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Resituating the Local in Cohesion and Territorial Development

## D5.2

### Report on multi-scalar patterns of inequalities



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## Report Information

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## 1. Introduction

In the EU, spatial inequality is often conceptualised as regional inequality, and as a consequence it is measured at the level of large EU regions. Such measures show a large variation in income between European countries and also within countries. At the same time, measuring inequality at this large geographical scale hides variation in income at a more local level, such as metropolitan areas, cities, neighbourhoods and even streets. These within-region levels of inequality can be much more pronounced than between-region levels of inequality, and they can be crucial in understanding the socio-economic outcomes of individuals. To get more insight into the exposure of individuals to concentrations of poverty and their experiences of inequality, it is important to measure spatial inequality at multiple geographical scales.

This report forms Deliverable 5.2 of the EU Horizon 2020 research project RELOCAL - 'Resituating the local in cohesion and territorial development'. The overall aim of Work Package 5 is to demonstrate how spatial inequalities can be measured over time using microdata (i.e. individuals, households). This Work Package builds on the work carried out in Work Package 2, which uses existing data sources to provide an overview of spatial inequalities at the level of EU regions. Work Package 5 addresses the spatial scale of inequalities at multiple geographical scales, using methods that do not depend on predetermined regions. The latter is important because the efficiency of specific policy interventions directed towards spatial inequalities is scale-dependent and hence it should be based on well-defined and meaningful measures of spatial variation in living conditions.

However, most current measures of spatial inequality are based on statistical aggregates for fixed geographical sub-divisions such as countries, NUTS-regions, municipalities, or census tracts. This is problematic since measures based on such bureaucratic sub-divisions are sensitive to how the boundaries of the areas have been drawn. In the literature this phenomenon is called the Modifiable Area Unit Problem (MAUP) and it has been demonstrated that measures of spatial inequality can be more strongly influenced by how the geographical units have been constructed than by the underlying spatial variation (Openshaw,

1984). A discussion on the geographies used to measure spatial inequalities is also important when investigating the effects of spatial inequalities on outcomes of individuals (which will be the focus of Task 5.3). For example, if someone lives in a low income region, but just on the border of a much wealthier region, then the characteristics of the low income region might be a poor predictor of the labour market outcomes of this individual who might work in the neighbouring region. In this case alternative conceptualisations of spatial inequality are needed to understand individual outcomes. The aim of this Work Package is to demonstrate the utility of more spatially flexible measures of spatial inequalities that do not depend on predetermined administrative regions.

Task 5.2, which will be reported in this report, has two main objectives:

- I. Identify the spatial patterns of inequality at different geographical scales in order to show how the MAUP can lead to inaccurate interpretation of spatial inequalities (and consequently policy interventions);
- II. Propose standardised tools for the analysis of spatial patterns of inequality at more appropriate geographical scales and how such tool can be applied in countries with different access to detailed geographical data.

It is important to emphasise that the aim of Work Package 5 is to *demonstrate* how spatial inequalities can be measured over time using microdata. As a *demonstrator project*, this report will show what the possibilities are when data is available at a very low spatial scale. As identified in Deliverable 5.1, for the purpose of task 5.2 suitable data was available for Finland, Sweden, The Netherlands, and the UK (i.e. England and Scotland). In the remainder of this report we will discuss data and outcomes for these five countries, and we will highlight some of the shortcomings of existing data.

## 2. Background

Inequalities among individuals in achieved socioeconomic status (e.g. income, employment, education) result both from differences in individual characteristics (including intergenerational effects), and differences in contextual characteristics. Part of the relevant context is the environmental (or spatial) context within which people live and act. At the regional level, this environmental context provides a spatial opportunity structure, which includes for example job opportunities and schools. In addition, there might be other environmental context effects on individual outcomes, often referred to under the broad term of neighbourhood effects. Neighbourhood effects refer to causal effects of the residential neighbourhood on individual outcomes, over and above the effect of individual characteristics.

Consequently, individuals can be disadvantaged by where they happen to live. An important question is how exactly place impacts on socio-economic chances throughout the life course. This question will be addressed in more detail in Task 5.3 and reported in Deliverable 5.3. The mechanisms through which the residential or environmental context affects individual outcomes may operate at different spatial scales, ranging from regional labour markets (e.g. types of jobs and associated wages), to social networks and peer groups within the immediate environment or community. In order to come to a better understanding of the consequences of spatial inequality for individuals, it is important to look at spatial inequalities at different geographical scales.

The role of scale is not only important when investigating contextual effects on individual outcomes, but also when analysing patterns of spatial inequality. Different patterns of spatial inequality can emerge depending on the geographical scale which is used. Poverty and disadvantage can be concentrated in particular regions, cities, neighbourhoods, or even streets. Spatial inequalities within regions might be much larger than between regions, which is important for the development and implementation of policy measures to counter inequality. Analysing spatial inequality at a larger geographical scale might mask substantial variation as smaller geographical scale.

We can learn about the role of scale in measuring poverty concentrations by zooming in from NUTS-3 regions to residential neighbourhoods. To illustrate this we use some data from the Netherlands. Figure 1 shows the share of individuals with a low income for NUTS-3 regions in the Netherlands.<sup>1</sup> Figure 2 is on the same geographical level, but is zoomed in to the municipality of Rotterdam. As can be seen in this Figure, the municipality of Rotterdam and neighbouring municipalities have similar average shares of individuals with a low income (between 33.7 and 34.8 %). In Figure 3 the same data is presented at the level of municipalities. The share of individuals with a low income in Rotterdam is between 41 – 54 %, which is considerably higher than what could be seen in Figure 2. Then zooming in further to district and neighbourhood level in Figure 4 and 5, substantial variation in the share of individuals with a low income emerges within the municipality of Rotterdam. This variation was masked when looking at higher geographical scales. At the neighbourhood level, the share of individuals with a low income ranges from 3 to 99%. This shows that within the city region of Rotterdam there is a very high degree of variation between neighbourhoods in the level of poverty. In fact, the variation in income between neighbourhoods is much larger than the variation in incomes between regions.

If the spatial distribution of poverty would be analysed at higher geographical scales, such as whole regions, the variation at lower geographical scales would be invisible. However, these concentrations at lower geographical scales might be relevant for the socio-economic outcomes of individuals that reside in these areas. The map in Figure 5, at the lowest spatial scale, shows clear ‘social frontiers’ (Dean, Dong, Piekut, & Pryce, 2018), meaning that there are strong concentrations of individuals with a low income next to concentrations of better-off individuals. For the individuals living close to these micro level social frontiers, their immediate spatial surroundings might affect their perception of poverty to a larger degree than regional differences in poverty.

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<sup>1</sup> As can be seen in Figure 1 and 2, the concentration of individuals with a low income in the NUTS-3 regions and municipalities in some areas near the German and Belgium border is higher. Because we use register data from Statistics Netherlands, for which the income data is based on tax declarations, we could be missing income earned in Germany or Belgium.

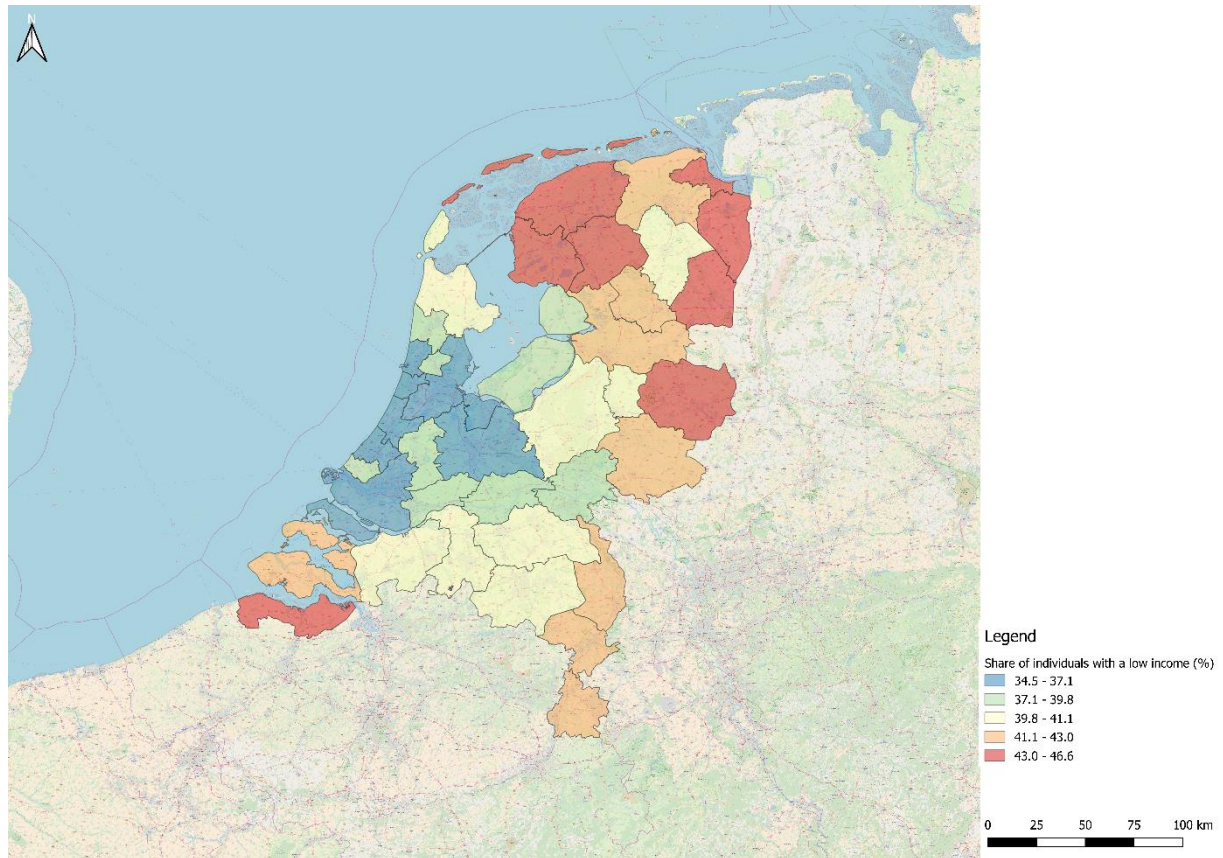


Figure 1 Concentration of poverty in the Netherlands at NUTS3-level

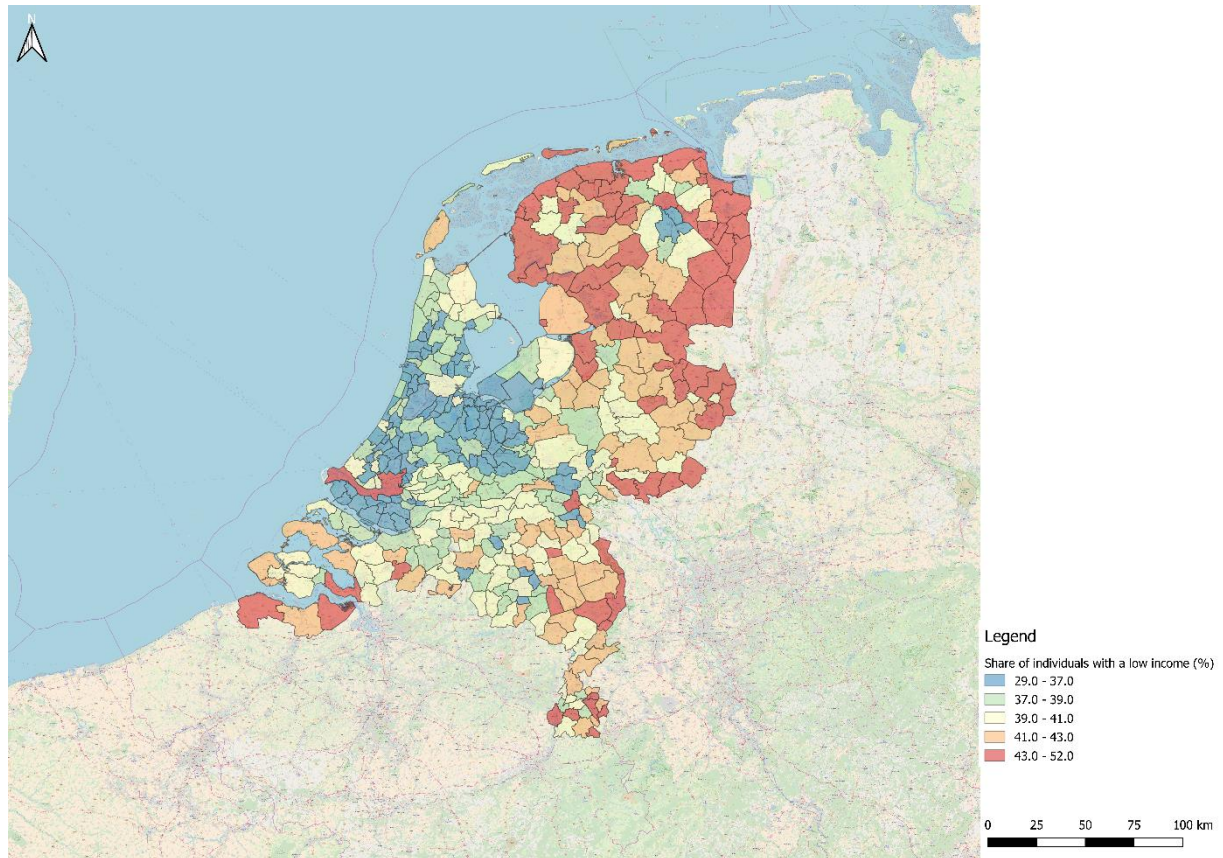


Figure 2 Concentration of poverty in the Netherlands at municipality level

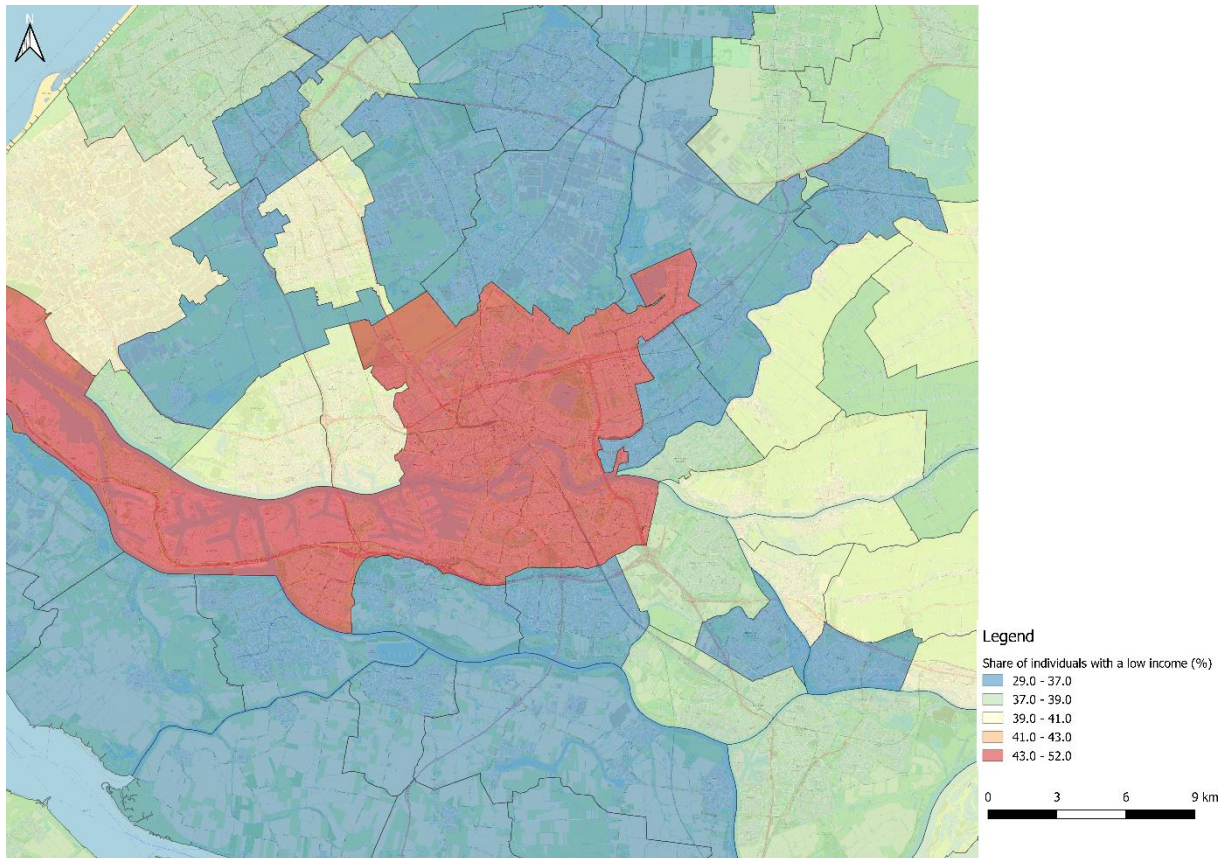


Figure 3 Concentration of poverty in Rotterdam at municipality level

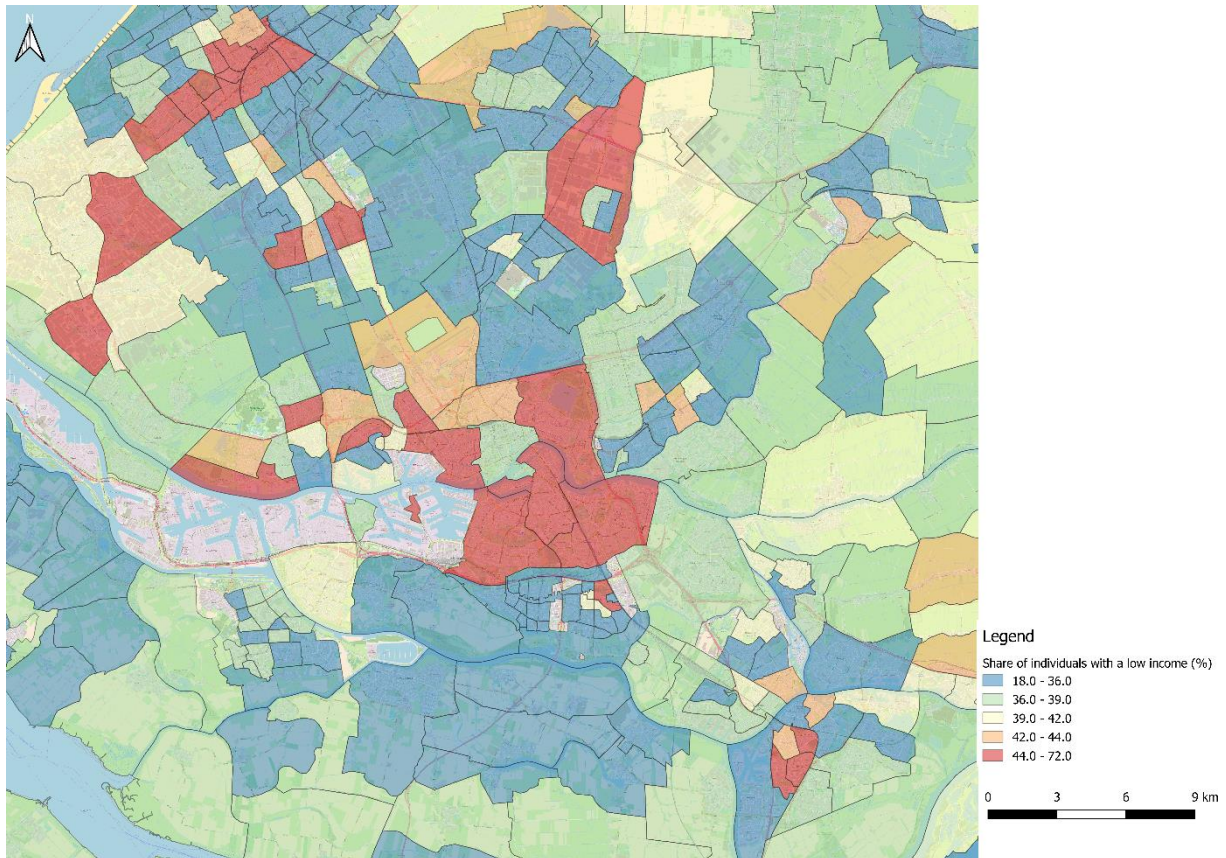


Figure 4 Concentration of poverty in Rotterdam at district level

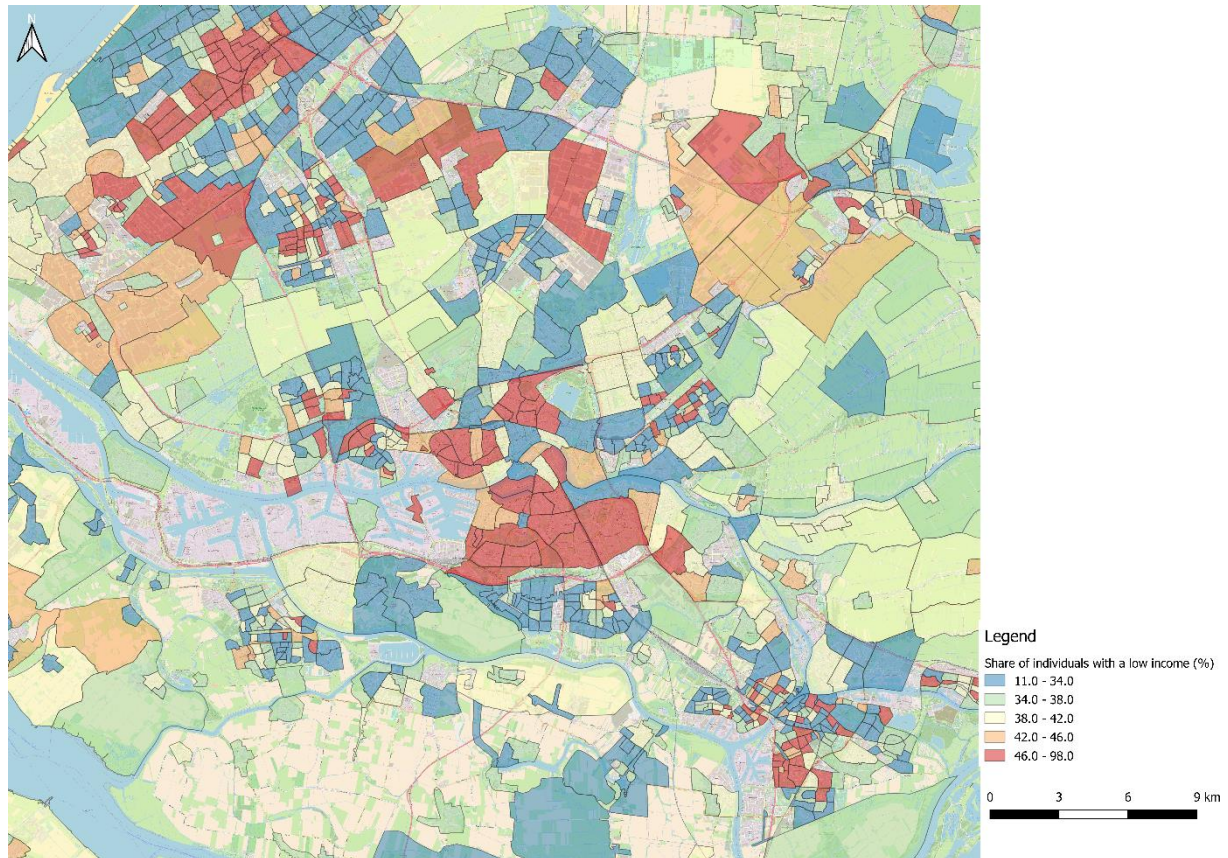


Figure 5 Concentration of poverty in Rotterdam at neighbourhood level



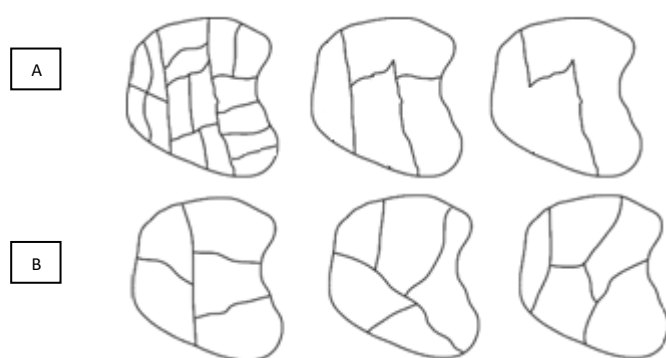
### 3. Defining neighbourhoods

#### 3.1. Spatial scale

In this report we promote an alternative approach to measuring spatial inequalities using flexible geographies. This approach is most effective when starting from very small spatial building blocks, or small neighbourhoods. There is no unique definition of *neighbourhood* and which geographical boundaries provide the best approximation for it. The latter will depend to some degree on the specific outcome of interest, such as for example, employment status, earnings and income, physical and/or mental health. The literature investigating the role of neighbourhood effects on individual outcomes is generally in favour of using very small geographies as a way to approximate the “real” neighbourhood or spatial context of individuals. The assumption is that *spatial proximity* is a good indicator of *social belonging*. Under this assumption, small geographic units can be viewed as providing a good measure of the social and economic contexts affecting individuals’ outcomes.

