy differences influence to the differences in the contributors of LS. Individuals living in proximity to each other, but on opposite sides of a boarder, will not have significantly different values. However, different policies may apply to them.

Table 1 summarizes the mean, standard deviation, and range of the variable coefficients. The variables were standardized to allow comparisons. The mean of the coefficients ranges from -0.123 (dsat) to 0.137 (age-squared). The highest standard deviation is experienced by the Human_1 variable at 0.0819. All the variables, except built capital, experience coefficients both negative and positive in one of the SAs. For example, the Human_1 variable, has the greatest range, from a minimum value of -0.1898 to a maximum value of 1.024. This means that in a small number of SAs, the variable looking at health, fitness, and work-life balance is slightly detrimental to life satisfaction, while in the majority of SAs, it is quite positive. There are only a very small number of SAs (less than 8% of the total) that consist of a Human_1 variable coefficient that is negative (Figure 5).

How these coefficients are distributed can be seen in Figure 5. Most are in a normal distribution around the mean, with minor exceptions. For example, built capital is distributed around the mean of 0.1004, however, 10% of the SAs have a much higher coefficient of between 0.18 and 0.20. These could be SAs that have lower built capital, so any increase provides them with a significant increase to LS. The built capital is the only variable with coefficients that approach zero in some SAs, but never go to negative. These distributions show that life satisfaction is complicated and varies significantly between individuals, and hence SAs.

Policy Implications

There are many variables that contribute to overall human life satisfaction. The goal of government is to maximize the positive impact of those variables (Kubiszewski et al. 2010; Costanza et al. 2016), and hence LS and human wellbeing. However, as this paper shows, the impact of these variables vary from region to region, and potentially from person to person. This implies that federal policies may have different impacts on individuals around the country, making it critical that policies are focused to the correct scale to ensure the population's values are considered.

However, there is a trade-off between applying a 'global' policy to a region, versus taking into account the spatial heterogeneity of the region. Applying a 'global' policy provides simplicity and statistical efficiency to policymaking, while providing a useful benchmark. But, these policies may not target all individuals as expected across the region as they hide marginal responses to a policy. For instance, the impact of adopting a 'global' policy may be negative in some regions despite being positive overall. This is due to spatial heterogeneity in the relationship between the policy targeted variable and human wellbeing. More localized and disseminated policies provide a targeted approach, ensuring that the impact on individuals is more direct and reducing the risk of negative impacts being felt in marginalized areas. But these policies are also more complex to implement and analyse and they require more resources. It is unknown how much information is lost when using a 'global' policy and analysis versus the effort to implement policies at more distributed scales (Ali et al. 2007).

In this paper, we show that almost every variable is critical to human wellbeing in some region of Australia. For some variables, regional policy interventions can easily increase the average life satisfaction of the individuals within a region For example, policies targeting increases in built capital will have the greatest impact on life satisfaction in much of the southern part of Western Australia, whilst policies for the Northern Territory would be better target towards increasing human capital, and policies for much of South Australia and NSW should be targeted towards increasing social capital. However other variables, such as standard deviation in LS, may be much more difficult to influence by policy. Previous research (Kubiszewski et al. 2019) has looked at differences in LS at different scales in Australia. Understanding the distribution of LS, and the reason behind these differences, is critical to the development of the appropriate polices to best improve people's condition.

For certain variables, such as age and gender, more information around potential prejudices, or advantages, to a portion of the population need to be investigated. For example: Are elderly people provided more benefits in certain regions versus others in areas that age is positively correlated with LS? Are females discriminated against more in regions that indicate females are significantly less satisfied with their lives? The results of this paper demonstrate that policies undertaking a one-size-fits-all approach may experience significantly different outcomes depending on region (Cash et al. 2006).

Another advantage of using GWR, instead of a 'global' analysis and policy, is that offsetting impacts are significantly reduced. For example, living in a city individuals enjoy the social aspects of a large population, which includes bars, availability of public transportation, networking. However, a large population also brings with it traffic congestion, noise, pollution, and increased living expenses. These two impacts of a large population can offset each other depending on where in a city an individual lives. GWR can resolve some of this problem by analysing different areas of a city separately, informing sub-regional policies.

Questions still remain are around why such regional clustering happens. If a truly random distribution existed, each of the SA2s would potentially have a different variable that had the greatest impact on LS. But that is not what we see. We see groupings where regions, multiple adjacent SA2s, all have the same variable that has the greatest impact on LS. So, do people move to live near others with shared values? Does moving into a community change an individual's values? Do the policies in these regions, sometimes across state boarder, have enough influence to change how LS is perceived? These are all questions for future research.

Acknowledgements

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Figure 1: Map showing the explanatory power (R^2) of the model assessing the relationship between life satisfaction (LS) and contributing variables for each SA2. An explanation of the contributing variables seen here can be found in the section 'Methods > Variables included within the final model.'

Figure 2: Map showing, for each SA2, the variables that have the greatest positive impact on life satisfaction within that SA2. The range of values for this map can be found in Table 1, column 'Max'. An explanation of the variables seen here can be found in the section 'Methods > Variables included within the final model.' Only those variables that have the largest positive impact in at least one SA2 region are shown on this map.

Figure 3: Map showing, for each SA2, the variable coefficients having the largest negative impact on life satisfaction, within that SA2. Within a number of SA2s, no variable had a negative impact on life satisfaction, this is represented by the description 'no negatives'. The range for this map can be found in Table 1, column 'Min'. An explanation of the variables seen here can be found in the section 'Methods > Variables included within the final model.' Only those variables that have the largest negative impact in at least one SA2 region are shown on this map.

Figure 4: Map of variables with the greatest absolute value impact on life satisfaction in each of the SA2s, indicating the variables that matter most to LS in each location, whether positive or negative. The range for this map can be found Table 1, column 'Abs. value'. An explanation of the variables seen here can be found in the section 'Methods > Variables included within the final model.'

Figure 5: These nine bar charts show the range and distribution of the coefficients for each variable. An explanation of the variables seen here can be found in the section 'Methods > Variables included within the final model.'

Figure 6: A map of the life satisfaction values in each SA2.

Table 1: Descriptive statistics showing the mean, standard deviation, and range of each variable coefficient. An explanation of the variables seen here can be found in the section 'Methods > Variables included within the final model.'

Figure A1: Maps showing the spatial distribution of each variable and the extent of its impact on life satisfaction in each SA2.

Table A1: Variables used within GWR model. Factor scores (in parenthesis) extracted using principal components analysis to generate composite variables.

