URBAN TRANSPORT EMISSIONS AND ENVIRONMENTAL JUSTICE ASSESSMENTS – WHY SPATIAL UNITS MATTER

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1. INTRODUCTION

1.1. Road transport emissions, health and environmental justice

Many studies have investigated or reviewed the health effects of emissions from road transport (cf. Thomas & Harrison 2004; WHO & UNECE 2004; WHO Regional Office for Europe 2004 for example). There is general consensus that prolonged exposure to such emissions has detrimental health effects such as an increased risk of all-cause and circulatory mortality for people with respiratory conditions (Jerrett et al. 2009), a positive association between the occurrence of bronchitis and other respiratory diseases in infants (Coneus & Spieß 2010) or an exacerbation of asthma in children aged 0-14 (Samoli et al. 2011). Some studies have used the proximity of residential location to heavily trafficked roads as a proxy for emission exposure and have shown, for example, a positive association between this factor and increased cardiopulmonary mortality of a 55-69 yr. old cohort in the Netherlands (Hoek et al. 2002), increased rates of clinically manifest coronary heart disease in a 45-74yr. old cohort in Germany (Hoffmann et al. 2006) and a coincidence of diesel particulate matter exposure and asthma-related hospitalizations in Massachusetts, USA (McEntee & Ogneva-Himmelberger 2008).

It has furthermore been shown that the negative health effects of exposure to emissions from road transport tend to be greater for people of lower socio-economic status (Bolte & Kohlhuber 2009, Deguen & Zmirou-Navier 2010). Combined with the fact that households belonging to ethnic minorities and/or to lower income groups are often more likely to live in residential locations that are more exposed to transport emissions (see e.g. Ringquist 2005 and Bolte & Kohlhuber 2008 for reviews) it is clear that road transport *can* and in many locations *does* have a strong connection with questions of environmental justice (EJ).

1.2. The spatial aspects of environmental justice studies

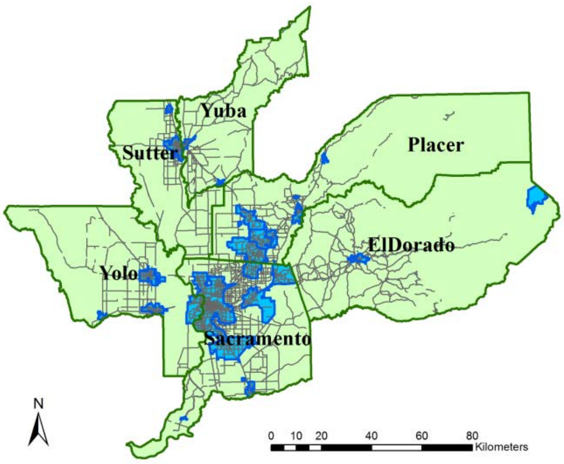
The geographical unit used in studying environmental justice issues can have an effect on the findings (Szasz & Meuser 1997, Payne-Sturges et al. 2006). Using larger geographic units (such as ZIP code or post code areas) for defining affected populations might for example mask effects occurring at a smaller spatial scale. This phenomenon is known as the Modifiable Areal Unit Problem or MAUP (O'Sullivan & Unwin 2010, Chapter 2). Both Mennis (2002) and Schweitzer & Stephenson (Jr.) (2007), among others, cite several EJ studies which illustrated the MAUP phenomenon by showing differences in findings of EJ analyses depending on the spatial units chosen for analysis. All of these studies were concerned with polluting land-uses such as pig farms or industrial facilities (i.e. point sources), however, and not with road transport emissions (i.e. line sources).

A further aspect of – statistically - analysing any relationship between the emission burdens of a given spatial unit and the socio-economic characteristics of the population of this unit is the possibility of spatial autocorrelation. According to Tobler's first law of geography *"[...] everything is related to everything else, but near things are more related than distant things"* (Tobler 1970, p.236–236). Thus, spatial (auto)correlation of variables should be expected in EJ analyses, which generally hypothesise that neither environmental burdens nor the population are randomly or evenly distributed in space. This influences, which statistical models can usefully be applied to the data in any study (Maantay 2007). If the statistical model - e.g. ordinary least squares regression - assumes a random distribution and thus independent residuals of any variable, the resilience of statistical findings is going to suffer if the residuals are in fact *not* (spatially) independent.

Lastly, one needs to look at the way that the spatial distribution of the population under investigation is represented. Irrespective of whether one uses e.g. one of the U.S. Census' units or the statistical areas in Germany, the underlying assumption is generally that within each areal unit, the resident population is evenly distributed. There is, however, generally an inverse relationship between population density and unit size in any one class of spatial statistical unit. Thus, the larger these units are in size, the less likely the assumption of an even distribution of the population within them is likely to hold true. But even in densely populated areas, census or statistical polygons can include water bodies, parks or commercial areas with few or no residents. Thus, if only parts of such polygons are considered to hold affected populations (e.g. if the area affected by certain emissions is defined by a buffer around the source), those parts included in the analysis may or may not actually be inhabited by a proportionate share of all the people found in that spatial unit. Conversely, they could all live in the affected part or nobody might live there if it happened to be, for example, a parking lot and affected populations in individual analysis unit or in entire study areas can be over- or underestimated, potentially significantly. An approach that can be used to alleviate this problem is dasymetric mapping, a technique, which "aims to refine the spatial accuracy of aggregated data by using ancillary information to partition space into zones that better reflect the statistical variation of population." (Sleeter 2008, p.1). The more detailed the information on population densities used, the more accurate a reflection of the actual spatial distribution of residential populations will be possible.