The neighbourhood has been recognized as an important unit of interest for many years and across various academic disciplines. The “neighbourhood effects” literature examines the consequences of neighbourhood characteristics on individual outcomes. There are, however, many approaches to studying contextual effects and neighbourhood definitions vary widely, including administrative, functional and emotional approaches. What is clear is that analytical results are sensitive to the definition and operationalisation of the neighbourhood. Neighbourhood definitions influence neighbourhood-level inequality measures and their effects on individual outcomes, which is known as the Modifiable Areal Unit Problem (MAUP; Gauvin et al., 2007; Kwan, 2012; Openshaw, 1984).

The MAUP involves that the same data yield different results when aggregated in different ways. Two aspects of the MAUP can be distinguished: a scaling effect which entails that results may differ depending on the size of the geographical units, and a zoning effect which entails that results may differ depending on how the study area is divided up, even at the same geographical scale, see Figure 1.



*Figure 6 A) the scale problem with three levels of analysis. B) the zonation problem. Each of the diagrams demonstrates a division of a sample space into 5 distinct areal units (adapted from Manley (2006)).*

The empirical neighbourhood effects literature, often uses data which comes with pre-determined administrative neighbourhoods, at one specific neighbourhood scale. Administrative neighbourhood definitions are often used because of readily available data (Sleutjes, de Valk, & Ooijevaar, 2018). Studies have made use of different neighbourhood definitions, including census blocks, block groups, tracts, zip code areas, wards, districts and neighbourhoods as defined by the cities and national governments. These neighbourhood definitions vary between countries, but even within countries administrative neighbourhoods vary strongly in geographical size and population counts. In addition to this variation, the definitions of administrative neighbourhoods can change over time. Although this is not problematic when cross-sectional studies are undertaken, when longitudinal data is used it can become problematic to determine whether an outcome is the result of a changing context rather than the result of changes in the geography of the context.

A major problem is that the spatial scales for which data is available, do not always match the scales which are relevant for the processes under study. Geographical processes occur at particular scales, and studying them at the wrong scale may lead to misleading outcomes. For example, many sociological processes, such as social networking, social support and peer influence take place at either micro scales (e.g. building blocks, squares, streets) or scales that

transcend administrative area delineations. Increasing availability of individual level, geocoded data allows scholars to study contextual effects using ‘bespoke’ geographical units which are more relevant to the specific problem under study than standard administrative units. These kind of data make it possible to address both the scale effect and the zonation effect from the MAUP. We will now turn to both types of effect in more detail.

### 3.2. Scaling effect

Defining neighbourhoods as too large geographical units will often result in the underestimation of neighbourhood effects (e.g. Andersson & Malmberg, 2015; Dinesen & Sønderskov, 2013; Kwan, 2012; Spielman, Yoo, & Linkletter, 2013). Within larger neighbourhoods with low poverty levels, there might still be smaller spatial concentrations of poverty, which can be highly relevant for the individuals living there. Or the other way around, within larger neighbourhoods with high levels of poverty, there might be smaller concentrations of relative wealth. When using higher levels of aggregation, such as predefined neighbourhoods, these potential local concentrations of poverty or wealth are ignored. The literature on the MAUP argues that it is important to use data with information on very small geographical units as this provides a flexible starting point which allows the aggregation of data to larger geographical units, whereas data for larger geographical units of analysis precludes examining local variability.

### 3.3. Zonation effect

The zonation effect of the MAUP entails that contextual measures and effects differ based on how the study area is divided up, even at the same geographical scale. Based on how borders are drawn, individuals can get a complete different measure of the characteristics of their residential context. What predefined definitions of neighbourhoods have in common is that they have non-overlapping boundaries: the areas do not overlap with one another (Hipp & Boessen, 2013). Defining neighbourhoods with non-overlapping boundaries might be

deficient especially for individuals living on the boundaries of these neighbourhoods. These individuals are assumed to be affected by an environment further away from them rather than the environment closer to them, but across neighbourhood boundaries (Hipp & Boessen, 2013). A solution to this problem is to construct individualised, ego-centric defined neighbourhoods (also called bespoke neighbourhoods). These are constructed around each individual rather than based on top-down administrative delineations.

### 3.4. Bespoke neighbourhoods

In order to address the problems of scaling and zonation, scholars from different academic fields (e.g. geography, demography, health studies, sociology and criminology) are increasingly using bespoke neighbourhoods to measure spatial contexts. Different terms are used to label bespoke neighbourhood, including individualised neighbourhoods, scalable neighbourhoods, egocentric neighbourhoods, egocentric buffers, egohoods, overlapping neighbourhoods, and individual social environments. The first study that made use of bespoke neighbourhoods was by MacAllister et al. (2001). Similar approaches have been suggested by Malmberg, Andersson, and Östh (2011) and by Hipp and Boessen (2013).

These bespoke measures are more spatially flexible when built up from very small spatial units (such as individual addresses, or 100 by 100 meter grid cells or equivalent). Increasing availability of individual level geo-referenced data, in combination with the increasing processing speed of computers, and the development of new software for processing geo-coded data, have made it possible to largely circumvent the aforementioned Modifiable Areal Unit Problem (MAUP) by constructing statistical aggregates for individualised, multi-scalar, ego-centric neighbourhoods. Two different methods to create such bespoke neighbourhoods can be distinguished, differing in the way they define spatial scale of the neighbourhood. The first method draws neighbourhoods based on a predetermined equal number of nearest neighbours (Malmberg et al., 2011). This method results in areas of different sizes without fixed borders, but with fixed population counts (also known as the k-nearest neighbours approach). The second method draws neighbourhoods based on equal geographical sizes

(Hipp & Boessen, 2013; Petrović, van Ham, & Manley, 2018). This alternative method results in areas of equal geographical sizes, with fixed borders, but with varying population counts. Using either of these two approaches, measures of spatial variation will no longer be linked to a specific geographic subdivision such as larger administrative neighbourhood, but instead capture a high degree of underlying micro variation. Such derived measures are independent of existing higher scale geographical sub-divisions and are essential for a detailed assessment of spatial inequalities. Each approach has pros and cons, but for the purpose of this report we have chosen to use the first method (based on the k-nearest neighbours) as this method standardizes the measures calculated for equal population sizes, which makes it easier to compare results across countries with different levels of population density

Several studies examined the sensitivity of the results to the definition of the neighbourhood by including multiple neighbourhood definitions. Overall, it seems that neighbourhood effects are stronger when neighbourhoods are defined as micro-scale, individualized neighbourhoods. Using larger/administrative neighbourhood definitions can lead to an underestimation of neighbourhood effects (Andersson & Malmberg, 2015; Buck, 2001; Dinesen & Sønderskov, 2015; Fowler, 2016).

Although the individualized, egocentric neighbourhood approach makes sense when research questions address local environmental factors on individual outcome, other research questions might require other neighbourhood definitions. Administrative neighbourhoods have long histories and reputations, and are used by cities for policies. It depends on the nature of the research question how the neighbourhood should be defined and it is important to choose a spatial scale and definition that matches the research question. Most important is that the definition of the neighbourhood should be driven by theory, not data.

### **3.5. Data requirements**

The data inventory from Task 5.1 of Work Package 5 from the RELOCAL project, which resulted in Deliverable 5.1, served as preparation for Task 5.2 and 5.3. The Data availability inventory

(Deliverable 5.1) gives an overview of what type of data are available in which country. In order to be able to carry out Task 5.2 and 5.3 we need two types of data:

- I. Contextual level data on aspects that are relevant for measuring spatial inequality at a very low geographical scale (e.g. income, unemployment);
- II. Longitudinal geocoded individual level data on socio-economic outcomes.

For Task 5.2. contextual level data on income at a very low geographical scale would be sufficient, whereas for Task 5.3 both types of data are needed, and it must be possible to link these two types of data. In other words, it must be possible to identify in which small geographical area an individual lives (using survey or administrative individual level data).

The data inventory has shown that within the RELOCAL consortium countries, suitable data to carry out Task 5.2 and Task 5.3 are available only in the Netherlands, Sweden, UK and Finland. This was already envisaged when the project proposal was written, and therefore Work Package 5 was explicitly designed as a demonstrator project which aims to show the possibilities when the required data is available. We therefore decided to include analyses of data from the Netherlands, Sweden, the UK (i.e. England and Scotland) and Finland in the current report.

### **3.6. The current report**

The main focus of the current report is to show that (i) the choice of spatial scale and degree of spatial/social proximity (i.e. number of neighbours) matters for understanding spatial inequalities, and (ii) propose more flexible ways of constructing multi-scale spatial units for the purpose of neighbourhood effects research.

## 4. Method

### 4.1. EquiPop

One of the objectives of this report is to demonstrate how standardized tools for the analysis of spatial inequality can be used on different types of geographical data. As outlined in the original research proposal, we have used EquiPop, which is a specialized software-program for the calculation of the k-nearest neighbours, to construct individualized egocentric neighbourhoods. The software has been developed by John Östh at Uppsala University. (<http://equipop.kultgeog.uu.se/>).

As discussed in the previous section of the report, measuring poverty using fixed borders for administrative neighbourhoods, can lead to the emergence of the MAUP. In addition, when the aim is to compare measures between cities, regions and countries, it is a problem that definitions and sizes of neighbourhoods can vary considerably, also over time. This restricts the possibility to reliably compare levels of spatial inequality and segregation.

The k-nearest neighbour approach, as used in the EquiPop software, provides a tool to draw neighbourhoods at different geographical scales for different types of detailed geographical data. The computation of measures of spatial inequality are based on individualised scalable neighbourhoods, based on fixed population counts. For the current report, we used different scales, ranging from the 200 to the 51,200 nearest neighbours. Preferably, the building blocks which are used as a starting point for the EquiPop analyses are very small and regular. Ideally small grids, such as 100 by 100 meter grid cells or equivalent are used. Individual level data from government registers, or from census data then needs to be aggregated to these small spatial units.

The regulations for use of EquiPop software includes the prohibition to profit from the use of the software, for instance users may not sell research reports, presentations and other forms of output and analyses that were produced via EquiPop (<http://equipop.kultgeog.uu.se/Legal/untitled.html>). In principle the software is open access for academic research purposes and student work.

## 4.2. Cross-national comparison

Since RELOCAL is an international comparative project, in this report we included analyses for as many countries from the RELOCAL consortium as possible, depending on data availability. The k-nearest neighbours analyses were carried out using EquiPop software on data from the Netherlands, Sweden, Finland and the UK (i.e. England and Scotland). The software was used, to compute comparative measures of spatial inequality that are independent of larger administrative geographical units. This approach makes it possible to compare patterns of socioeconomic segregation between regions and countries and to determine the extent to which these patterns are similar or different. This cross-national approach is beneficial as it enables us to demonstrate how standardized tools can be applied to different types of geographical data. This was done for Sweden and the Netherlands using individual level data and for Finland, Scotland, and England using aggregated data at a low spatial scale.

## 5. Data

### 5.1. General description of the data

#### 5.1.1 Sweden

For Sweden we use a collection of registers managed at Statistics Sweden, accessed via the MONA system (Microdata online access) (<http://www.scb.se/mona-en/>). The Swedish register data is administered in the so called *Geographical context* project in the department of Human geography at Stockholm University. In Geographical context, information about geographical coordinates are based on the geography database (Geografidatabasen), which contains annual geographical information connected to properties, with coordinates collected by the Swedish mapping, cadastral and land registration authority (Statistics Sweden, 2011).

The general terms of agreement contain, among others, regulations that prohibit the sale or otherwise commercial exploitation of material. It also includes a clause stating that personal data should be treated within the framework of the personal data act. The confidentiality agreement needed to use the data contains regulations on who may use these data and under which conditions. An important clause states that material may only be published in a way so that single individuals or business identities are not disclosed. With EquiPop the output is always aggregated on coordinates and will thus not disclose identities.

Research conducted within RELOCAL WP5, falls within this project, “Geografisk kontext: Ett nytt sätt att mäta vad omgivningen betyder för individens livsbana” (Geographical context: A new way to measure what context means for individual life courses). This project has been approved by the Stockholm Regional Ethical Vetting Board (Regionala Etikprövningsnämnden i Stockholm). The project description describes that geographical coordinates will be used to construct contextual variables for differently sized individualized neighbourhoods and to link contextual data to individual data, but that coordinates will not be used to identify individuals. Data are kept by Statistics Sweden on a server that project members can connect to. Identifiable data may under no circumstances be exported from Statistics Sweden.

### 5.1.2 Netherlands

For the Netherlands the data sources are the Social Statistical Database (SSD, or Sociaal Statistisch Bestand, SSB, see Bakker (2002); Houbiers (2004)) and the Regional Income Study (RIO, Regionaal Inkomensonderzoek. The SSD data covers the entire population of the Netherlands, from 1999 – 2010 (with residential histories back to 1995), and contains data from a range of government registers. The SSD consist of a number of linked registers including demographic, socio-cultural, and socioeconomic characteristics of the population. Although the name suggests it is one dataset, the SSD consists of several datasets which can be linked upon request. The Regional Income Study was based on a sample study until 2009, and covers the entire population of the Netherlands since 2010 (integral observation). The RIO data is of high quality and contains information on disposable individual and household income. The SSD and RIO data can be geocoded to include information on neighbourhoods. The data can be accessed through a secure remote access facility which has been set up by Statistics Netherlands. Under strict conditions organizations may be granted access to the microdata (see <https://www.cbs.nl/en-gb/our-services/customised-services-microdata/microdata-conducting-your-own-research/requirements-for-remote-access>). The data from the Netherlands, and the conditions of access, is very comparable to the data from Sweden.

### 5.1.3 Finland

For Finland, the Grid Database 2012 of Statistics Finland is used. The Grid Database is a chargeable product that contains Statistics Finland's coordinate-based statistical data calculated by map grid in eight data groups. The Grid Database is updated annually with the latest statistical data. The database is available as map range (MapInfo or Esri Shapefile) or as database (dBase), and since 2011, it is produced in the ETRS89-TM35FIN coordinate system (EUREF-FIN). The available smallest grid size is 250 m x 250 m. Data protection is the same for the 250 m and 1 km grid squares: the data within the grid square are confidential, and protected, the sum of total populations is given (e.g. total number of households, total

number of workplaces), but the data is generally confidential if the grid contains fewer than 10 people.

The 'Consumer structure' data groups of the Grid Database contains the relevant information for this analysis. The total number of *Income recipients* per grid contains the number of inhabitants in the grid aged 18 and above who have a taxable income. Taxable income includes wages and salaries, entrepreneurial income, and other taxable income (e.g. other earned income, pension income, unemployment benefits and other social benefits). As an indicator of poverty, the *income category* variable is used where income recipients are placed in order according to income and dividing them in ten groups containing the same amount of income recipients. For more information, see [https://www.stat.fi/tup/ruututietokanta/tietosisalto\\_en.html](https://www.stat.fi/tup/ruututietokanta/tietosisalto_en.html).

#### 5.1.4 England and Scotland

A survey of socio-economic data available for small areas in the UK, revealed that such data essentially originates from Census-based data as this is still the main source of small-scale geographical data. In some cases, administrative register-type data have also been made available, but unlike Sweden, Finland, and the Netherlands this type of data is not generally available for research purposes. The Indices of Multiple Deprivation (IMD) provide a good starting point to assess the existence of neighbourhood-level socio-economic indicators, where neighbourhoods are defined at the level of Lower Super Output Areas (LSOAs), which correspond to Data Zones (DZs) in Scotland. Data for Wales is not analysed for this report as there are no RELOCAL case studies in Wales.

Amongst the possible socio-economic indicators to be studied it was considered that income would provide the most comparable analyses of multi-scale spatial inequality. Although the IMD for Scotland and England contain a domain about income, at the level of LSOAs (which correspond to DZs in Scotland), the actual data used to construct this indicator is not a direct measure of income.

In the case of the Scottish IMD, the income domain provides data on the number or proportion of people defined as income deprived. Individuals are defined as being income deprived if they received one or more of the following social benefits, as recorded by the Department for Work and Pensions (DWP): Adults and Children in Income Support (IS) or Income-based Employment and Support Allowance Households; Adults and Children in Job Seekers Allowance (JSA) households; Adults in Guarantee Pension Credit Households; and Adults and Children in Tax Credit Households on low incomes.

In the case of the income domain in the IMD for England, the indicator measures the proportion of the population experiencing deprivation relating to low income, where the definition of low income includes both those people who are out-of-work, and those who are in work but have low earnings (and satisfy the respective means tests).

As a result, the binary indicators used in the income domains of the IMDs do not provide a direct measure of income and cannot be used to derive indicators for income-related poverty as is the case of the at-risk-at-poverty (AROP) indicator (i.e., the proportion of households with income below 60% of the median income). In addition to not being direct measures of household income, the indicators used in the IMD indices are not easily comparable with income indicators for the other countries in this analysis, namely, Sweden, the Netherlands, and Finland. As a result, we looked for indicators of actual household income.

The best direct measures of income available for small geographical areas were the small area estimates of household income, which are produced by the Office for National Statistics (ONS) for MSOAs in England and the Scottish Neighbourhood Statistics for DZs (i.e. LSOAs) in Scotland. These small area income statistics consist of model-based small-area estimates and thus are not actual measures of household income. Further details on the geographies available in the data and the income-based poverty indicator used in the analyses carried out for this report are described in sections 5.2.4 and 5.3.4 respectively.

## 5.2. Geographies available in the data

Below we give brief descriptions of the geographies used for each of the countries. We strived to use as small possible geographical areas as possible for each country, and the geographies that we used depend on data availability and access, but also on data protection rules, which differ between countries. Also within countries the geographies available can differ between urban and non-urban areas. A consequence of using small geographical areas is that for areas with small cell counts there is no data available because small cell counts might violate data projection rules. These rules are different for each of the countries.

### 5.2.1 Sweden

For the analyses of the Swedish data we used 250 by 250 meter grid cells in urban areas (defined as localities consisting of a group of buildings normally not more than 200 metres apart from each other, and with at least 200 inhabitants), and 1000 meter squares outside these urban areas, based on the 2010 urban subdivisio. The urban and rural grids are positioned in a way so that 16 urban grid cells can fit into one rural grid cell, see (Nielsen et al., 2017, p. 24-25).

### 5.2.2 Netherlands

For the Netherlands data the lowest available geography are 100 by 100 meter grids. This data can be used with special permission from Statistics Netherlands. The individual level longitudinal data is geocoded so that for each individual in the data it is known in which grid cell they live. Using this data it is possible to aggregate population characteristics (such as income) on the level of 100 by 100 meter grid cells and higher. So using small building blocks, the data can also be aggregated on other scales, for example 500 by 500 meter grid cells or higher. In addition to these small grid cells, also alternative geographies are available in the data, such as official neighbourhood definitions, and postal codes. But also higher scale geographies such as municipalities and regions. For the purpose of this report, the indicator

of poverty is aggregated to 100m by 100 m grid cells, based on the grid system used by Statistics Netherlands.

### 5.2.3 Finland

Like in Sweden, for Finland the lowest spatial level at which individual level data can be aggregated are 250 by 250 meter grid cells in the larger urban areas, and 1 by 1 kilometer grid cells outside the larger urban areas. The reason that only larger grid cells are available outside urban areas is that smaller grids would lead to very low cell counts, which might violate the rule that it should not be possible to identify individuals from the data. When there are less than 10 people in a grid cell, no information on the cell population is released for data protection reasons.

### 5.2.4 England and Scotland

For England the smallest areas designed specifically for statistical purposes are the Census Output Areas (OAs). They are based on data from the Census and were built from postcode units. OAs were introduced in Scotland for the 1981 Census and in all the other countries of the UK at the 2001 Census. They were designed to have similar population sizes and be as socially homogenous as possible based on tenure of household and dwelling type (homogeneity was not used as a factor in Scotland).<sup>2</sup> In England and Wales, Census OAs are based on postcodes as at Census day and fit within the boundaries of statistical wards and parishes. The minimum OA size was 40 resident households and 100 resident people, but the recommended size is larger at 125 households. The total number of 2011 OAs is 171,372 for England and 10,036 for Wales, in comparison with 175,434 Output Areas in 2001.

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<sup>2</sup> Previously to the 2001 Census, small area statistics were aggregated and presented for areas drawn up for Enumeration Districts (EDs). The size and character of each ED was determined for operational purposes. It was also convenient to use the ED codes in processing and as the smallest output 'building brick', but variability made them less than ideal for statistical purposes.

OAs are the basis of Super Output Areas, which have been introduced as stable and consistently sized areas for Neighbourhood Statistics (NeSS). Super output areas (SOAs) were introduced in 2004 to improve the reporting of small area statistics from the 2001 Census, in particular the Indices of Deprivation and a range of additional Neighbourhood Statistics. The aim was to produce a set of areas of consistent size, whose boundaries would not change (unlike electoral wards), suitable for the publication of data such as the Indices of Deprivation. SOAs are an aggregation of adjacent OAs with similar social characteristics. There are two layers: Lower Layer Super Output Areas (LSOAs) typically contain 4 to 6 OAs with a population of around 1500 (between 1,000 to 3,000 residents and 400 to 1,200 households), while Middle Layer Super Output Areas (MSOAs) have on average a population of 7,200 (between 5,000 to 15,000 residents and 2,000 to 6,000 households). The hierarchy of Output Areas and the two tiers (LSOAs and MSOAs) are known as the Neighbourhood Statistics Geography. Small-area statistics such as those used in the current analysis are provided at the level of LSOAs or MSOAs.

In Scotland, Data Zones are the main geography used for the dissemination of results from Scottish Neighbourhood Statistics (SNS). The data zone (DZs) geography covers the whole of Scotland and nests within local authority boundaries. Data zones are the main small-area statistical geography in Scotland and consist of groupings of Census Output Areas (OAs). DZs correspond to the Lower Super Output Areas (LSOAs). DZs have populations of between 500 and 1,000 household residents, and there were 6,500 2001 DZs and 6,976 2011 DZs in Scotland for each census period respectively. Where possible, DZs borders respect physical boundaries and natural communities. They have a regular shape and, as far as possible, contain households with similar social characteristics. However, not all statistics are suitable for release at the DZ level because of data protection reasons or reasons of reliability, leading to the need for a statistical geography between the data zone and the local authority. The intermediate zones (IZs) are aggregations of data zones within local authorities and contain between 2,500 and 6,000 people. Small-area statistics such as those used in the current analysis are provided at the level of DZs (=LSOAs) or IZs.

### 5.3. Indicators of poverty

Ideally when doing international comparative research, the same poverty indicators are used in each country. Unfortunately comparable measures are not available as each country has different indicators and different definitions. Also within countries definitions can change considerably over time. In this section we briefly outline the indicators of poverty we used for each of the countries included in this report. It is important to note that there are many ways to measure poverty, and that there are also different categorisations of poverty by duration. For example, students are generally among those defined as being poor when looking at their income. However, students generally have a high earning potential and their poverty is often short term. Long term poverty, related to for example long term unemployment, is a completely different and more persistent and problematic type of poverty. The measures used for the purpose of this report do not distinguish between these different types. However, for the Netherlands and Sweden we were able to only include individuals aged 25 and older, so the student population is minimized in these countries.