Figure 1

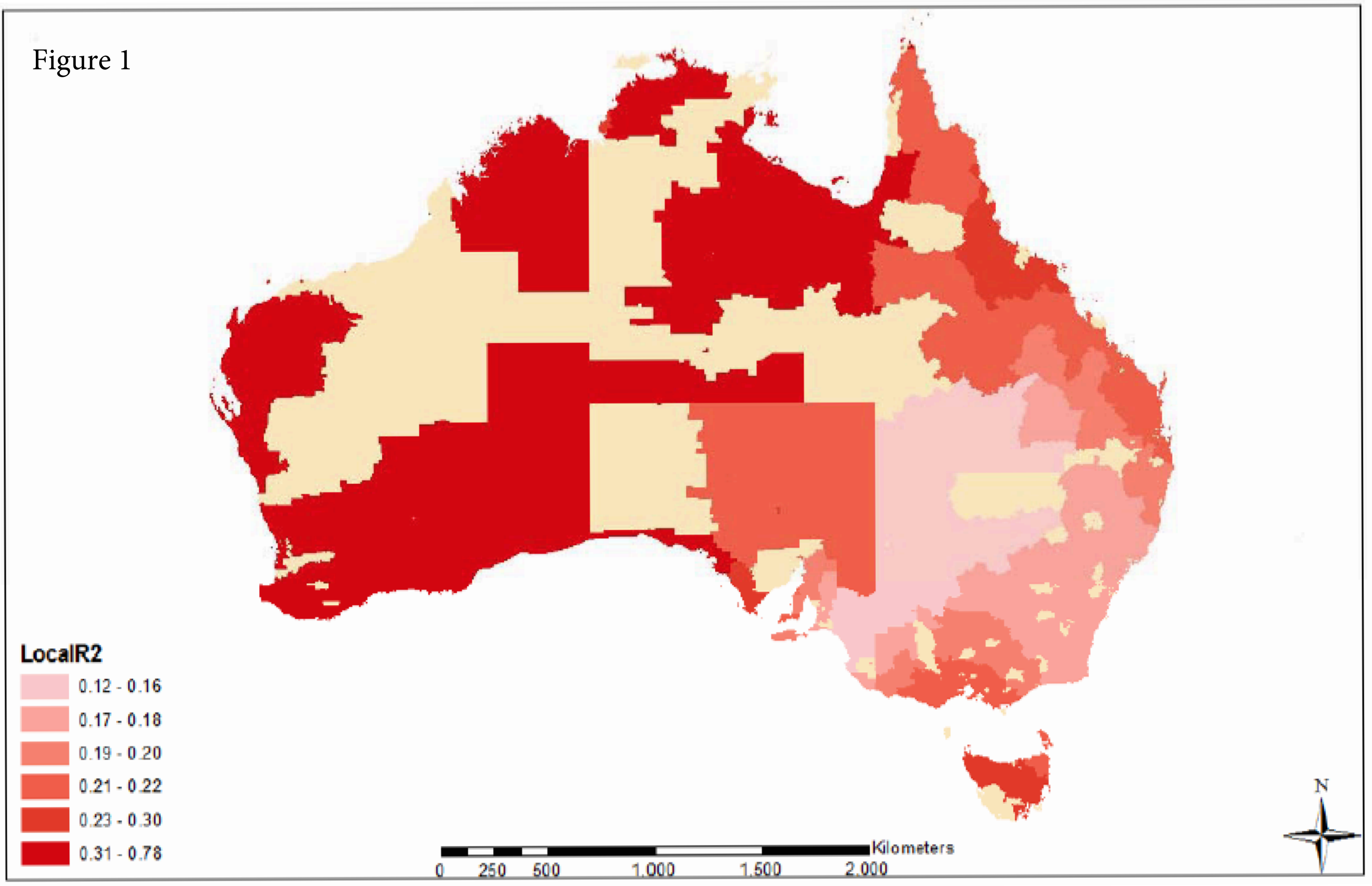
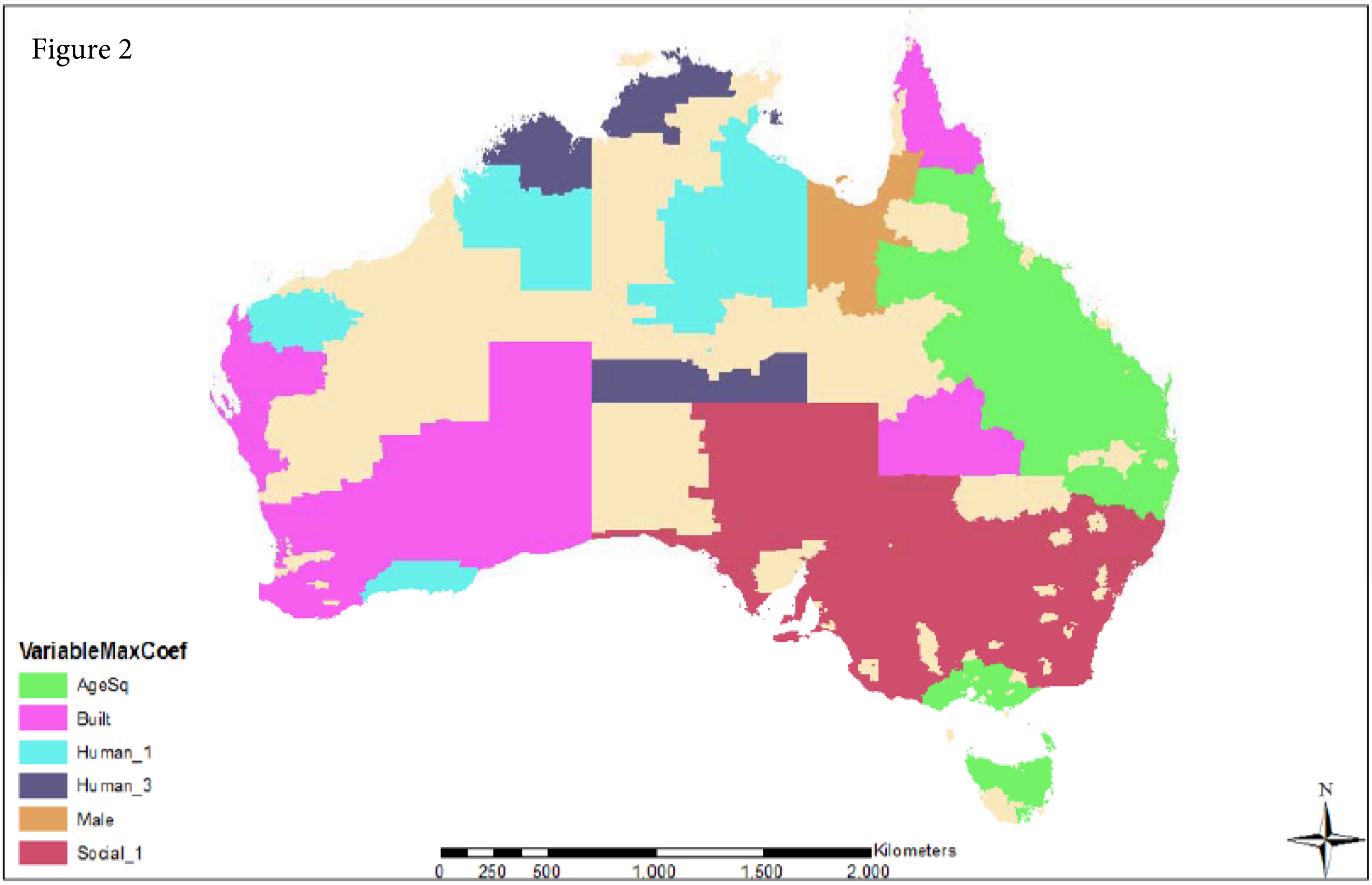

LocalR2
0.12 - 0.16
0.17 - 0.18
0.19 - 0.20
0.21 - 0.22
0.23 - 0.30
0.31 - 0.78
Kilometers
0
250
500
1,000
1,500
2,000
N

Figure 2



VariableMaxCoef
AgeSq
Built
Human_1
Human_3
Male
Social_1
Kilometers
0 250 500 1,000 1,500 2,000
N