1.3. The study region

The Sacramento Area Council of Governments (SACOG) is comprised of six counties in the upper Central Valley of California, USA: El Dorado, Placer, Sacramento, Sutter, Yolo and Yuba with a total population of over two million (see Figure 1). The work carried out in the study on which this paper is based included all six SACOG counties. However, only two of them will be covered in the following: Sacramento, the most populous and densely settled county and seat of the California state government, and Yolo, its more rural neighbour to the West, which is of similar size but has only 0.14 times as many inhabitants and is home to the University of California at Davis with 34,000 students and 23,000 staff. These counties were further differentiated into incorporated and unincorporated areas (see also Section 1.5), resulting in four individual datasets.



	area in km^2	population (rounded from 2010 Census)
El Dorado	4,640	181,100
Placer	3,890	348,400
Sacramento	**2,580**	**1,418,800**
Sutter	1,570	94,700
Yolo	**2,650**	**200,900**
Yuba	1,670	72,200
TOTAL	**16,990**	**2,316,000**

Figure 1: The six-county SACOG region (urban/incorporated areas are shown in blue)

1.4. Goals of this study

The study described here pursued three main goals:

- to conduct an EJ analysis of the distribution of road traffic emissions as represented by $PM_{2.5}$ in two counties found in the Upper Central Valley of California

- to use a new method of buffer based characterisation of emission distribution to define affected residential populations and quantify their level of affectedness and
- to compare the results of the EJ analysis at the census block level with the results obtained when using a dasymetric mapping approach at the land-use parcel level.

2. METHODOLOGY

2.1. Quantifying emission loads

Using proximity to roadways or traffic density to identify population groups that are differently exposed to road traffic emissions can provide a rough indication of affectedness and potential inequalities. Actual monitoring of emissions loads would result in the most accurate depiction of such phenomena but is highly resource intensive and generally not feasible on either a regional scale or with sufficient resolution to provide data for individual road sections. Monitoring also cannot be used to evaluate future scenarios. Emission dispersion modelling could be used for such a purpose but it, too, requires significant inputs of time and data. In this study I have therefore used an extended buffer based approach which allows a more differentiated and detailed quantification of emissions loads and can both be related to small spatial units – such as land-use parcels – *and* realistically applied in large scale analyses.

The emissions calculations are based on the loaded 2008 network from SACOG's regional travel demand model, SACSIM, and emission factors taken from the statutory California Emission Factors Model EMFAC2011 for the same analysis year (web-based data access[1]; see Air Resources Board 2011 for technical details). EMFAC2011 provides output for organic gases, carbon dioxide (CO_2) and monoxide (CO), nitrous oxides (NO_x), particulate matter (PM_{10} and $PM_{2.5}$) as well as sulphur oxides (SO_x). $PM_{2.5}$ (particulate matter with aerodynamic diameter $\leq 2.5\ \mu m$) was chosen for analysis in this study for the following reasons:

- $PM_{2.5}$ has been identified as the biggest contributor to environmentally induced burden of disease in a six-country European study, ahead of e.g. ozone, benzene and road traffic noise[2] (Hänninen & Knol 2011). Is has also been calculated to be the greatest contributor to external transport costs (including health costs) when compared to PM_{10} and NO_x (Maibach et al. 2007; Maibach et al. 2008).

- Outdoor concentrations of $PM_{2.5}$ have been shown to have a significant positive, moderately strong correlation with outdoor levels of CO, NO_2 and NO_x at four residential study sites in Southern California (Arhami et al. 2009).
- It is a U.S. National Ambient Air Quality Standard criteria pollutant (U.S. EPA - Environmental Protection Agency 2010), for which the limit value[3] has been exceeded in the study area in all but two years (2011, 2012) since 2000. This was not the case for PM_{10} (CA ARB - California Air Resources Board).
- The $PM_{2.5}$ State Annual Standard Designation Value has been exceeded in the study area every year since 2000 (ibid.).

The SACSIM network data contains information on the number of vehicles, the link length and the average speed travelled on each network link (in miles per hour – mph) for average annual daily traffic (AADT) loads and four different time periods: 7am-10am, 10am-3pm, 3pm-6pm and 6pm-7am. SACSIM does not contain any information on the composition and activity levels of the vehicle fleet on the different links, though. However, EMFAC provides emission factors for different pollutants – including $PM_{2.5}$ - in gms/vehicle mile for different speed bins at 5 mph intervals and these factors also incorporate information on the regional vehicle fleet. They can be extracted for different months, season or as an annual average and take into account variations in meteorological variables which influence volume and composition of emissions and can be differentiated by county. The vehicle miles travelled on spatially coincident, bidirectional road segments were combined and the emission factors then used to calculate $PM_{2.5}$ loads generated on each segment for all four time periods. These values were aggregated to 24hr loads to enable an analysis of the average overall emission loads a residential location would be exposed to throughout the day.

Evidence from the literature suggests different distances over which road traffic emissions can affect population. Appatova et al. (2008) cite evidence from the Netherlands for an increase in respiratory problems manifesting themselves in particular in children who live less than 300m from a motorway. They also reviewed studies showing ultra-fine particle concentrations to have been elevated up to about 300m from roadways with the most rapid decline found within 150m. However, a meta-analysis of emissions monitoring studies by Karner, Eisinger & Niemeier (2010) found, that $PM_{2.5}$ concentrations did not drop below 80% of the edge of road concentrations within 400m away from it and did not even reach 50% of the edge of road concentrations within the available data range (986m maximum). Data from the studies reviewed included measurements from freeways and arterial roads inside and outside of built-up areas. The great majority of the distance/concentration pairs did not reach beyond 150m from the edge of the roadway, though.