#### 5.3.1 Sweden

For Sweden we base our poverty indicator on the Eurostat definition of the at-risk-of-poverty rate. The rate is defined as the share of people with an equalised disposable income below the at-risk-of-poverty threshold, which is set at 60 % of the national median equalised disposable income after social transfers. To increase comparability, we decided to define income as disposable income by individual persons. Unlike the Eurostat definition our poverty indicator is restricted to persons aged 25 and above. (Nielsen et al., 2017, p. 12).

The individualized disposable income is obtained from Statistics Sweden's Longitudinal integration database for health insurance and labour market studies (LISA). The individualized disposable income variable in LISA is named `DispInkPersF04` for the year 2012. `DispInkPersF04` and is obtained by dividing the sum of all the family members' individual disposable incomes, and then multiplied by the individuals' consumption weights. Negative values have been set

to zero. DisplnkPersF04 is registered on the December 31 for each year (Nielsen et al., 2017, p. 29)

The poverty indicator used in for Sweden is defined as the share of persons aged 25 and above, and who have a personal disposable income below 60 % of the median level.

### 5.3.2 Netherlands

For the Netherlands we used an indicator of poverty that is defined as the share of individuals aged 25 and above, and who have a personal disposable income below 60% of the median level. Data for 2012 is used. The individual disposable income is obtained from the Regional Income Study (RIO, Regionaal Inkomensonderzoek) from Statistics Netherlands.

### 5.3.3 Finland

For Finland, existing income categories in the Grid Database are used. The income categories are formed by using deciles. Deciles are obtained by placing income recipients in order according to their income and dividing them in ten groups containing the same amount of income recipients. The income categories used are:

- Income recipients belonging to the lowest income category (income deciles 1- 2): inhabitants earning at most EUR 10,879 per year
- Income recipients belonging to the middle income category (income deciles 3-8): inhabitants earning EUR 10,880 – 37,890 per year
- Income recipients belonging to the highest income category (income deciles 9-10): inhabitants earning more than EUR 37,890 per year

The indicator that is used is defined as the share of individuals aged 18 and above who have a taxable income belonging to the lowest income category. Data for 2012 is used. For more information, see [https://www.stat.fi/tup/ruututietokanta/tietosisalto\\_en.html](https://www.stat.fi/tup/ruututietokanta/tietosisalto_en.html)

### 5.3.4 England and Scotland

The income indicator for England is calculated using a model-based method to produce estimates of household income using a combination of survey data from the Family Resources Survey and previously published data from the 2011 Census and a number of administrative data sources. The estimates are available at the level of middle layer super output area (MSOAs) in England for 2011/12. MSOAs have a mean population of 7,200 and a minimum population of 5,000. They are built from groups of LSOAs and constrained by local authority boundaries. The indicator consists of MSOA level estimates of the proportion and count of households below 60% of the UK median income after housing costs (AHC) and before housing costs (BHC) for 2013/14. The analysis uses the before housing cost indicator in order to make it more comparable to the Scottish case, for which there is no after housing cost at-risk-of-poverty rates indicator.<sup>3</sup>

Similarly, the income indicator for Scotland consists of small area model-based income estimates for the average household gross weekly income, referring to 2014 and Data Zones, which covers total income received by all adult members of a household, including welfare benefits, tax credits and housing benefit. The estimates reflect total income before any deductions are taken off for income tax, national insurance contributions and council tax etc. The indicator used is the count of households with gross household weekly income below 60% of the median national (Scottish) income. From this count it is possible to obtain the at-risk-of-poverty (AROP) rates. The information available refers only to household income before taking account of housing cost.<sup>4</sup> Finally, it is important to note that the Scottish islands have been excluded from the EquiPop analysis due to issues relating to the very sparse nature of population settlements in these remote areas (and also in the Highlands).

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<sup>3</sup> More information on the methodology can be found in the technical report available from the link: <https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/incomeandwealth/bulletins/smallareamodelbasedincomeestimates/2015-10-20>.

<sup>4</sup> Details about the main results and methodology can be found in the report available from the link: <https://www.ons.gov.uk/peoplepopulationandcommunity/personalandhouseholdfinances/incomeandwealth/bulletins/smallareamodelbasedhouseholdsinpovertyestimatesenglandandwales/financialyearending2014>.

*Table 1 Summary of variables used in bespoke neighbourhood analysis*

Country	Variable	Geography	Year
Sweden	Count and ratio of individuals aged 25+ with a disposable income below 60% of the median income in Sweden	250m by 250m or 1km by 1km grid cell	2012
Finland	Count and ratio of individuals aged 18+ who have a taxable income belonging to the lowest income category	250m by 250m or 1km by 1km grid cell	2012
Netherlands	Count and ratio of individuals aged 25+ with a disposable income below 60% of the median income in the Netherlands	100m by 100m grid cell	2012
England	Count and ratio of household with mean gross income below 60% of the UK median income (before housing costs) <sup>a</sup>	MSOA	2013/14
Scotland	Count and ratio of household with mean gross income below 60% of the UK median income (before housing costs) <sup>a</sup>	LSOA (=DZ)	2014

*Note:* <sup>a</sup> modelled estimates based on survey data



## 6. Results

Using EquiPop software we calculated for each grid cell, or alternative small geography, the proportion of individuals with a low income at different spatial scales. Starting with the proportion of people with a low income among the nearest 200 people, up to the percentage of people with a low income among the nearest 51,200 people. By increasing the scale, the contextual variable of each grid cell (which is a proxy for a residential location) measures poverty for a larger population, and by definition also a larger geography. As EquiPop uses the  $k$  nearest neighbours, and very small building blocks (small grid cells), it standardizes the measures calculated for equal population sizes, which makes it easier to compare results across different countries. This is especially an advantage at lower geographical scales.

However, as the data for the UK starts with relative large MSOAs as building blocks, which already contain 3,248 households on average, we cannot meaningfully calculate the poverty rate for  $k=200$  and  $k=1,600$ . As the underlying geographies already contain more households, there would not be any differences between measures calculated for the lowest spatial scales. Therefore, for England and Scotland we only report the results for larger spatial scales (i.e.  $k=12,800$  and  $k=51,200$ ). Because there are many differences between Sweden, the Netherlands and Finland on the one hand and the UK on the other hand regarding the data that has been used, we report the results separately. Not only the size of the building blocks is different, the indicator of poverty (based on households versus individuals) and the type of data used is different (modelled estimates based on survey data versus register data), which makes comparisons difficult.

The values derived as output from the analyses in EquiPop can be seen as representing the concentration of individuals (in Sweden, the Netherlands and Finland) or households (in England and Scotland) with a low income. In order to compare concentrations of poverty across countries, we follow the approach of Andersson et al. (2018) and present percentiles of these concentrations at different scales. Percentiles for Sweden, the Netherlands and Finland at a lower spatial scale are reported in Table 3 and plotted in Figure 7 and at a higher

spatial scale in Table 4 and Figure 8. Percentiles for England and Scotland at a higher spatial scale are reported in Table 5 and plotted in Figure 9.

These percentiles show the proportion of the population that is exposed to certain poverty levels in their residential area across countries and  $k$ -values (scales). This makes it possible to compare levels of segregation in terms of the concentration of low income.

The distance that has to be covered from a particular grid cell to reach a targeted population will of course depend on the population density. In sparsely populated areas in Sweden and Finland the buffer has to reach wider to encompass the same number of  $k$  nearest neighbours compared to for instance the Netherlands. For a brief comparison please see Table 2 in Andersson et al. (2018, p. 259).

In Table 2 the overall poverty rates in the data for Sweden, the Netherlands, Finland, England and Scotland are presented. As the poverty rates for England and Scotland are based on modelled estimates of household income, using survey data, they are not comparable to the poverty rates of Sweden, the Netherlands and Finland for which the poverty rates are based on register data. Furthermore, the poverty rates in England and Scotland are based on household income, which also prevents comparison to the other countries for which the poverty rates are based on individual income. The overall poverty rate in the Netherlands (22%) is higher compared to Sweden and Finland where poverty rates are similar (17%).

*Table 2 Overall poverty rate in the data for Sweden, the Netherlands, Finland, England and Scotland*

Country	Overall poverty rate
Sweden	17% <sup>a</sup>
Netherlands	22% <sup>a</sup>
Finland	17% <sup>a</sup>
England	16% <sup>b</sup>
Scotland	15% <sup>b</sup>

*Note:* <sup>a</sup> Based on register data and individual income; <sup>b</sup> Based on modelled estimates using survey data and household income

### 6.1. Concentration of poverty at low spatial scale in Sweden, the Netherlands and Finland

First, we study the concentration of poverty at a low spatial scale (the 200 nearest neighbours) in Sweden, the Netherlands and Finland. The percentiles for this scale are reported in the first row of Table 3 and plotted in the first row of Figure 7. The percentiles are on the x-axis and the corresponding percentage of individuals with a low income on the y-axis. Looking at the ten percent of the population living in the least poor areas, the line of the Netherlands is above the lines of the other countries. This indicates that in the Netherlands, even in the most affluent areas, there is still a substantial proportion of individuals with a low income. Ten percent of the population who lives in the most affluent areas, are still living in areas where 11-16% of the nearest 200 individuals has a low income. A possible explanation for this is the large social housing sector in the Netherlands, with social housing available in a large proportion of neighbourhoods. This indicates that even more affluent people are likely to live in relative close proximity of low income households in social housing.

The ten percent of the population living in the least poor areas in the other countries are exposed to lower percentages of individuals or households with a low income in their direct living environment. The percentage of individuals with a low income in these areas ranges in

Sweden from 4 to 8% and in Finland from 0 to 4%, indicating high levels of segregation in terms of the very local concentration of individuals and households with a low income.

If we look at the ten percent of the population living in the poorest areas (Figure X), we see that Sweden and Finland have the highest concentrations of individuals with a low income at the scale of the 200 nearest people. In the poorest areas in Finland 30 to 48% of the 200 nearest individuals has a low income, and in Sweden 27 to 47%. The concentration of poverty in the poorest areas in the Netherlands is lower compared to Sweden and Finland, ranging from 28 to 36%.

Overall, the pattern for the Netherlands indicates the lowest level of income segregation, whereas the pattern in Finland indicates the highest level of segregation at this low spatial scale. These results suggest that in Finland the housing stock at a very low spatial scale is very homogeneous, with people with similar characteristics living in close proximity from each other.

*Table 3 Percentiles for small and moderate spatial scale in Sweden, the Netherlands, and Finland*

Percentile	Sweden <i>k</i> =200	Netherlands <i>k</i> =200	Finland <i>k</i> =200
10	0.08	0.16	0.04
25	0.11	0.18	0.11
50	0.15	0.22	0.16
75	0.20	0.25	0.23
90	0.27	0.28	0.30
95	0.34	0.30	0.35
99	0.47	0.36	0.48
	<i>k</i> =1,600	<i>k</i> =1,600	<i>k</i> =1,600
10	0.10	0.18	0.09
25	0.12	0.20	0.13
50	0.16	0.22	0.17
75	0.20	0.24	0.22
90	0.25	0.26	0.27
95	0.31	0.28	0.30
99	0.44	0.32	0.38

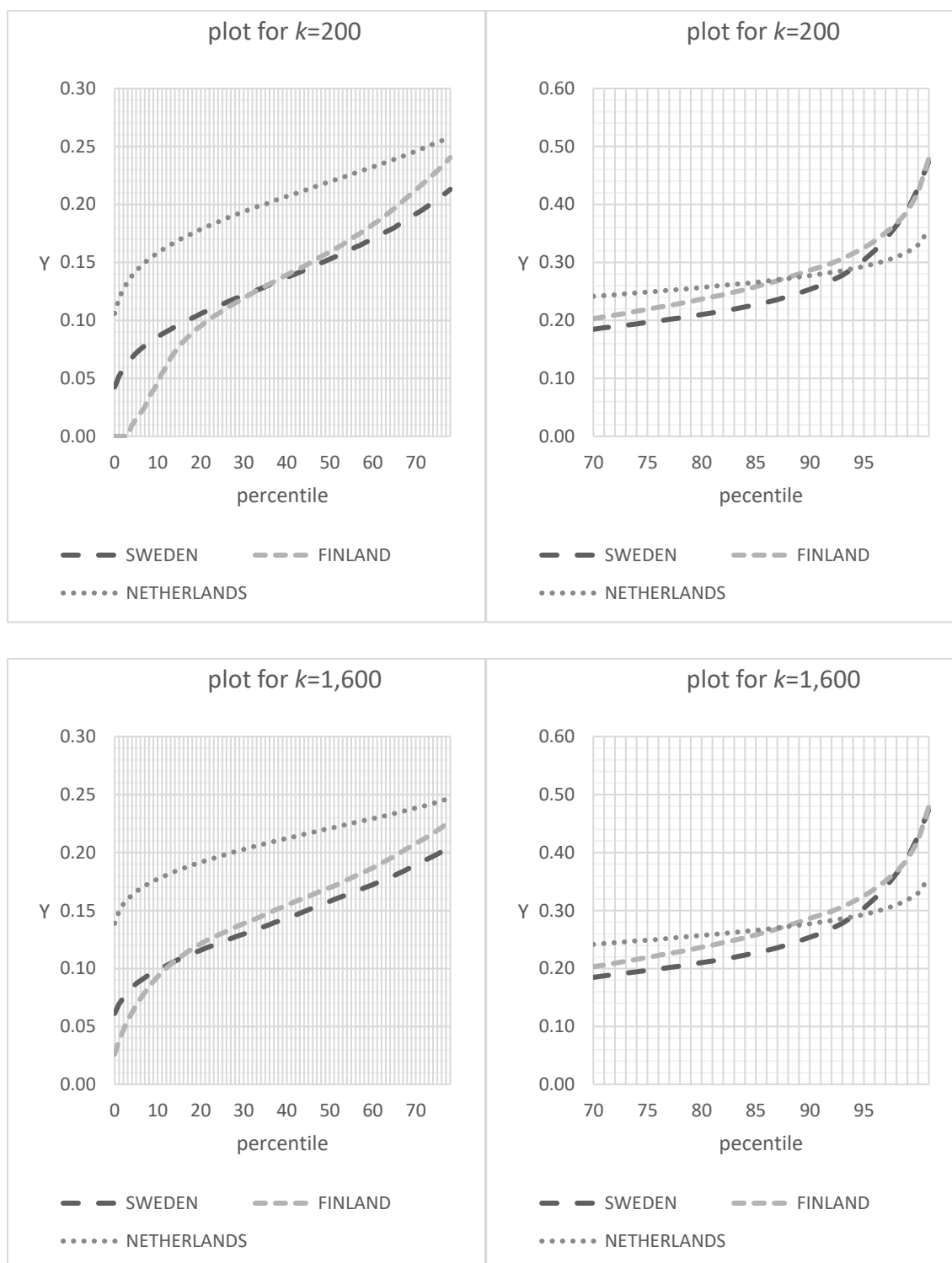


Figure 7 Concentration of poverty in bespoke neighbourhoods in Sweden, Finland, the Netherlands. Percentile values for k-values 200 and 1,600. Lower percentiles (<80) in column one and higher percentiles (>70) in column two.

## 6.2. Concentration of poverty at moderate spatial scale in Sweden, the Netherlands and Finland

Second, we look at the concentration of poverty at a moderate spatial scale (the 1,600 nearest neighbours; see Andersson et al. (2018)). The percentiles for this scale are reported in the second part of Table 3 and plotted in the second row of Figure 7. Concentrations of poverty at a moderate spatial scale show similar patterns in Sweden, the Netherlands and Finland compared to the lowest spatial scale. For the ten percent most affluent areas, we see again that the line for the Netherlands is above the lines for the other countries. In the areas with the lowest concentrations of poverty in the Netherlands, 14 to 18% of the 1,600 nearest individuals has still a low income. Sweden has concentrations of 6-10% in their most affluent areas. At a moderate spatial scale, Finland again has the lowest concentration of individuals with a low income in its most affluent areas with percentages ranging from 3 to 9%.

For the areas with the highest concentrations of poverty, Sweden and Finland have the highest concentration of individuals with a low income with concentrations between 25-44% and 27-38% respectively. The Netherlands (26-32%) has lower concentrations of poverty in their most poor areas.

## 6.3. Concentration of poverty at high spatial scale in Sweden, the Netherlands, Finland

Next, we look at the concentration of poverty at much higher spatial scales (the 12,800 and 51,200 nearest neighbours, which represent relatively large geographical areas). The percentiles for this scale are reported in Table 4 and plotted in Figure 8. At a high spatial scale, the patterns of poverty concentrations change slightly. The line for the Netherlands is again above the lines for Sweden and Finland, indicating the highest levels of poverty concentration in all areas. This is, however, not true for the top 5% of areas with the highest concentrations of poverty. Sweden and Finland, show very similar patterns up to the top 5% of areas with the highest concentrations of poverty. In the areas with the highest concentrations of poverty, Sweden shows the highest concentrations of individuals with a low income. This indicates that

at higher spatial scales in Sweden the poor are more segregated. Whereas at the lower spatial scales Sweden and Finland showed similar concentrations of individuals with a low income in their most poor areas, in Sweden these concentrations are higher when looking at a higher spatial scale.

*Table 4 Percentiles for large spatial scale in Sweden, the Netherlands and Finland*

Percentile	<i>Sweden</i>	<i>Netherlands</i>	<i>Finland</i>
	<i>k =12,800</i>	<i>k =12,800</i>	<i>k =12,800</i>
10	0.11	0.19	0.11
25	0.13	0.20	0.13
50	0.16	0.22	0.16
75	0.19	0.24	0.20
90	0.23	0.25	0.24
95	0.27	0.26	0.26
99	0.37	0.29	0.32
	<i>k =51,200</i>	<i>k =51,200</i>	<i>k =51,200</i>
10	0.12	0.19	0.13
25	0.15	0.21	0.14
50	0.16	0.22	0.16
75	0.18	0.23	0.19
90	0.20	0.25	0.23
95	0.24	0.25	0.25
99	0.32	0.27	0.28

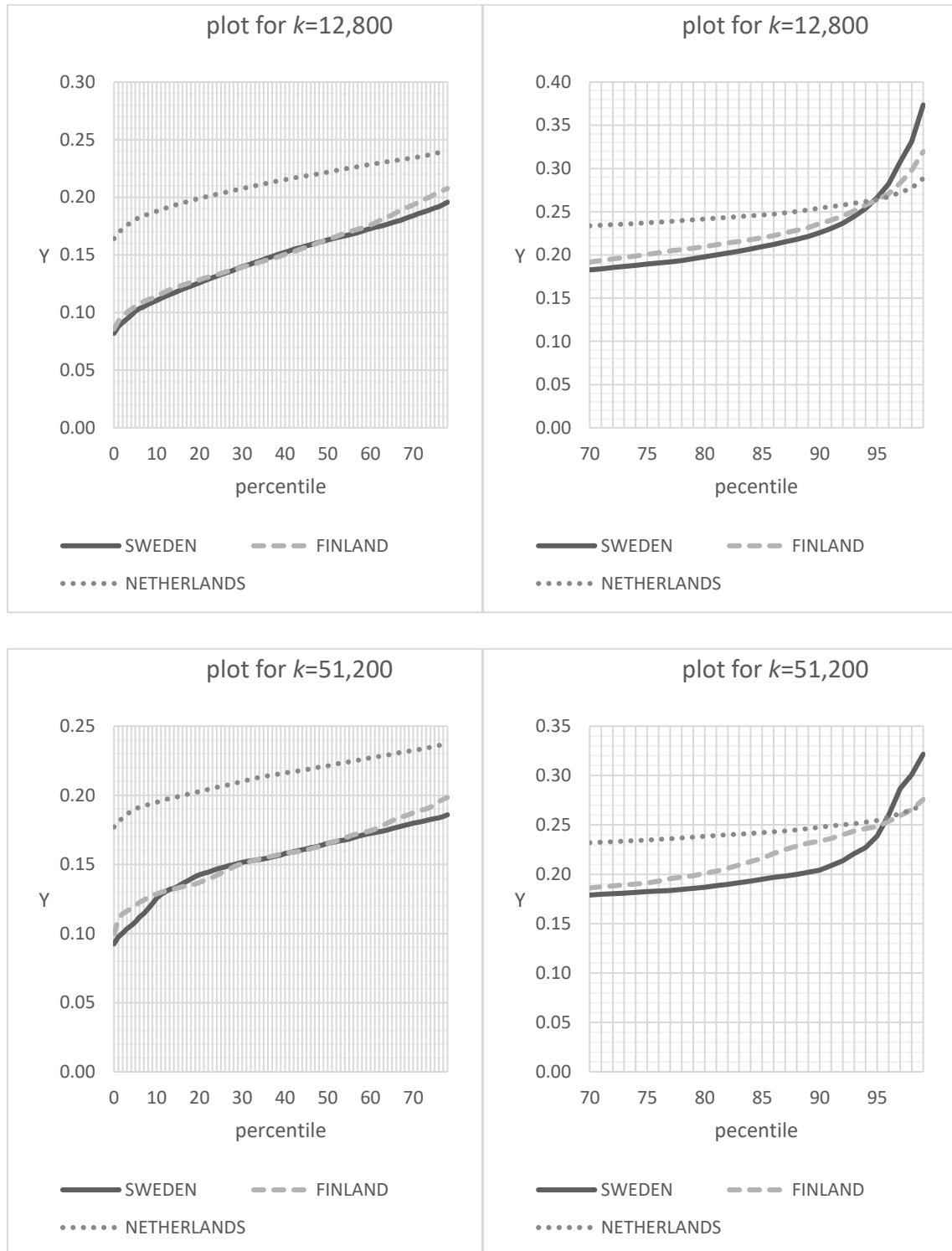


Figure 8 Concentration of poverty in bespoke neighbourhoods in Sweden, Finland, the Netherlands. Percentile values for k-values 12,800 and 51,200. Lower percentiles (<80) in column one and higher percentiles (>70) in column two.

#### 6.4. Concentration of poverty at high spatial scale in England and Scotland

As reported earlier, it is not meaningful to report the percentiles for the concentration of poverty at the lowest spatial scales ( $k=200$  and  $k=1,600$ ) for England and Scotland. The reason is that the underlying geography consists of relatively large areas with relatively large populations. As a consequence, there is hardly any variation between the measures at the lowest scales as they all measure the actual population in each geographical area. Only when the spatial scales become larger also the population of neighbouring areas are taken into account by the  $k$ -nearest neighbour method. The percentiles for the concentration of poverty at higher spatial scales (the 12,800 and 51,200 nearest neighbours) in England and Scotland are reported in Table 5, and plotted in Figure 9.

Looking at the percentile graphs, there seems to be little variation for  $k=12,800$  and  $k=51,200$  for England, while for Scotland the results are similar to what we found for Finland. The results for England could be due to the fact that the income data is modelled based on a sample (which is also the case for the Scottish data). Modelling income usually reduces the variation in the data. For this reason the results for England and Scotland should be interpreted with caution. The analyses for England and Scotland highlight that it is very important to have data available at a very low spatial scale, and that such data should be population data, and not measured for a sample.