Figure 3

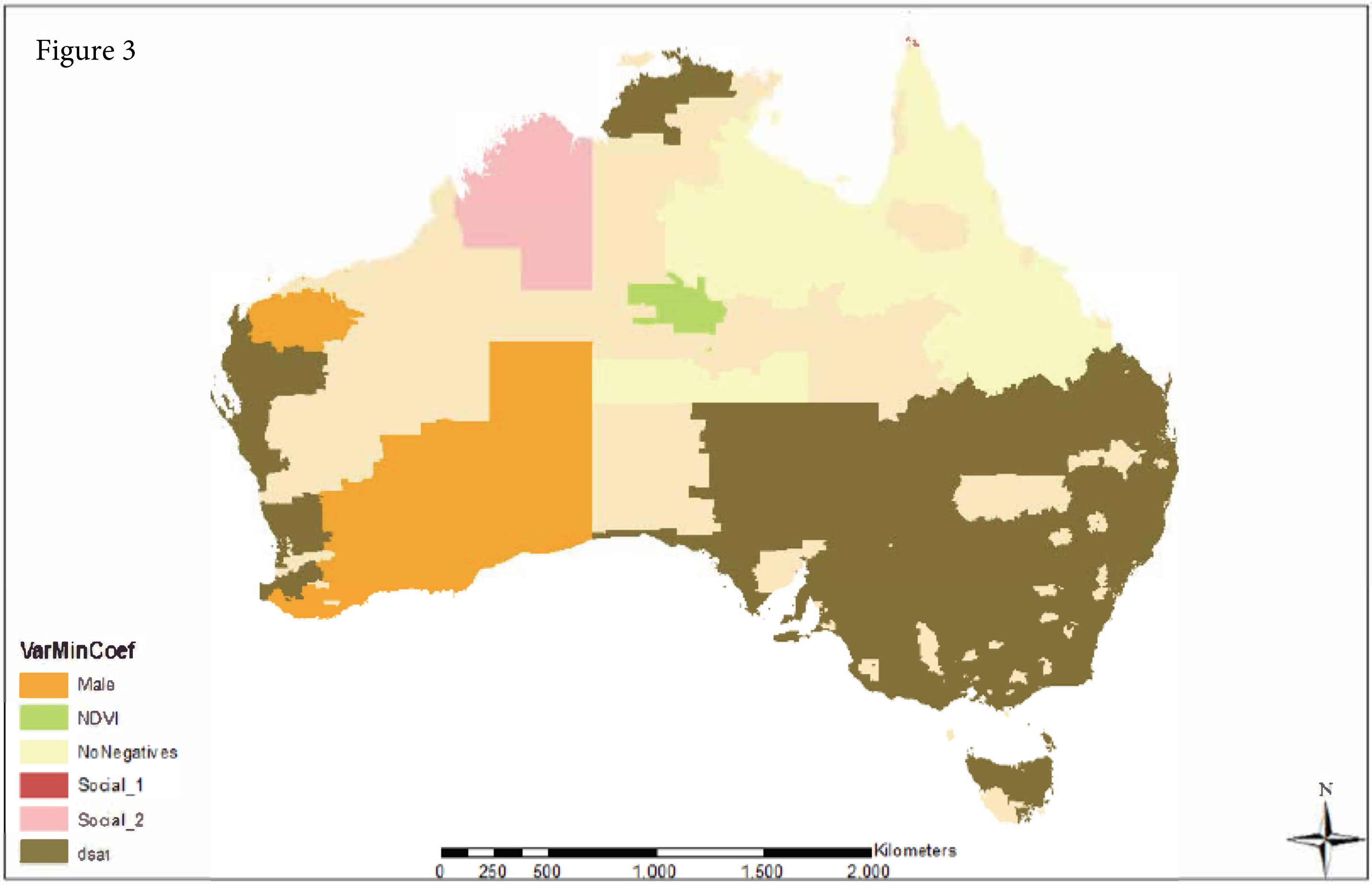

VarMinCoef
Male
NDVI
NoNegatives
Social_1
Social_2
dsat
0
250
500
1,000
1,500
2,000
Kilometers
N

Figure 4

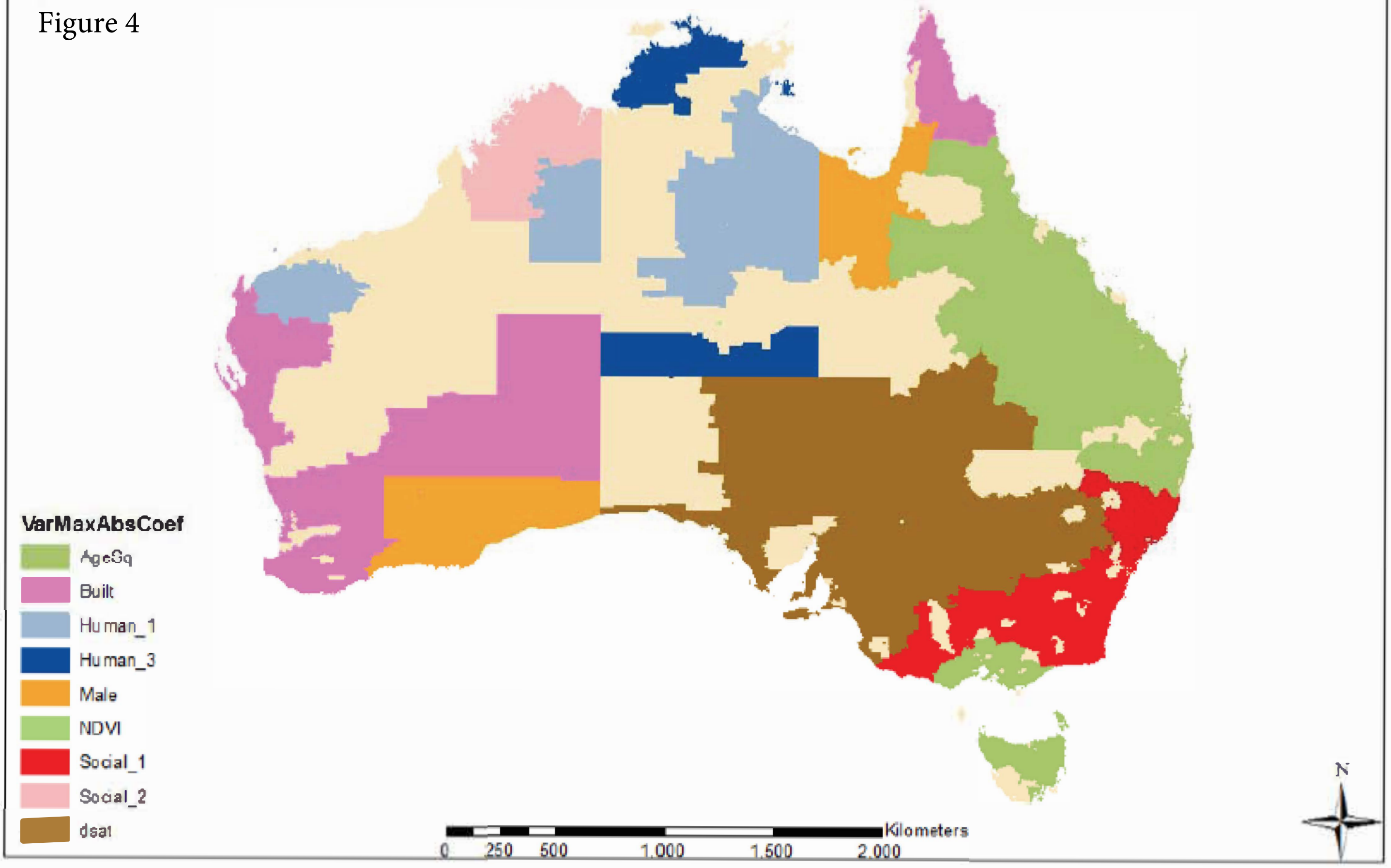

VarMaxAbsCoef
AgeSq
Built
Human_1
Human_3
Male
NDVI
Social_1
Social_2
dsat
0
250
500
1,000
1,500
2,000
Kilometers
N