In the state planning context, a distance of 150m is recommended by the California Environmental Protection Agency & California Air Resources Board (2005) to be kept free of sensitive land uses along freeways, urban roads with 100,000 vehicles/day and rural roads with 50,000 vehicles/day. Based on this guidance, Faust et al. (2014) chose 150m as a buffer distance for a traffic density indicator they constructed for the California Communities Environmental Health Screening Tool (CES).

Based on the evidence cited above and also to enable later comparative analyses with CES indicators, two different buffer distances were chosen for this study: 150m in incorporated and 300m in unincorporated areas (cf. Figure 1). The emissions load created on each road segment was then converted into a per area load (gms/1000m^2) for the buffer area of each network segment. Two different distances were chosen to account for the fact that dispersion patterns are – among other factors – affected by the presence or absence of buildings on or near the edge of the road and building density is higher in urban areas. In the study area, this is also evidenced by the fact that mean residential population density in incorporated areas is 5349 people/km^2 while in unincorporated areas it is 3120 people/km^2.

2.2. Socio-demographic data and spatial units analysed

Socio-demographic data

The socio-demographic variables were taken from block level data of the 2010 Decennial US Census. Blocks are the smallest areal unit for which the census data is made available and in urban areas, they do often consist of one street block while they can be much larger elsewhere. One goal was to characterise the population affected by road transport emissions in a more detailed way than the dichotomous classification into affected (inside the buffer) and unaffected (outside the buffer) often used in studies based on buffering emission sources (cf. Mennis 2002 and Buzzelli & Jerrett 2003 on this issue). Thus blocks were only included in further analyses if they a) contained reisdential population and b) intersected with the road network buffers created to calculate emission burdens (see Section 1.5). Lastly, the block polygons were clipped using the buffer polygons so that only those parts of blocks were carried forward which were found inside the area defined as affected by emissions. Population (pop) numbers were proportionately allocated to these clipped blocks: $\frac{area_{\,clipped}}{area_{\,original}}\ x\ pop_{original} = pop_{clipped}$ This approach assumes an even spatial distribution of the population in the block. For the two sample counties, the final selection contained 14,828 census blocks (or parts thereof[4]) covering 891.8 km^2 with a total population of 914,168 or 39.5% of the region's total (see Table 2 for descriptive statistics).

Socio-economic parameters included in the EJ analysis covered ethnicity and tenure types (Table 2). The latter is included as a proxy for household wealth, since the 2010 Census no longer included questions on household income[5]. Such information is now collected in the American Community Survey (ACS), an annual survey with a sample size of about 3.5 million addresses (U.S. Census Bureau 2012). The findings from this survey are published for 1-year, 3-year and 5-year samples with the latter being the most precise and least current[6] (since some of the data contained in it is five years old). The smallest census unit for which ACS data is made available is the block group, which is one level of aggregation above the block. In the SACOG region, the ACS data on median household income for the past twelve months shows significant correlation with two of the tenure types when the latter two variables are aggregated to the block group level (see Table 1; the analysis was run only for spacial units with population > 0). Tenure type was thus used as a stand-in for data on household income.

Table 1: Correlation between ACS 12 months median household income (independent variable; ACS) and tenure types from 2010 Census in the SACOG region.

dependent variable	**Pearson's *r***	**significance**	**effect size r^2**
owned with mortgage or loan	0.021	p = .419	-
owned free and clear	0.675	p < .001	0.456
renter occupied	-0.628	p < .001	0.394

Table 2: Descriptive statistics for Sacramento and Yolo counties at census block and parcel levels

	Sacr. inc.		**Sacr. uninc.**		**Yolo inc.**		**Yolo uninc.**	
	blocks	**parcels**	**blocks**	**parcels**	**blocks**	**parcels**	**blocks**	**parcels**
N	7 408	99 407	5 435	109 679	1 341	19 446	643	4 599
toal area in km^2	178.42	86.29	447.44	205.81	40.03	18.04	225.26	47.26
	mean ± *SD*							
mean population	54 *± 78*	4 *± 14*	75 *± 105*	4 *± 12*	68 *± 110*	5 *± 18*	21 *± 105*	3 *± 18*
mean area in km^2	0.02 *± 0.04*	0.001 *± 0.001*	0.08 *± 0.20*	0.002 *± 0.004*	0.03 *± 0.05*	0.001 *± 0.001*	0.35 *± 0.43*	0.01 *± 0.01*
percentage of people belonging to different racial / ethnic groups								
White	58.2 *± 26.3*	57.5 *± 24.9*	68.8 *± 23.4*	70.2 *± 20.9*	68.8 *± 18.7*	68.9 *± 16.7*	72.0 *± 28.8*	69.3 *± 27.9*