*Table 5 Percentiles for large spatial scale in England and Scotland*

Percentile	<i>England</i>	<i>Scotland</i>
	<i>k =12,800</i>	<i>k =12,800</i>
10	0.11	0.12
25	0.14	0.13
50	0.15	0.16
75	0.17	0.19
90	0.18	0.22
95	0.20	0.26
99	0.22	0.33
	<i>k =51,200</i>	<i>k =51,200</i>
10	0.12	0.12
25	0.14	0.14
50	0.15	0.16
75	0.16	0.19
90	0.18	0.22
95	0.19	0.24
99	0.21	0.29

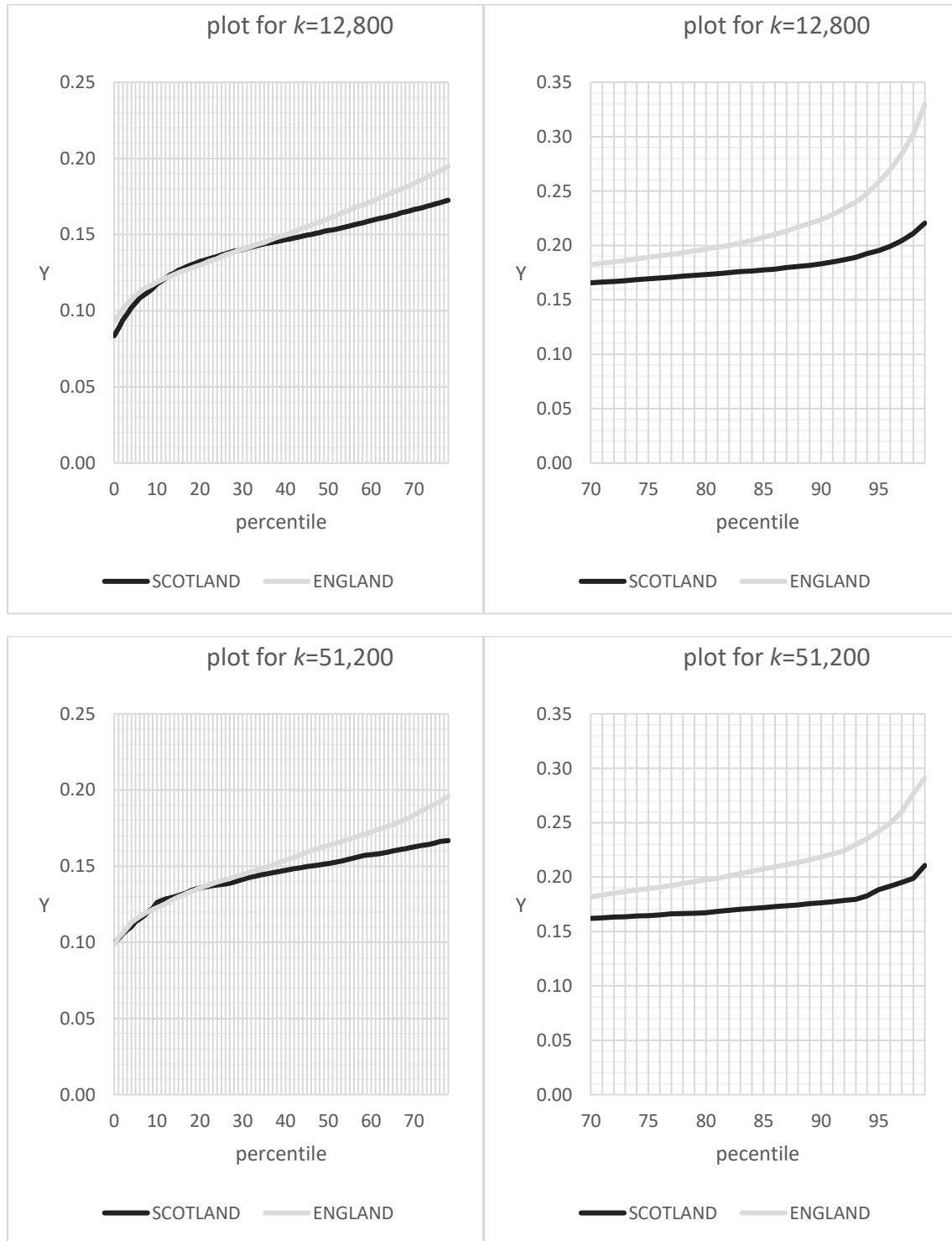


Figure 9 Concentration of poverty in bespoke neighbourhoods England and Scotland. Percentile values for  $k$ -values 12,800 and 51,200. Lower percentiles ( $<80$ ) in column one and higher percentiles ( $>70$ ) in column two.

## 6.5. Concentration of poverty in the case study areas

The main part of the RELOCAL project consist of case studies which will be carried out in Work Package 6. In this report we demonstrate the effects of measuring poverty concentrations at different geographical scales for selected case study areas within Sweden, the Netherlands, Finland and the UK. For the UK, we present two maps, both at a large geographical scale ( $k=12,800$  and  $k=51,200$ ). We present four maps per case study area in Sweden, the Netherlands and Finland: two maps showing poverty concentrations at a large geographical scale ( $k=12,800$  and  $k=51,200$ ), one map at a medium scale ( $k=1,600$ ), and one map at a very small scale ( $k=200$ ). These different spatial scales represent different scales of exposure to poverty for people living in the case study areas. In urban environments, the scale of the 200 nearest neighbours represents the direct living environment of people in their street and the houses around them. This is the level at which people have direct contact with others, the level at which peer group effects and role model effects might play a role. At the slightly higher scale of the 1,600 and the much higher scale of 12,800 nearest neighbours, the measure of poverty relates to people in your residential environment, but not people you would have direct contact with. These larger scales represent the people you would meet in the shopping centre, schools, work places, or for example bus stops. But these higher scales are also the scales at which people form mental maps of cities; maps within which people attach reputations to certain areas. The much higher scale of the nearest 51,200 neighbours measures more regional circumstances, for example related to labour market characteristics. A high proportion of low income people on this large scale is an indicator of relatively poor regional labour market circumstances. Below, for each case study area, we present maps from the highest to the lowest spatial scales. The locations of the case study areas in each country can be found in Appendix A – Locations of the case study areas.

### 6.5.1 Sweden – Stockholm

One of the case study areas in Sweden is the municipality of Stockholm. This is a predominately urban area in which there is a wide variety of areas. There are areas with very

high degree of first and second generation migrants, unemployment is high, criminality is very high, there is extensive poverty and low education levels. But there are also areas where the opposite is true. The size of the area is 187.16 km<sup>2</sup>. In Figure 8 and 9 the concentrations of individuals with a low income is shown for the two highest scales: 51,200 and 12,800 nearest neighbours. The spatial resolution of the maps are based on 1km by 1km and 250m by 250m grid cells, depending on whether the area is defined as urban or not. At these large spatial scales, it can be seen that the inner city of Stockholm almost entirely consist of areas with the lowest shares of individuals with a low income (blue), while the poor are concentrated at the outskirts of the city (red). Zooming further in to a smaller spatial scale in Figure 10 ( $k=12,800$ ) and 11 ( $k=200$ ), however, shows that there is substantial variation within these larger geographical areas. At the lowest spatial scale ( $k=200$ ) in Figure 11, very clear ‘social frontiers’ (Dean et al., 2018) can be observed; these are areas with the highest proportions of poverty next to areas with the lowest proportions of poverty. These variations at very low spatial scale are masked at higher spatial scales. Both the higher and the lower spatial scales have different meanings for the experienced and perceived levels of spatial inequality in the city. At the highest scale there are clear distinctions between the centre of the city and the suburbs. These distinctions are related to the spatial opportunity structure in the city, but also to the reputations of areas to the wider population. At variation in poverty at the much lower spatial scales are also important for the experienced inequality by individuals living in these areas. Living in a small area with a high poverty concentration, but close to relative wealthy areas increases experiences of relative wealth and poverty in the direct residential environment.

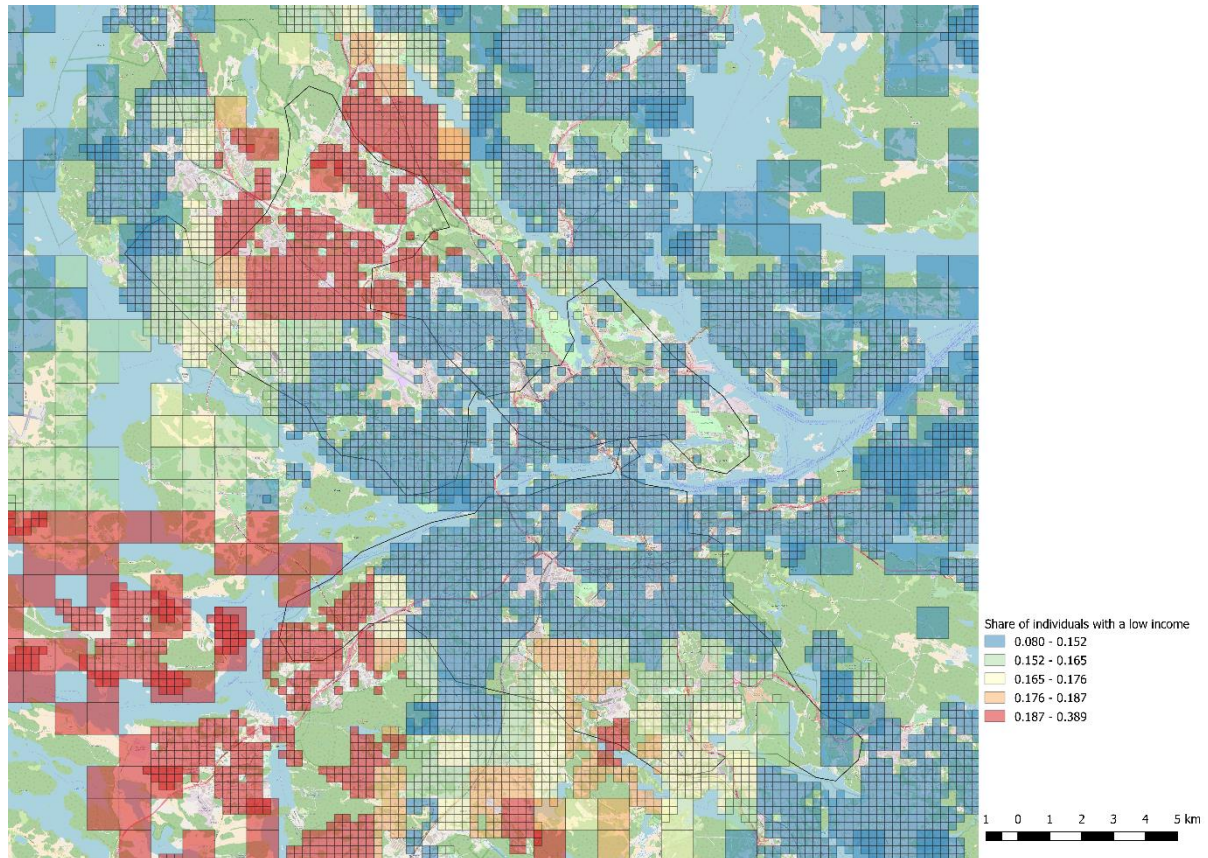


Figure 10 Share of individuals with a low income in Stockholm for  $k=51,200$

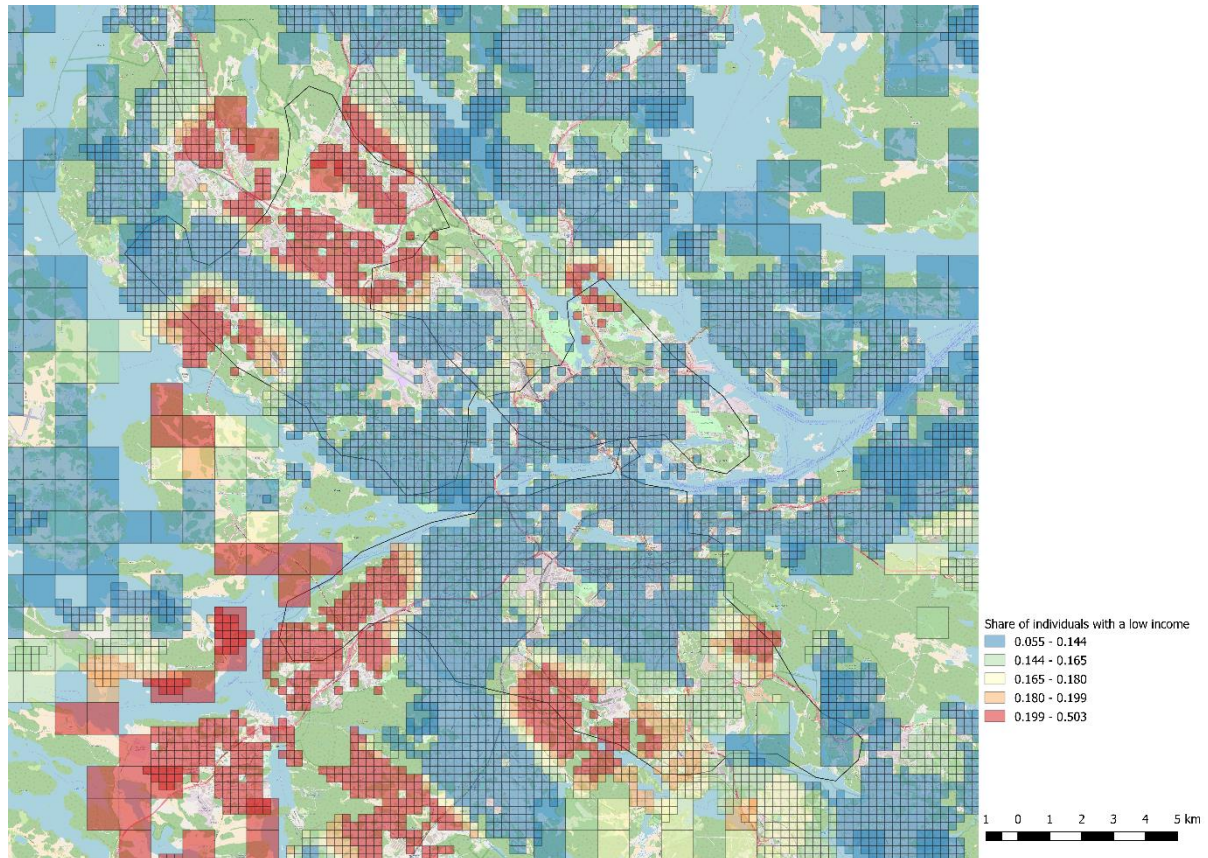


Figure 11 Share of individuals with a low income in Stockholm for  $k=12,800$

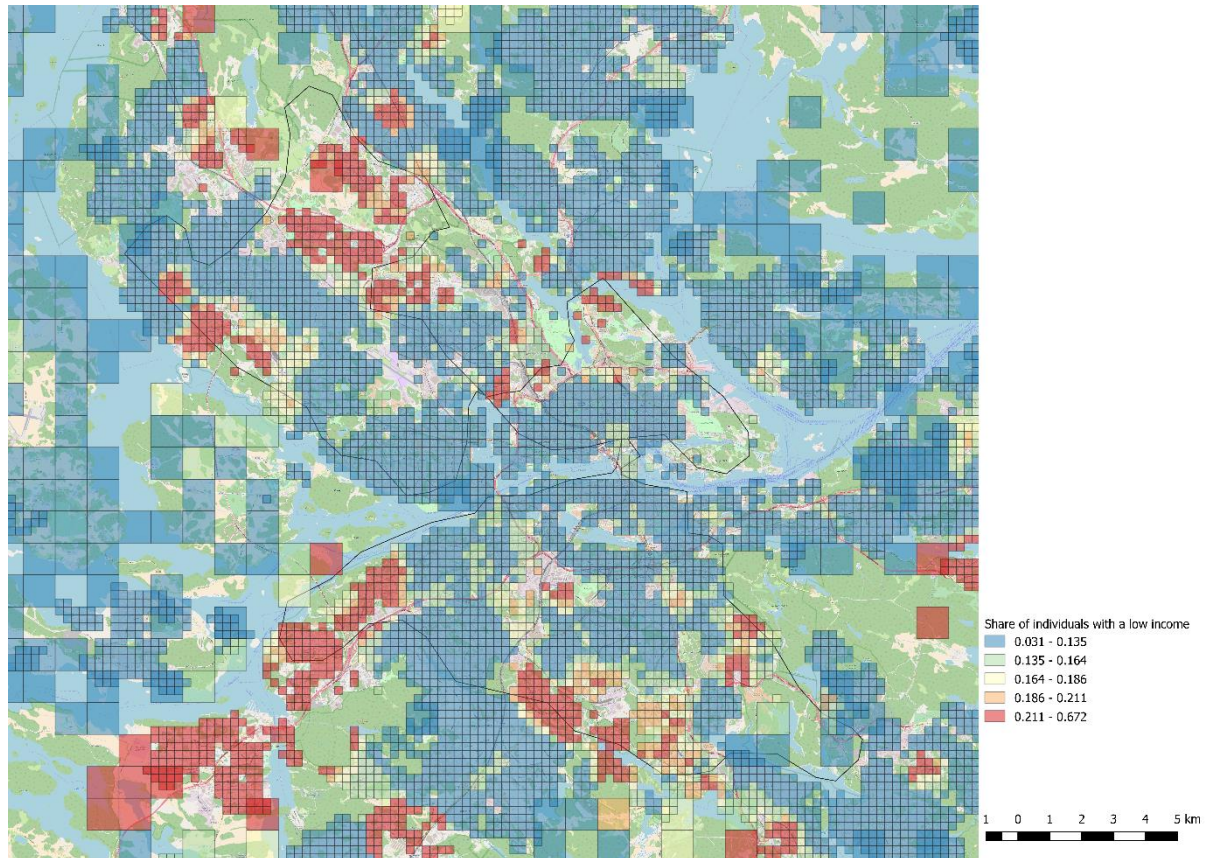


Figure 12 Share of individuals with a low income in Stockholm for  $k=1,600$

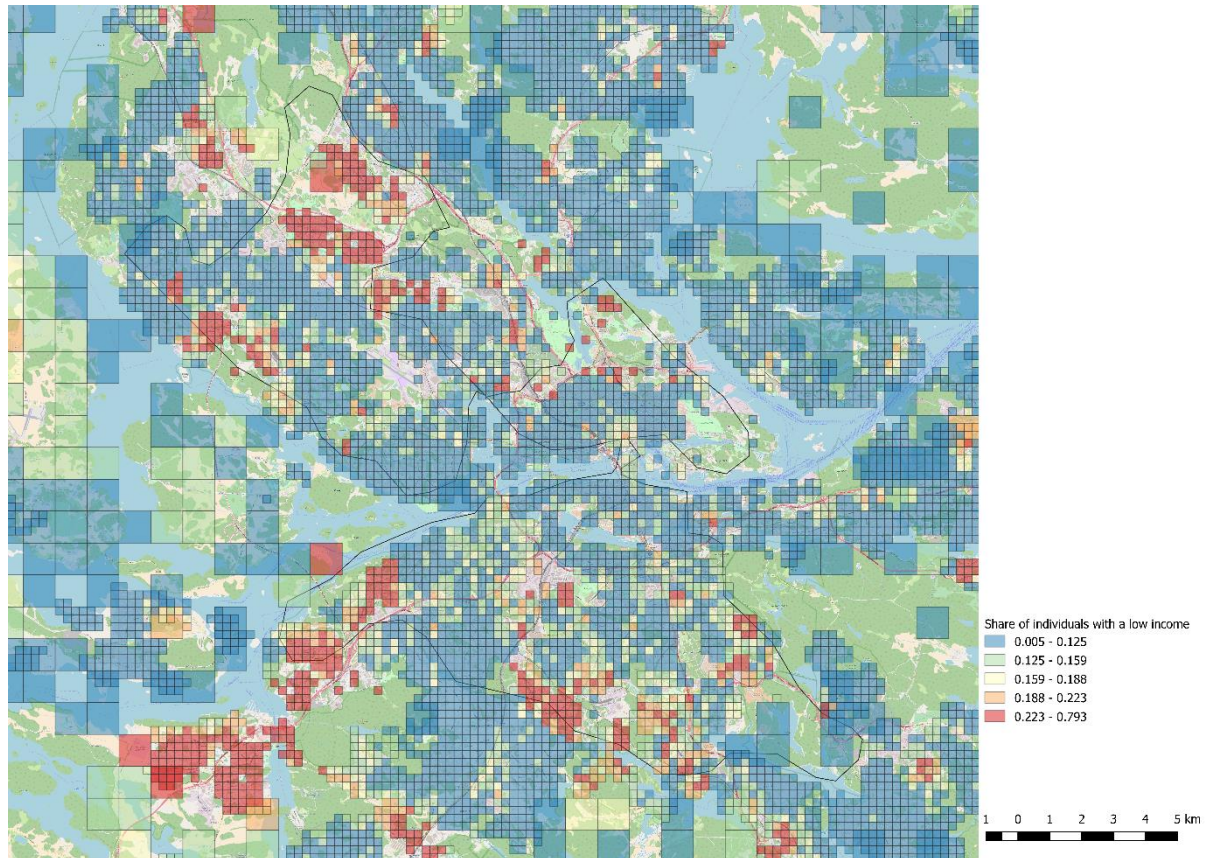


Figure 13 Share of individuals with a low income in Stockholm for  $k=200$

### 6.5.2 Sweden – Västerbotten

The second case study area in Sweden is Västerbotten county, a large (55,432 km<sup>2</sup>) predominantly rural and sparsely populated area. The population is largely concentrated along the coast. Inland communities are getting depopulated due to a lack of basic service provision (hindered by long travel distances). Finally, many smaller municipalities have generally below-average levels of education compared with that of the country as a whole. As the whole county of Västerbotten is too large to plot in a map, we zoomed in on a part of the county to be able to show the concentration of poverty based on 1km by 1km and 250m by 250m grid cells. Figure 12 shows the concentration of individuals with a low income at the largest geographical scale of 51,200 neighbours. As shown on the map, at this scale the area as a whole has a low concentration of individuals with a low income, ranging from 8 to 15% of the nearest 51,200 neighbours. However, when we look at smaller spatial scales, we see that within the area there is actually a lot of variation in the concentration of poverty. These concentrations of poverty are averaged out and therefore masked when looking at a higher spatial scale. Looking at the lowest scale in Figure 15 ( $k=200$ ), we again see clear 'social frontiers', as indicated by areas with high concentrations of poverty (22 to 79% of the nearest 200 individuals) next to areas with very low concentrations of poverty (3 to 14% of the nearest 200 individuals).