Figure 5

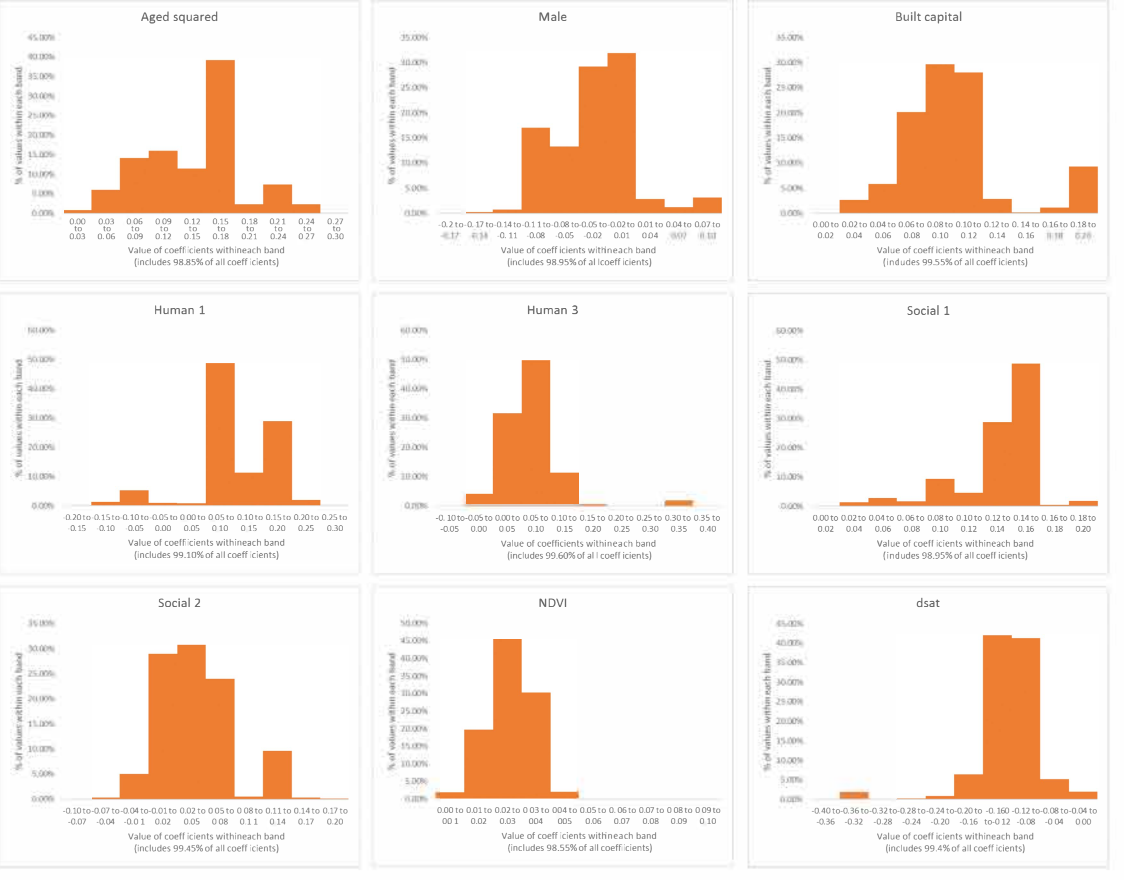
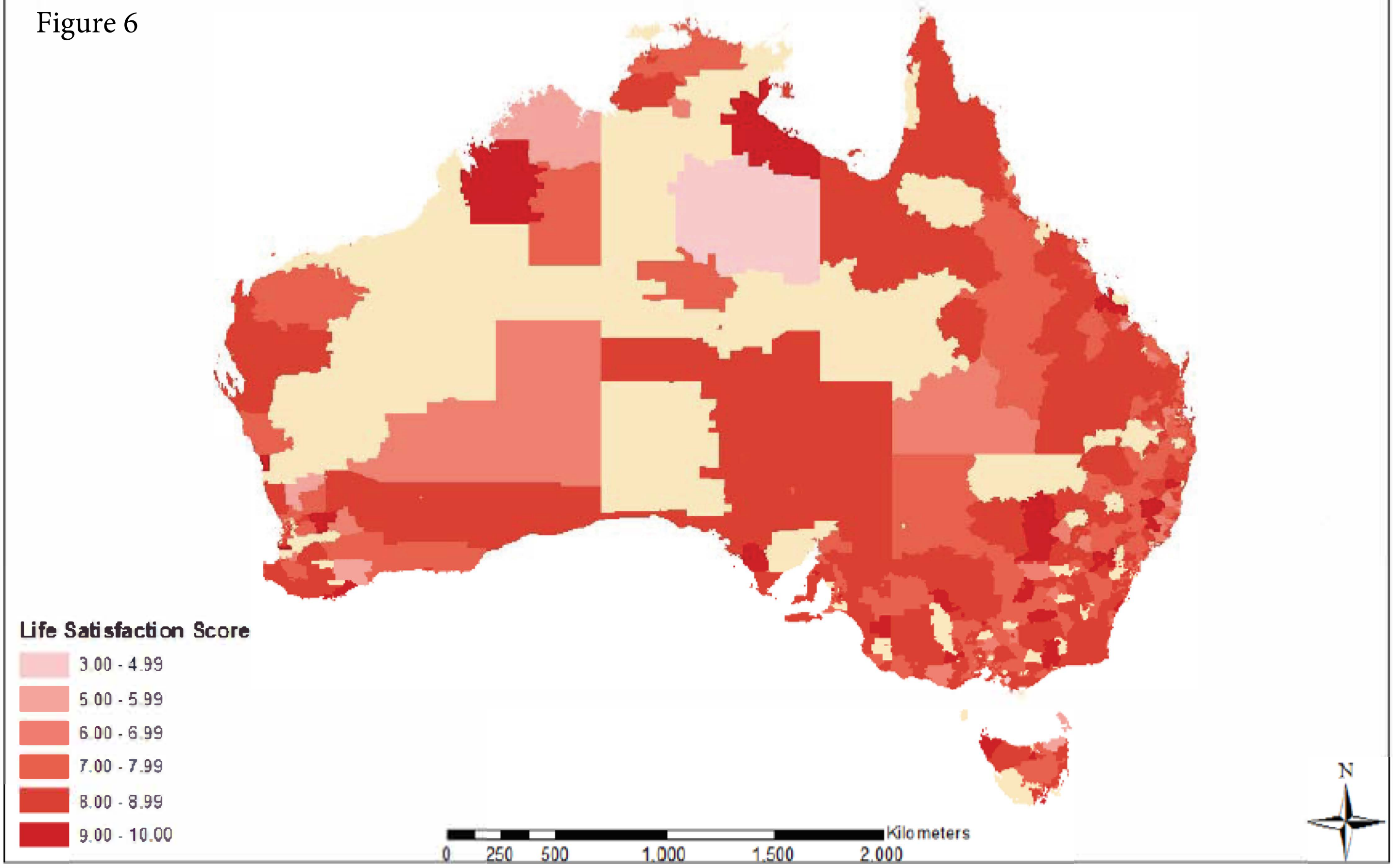

Aged squared
Value of coefficients withineach band
(includes 98.85% of all coefficients)
Male
Value of coefficients withineach band
(includes 98.95% of all coefficients)
Built capital
Value of coefficients withineach band
(indudes 99.55% of all coefficients)
Human 1
Value of coefficients withineach band
(includes 99.10% of all coefficients)
Human 3
Value of coefficients withineach band
(includes 99.60% of all coefficients)
Social 1
Value of coefficients withineach band
(indudes 98.95% of all coefficients)
Social 2
Value of coefficients withineach band
(includes 99.45% of all coefficients)
NDVI
Value of coefficients withineach band
(includes 98.55% of all coefficients)
dsat
Value of coefficients withineach band
(includes 99.4% of all coefficients)

Figure 6



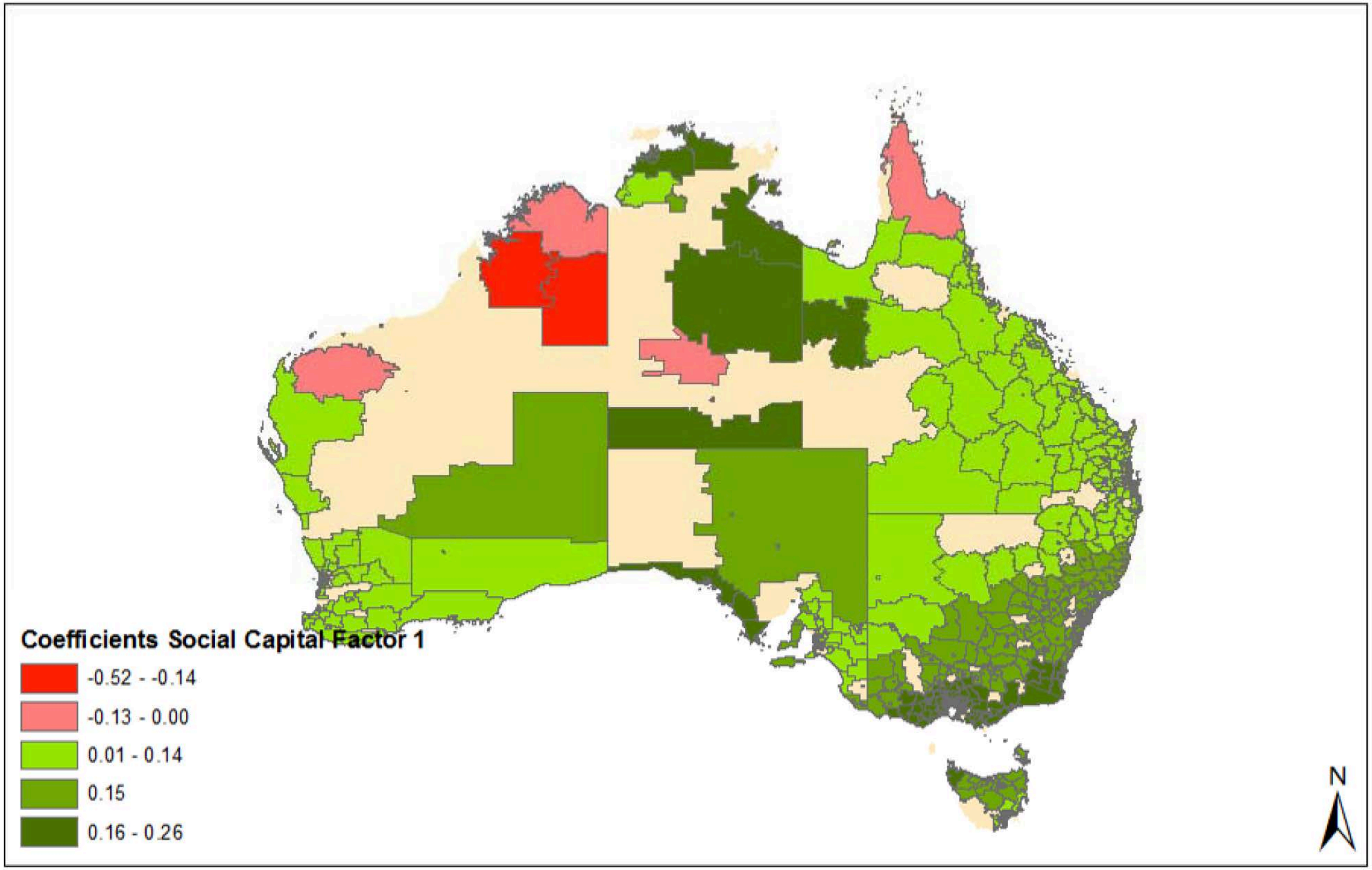
Life Satisfaction Score
3.00 - 4.99
5.00 - 5.99
6.00 - 6.99
7.00 - 7.99
8.00 - 8.99
9.00 - 10.00
Kilometers
0
250
500
1,000
1,500
2,000
N