	Sacr. inc.		Sacr. uninc.		Yolo inc.		Yolo uninc.	
	blocks	parcels	blocks	parcels	blocks	parcels	blocks	parcels
Hispanic	22.2 *± 17.9*	22.0 *± 15.7*	18.4 *± 17.8*	17.5 *± 14.0*	28.2 *± 23.0*	28.6 *± 21.8*	33.1 *± 32.6*	39.1 *± 32.5*
Asian	14.0 *± 16.5*	15.0 *± 15.4*	8.9 *± 13.4*	8.9 *± 11.3*	9.3 *± 11.9*	9.2 *± 10.6*	3.1 *± 10.3*	2.8 *± 6.9*
Black / African American	9.8 *± 12.7*	9.6 *± 10.9*	6.3 *± 9.6*	6.3 *± 7.9*	2.3 *± 4.7*	2.0 *± 3.7*	0.9 *± 4.0*	1.2 *± 4.8*
Other race	9.3 *± 12.0*	9.2 *± 10.5*	7.7 *± 12.0*	7.0 *± 9.1*	12.7 *± 15.1*	12.5 *± 13.5*	18.1 *± 25.6*	20.5 *± 26.8*
Native American	1.1 *± 3.0*	1.0 *± 2.2*	1.1 *± 2.8*	1.0 *± 2.0*	1.1 *± 3.7*	1.12 *± 2.9*	1.2 *± 5.3*	1.6 *± 7.8*
percentage of households with different tenure types								
owned with a mortgage or loan	45.3 *± 27.6*	51.8 *± 23.2*	50.6 *± 25.3*	54.6 *± 20.7*	44.0 *± 27.5*	46.8 *± 24.6*	33.3 *± 30.2*	33.7 *±26.9*
own free and clear	13.0 *± 15.4*	12.5 *± 11.4*	18.1 *± 17.7*	15.8 *± 12.1*	15.5 *± 16.1*	16.2 *± 15.4*	25.0 *± 27.0*	23.2 *± 22.0*
renter occupied	40.1 *± 30.4*	35.3 *± 24.9*	31.3 *± 28.0*	29.5 *± 23.1*	40.2 *± 31.2*	36.8 *± 27.1*	41.1 *± 33.6*	42.7 *± 33.4*

Land-use parcels and dasymetric population mapping

Due to the MAUP phenomenon (Section 1.2), it is generally desirable to carry out EJ analyses based on populations mapped at the smallest possible spatial scale. In addition, dasymetric mapping of populations provides more realistic population surfaces than assuming a uniform population distribution throughout spatial units such as census blocks. The U.S. Geological Survey has made available a dasymetric mapping extension (DME) that can be integrated into ESRI's ArcGIS environment (Sleeter & Gould 2008[7]). This extension was used to reallocate the population from the homogenous distribution within census blocks to a density raster based on land-use parcels from the SACOG land-use model I-PLACE^{3}S for 2008[8]. The land-uses in the parcels were reclassified into 4 density classes. The I-PLACE^{3}S parcel GIS layer noted only the number of dwelling units, not the number of inhabitants per parcel. The density classifications were thus based on a combination of the place types and the density of dwelling units on each parcel (Table 3).

Table 3: Allocation of density classes for dasymetric mapping of census population

density class	dwelling units per acre	place type (from I-PLACE^{3}S)
1 = high density	25 and above	high density residential; urban residential; mixed use, residential focus; intense urban residential
2 = medium density	8 - 24.9	medium-high density ; medium-high density residential; mixed use, employment focus
3 = low density	0.1 - 8	rural residential; farm home; very low density residential; low density residential
4 = no residential use	0	all others

Table 4 shows the data and settings used in the DME. Running the tool results in a raster layer in which each cell is allocated a number of residents. Resolution of the raster can be chosen by the user and was set at 10mx10m for this study. The raster was then converted into a points layer in order to allocate population to each land-use parcel.

Table 4: Data and settings used in dasymetric mapping extension in ArcGIS

data / parameter for dasymetric mapping extension in ArcGIS	implementation in this study
population layer	census block boundaries and data from Census 2010
ancillary layer	2008 land-use parcel footprints from SACOG's I-PLACE[3]S scenario planning tool rasterized to 10mx10m cells in accordance with density classes shown in Table 3
population count data	total population of census blocks
percent (fraction) of source unit that must be covered by the ancillary class	0.8 (determines the minimum area of a block that needs to be covered by one of the density classes in order for it to be included in empirical determination of 'population density fractions'; cf. Sleeter & Gould 2008, p.15)
uninhabited ancillary class	4

Figure 2 shows an example of the differences in spatial population allocation between the block based and the dasymetrically mapped parcel, based method. The sample census block from the SACOG region has a population of 587. The road buffer (dotted red line) chosen to represent the area affected by emissions from the road network (solid red line) covers 42% of the block, corresponding to 249 inhabitants if an even distribution was assumed. However, the parcel data shows that a sizeable portion of the block's area covered by the buffer is not inhabited (grey shading). When reallocating the population through dasymetric mapping (represented by the points[9]), only 203 or 34.5% of the block population are found to live within the buffer zone. While

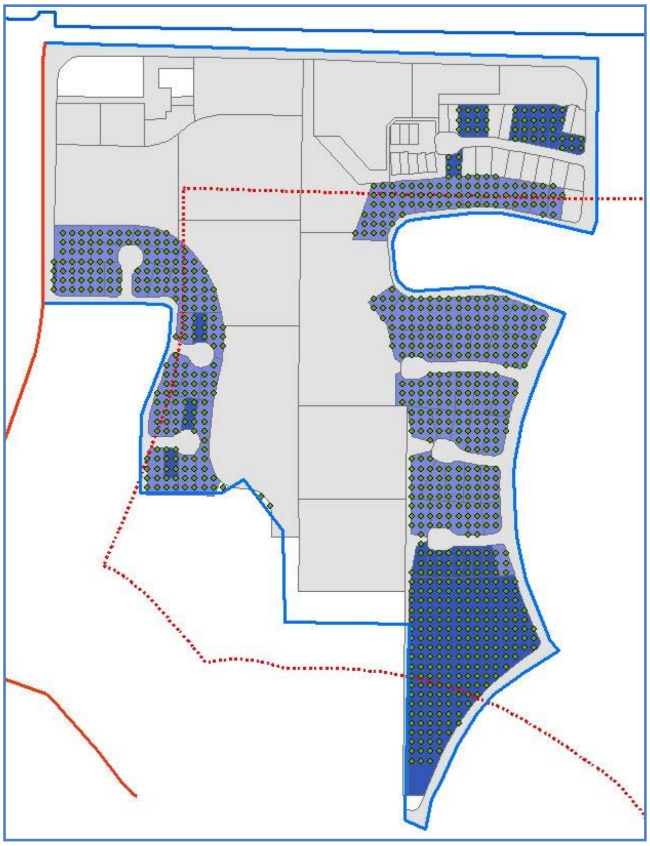


Figure 2: Census block showing result of population reallocation through dasymetric mapping