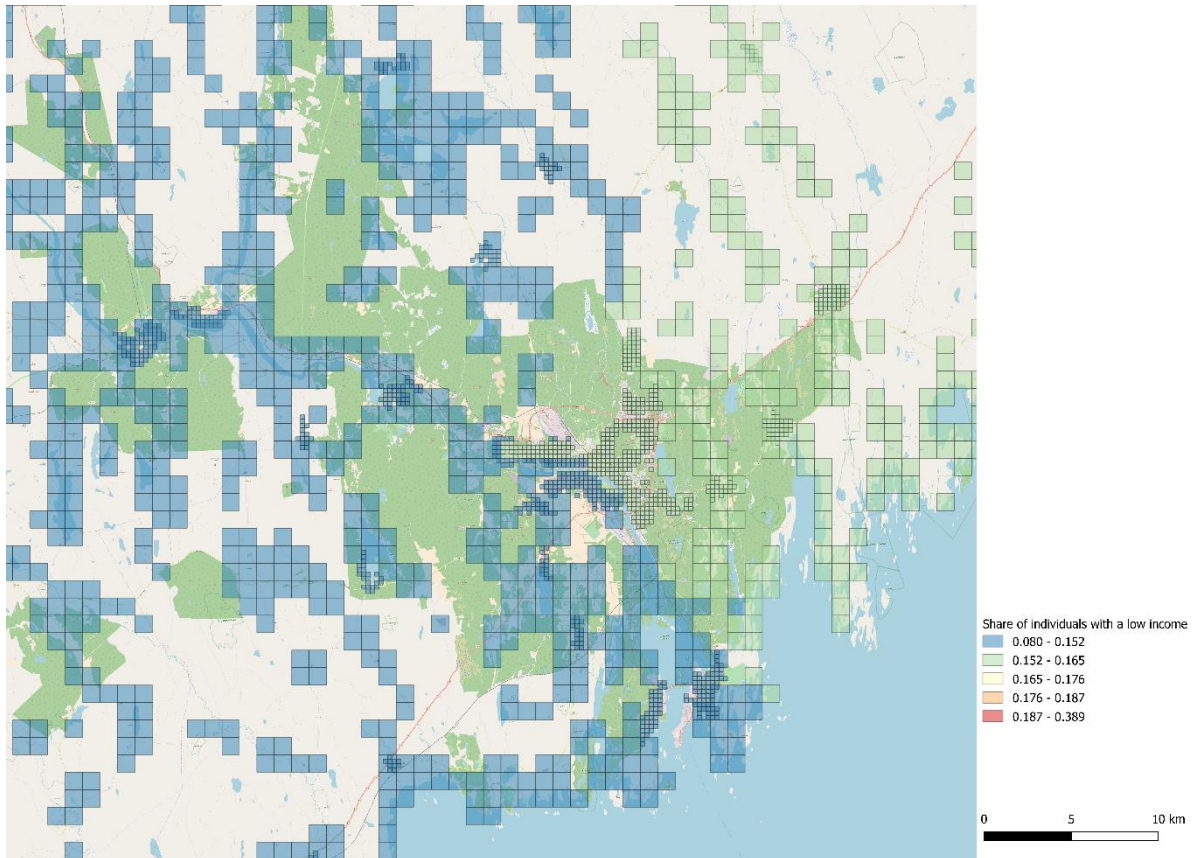


Figure 14 Share of individuals with a low income in Västerbotten for  $k=51,200$

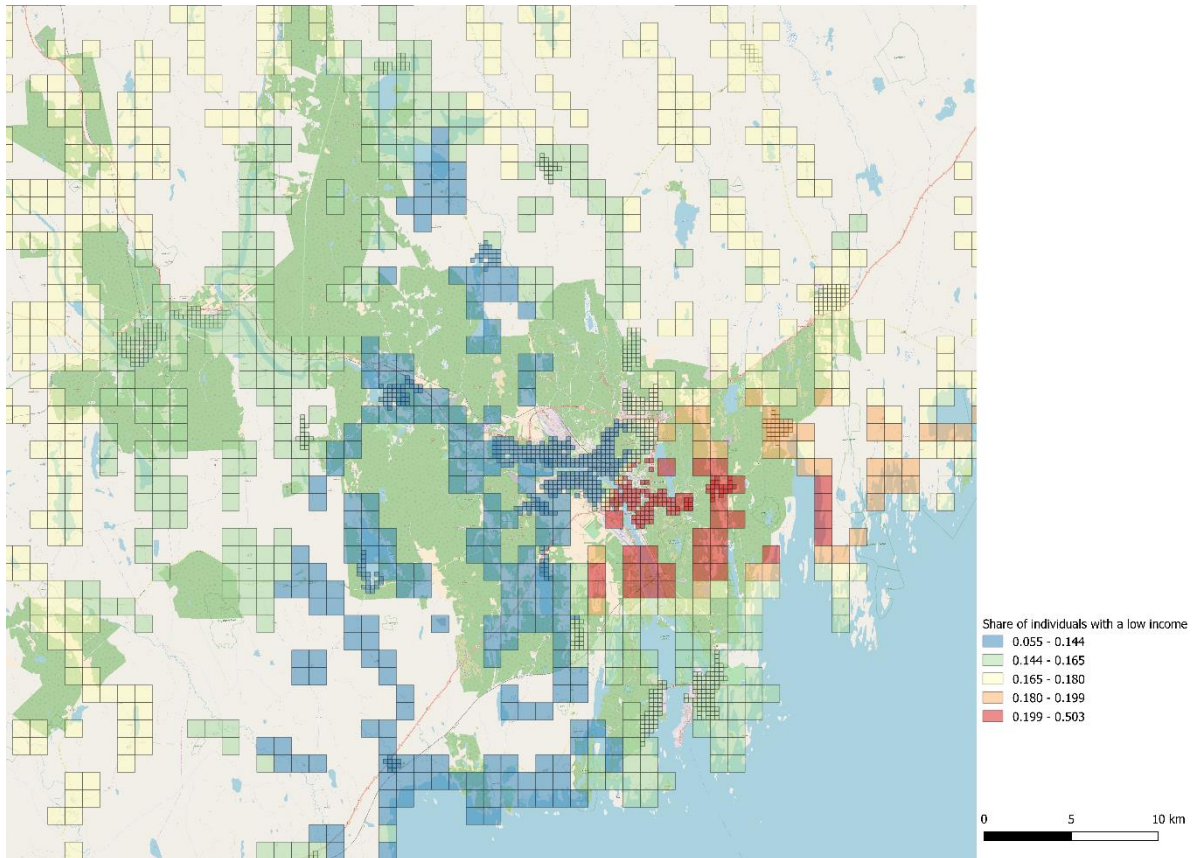


Figure 15 Share of individuals with a low income in Västerbotten for  $k=12,800$

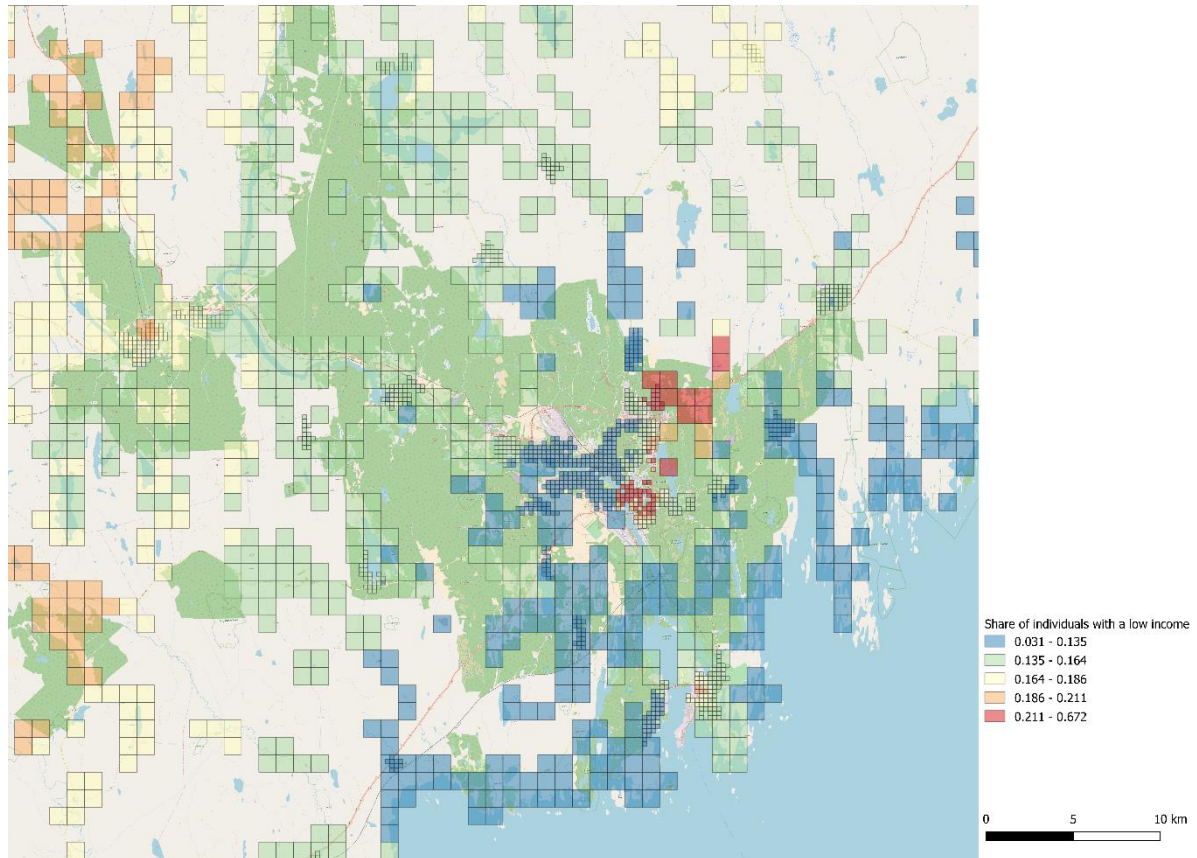


Figure 16 Share of individuals with a low income in Västerbotten for  $k=1,600$

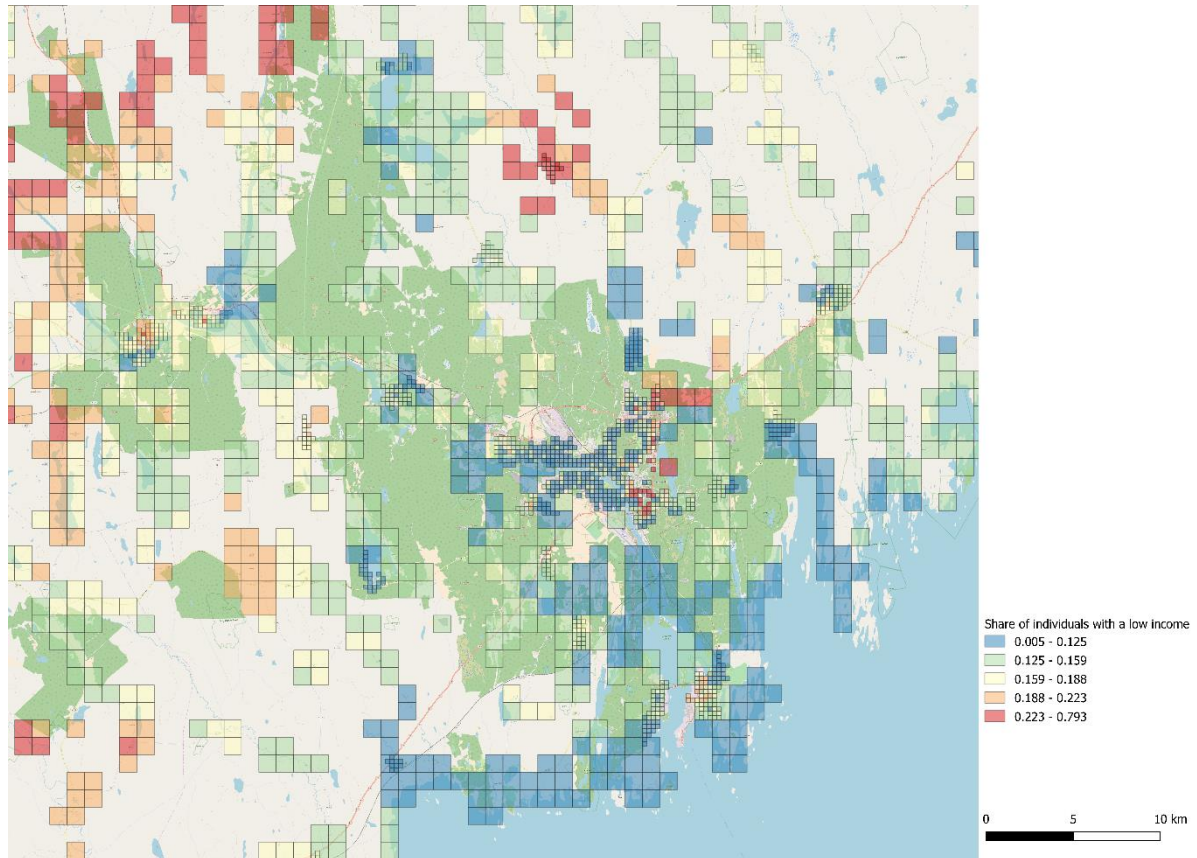


Figure 17 Share of individuals with a low income in Västerbotten for  $k=200$

### 6.5.3 The Netherlands – Rotterdam Zuid

The first cases study area that has been selected for the Netherlands is Rotterdam Zuid, the South Bank of Rotterdam, which is the second largest city in the Netherlands. The urban area is characterised by persistent deprivation and has the lowest scores in all of the Netherlands on characteristics such as unemployment, education, crime and general liveability. Looking at the concentration of poverty at the large and medium geographical scales, as plotted in Figures 16, 17 and 18, we see that the complete area has high concentrations of poverty. Almost all parts of Rotterdam Zuid fall in the top 20% of areas with the highest concentrations of poverty in the Netherlands. However, if we look at the poverty concentrations at the lowest spatial scale (k-200) as plotted in Figure 19, we see that within the case study area there is substantial variation in the concentration of poverty. Although the greater part of Rotterdam Zuid still falls in the top 20% of areas with the highest concentration of poverty, there are also parts that are relatively affluent, belonging to 20% areas with the lowest concentrations of poverty.

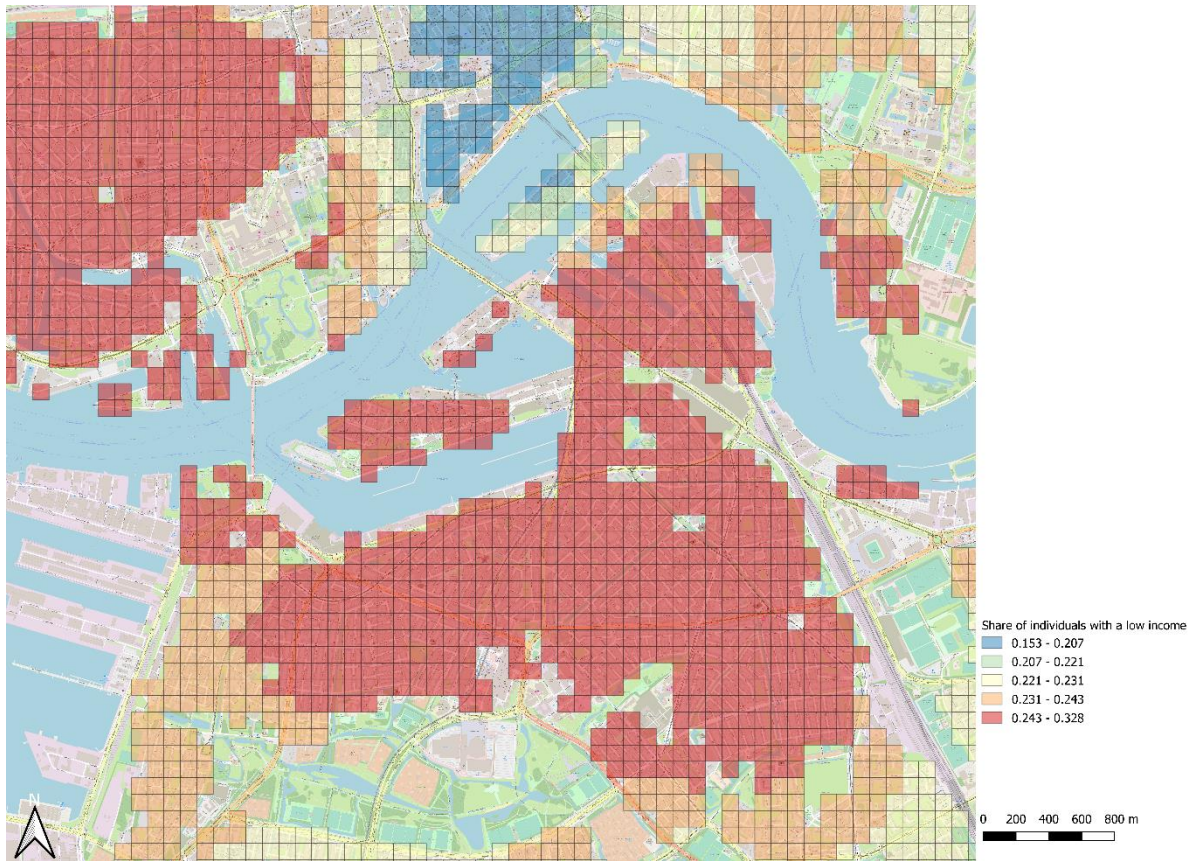


Figure 18 Share of individuals with a low income in Rotterdam Zuid for  $k=51,200$

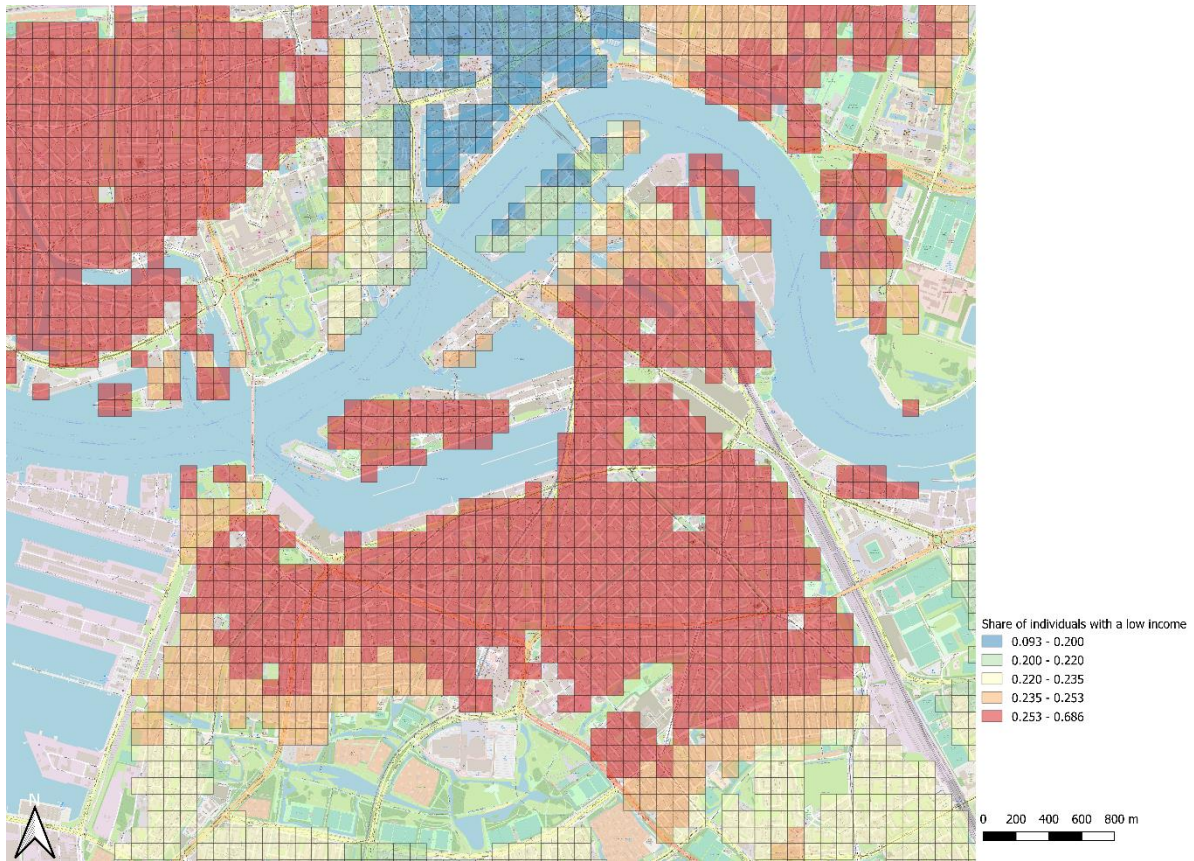


Figure 19 Share of individuals with a low income in Rotterdam Zuid for  $k=12,800$

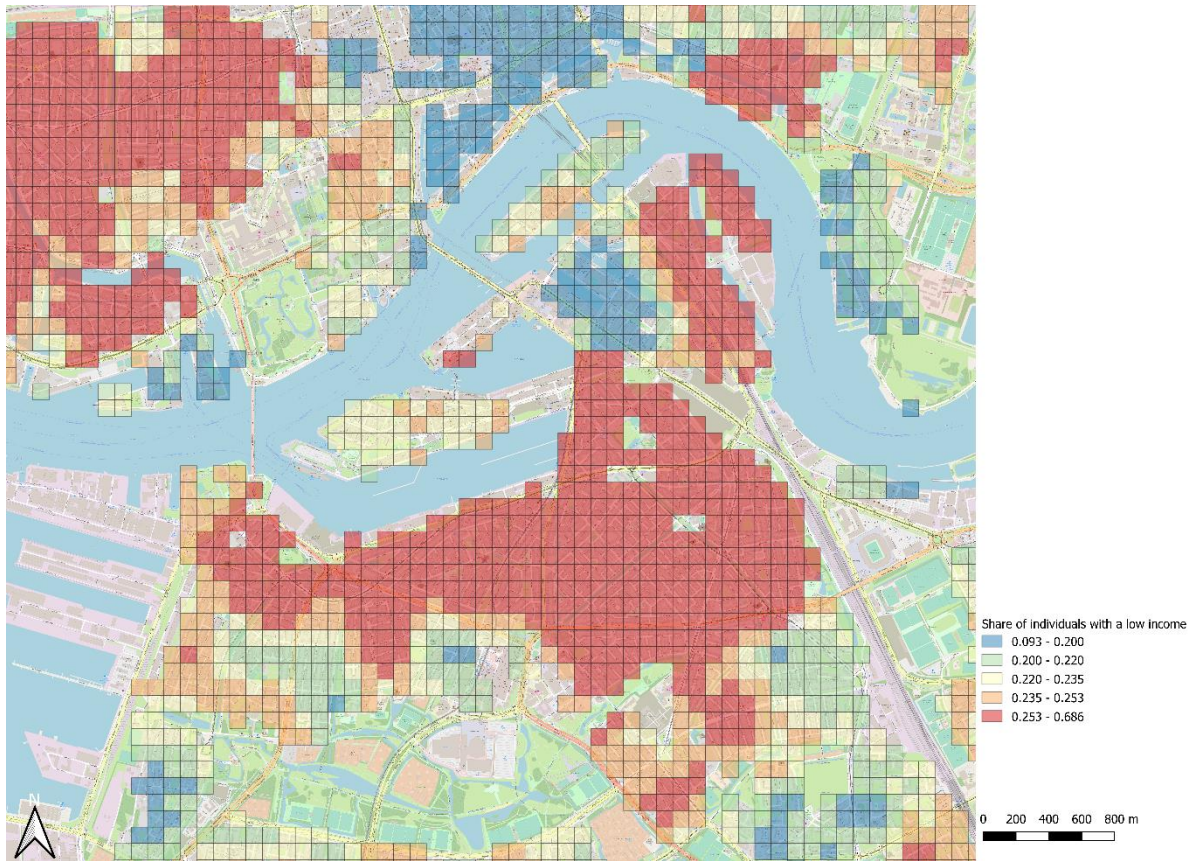


Figure 20 Share of individuals with a low income in Rotterdam Zuid for  $k=1,600$

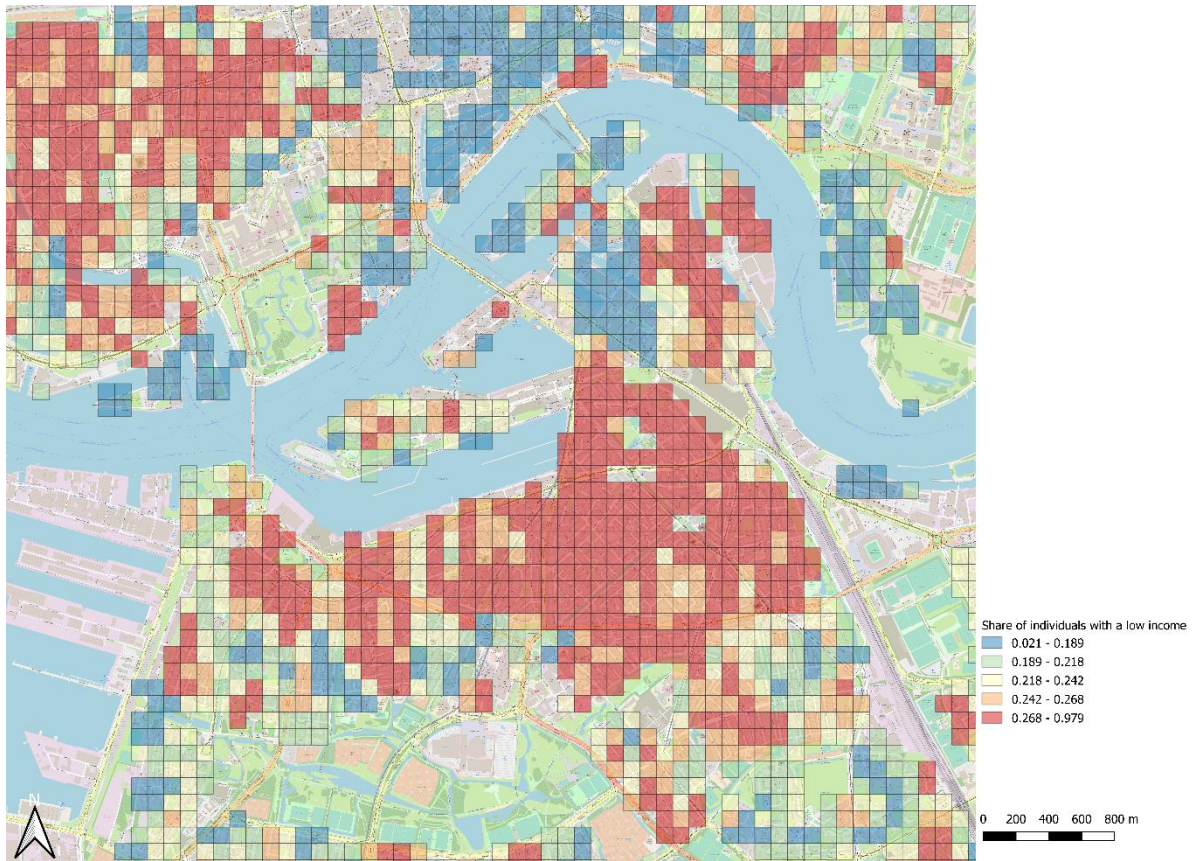


Figure 21 Share of individuals with a low income in Rotterdam Zuid for  $k=200$

#### 6.5.4 The Netherlands – Groningen

The second case study area that has been selected in the Netherlands is the region of North East Groningen. The area is predominantly rural, and income and education levels are below the national average. As the whole area of North East Groningen is too large to plot in a map, we zoomed in on the municipality of Groningen to be able to show the concentration of poverty based on 100m by 100m grid cells. At the largest spatial scales, mapped in Figures 20 and 21, there is a clear pattern of concentrated poverty in the city centre of Groningen, and more affluent areas can be found in the South and North East of the city. At a moderate and low spatial scale, we see again that there is substantial spatial variation in the percentage of individuals with a low income. In those areas which are characterised as relatively affluent at higher scales, at lower scales concentrations of poverty can be found. And in the city centre, which is relatively poor on a higher scale, there are clear pockets of relatively affluent grid cells. As we have seen in the other case study areas, in Groningen there are ‘social frontiers’ (Dean et al., 2018) as well, with areas falling in the top 20% of most poor next to areas belonging to the top 20% most affluent right next to each other.