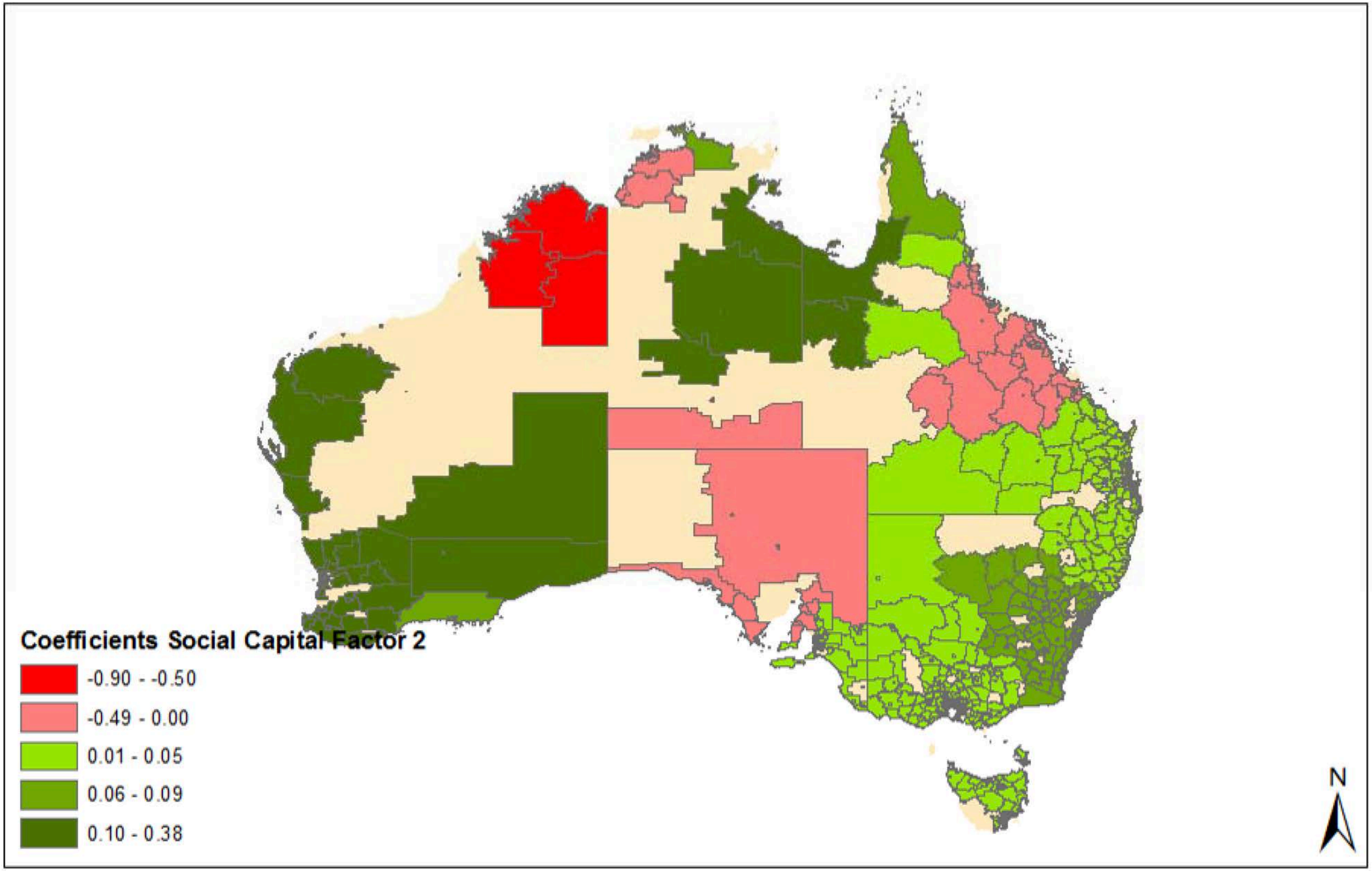
Table 1

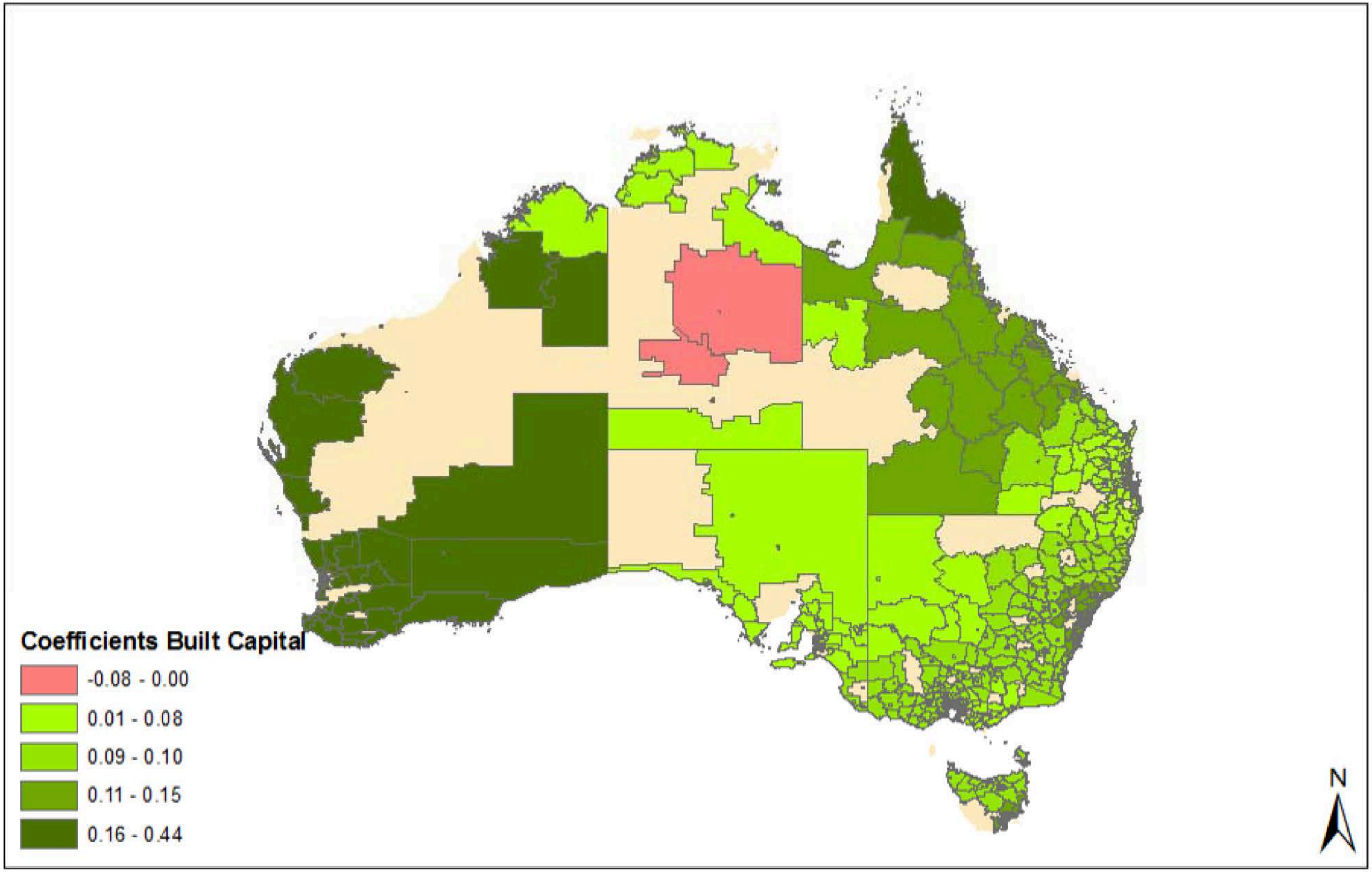
GWR coefficients - descriptive statistics