absolute population numbers change, the socio-economic population characteristics associated with each point remain the same throughout every block (share of ethnic groups, % of households with different tenure types). As with the census blocks, only parcels or parts thereof found within the chosen buffer distances of the road network were included in further analyses. In Sacramento and Yolo County, these totalled 233,131 containing a population of 890,295 and covering an area of 357.4 km^2 (see Table 2 for descriptive statistics). A comparison with these numbers for the blocks shows the effect of the dasymetric mapping: the combined are of the parcels is much smaller as large parts of blocks in the buffers are uninhabited and the total population number is somewhat smaller, indicating that a proportional reallocation of the block population to the buffer areas overestimates the number of residents.

For simplicity, the term 'block' will be used from here on to describe both entire census blocks or parts thereof found within the road network buffer. The same applies to 'parcel' as referring to entire or clipped land-use parcels.

2.3. Allocating emission loads

The SACSIM model network does not fully coincide with the real world road network as in some places the geometry is simplified or model links offset from their real counterparts. However, only residential areas were to be included in this analysis that were within the chosen buffer distance(s) of the real network so that they could actually be exposed to emissions, by the definition chosen here. Thus both land-use parcels and census blocks were clipped by the respective buffer widths when applied to the *actual* network's center line so that only blocks or parcels within that area remained in the analysis – but were subsequently removed if their emission loads were zero. This approach meant that spatial units found within 150m or 300m respectively of the *real road network* might not be included in the analysis if they were not captured by the buffer of the *model network* used for the emissions calculations – but not vice versa.

Overlapping link buffers were intersected and broken up into buffer fragments with homogeneous emissions loads. Thus an overlap between two buffers (A = x $gmsPM_{2.5}/1000m^2$; B = y $gmsPM_{2.5}/1000m^2$) would result in three buffer fragments, the emissions loads for the overlap area AB being x+y $gmsPM_{2.5}/1000m^2$. Only model network links that have an equivalent in the real road network were used. Functional model links without such a counterpart were excluded. The clipped spatial units were then intersected with the buffers of the modelled network and the per area load from each buffer intersecting or covering a unit was added up to generate the overall per area load of each parcel (in the case of incomplete buffer-unit intersects, the load was averaged to the full area of the parcel, assuming an even dispersion).

2.4. Analysing the population affected

Unless otherwise stated, all tests and procedures referred to in the following were carried out in the free R Language and Environment for Statistical Computing (R Core Team 2012). Reading the data from an ArcGIS format into R was performed using the R package *rgdal* (Bivand et al. 2013) and *spdep* (Bivand 2013) was used for spatial regression modeling.

This study had two analytical goals: to establish whether using different spatial analysis units for an environmental justice analysis would yield different results and to find out, what these results would be. Since the data is of a spatial nature, there was a chance of spatial autocorrelation for any statistical models (i.e. spatial patterns in the residuals or errors) – positive in this case, as it was likely that the emissions loads for neighbouring spatial units were more similar than for distant ones.

In order to test for spatial autocorrelation, spatial weights matrices are required which in turn rely on a definition of neighbourhood and neighbour distances. In the case of spatial polygons, these are generally measured between centroids (though weighted centers can also be defined). For the parcels, the same distance was chosen as the buffer width, i.e. 150m for incorporated (inc.) areas and 300m for unincorporated (uninc.) ones as these were the distances over which dispersion is modelled in this study and thus they reflect the distances over which the emissions loads of parcels might be correlated. Furthermore, the size of the parcels meant that throughout the study area, square parcels of mean + 1 SD in area would have edge lengths that would allow for neighbours within the chosen distances (Sacramento inc.: 52m, Sacramento uninc.: 79m, Yolo inc.: 52m, Yolo uninc.: 142m). These measures were different for the blocks (Sacramento inc.: 260m, Sacramento uninc.: 533m, Yolo inc.: 282m, Yolo uninc.: 886m). Exploratory analyses showed that too many blocks would have had no neighbours using the (buffer) distance based definition of neighbourhood and simply enlarging these distances made no sense from the point of view of the phenomenon being studied. Block neighbourhood was thus defined by a queen style contiguity, which is fulfilled if two polygons share at least one boundary point. Global Moran's *I* tests for spatial autocorrelation were carried out on the 24hr $PM_{2.5}$ emission loads for each spatial unit using these neighbourhood definitions. The result were significant in all datasets (see Table 5).

Table 5: Neighbourhood definitions, Global Moran's *I* and no. of units without neighbours in the study area

	Sacr. inc.		Sacr. uninc.		Yolo inc.		Yolo uninc.	
	blocks	**parcels**	**blocks**	**parcels**	**blocks**	**parcels**	**blocks**	**parcels**
definition of neighbourhood	queen	dist.: 150m	queen	dist.: 300m	queen	dist.: 150m	queen	dist.: 300m
Global Moran's *I* for 24hr $PM_{2.5}$ emissions	0.4504	0.7679	0.4988	0.7392	0.1763	0.8235	0.1302	0.8960
significance	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$	$p<0.001$
no. of spatial units without neighbours (% of sample)	56 (0.8)	98 (0.09)	38 (0.7)	83 (0.08)	15 (1.1)	16 (0.08)	33 (5.1)	128 (2.8)

Spatial regression analyses were thus required to obtain robust statistics on the relationship between the emission and population variables. However, it was also found, that a number of units did not have neighbours when using the above definitions (see Table 5). Since such a situation affects the reliability of spatial statistical procedures, these units were dropped from subsequent analyses.