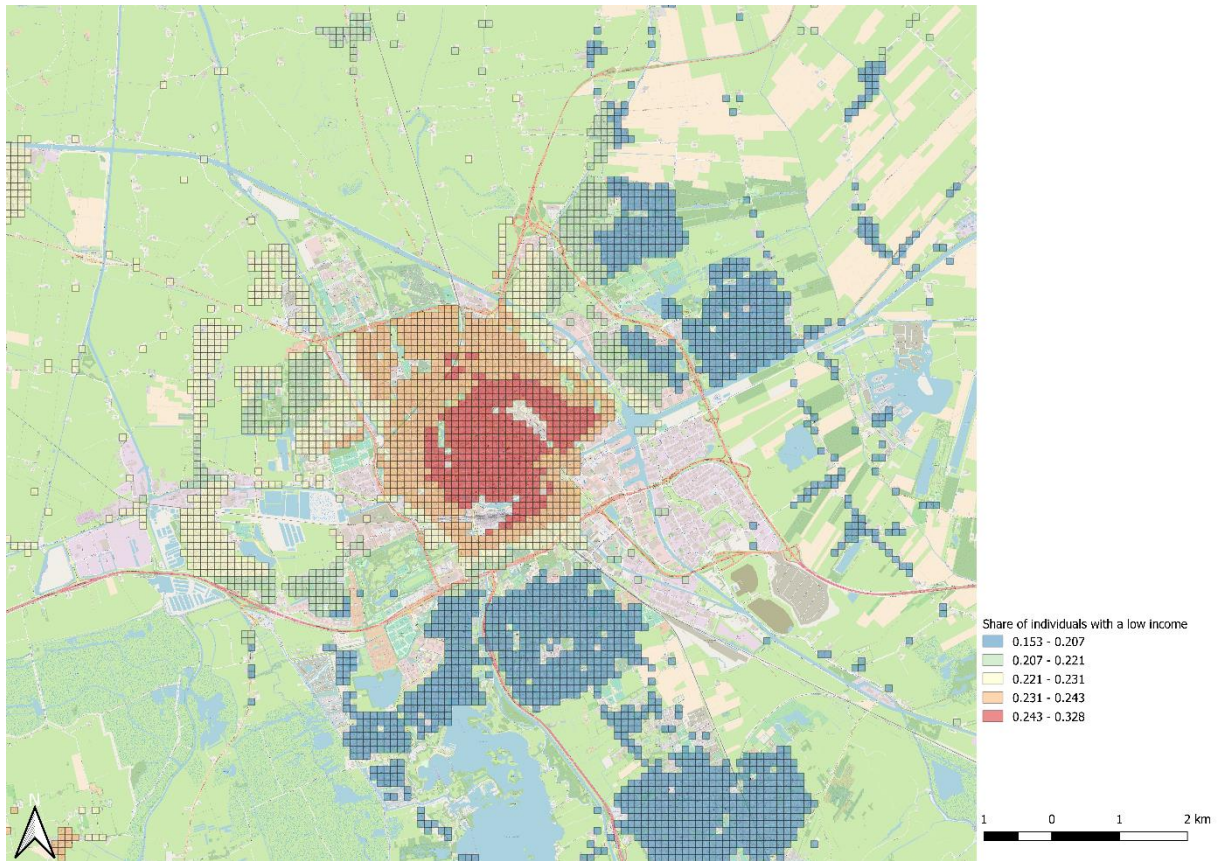


Figure 22 Share of individuals with a low income in Groningen for  $k=51,200$

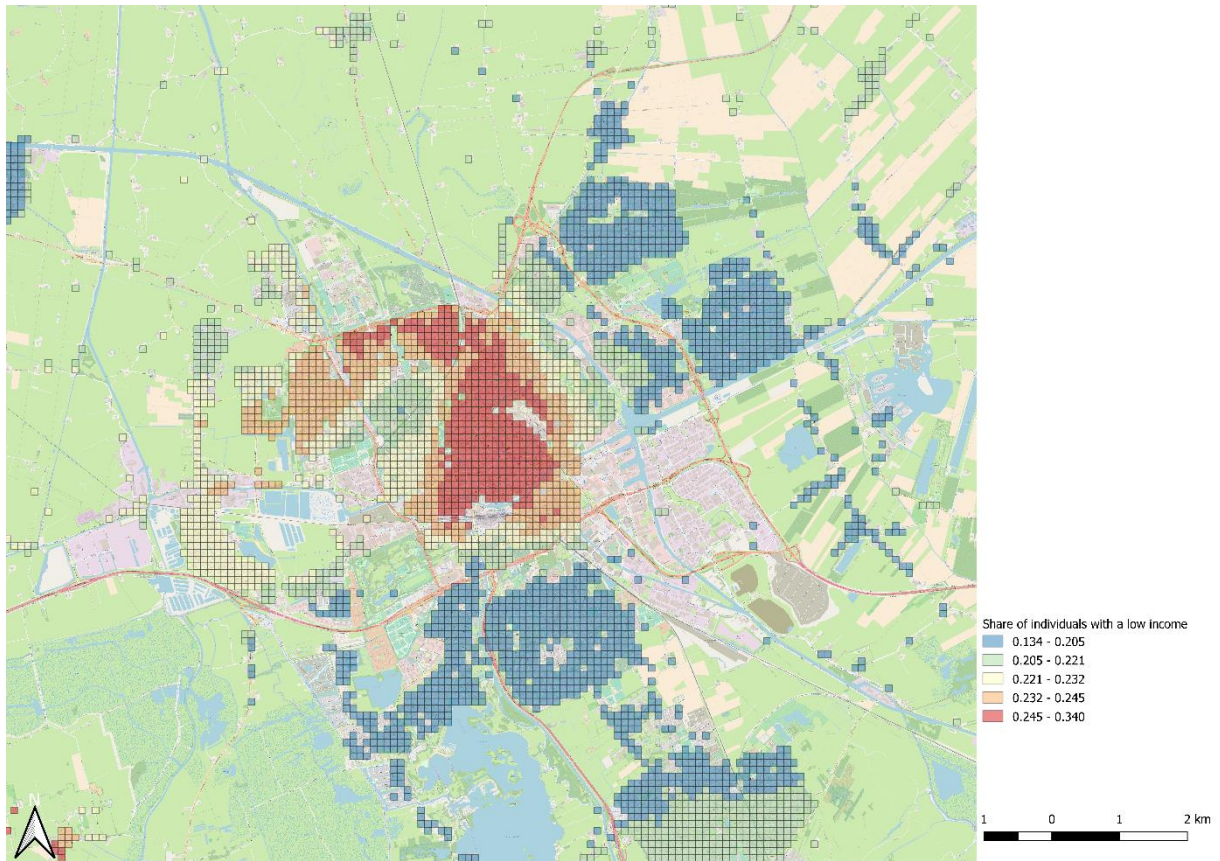


Figure 23 Share of individuals with a low income in Groningen for  $k=12,800$

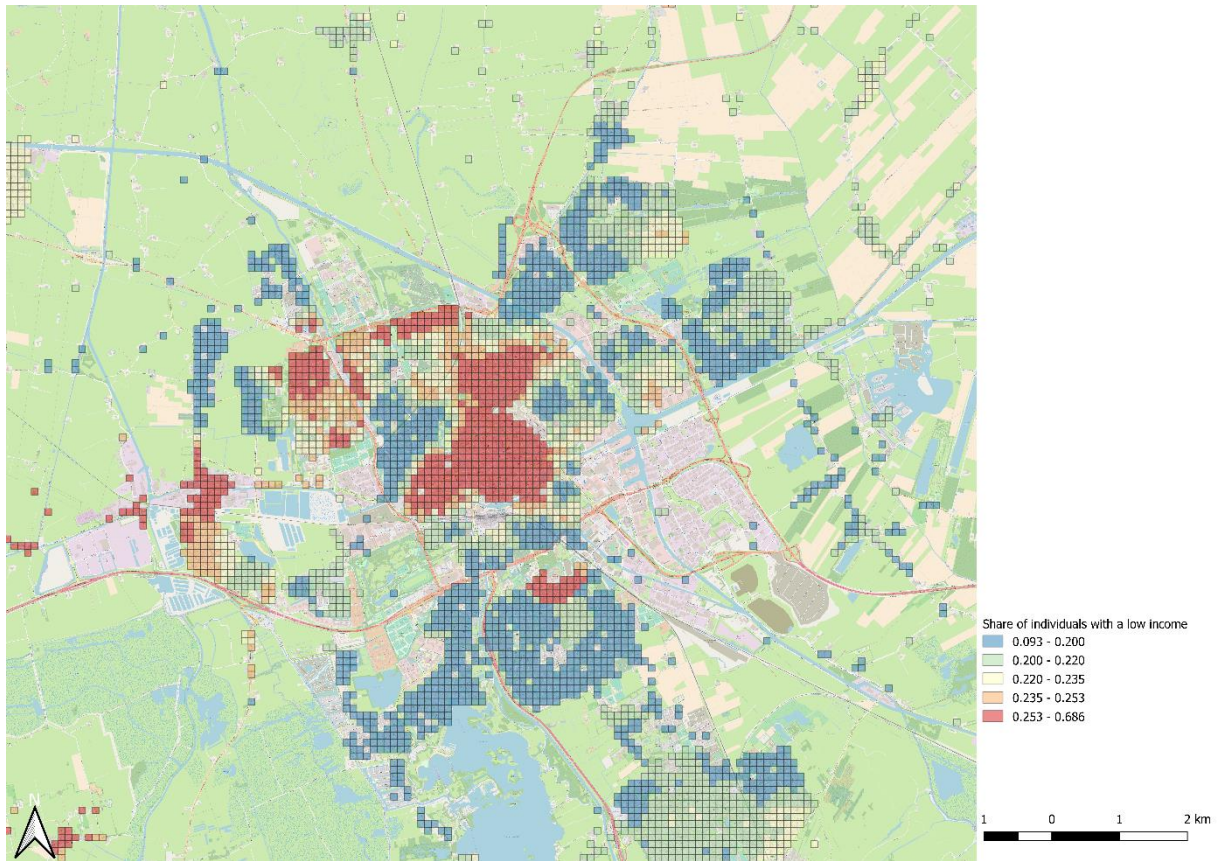


Figure 24 Share of individuals with a low income in Groningen for  $k=1,600$

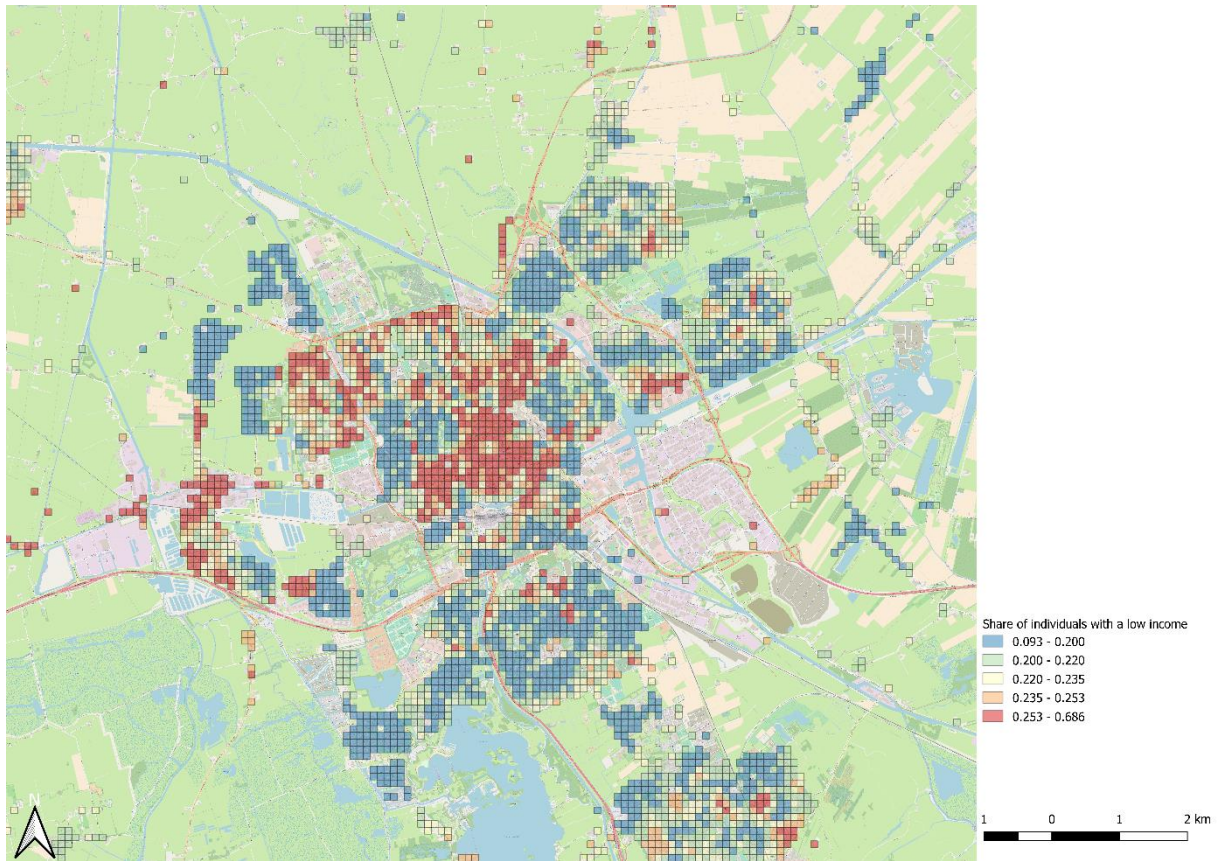


Figure 25 Share of individuals with a low income in Groningen for  $k=200$

### 6.5.5 Finland – Kotka

The first case study area that has been selected in Finland is the region of Kotka (277.74 km<sup>2</sup>), which is intermediate on the urban-rural scale. The region has suffered from population decline during the last decades and compared to national averages, the region is also an underperformer in terms of development of GDP and unemployment. Also for this case study area, we zoomed in on a part of the area in order to be able to plot concentrations of poverty based on a 250m by 250m grid. As shown in Figure 26-Figure 29, at large and medium geographical scales, there is almost no variation in the concentration of poverty in this area. At these larger geographical scales all areas fall in the top 20% of areas with the highest concentration of individuals with a low income in Finland. At low geographical scales we see a little more variation. Within the relatively poor area, there are areas falling in the top 20% of areas with the lowest proportion of individuals with a low income.