	Mean	Std Dev	Min	Max	Abs. value
Age Squared	0.1374	0.0614	-0.3005	0.4304	0.4304
Male	-0.0326	0.049	-0.3219	0.2913	0.3219
NDVI	0.0234	0.0541	-0.8392	0.643	0.8392
dsat	-0.1231	0.0506	-0.4376	0.4203	0.4376
Built capital	0.1004	0.0389	0.0064	0.6193	0.6193
Social 1	0.1296	0.041	-0.4404	0.2695	0.4404
Social 2	0.0392	0.0533	-0.8909	0.4632	0.8909
Human 1	0.1018	0.0819	-0.1898	1.024	1.024
Human 3	0.0614	0.0639	-0.0562	0.7427	0.7427

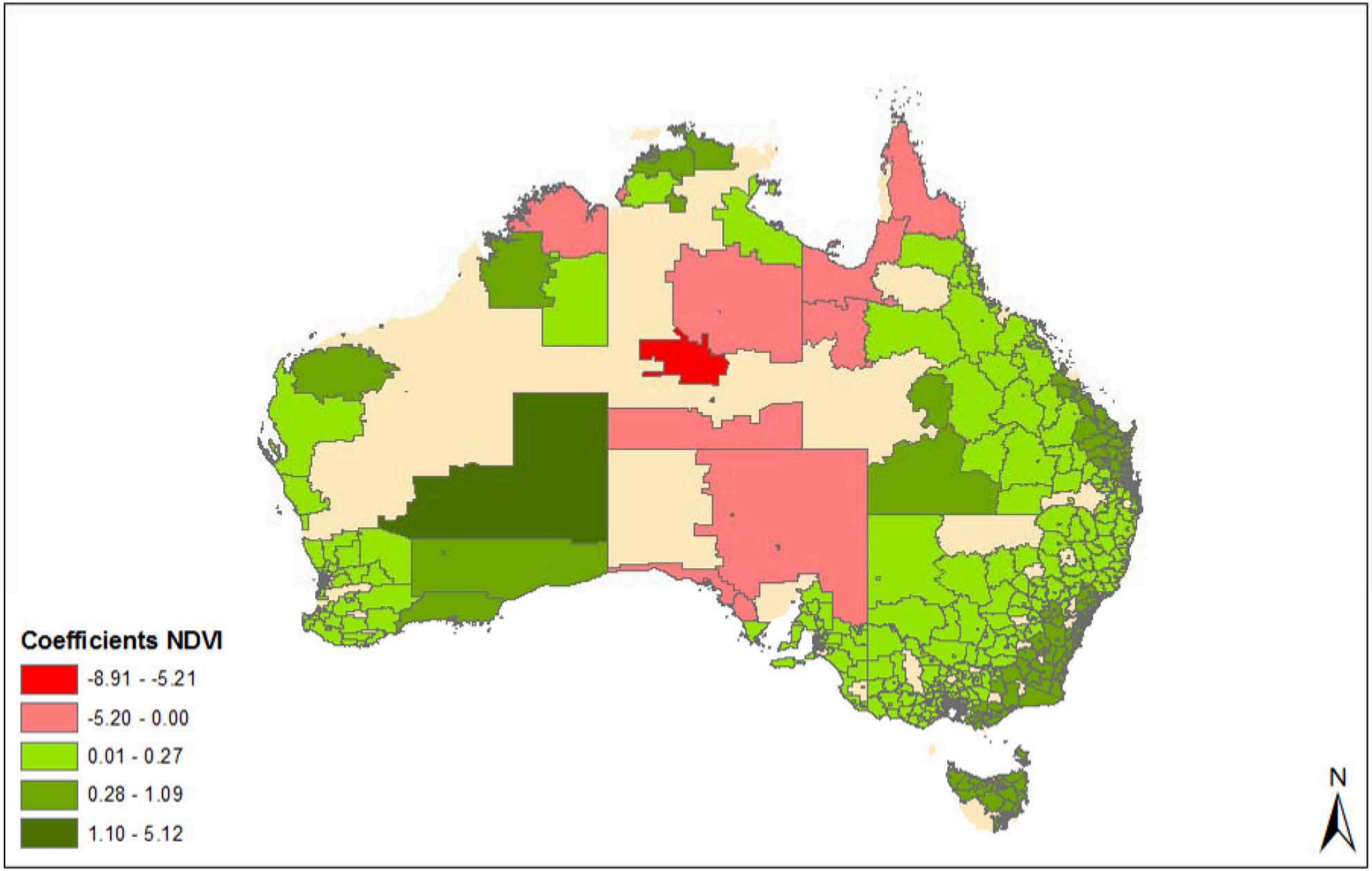
Figure A1: Maps showing the spatial distribution of each variable and the extent of its impact on life satisfaction in each SA2.