The spatial error model was chosen for the spatial regression analyses with the 24 hr $PM_{2.5}$ load in gms/1000m^2 as the response variable and the population metrics as the explanatory variables (see Kissling & Carl 2008 for a discussion of the advantages of this model over the alternative spatial lag and mixed models). It was not expected that any combination of the population variables could actually explain a significant part of the variation in the emissions loads but interest lay instead on finding out whether there were correlations between the two. Thus only univariate regression models were run. In the model output, R also provides Akaike's Information Criterion (AIC) for the spatial model as well as the non-spatial equivalent and this metric can be used to ascertain, which model is the better fit to the data (smaller AIC values indicate a better fit, cf. Bivand, Pebesma & Gómez-Rubio 2008; Field, Miles & Field 2012). However, in spatial regression, there is no direct equivalent of the r^2 value that can be calculated from non-spatial regression models. It is thus not possible to quantify shared variability in the data.

3. FINDINGS

Table 6 shows the results of the emissions allocation. For both blocks and parcels, the loads are noticeably higher in incorporated areas with denser traffic and the difference is more marked in Yolo county, which in its unincorporated areas is characterised by more rural land uses and lesser densities than Sacramento county (less population in larger spatial units, cf.

Table 2, also a less dense road network). The emission loads vary quite widely, as would be expected considering that all types of roads, from interstates to residential collectors, were included in the analysis.

Table 6: Descriptive statistics for 24hr $PM_{2.5}$ emission loads of census blocks and parcels

24 hr $PM_{2.5}$ in $gms/1000m^2$	Sacr. inc.		Sacr. uninc.		Yolo inc.		Yolo uninc.	
	blocks	**parcels**	**blocks**	**parcels**	**blocks**	**parcels**	**blocks**	**parcels**
mean	1.00353	0.81913	0.48397	0.430840	0.77237	0.64667	0.23190	0.15836
SD	*2.25153*	*1.63615*	*1.44411*	*0.80257*	*2.86314*	*1.32230*	*0.63654*	*0.24701*

Table 7 shows the results of the spatial analyses, reporting the regression coefficient beta, its standard error and the level of significance. The outputs in R also showed that in all cases, the spatial models were a better fit with the data than non-spatial linear regression (smaller AIC values for the spatial models) but - as expected - spatial effects in the data had not been fully removed by any model (as indicated by significant likelihood ratios for Lambda[10] throughout). Significant relationships were found between a number of the population variables and emission loads (8 for block based metrics, in Sacramento County only; 24 for parcel based metrics) and there are clear differences in the findings between the two spatial resolutions. In two cases, findings are significant at the block level but not at the parcel level (for % of Asian population in inc. as well as uninc. areas in Sacramento County) while the opposite is true for 18 cases (in both counties). In 6 cases, results were significant at both the block and the parcel level, however, in the case of percentage of White population in incorporated areas in Sacramento county, the association is positive at the block level and negative at the parcel level.

Table 7: Results of univariate spatial error regression models run with 24hr $PM_{2.5}$ emission load as outcome variable (significant results in bold type, negative associations in green)

		Sacr. inc		Sacr. uninc		Yolo inc.		Yolo uninc.	
		blocks	**parcels**	**blocks**	**parcels**	**blocks**	**parcels**	**blocks**	**parcels**
White	beta	**0.00214**	**-0.00168**	-0.00064	**-0.00102**	-0.00320	**-0.00083**	0.00006	0.00015
	SE	**0.00103**	**0.00023**	0.00070	**0.00011**	0.00417	**0.00038**	0.00079	0.00009
	p =	**p < 0.05**	**p < 0.001**	p = 0.361	**p < 0.001**	p = 0.442	**p < 0.05**	p = 0.942	p = 0.084
Hispanic	beta	-0.00016	**0.00132**	-0.00008	**0.00078**	-0.00321	-0.00033	-0.00087	**-0.00030**
	SE	0.00122	**0.00025**	0.00079	**0.00013**	0.00394	0.00041	0.00071	**0.00008**
	p =	p = 0.893	**p < 0.001**	p = 0.917	**p < 0.001**	p = 0.415	0.411	p = 0.223	**p < 0.001**
Asian	beta	**-0.00478**	-0.00053	**0.00214**	0.00031	0.01231	**0.00128**	0.00312	0.00035
	SE	**0.00145**	0.00029	**0.00106**	0.00017	0.00642	**0.00065**	0.00216	0.00028
	p =	**p < 0.001**	p = 0.0694	**p < 0.05**	p = 0.060	p = 0.055	**p < 0.05**	p = 0.149	p = 0.218
Black / African American	beta	0.00013	**0.00267**	0.00238	**0.00193**	0.00771	**0.00815**	0.00481	**-0.00099**
	SE	0.00174	**0.00036**	0.00134	**0.00020**	0.01360	**0.00146**	0.00543	**0.00049**
	p =	p = 0.939	**p < 0.001**	p = 0.0758	**p < 0.001**	p = 0.571	**p < 0.001**	p = 0.376	**p < 0.05**