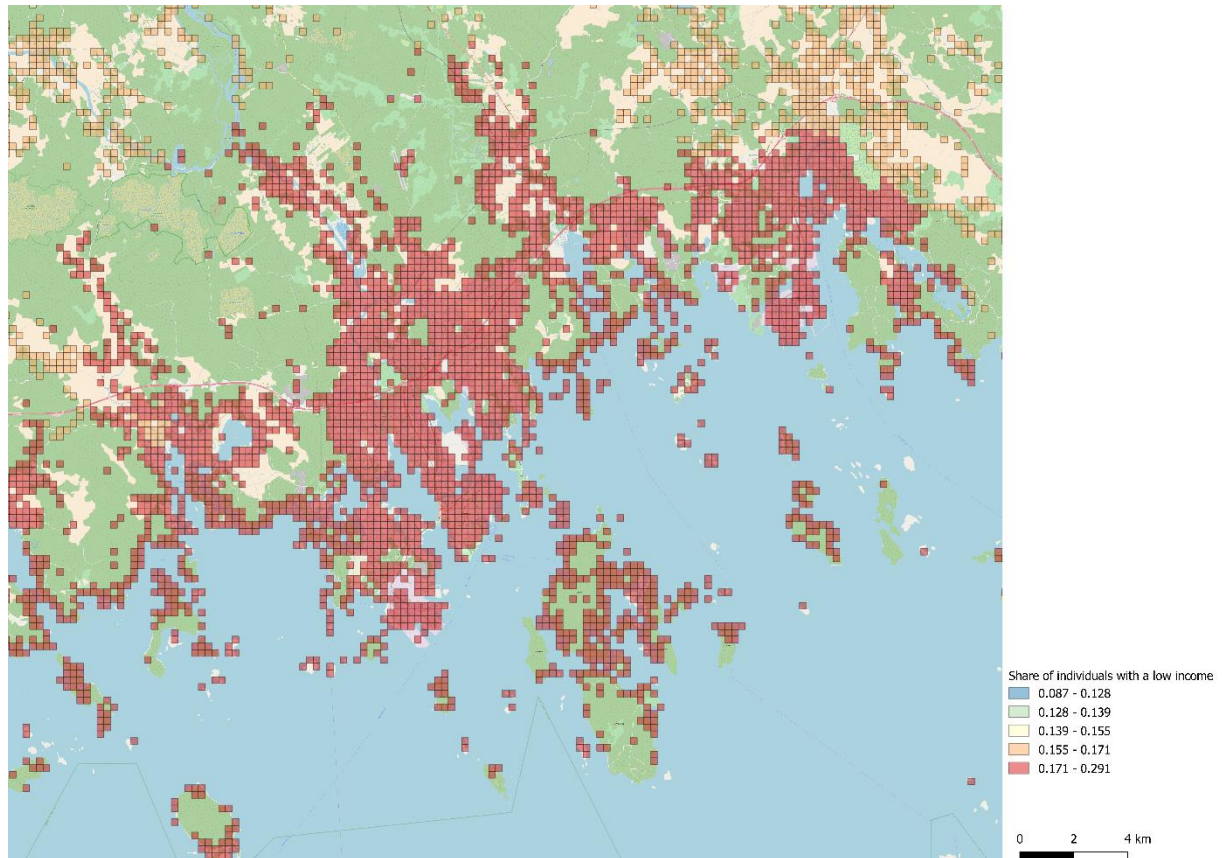


Figure 26 Share of individuals with a low income in Kotka for  $k=51,200$

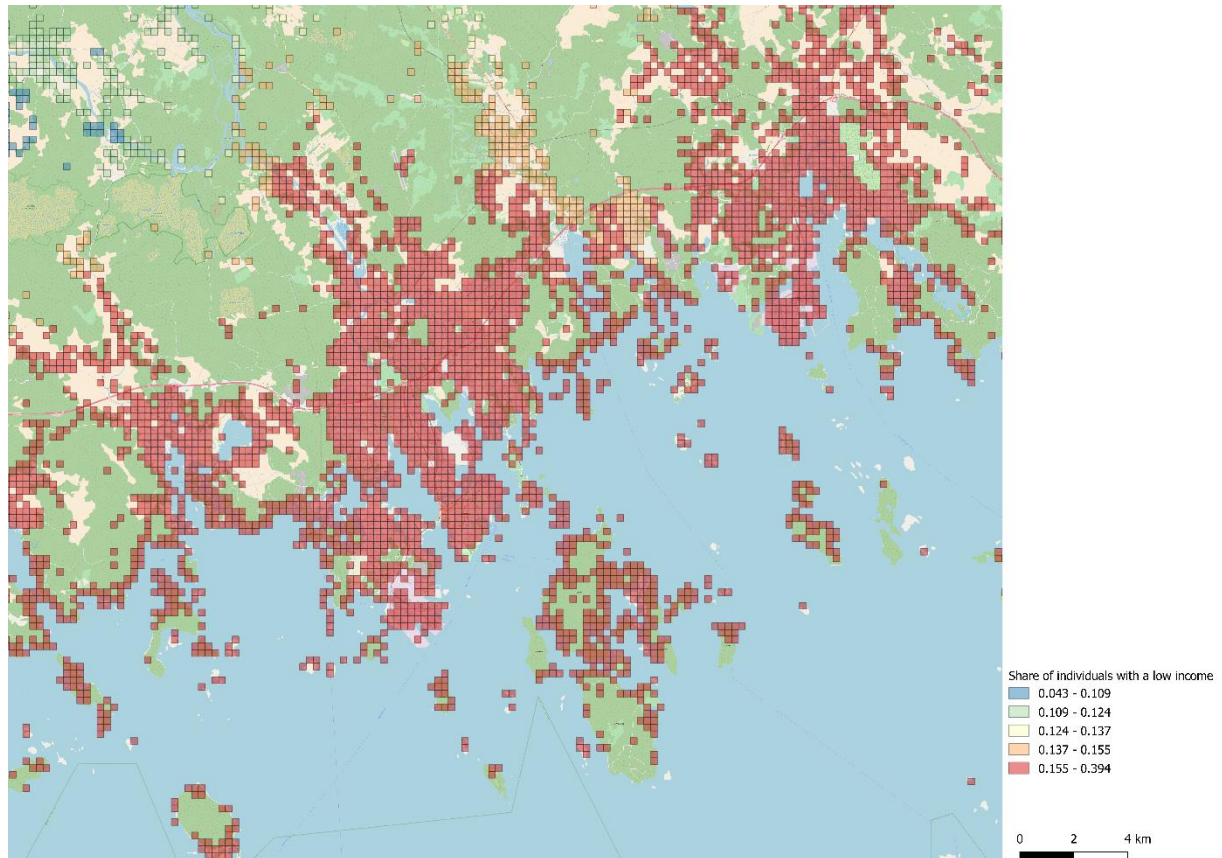


Figure 27 Share of individuals with a low income in Kotka for  $k=12,800$

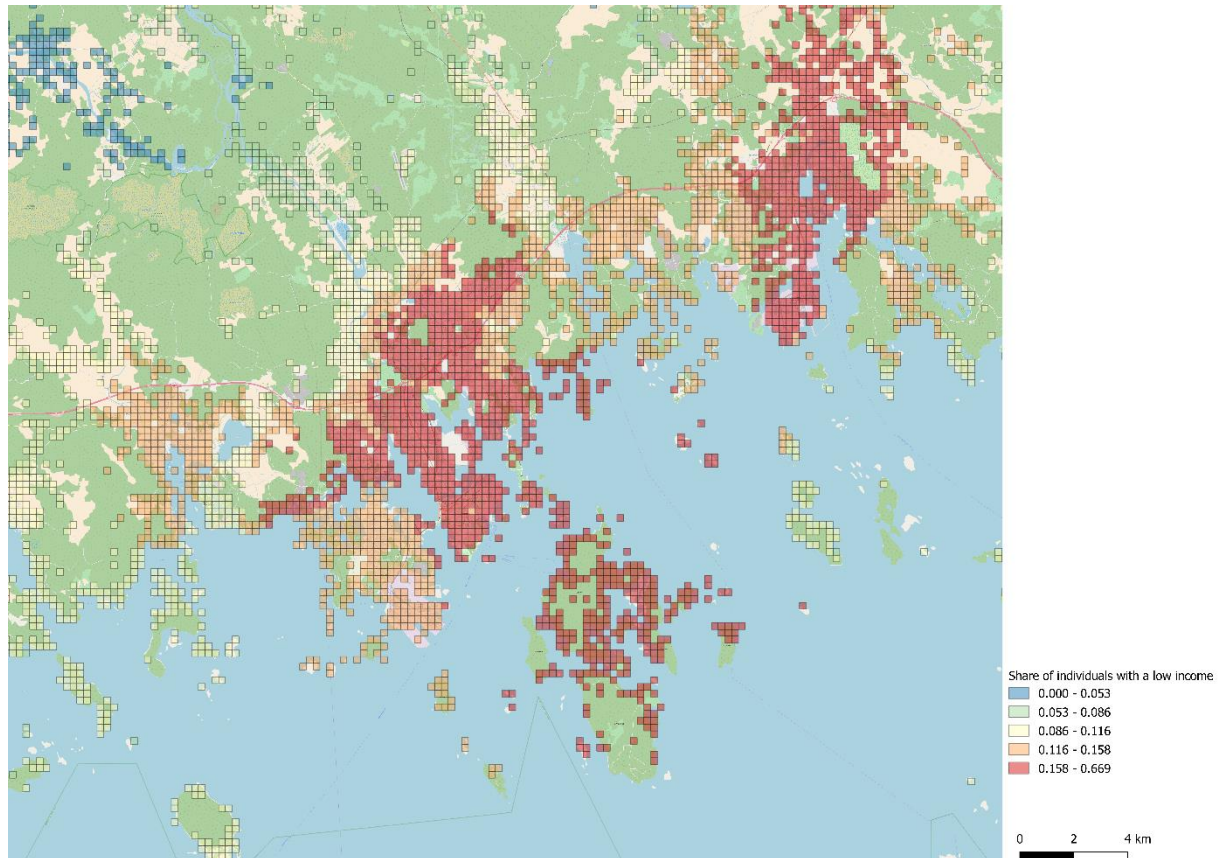


Figure 28 Share of individuals with a low income in Kotka for  $k=1,600$

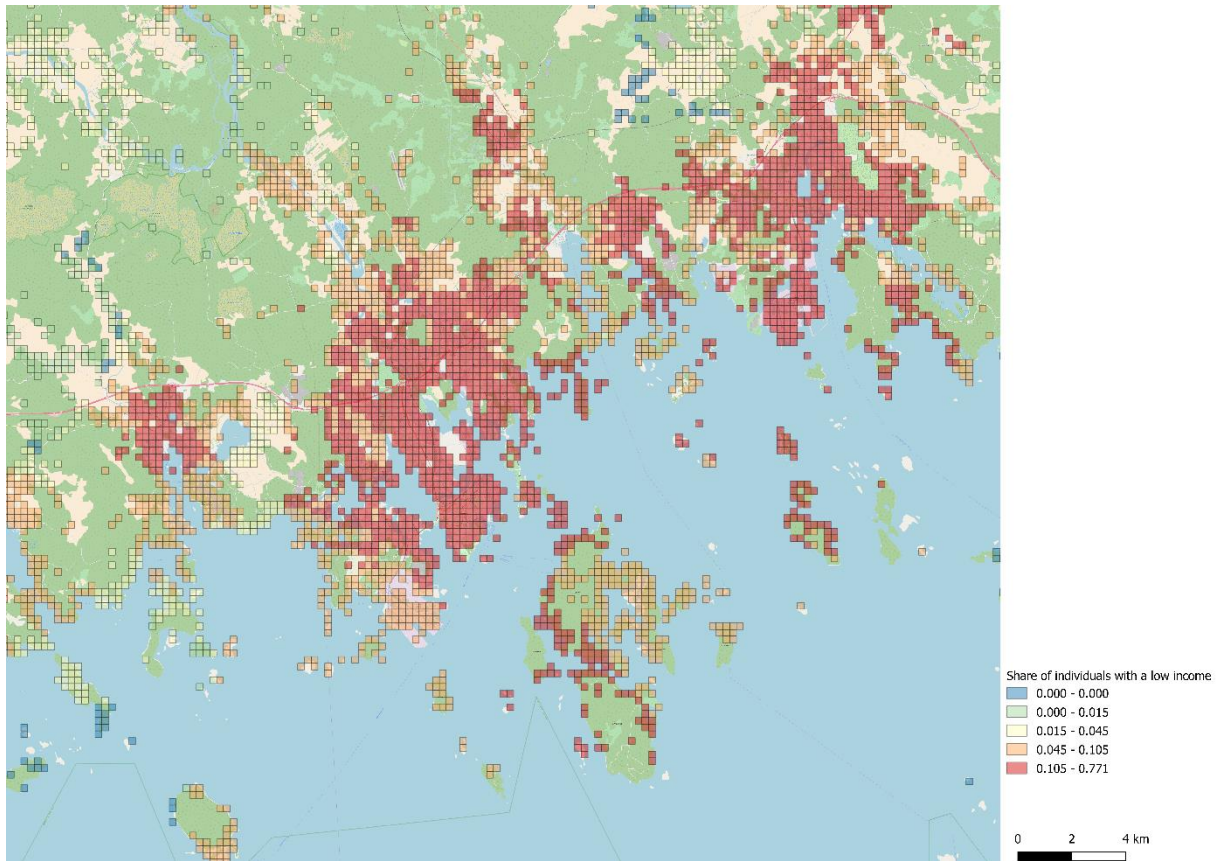


Figure 29 Share of individuals with a low income in Kotka for  $k=200$

### 6.5.6 Finland – Lieksa

The second case study area that has been selected in Finland is the predominantly rural municipality of Lieksa in the Eastern part of the country. Lieksa suffers from high levels of unemployment and low levels of general wellbeing. At the highest spatial scale as mapped in Figure 28, the concentration of poverty in the area is moderately high with all areas falling in the third and fourth quintile. Zooming further in towards lower spatial scales In Figures 29-31, we see that this average moderate poverty concentration at the highest geographical scale is due to a strong concentration of individuals with a low income in the city centre and low concentrations of poverty in the outskirts of Lieksa. Also in rural areas the method presented shows the value of zooming in on smaller scale areas when investigating spatial inequality.

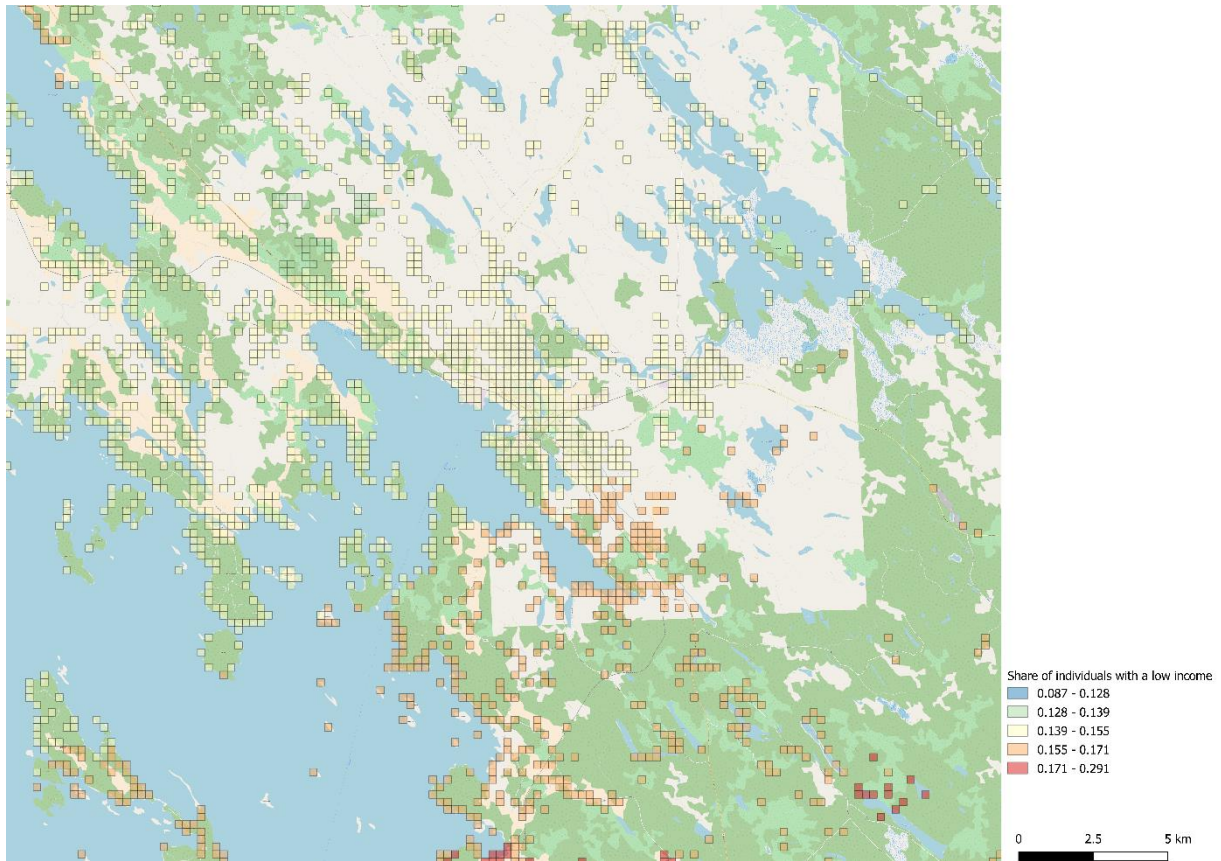


Figure 30 Share of individuals with a low income in Lieksa for  $k=51,200$

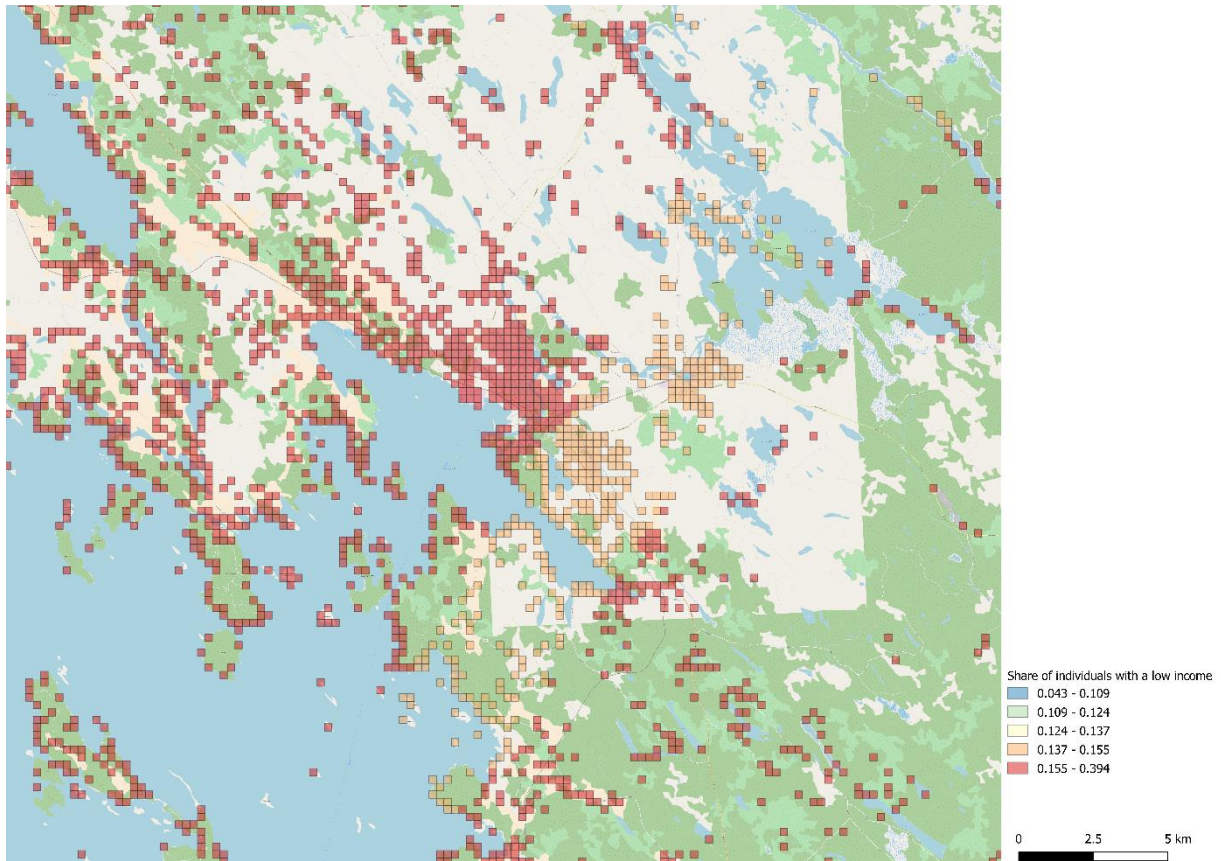


Figure 31 Share of individuals with a low income in Lieksa for  $k=12,800$

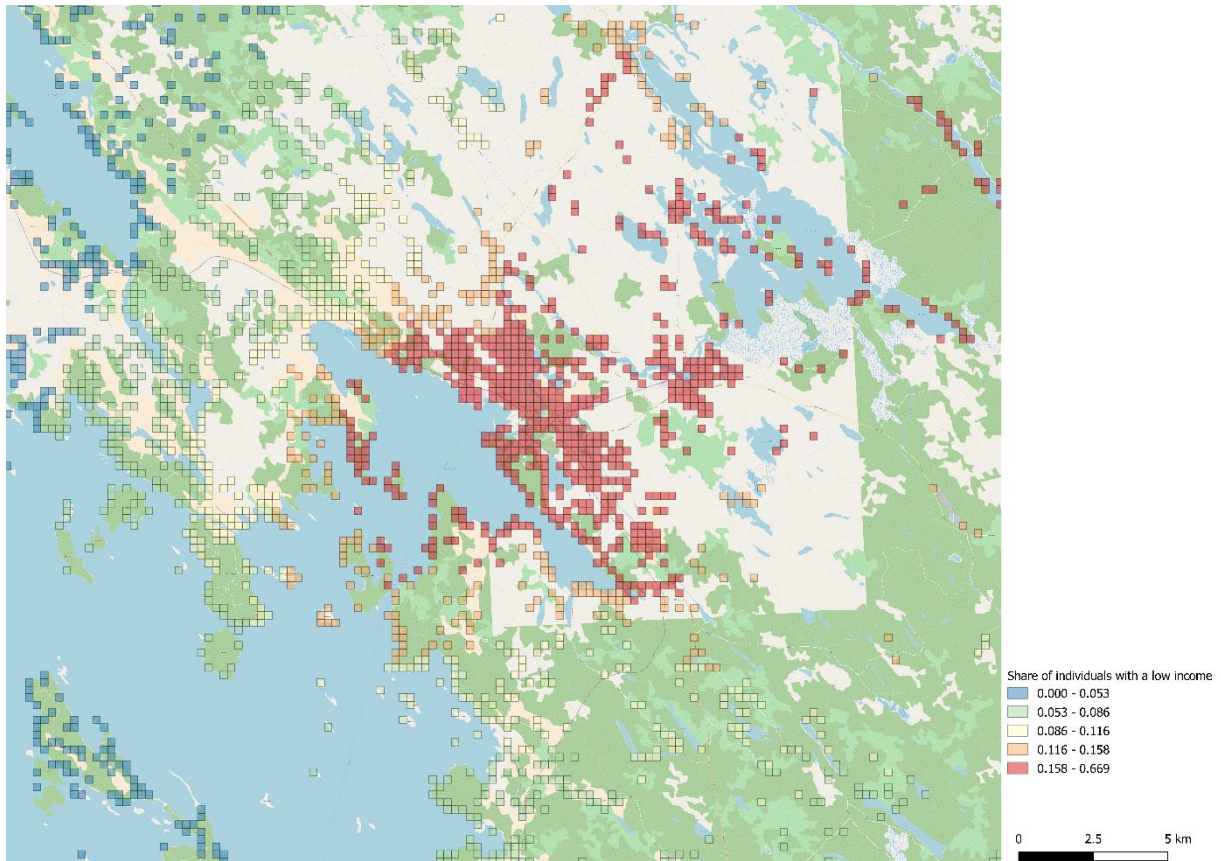


Figure 32 Share of individuals with a low income in Lieksa for  $k=1,600$

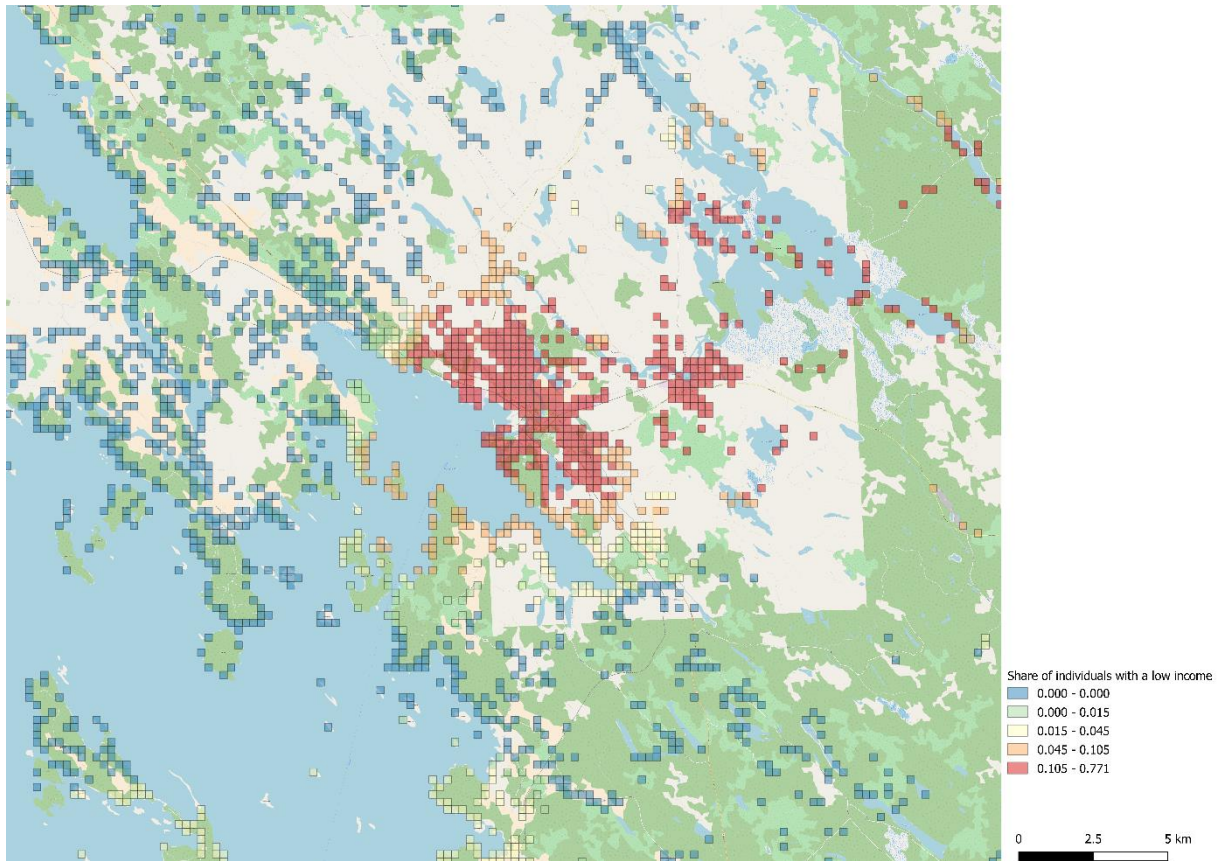


Figure 33 Share of individuals with a low income in Lieksa for  $k=200$

### 6.5.7 UK – Lewisham Borough

The first case study area that has been selected in the UK is the Ladywell ward of the London Borough of Lewisham. Lewisham is a growing Inner London borough, with a population estimated at 301,000 in 2016, almost half of whom are from an ethnic minority background. Lewisham scores high on levels of deprivation for income, crime, housing and services and living environment, compared to other England Local Authorities. In Figure 34 and Figure 35 the concentration of households with a low income are mapped based on a 1km by 1 km grid for the two highest scales. As noted before, we do not show the maps for the two lowest scales as this would not be meaningful. Although not as clear as for the previously discussed case study areas, also here it can be seen that zooming in on a smaller scale reveals more localised concentrations of inequality which are missed when inequality is only studied for the highest scale.