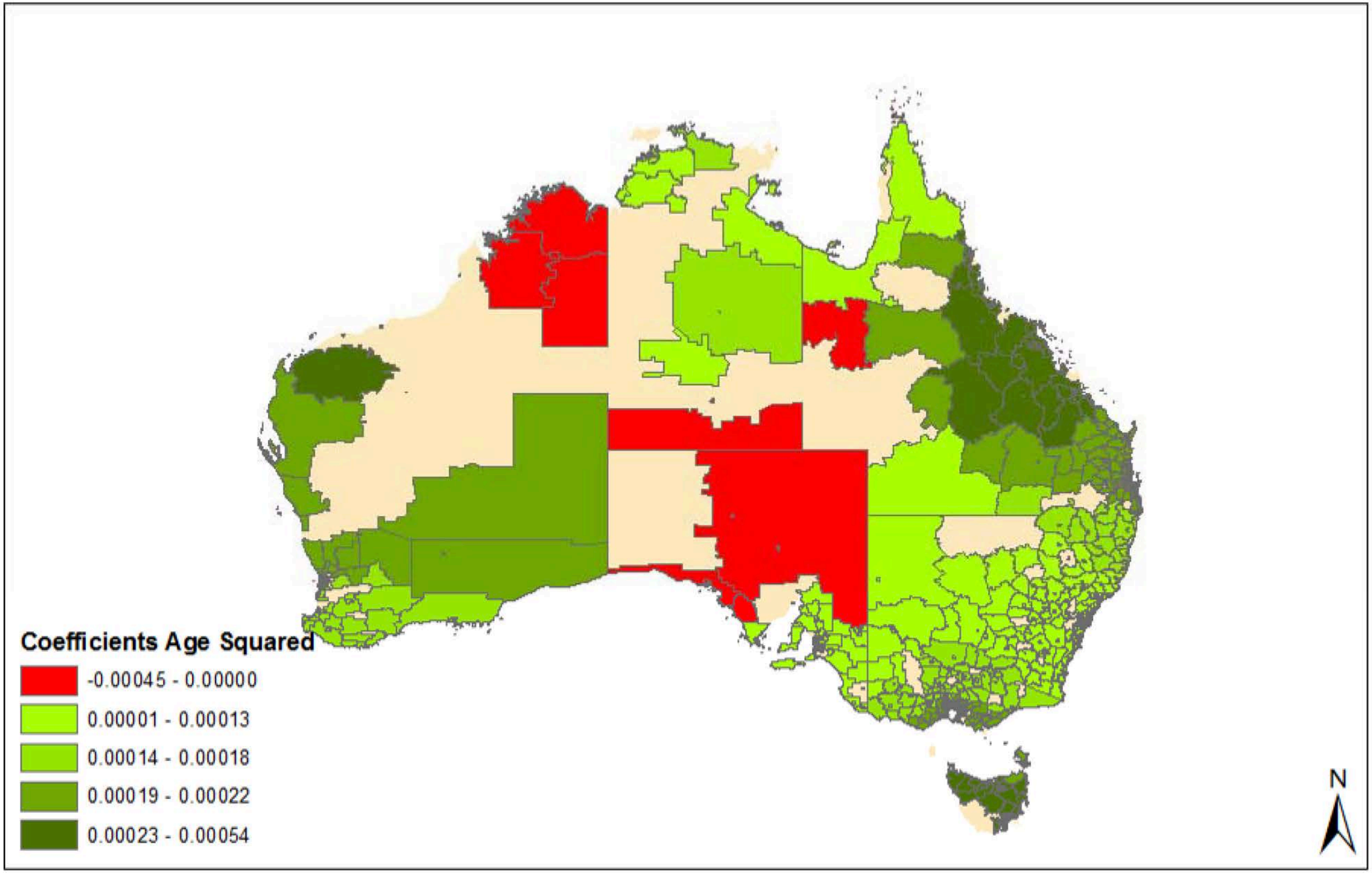

Coefficients Social Capital Factor 2
-0.90 - -0.50
-0.49 - 0.00
0.01 - 0.05
0.06 - 0.09
0.10 - 0.38
N

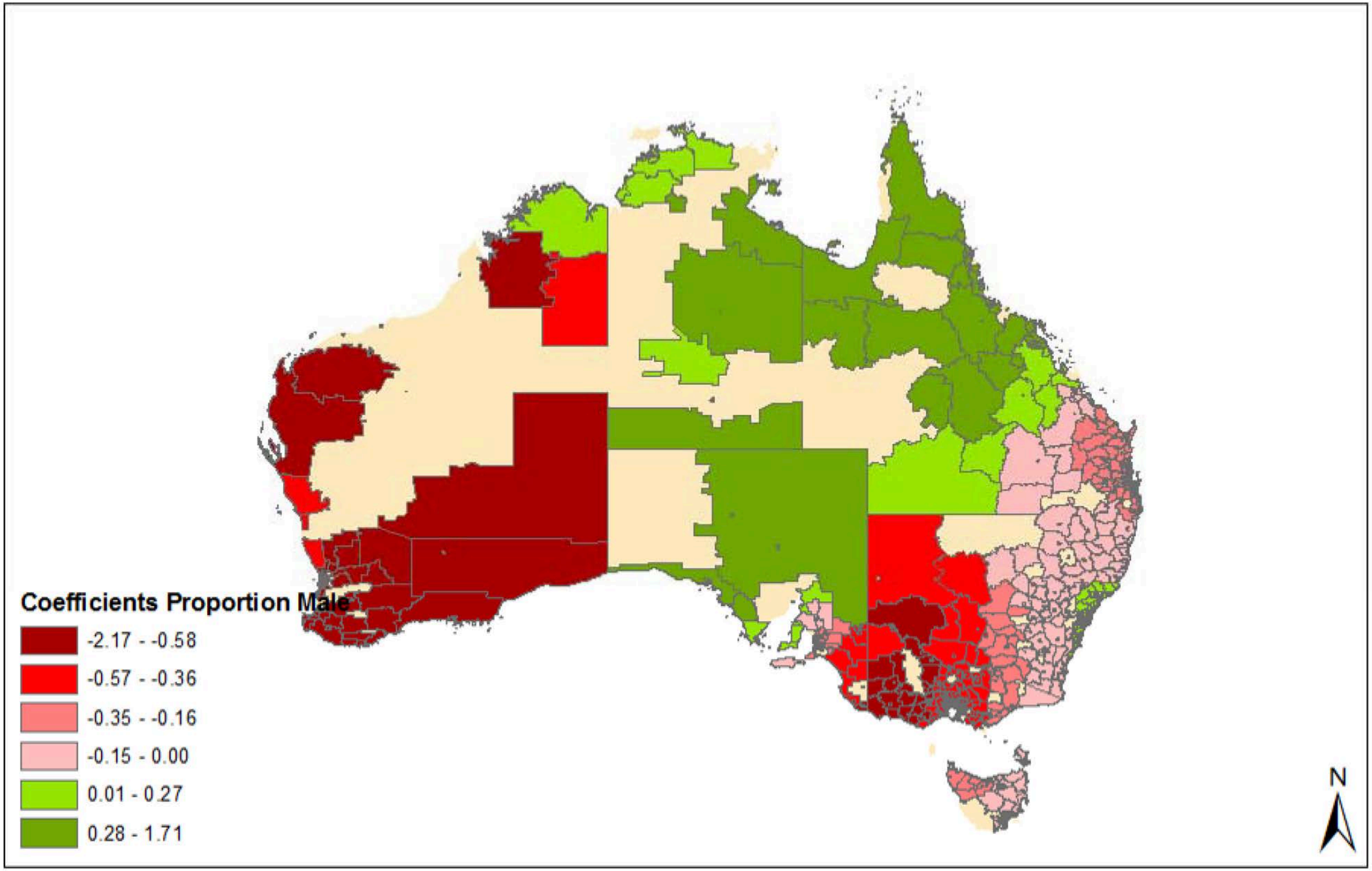


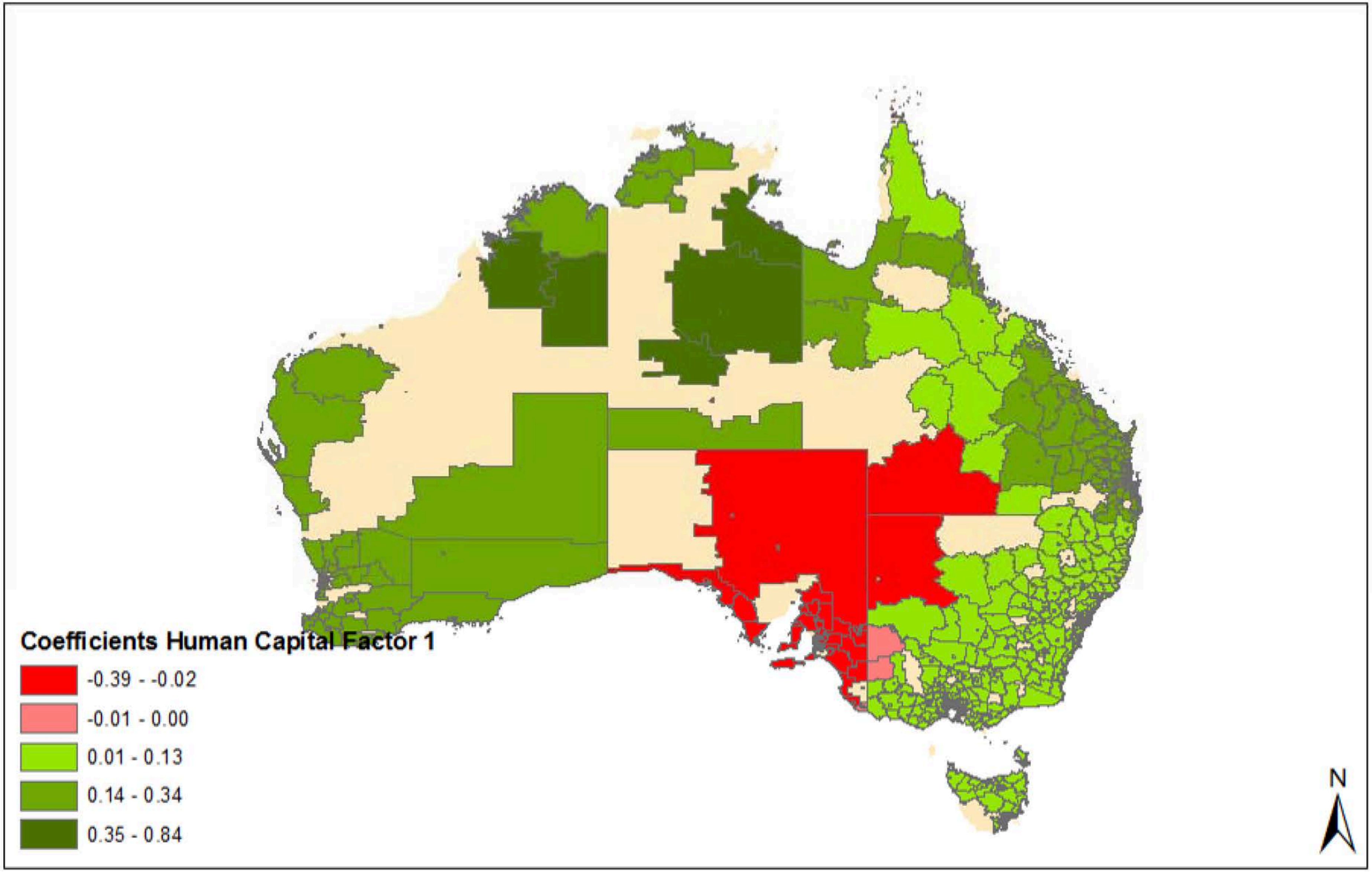
Coefficients Built Capital
-0.08 - 0.00
0.01 - 0.08
0.09 - 0.10
0.11 - 0.15
0.16 - 0.44
N