		Sacr. inc		Sacr. uninc		Yolo inc.		Yolo uninc.	
		blocks	parcels	blocks	parcels	blocks	parcels	blocks	parcels
other	beta	-0.00010	**0.00068**	-0.00133	0.00019	-0.00282	-0.00018	-0.00056	-0.00009
	SE	0.00172	**0.00033**	0.00103	0.00018	0.00529	0.00052	0.00090	0.00009
	p =	p = 0.952	**p < 0.05**	p = 0.195	p = 0.287	p = 0.594	0.727	p = 0.535	p = 0.356
Native American	beta	-0.00163	-0.00074	0.00000	-0.00065	0.01472	**-0.00410**	-0.00122	0.00084
	SE	0.00574	0.00117	0.00384	0.00060	0.02559	**0.00203**	0.00406	0.00045
	p =	p = 0.777	p = 0.526	p = 0.999	p = 0.283	p = 0.565	**p < 0.05**	p = 0.763	0.061
owned with mortgage	beta	**-0.00403**	**-0.00127**	**-0.00115**	**-0.00089**	-0.00253	**-0.00148**	0.00019	-0.00012
	SE	**0.00091**	**0.00018**	**0.00057**	**0.00008**	0.00306	**0.00028**	0.00078	0.00009
	p =	**p < 0.001**	**p < 0.001**	**p < 0.05**	**p < 0.001**	p = 0.409	**p < 0.001**	p = 0.805	p = 0.203
owned free and clear	beta	**-0.00379**	**-0.00123**	-0.00019	**-0.00169**	-0.00632	**-0.00108**	-0.00076	**-0.00029**
	SE	**0.00148**	**0.00032**	0.00076	**0.00013**	0.00473	**0.00042**	0.00082	**0.00010**
	p =	**p < 0.05**	**0.000**	p = 0.802	**p < 0.001**	p = 0.182	**p < 0.01**	p = 0.353	**p < 0.01**
rented	beta	**0.00270**	**0.00133**	**0.00105**	**0.00119**	0.00418	**0.00184**	0.00039	**0.00024**
	SE	**0.00080**	**0.00016**	**0.00052**	**0.00007**	0.00265	**0.00024**	0.00068	**0.00008**
	p =	**p < 0.001**	**p < 0.001**	**p < 0.05**	**p < 0.001**	p = 0.114	**p < 0.001**	p = 0.571	**p < 0.01**

For the tenure variables, the significant relationships take the same direction throughout all datasets – negative for both types of ownership, positive for share of households in rented accomodation. This is not the case for the ethnicity/race variables for which both positive and negative associations were found – with the exception of Native American and 'other' ethnicities since for both only one significant result was obtained.

4. DISCUSSION

4.1. Spatial scales of analysing inequity

One of the goals of this study was to compare the results of EJ analyses at different spatial scales to investigate the effects of the Modifiable Areal Unit problem or MAUP. The units entered into this comparison were census blocks – the smallest spatial unit of the decennial census - with an assumed even spatial distribution of their population on the one hand and land-use parcels with a density based reallocation of the population on the other. Results differed clearly between the two scales, mostly in the sense that more significant associations were found between population metrics and the emissions measure at the parcel than at the block level. In some case, the opposite was true, though. And in one case, results were significant at both scales but showed the correlation going in different directions: the proportion of white households in blocks in incorporated areas of Sacramento county was positively associated with $PM_{2.5}$ emissions at the block level (i.e. a higher proportion of households correlated with higher emission loads) while the opposite was found at the parcel level.

In general, regression models are more likely to yield significant results for larger samples even for smaller effect sizes, i.e. regression coefficients. However, the findings of this study include several cases for which the significant associations at the parcel level also showed larger effect sizes than the non-significant block level counterparts (e.g. for the Hispanic population in Sacramento county or the Black / African American population in inc. areas of Yolo county, cf. Table 7). In a further two cases – for the Asian population in Sacramento county's inc. and uninc. areas - findings were significant at the block level but not at the parcel level. The diverging results found in the two different area types could be illustrating relationships that are simply not significant at a finer spatial scale – the results at the parcel level point in the same direction but probability values are just above the 95% level of significance and effect sizes are much smaller. The opposing directions of the findings might, however, indicate a similar trend as the findings of Benner et al. (2010), who note that in some parts of Sacramento County, the income of Asian households falls into the highest category of their analysis while in other areas of the county, it is in the lowest.

Overall, the findings of this study strongly suggest that using the smallest possible spatial scale of analysis yields more differentiated results and reveals processes or – in this case – associations between population and emission variables that are obscured at a larger scale. The following discussion will thus focus on the findings at the land-use parcel level.

4.2. Implications for Environmental Justice

In a Californian context, the two counties investigated in this study are neither disproportionately burdened by environmental stressors nor is their population disproportionately disadvantaged: the California Environmental Health Screening Tool has assigned the census tracts in this area a mean pollution burden score of 3.5 (possible range: 0.1-10, compiled from data on e.g. PM2.5 and diesel PM concentrations; traffic density, drinking water quality, pesticide use and toxic release facilities). The mean score for population characteristics is 5.1 (same range; incorporating e.g. incidences of asthma and low birth weight infants, educational attainment, poverty and unemployment) – just above the average for the state (Faust et al. 2014). However, the Sacramento Scorecard, another set of indicators that focuses on the SACOG region, has shown that while the region is generally well integrated in terms of e.g. racial diversity, there are also clear signs of disparity at the census tract level (Benner et al. 2010). This is for example evidenced by a disproportionately high share of African American and Latino households found in tracts with the lowest median household incomes.