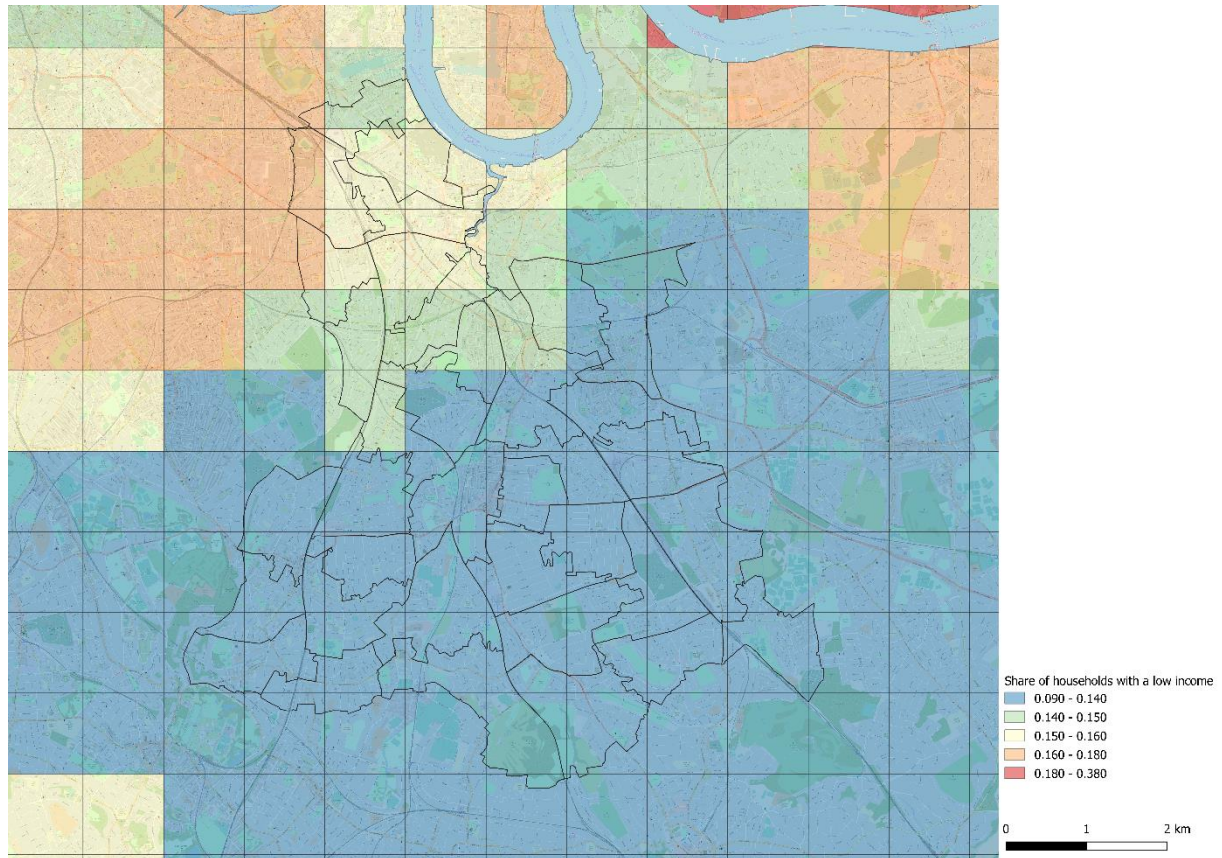


Figure 34 Estimated share of households with a low income in Lewisham Borough for  $k=51,200$

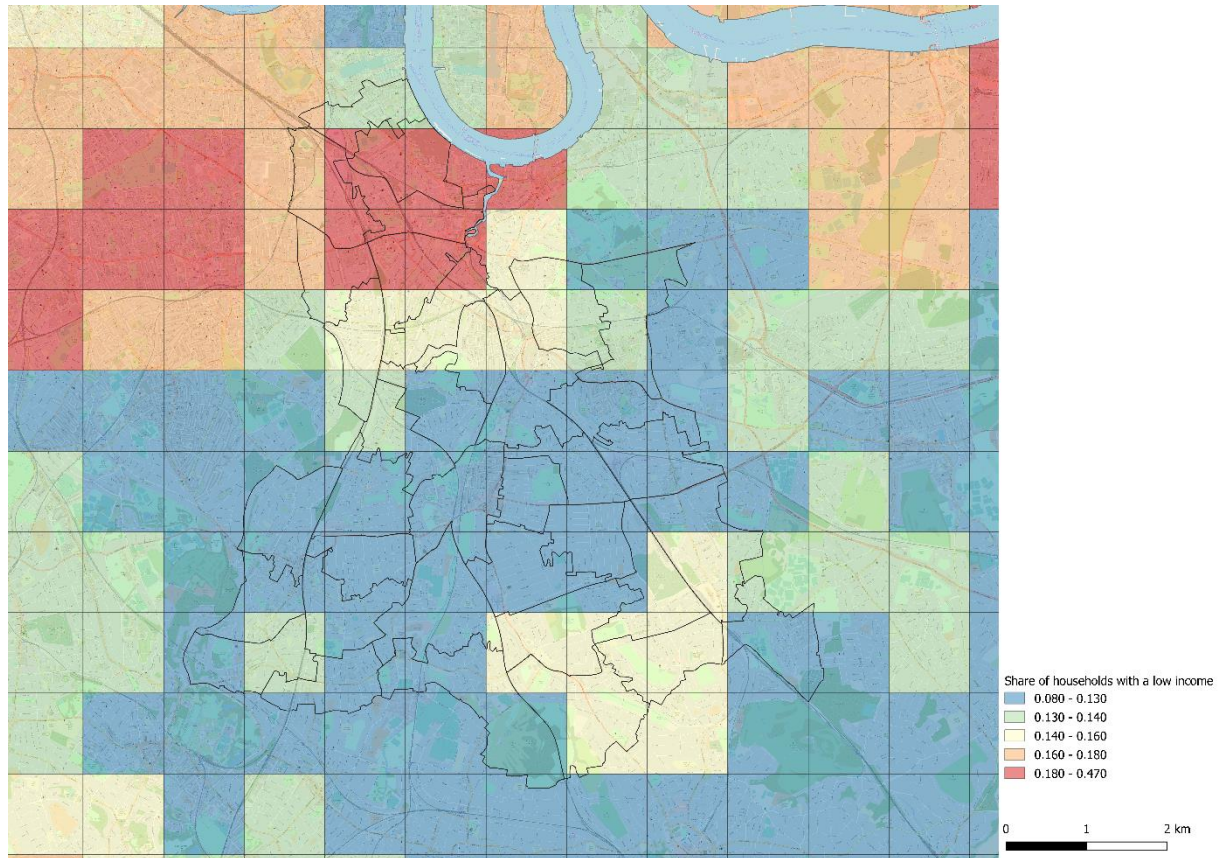


Figure 35 Estimated share of households with a low income in Lewisham Borough for  $k=12,800$

### 6.5.8UK - Northumberland

The second case study<sup>5</sup> that has been selected for England is a rural area located within the Northumberland Uplands Local Action Group (NULAG) area and in particular the Northumberland National Park Authority (NNPA). This is England's most remote and sparsely populated rural area, bordering Scotland to the north. The population of 55,000 (density 17/km<sup>2</sup>) faces familiar challenges of other deep rural areas, such as isolation, problems maintaining public services, a lack of good quality jobs and a lack of affordable housing. At high geographical scale (Figure 36), we see that the concentration of poverty in Northumberland is low to moderate. At this spatial scale, all areas in the county fall in the 60% of all areas in England with the lowest concentrations of poverty. Looking at a slightly lower spatial scale ( $k=12,800$ ) in Figure 37, we see that the concentration of households with a low income is especially somewhat higher in the Northern part of the county.

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<sup>5</sup> There is a third case study located in one of the most remote islands of Scotland (Outer Hebrides). As noted earlier, we have excluded these islands from the EquiPop analysis due to the very sparse population settlement patterns, which make the bespoke neighbourhood approach based on small areas inappropriate.

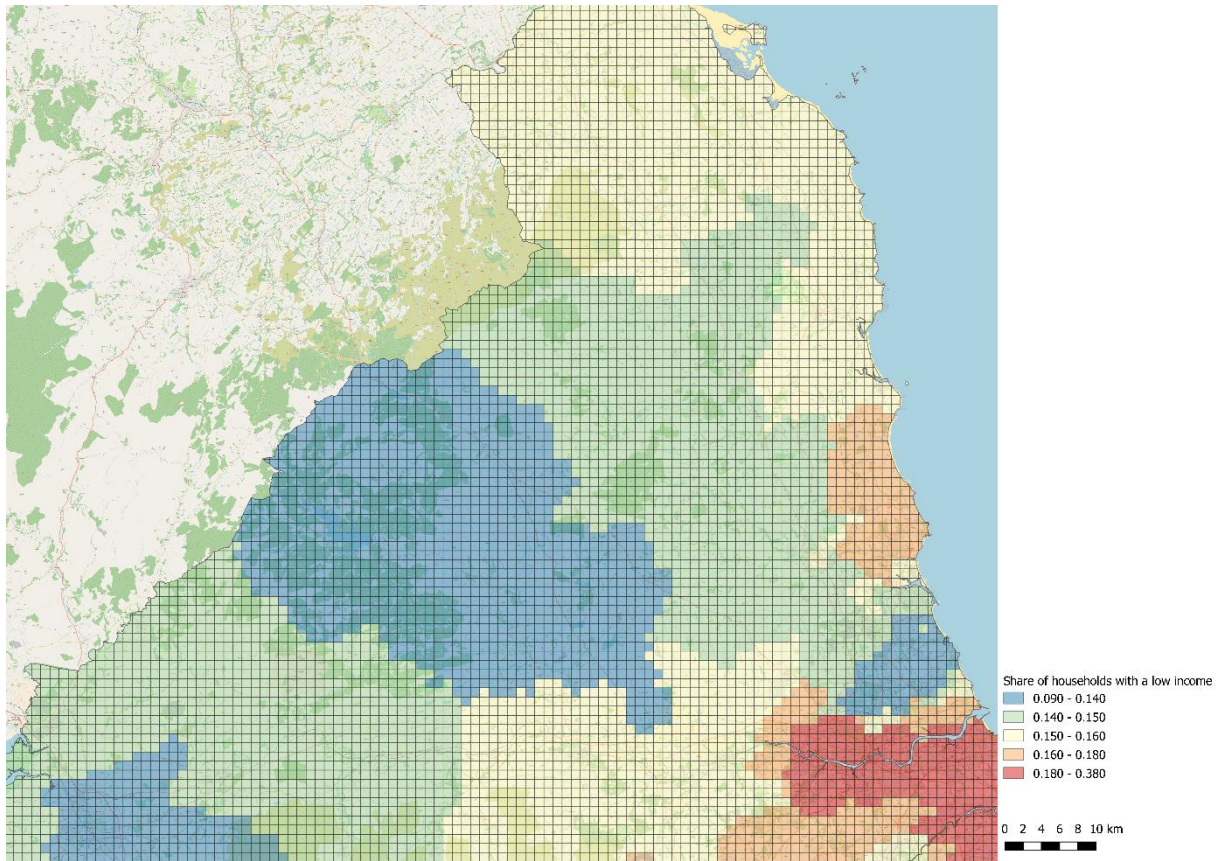


Figure 36 Estimated share of households with a low income in Northumberland for  $k=51,200$

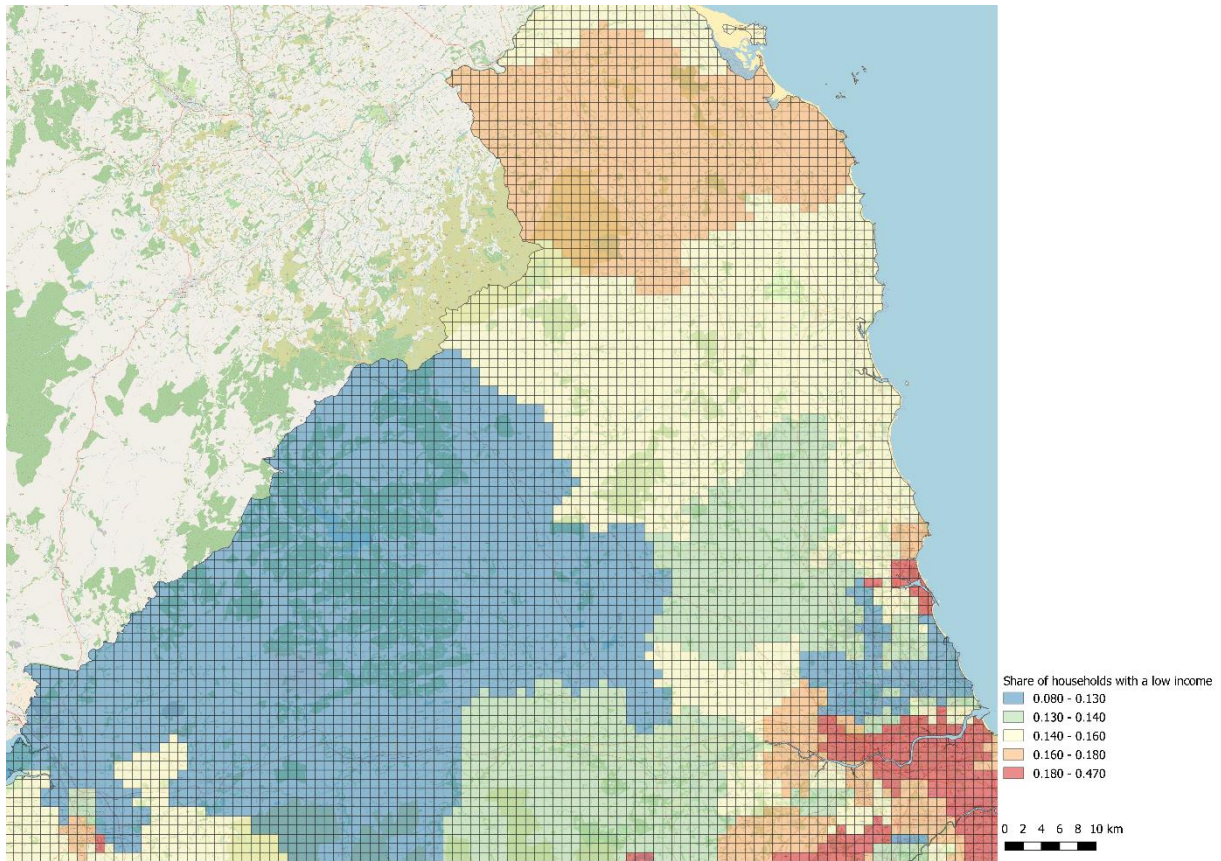


Figure 37 Estimated share of households with a low income in Northumberland for  $k=12,800$



## 7. Conclusion

The main objective of this report on Task 5.2 of the EU Horizon 2020 research project RELOCAL - ‘Resituating the local in cohesion and territorial development’ was to demonstrate how standardized tools can be used for the analysis of patterns of spatial inequality, and how such tools can be applied to different types of geographical data in different countries. By using the *k*-nearest neighbours method we showed patterns of spatial inequality at different spatial scales in a cross national comparison for Finland, Sweden, The Netherlands, England and Scotland, and we showed how these patterns differ by geographical scale. Comparing the patterns of spatial inequality at the lowest spatial scale across Sweden, Finland and the Netherlands, we find the highest level of segregation can be observed in Finland, and the lowest level of segregation can be observed in the Netherlands. In addition, we find very similar patterns in Sweden, England and Scotland with levels of segregation between Finland and the Netherlands at this geographical scale. A possible explanation for this is the large social housing sector in the Netherlands, with social housing available in a large proportion of neighbourhoods. This indicates that even more affluent people are likely to live in relative close proximity of low income households in social housing.

In addition, we mapped patterns of spatial inequality for a selection of case study areas which will be used in Work Package 6. For each case study area we zoomed in from higher scales to very detailed lower scales, although for the UK we could not go down to the lowest scales. This exercise gave insight into the spatial scales which are relevant to understand the experiences of poverty by people living in the case study areas. At the higher spatial scale, the case study areas seem homogenous in terms of poverty levels. At lower spatial scales, however, the case study areas show a lot of spatial variation in poverty. Particularly interesting are the ‘social frontiers’ (Dean et al., 2018) that emerge: small areas with a high concentration of poverty next to small areas with a low concentration of poverty. With regard to the case studies, these ‘social frontiers’ might be particularly interesting as these are the areas in which individuals most likely experience spatial inequality in their direct residential environments.

The countries analysed in the current report had different geographical data available. The finest geographical detail was available in the Netherlands, with data for 100m by 100m grid cells. Finland and Sweden both had data available at the level of 250m by 250m grid cells in urban areas and 1km by 1km grid cells outside urban areas. Data for England and Scotland used for the analyses in this report had less geographical detail, with data on income available for Middle Layer Super Output Areas and Lower Layer Super Output Areas respectively. The lack of geographical detail for England and Scotland was due to the fact that we decided to use income data for the UK as well. And this income data is only available for relatively large areas. Of course there is more detailed geographical data available when using, for example, the index of multiple deprivation. But as this is a demonstrator project, we wanted to show what can be done using relatively similar indicators of poverty for each country. And this came at the expense of geographical detail, which proved to be problematic; for analysing patterns of spatial inequality by using bespoke neighbourhoods, data is needed at a really low spatial level. The strength of the  $k$ -nearest neighbours method used (using the EquiPop software) is that different types of data can be used to provide standardized measures of poverty concentration. By using the EquiPop software, for each geographical unit, the  $k$  nearest neighbours are calculated. This means that regardless of the geographical unit used as input for the analyses, the proportion of individuals (for Sweden, the Netherlands and Finland) or households (England and Scotland) with a low income are in all countries based on the same  $k$  neighbours. The bespoke neighbourhood approach is most effective and accurate when applied to very small spatial building blocks, such as available for the Netherlands. This unfortunately means that it cannot yet be applied to many countries, especially if the interest is on income.

To conclude, this demonstrator project has shown the value of mapping spatial inequality at various spatial scales. It has shown that spatial income inequality within regions is much more pronounced than between regions. The lower the geographical scale, the more variation in poverty concentrations. The effect of scale on measuring spatial inequality is not just a methodological gimmick; it is likely that people experience inequality at different spatial scales and that each spatial scale has its own independent effect on individual outcomes.

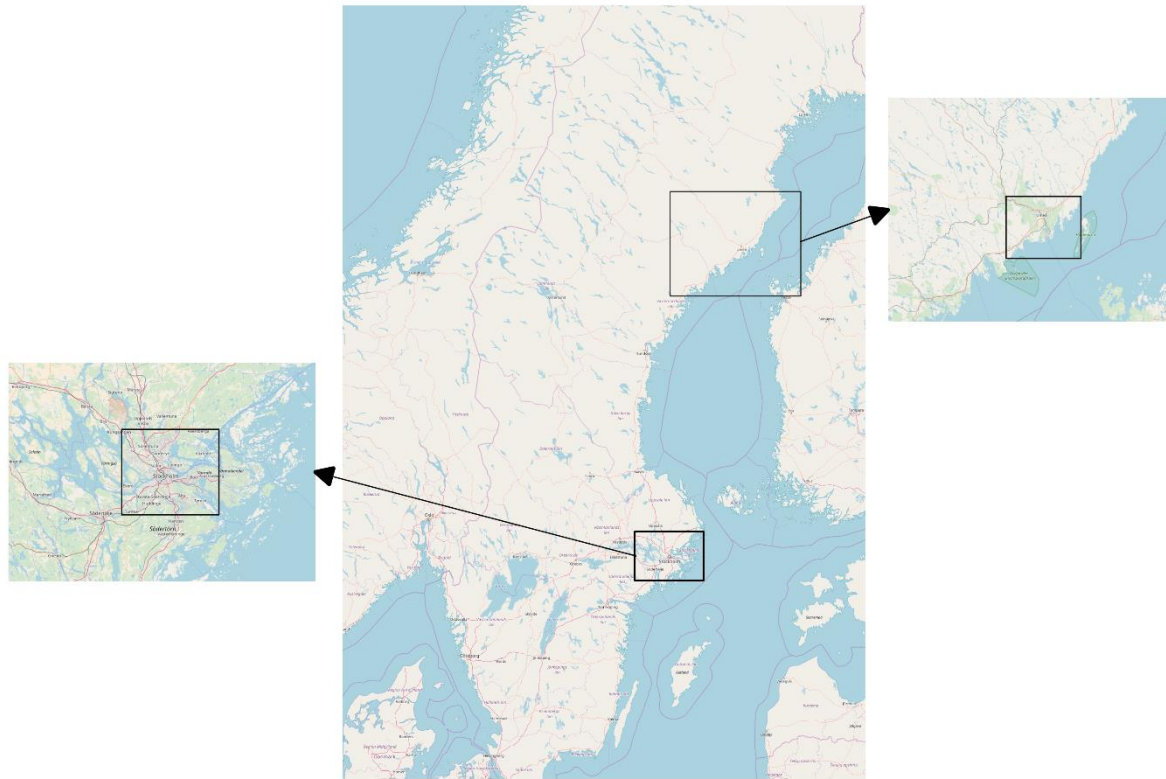
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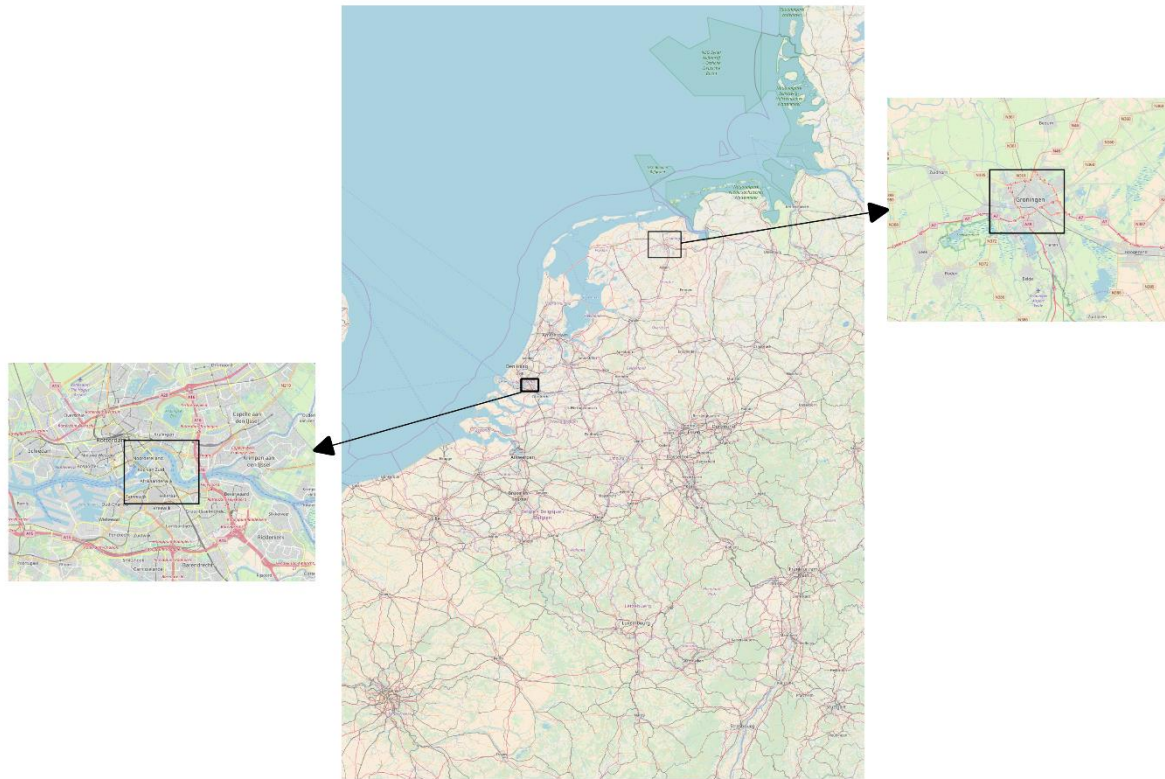
## **Appendix A – Locations of the case study areas**

## Locations of the case study areas in Sweden



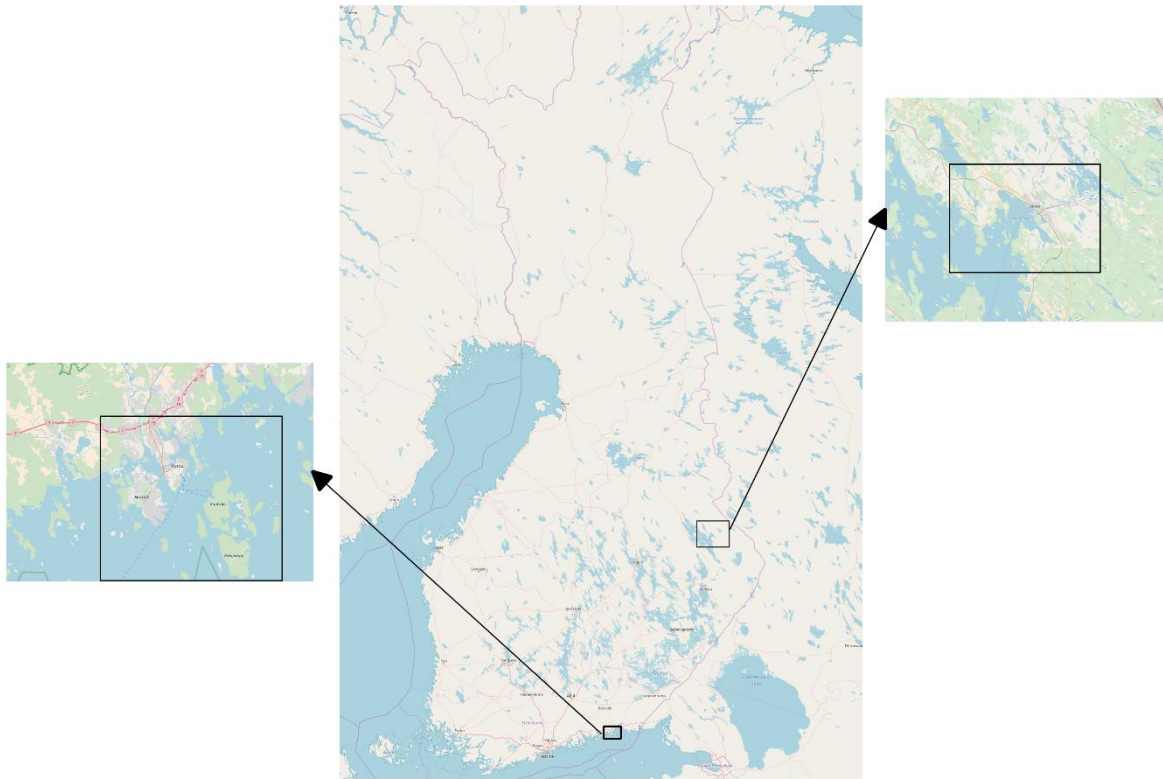
*Figure 38 Locations of the case study areas in Sweden: Stockholm (left) and Västerbotten (right)*

## Locations of the case study areas in The Netherlands



*Figure 39 Locations of the case study areas in the Netherlands: Rotterdam Zuid (left) and Groningen (right)*

## Locations of the case study areas in Finland



*Figure 40 Locations of the case study areas in Finland: Kotka (left) and Lieksa (right)*

## Locations of the case study areas in UK



*Figure 41 Locations of the case study areas in the UK: Lewisham Borough (left) and Northumberland (right)*