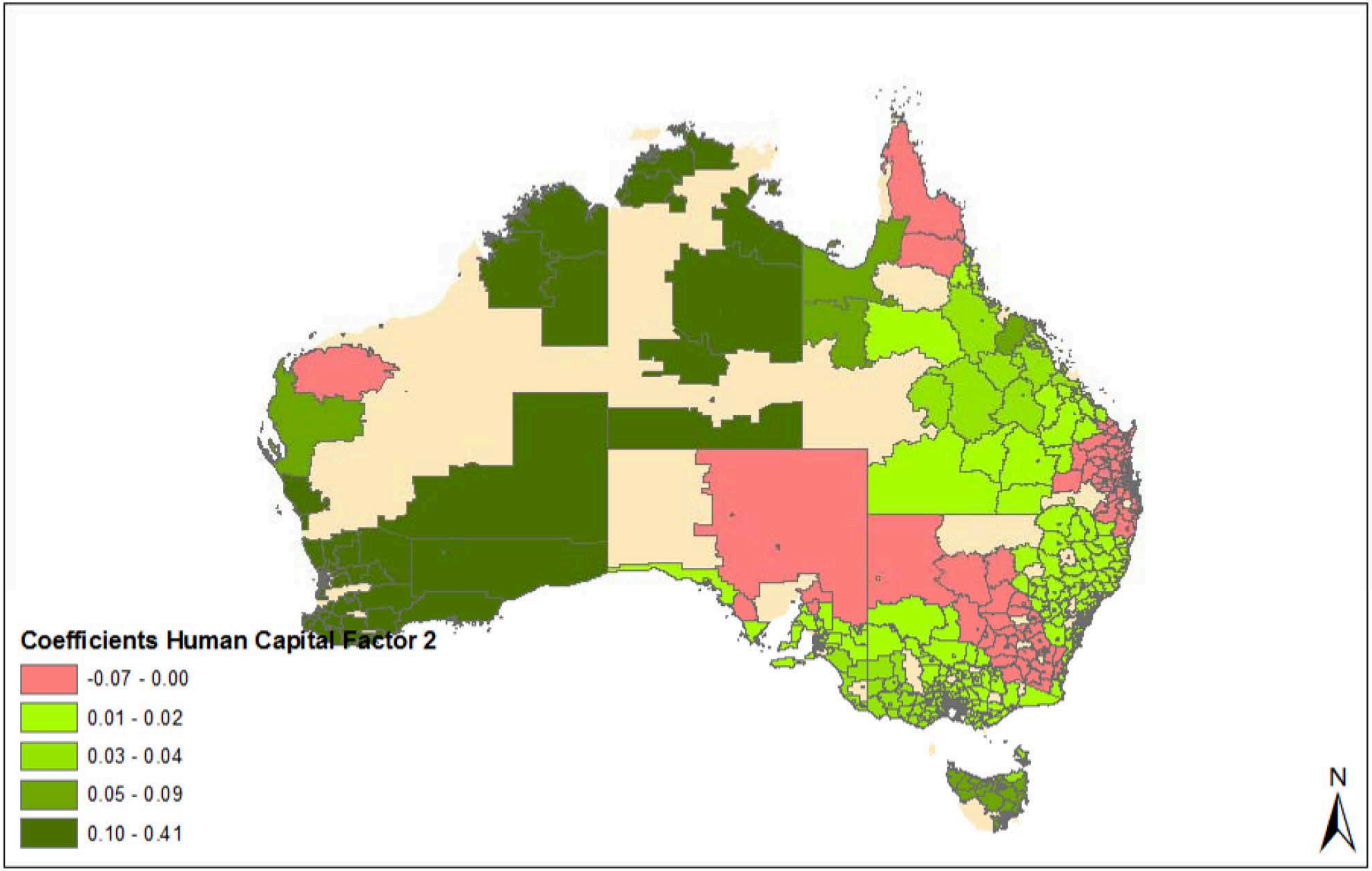


Coefficients NDVI
-8.91 - -5.21
-5.20 - 0.00
0.01 - 0.27
0.28 - 1.09
1.10 - 5.12
N


Coefficients Age Squared
-0.00045 - 0.00000
0.00001 - 0.00013
0.00014 - 0.00018
0.00019 - 0.00022
0.00023 - 0.00054
N


Coefficients Proportion Male
-2.17 - -0.58
-0.57 - -0.36
-0.35 - -0.16
-0.15 - 0.00
0.01 - 0.27
0.28 - 1.71
N


Coefficients Human Capital Factor 1
-0.39 - -0.02
-0.01 - 0.00
0.01 - 0.13
0.14 - 0.34
0.35 - 0.84
N



Coefficients Human Capital Factor 2
-0.07 - 0.00
0.01 - 0.02
0.03 - 0.04
0.05 - 0.09
0.10 - 0.41
N

Appendix Table 1.

Abbreviated variable name	**Full variable name**	**Variable description**
AgeSq	Age squared	Square of average age of respondents within each SA2 based on last birthday on June 30, 2016
Built	Built capital	Composite variable generated using PCA – Proportion of population owning their own home (0.823) – Log of household income (0.823)
Human_1	Human capital 1	Composite variable generated using PCA – Proportion of population engages in physical activity (0.719) – Proportion of population who do not have long-term health problem (0.806) – Proportion of population not educated to university level or higher (-0.421) – Average hours worked per week (0.716)
Human_3	Human capital 3	Composite variable generated using PCA – Proportion of population Indigenous (Aboriginal and/or Torres Strait Islander) (0.692) – Proportion of population employed (-0.746)
Male	Male	Proportion of respondents within each SA2 that are male
NDVI	Normalised Difference Vegetation Index (NDVI)	Weighted average NDVI across SA2, weighting by size of geographic area represented by different NDVI values
Social_1	Social capital 1	Composite variable generated using PCA – Proportion in a relationship (0.861) – Proportion not separated or divorced (0.670) – Proportion of respondents indicating no other adults present during survey (0.693)
Social_2	Social capital 2	Composite variable generated using PCA – Hours spent doing volunteering/ charity work per week (0.858) – Proportion not having children (0.564)
dsat	Standard deviation in life satisfaction	Standard deviation in life satisfaction within each SA2 region