The findings from this study also show that the share of certain groups of the population is significantly more likely to be higher in areas more affected by $PM_{2.5}$ emissions from road traffic, at least in some areas. And the opposite is true for other groups (mostly, but not exclusively, households living in homes they own and non-Hispanic White people).These associations are in general in line with findings from many other EJ studies (cf. reviews by Szasz & Meuser 1997; Walker et al. 2003; Ringquist 2005; Bolte & Kohlhuber 2008): higher $PM_{2.5}$ loads in the land-use parcels correlate significantly with a higher share of Hispanics, Blacks/African Americans and people (self-)classified as belonging to ‘other’ ethnicities in inc. areas of Sacramento county as well as for Hispanics and Black/African Americans in uninc. areas there. For Whites, the correlation is negative throughout Sacramento county as well as in inc. areas of Yolo county – where there is a positive correlation for Asians and Black/African Americans but also a negative one for Native Americans. In Yolo’s uninc. areas, the correlation is significant (and negative) only for Hispanics and Blacks/African Americans. The somewhat equivocal nature of these findings could have several reasons. In more rural areas – such as uninc. parts of Yolo county – residential locations found further away from busy roads might actually be more affordable if they are in areas with reduced accessibility by transport and / or to shops and services. Households belonging to ethnic minorities which are economically disadvantaged might thus be more likely to be found in these locations. Such an effect would be in line with the findings by Benner et al. (2010) but would need further investigation to be confirmed.

The different tenure types were used as an indicator for household wealth (cf. also Benner et al. 2010), which is more directly associated with socio-economic status than ethnicity. For these, the evidence is more unequivocal than for the ethnicity variables: in all but Yolo’s uninc. areas, a high share of households owning their homes with a mortgage was significantly correlated with lower emission loads. The same type of correlation was found in all areas for households owning their homes free and clear and the correlation was reversed everywhere for households living in rented homes. Their share is consistently significantly *higher* in areas with higher emission loads.

Several of the review studies cited above noted that different EJ studies found different levels of inequity for different sub-groups of the population depending on their geographic focus, their spatial scale of analyses and the exposure indicators that were used. In this study, the analytical scale is appropriate for the pollutant investigated as it is local rather than regional in effect and also – unlike ozone or NO_2 for example – it is a primary pollutant directly associated with road traffic. Furthermore, analytical inaccuracies created by spatial aggregation or the MAUP have been avoided as far as possible by basing the investigation on the land-use parcel level.

5. CONCLUSIONS

Overall, this study has clearly documented environmental inequity relating to the exposure of some ethnic minorities and economically weaker households to $PM_{2.5}$ from road transport for the study area, two counties in the SACOG region of Northern California.

The comparative analyses carried out in this study have also demonstrated that using different spatial units for environmental justice investigations can yield dramatically different findings and since the effect scale of the pollutant under investigation – $PM_{2.5}$ from road traffic - fits well with the level of spatial detail at which the population was mapped it is posited that the parcel-level based findings, i.e. those at a finer resolution, are more reliable than those obtained at a block level.

Furthermore, the methodology developed here, which is a combination of small scale, buffer-based emission quantifications and density-related or dasymetric population mapping, is well suited to equity analyses for large areas. It thus fills a gap between the rougher proxies for emissions such as traffic volumes or densities and highly resource intensive methods such as dispersion modelling, which might not be feasible for all administrations interested in such issues. Another approach, creating pollution surfaces through statistical interpolation of data from monitoring stations, is highly reliant on the density of the monitoring network and this is often relatively sparse: 7 stations monitor $PM_{2.5}$ in the six county SACOG region[11] and there are four in the German City of Hamburg[12] (population: 1.8 Million; area: 752 km^2). The result would not tally well with higher resolution population maps. The methodology presented here requires the availability of loaded traffic networks from e.g. travel demand models, a geography information system software and the availability of an emissions inventory or model applicable to the region under investigation. All of these resources are becoming increasingly available to transport and urban planners throughout Europe. Since an increasing interest in analysing EJ-related questions and in mitigating inequities once they are diagnosed can currently be observed in Germany, for example, at least at the federal level (cf. Böhme & Bunzel 2014), it is expected that methods such as the one presented here will be of growing interest to both planning professionals and researchers.

A future step that will be taken to further validate this methodology is to compare its results with some representative values obtained through emission dispersion modeling.

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NOTES

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1 see www.arb.ca.gov/emfac [last accessed Aug. 22nd 2014]
2 The effects of PM10 were also analysed in this study but "*due to the overlap between these two indicators, in the aggregate results only the results for $PM_{2.5}$ are included.*" (ibid., p.45).
3 national 24-hour Standard Design Value from 2006 of 35µg/m^3
4 Note that depending on spatial configurations some census blocks contributed more than one polygon to the set of spatial units analysed.
5 The long form that was previously administered to a sample of the population was eliminated in the 2010 census.
6 cf. http://www.census.gov/acs/www/guidance_for_data_users/estimates/ [last accessed Aug.22nd 2014]
7 see http://geography.wr.usgs.gov/science/dasymetric/data.htm for downloads [last accessed May 5th 2014]
8 cf. www.sacog.org/services/scenario-planning/ [last accessed April 29th 2014]
9 Each point represents different numbers of residents depending on the settlement density class associated with the parcel in which it is located.
10 Lambda is the spatial autoregressive coefficient. The Likelihood Ratio Test compares the model with no spatial autocorrelation (lambda = 0) with the one allowing for it. If the result is significant, there is residual autocorrelation in the model (cf. Anselin 2003, p. 13ff).
11 cf. www.epa.gov/airdata/ad_rep_mon.html [last accessed Nov. 3rd 2012]
12 cf. luft.hamburg.de/clp/messstationen-aktuelle-messdaten/clp1/ [last accessed Aug. 29th 2014]