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The impact of social capital, land use, air pollution and noise on individual morbidity in Dutch neighbourhoods

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ABSTRACT

Background: Both social and physical neighbourhood factors may affect residents' health, but few studies have considered the combination of several exposures in relation to individual health status.

Aim: To assess a range of different potentially relevant physical and social environmental characteristics in a sample of small neighbourhoods in the Netherlands, to study their mutual correlations and to explore associations with morbidity of residents using routinely collected general practitioners' (GPs') data.

Methods: For 135 neighbourhoods in 43 Dutch municipalities, we could assess area-level social cohesion and collective efficacy using external questionnaire data, urbanisation, amount of greenspace and water areas, land use diversity, air pollution (particulate matter (PM) with a diameter < 10 μm (PM_{10}), PM < 2.5 μm ($PM_{2.5}$) and nitrogen dioxide (NO_2), and noise (from road traffic and from railways). Health data of the year 2013 from GPs were available for 4450 residents living in these 135 neighbourhoods, that were representative for the entire country. Morbidity of 10 relevant physical or mental health groupings was considered. Individual-level socio-economic information was obtained from Statistics Netherlands. Associations between neighbourhood exposures and individual morbidity were quantified using multilevel mixed effects logistic regression analyses, adjusted for sex, age (continuous), household income and socio-economic status (individual level) and municipality and neighbourhood (group level).

Results: Most physical exposures were strongly correlated with degree of urbanisation. Social cohesion and collective efficacy tended to be higher in less urbanised municipalities. Degree of urbanisation was associated with higher morbidity of all disease groupings. A higher social cohesion at the municipal level coincided with a lower prevalence of depression, migraine/severe headache and Medically Unexplained Physical Symptoms (MUPS). An increase in both natural and agricultural greenspace in the neighbourhood was weakly associated with less morbidity for all conditions. A high land use diversity was consistently associated with lower morbidities, in particular among non-occupationally active individuals.

Conclusion: A high diversity in land use of neighbourhoods may be beneficial for physical and mental health of the inhabitants. If confirmed, this may be incorporated into urban planning, in particular regarding the diversity of greenspace.

Abbreviations: BAG, base registrations addresses and buildings; EHR, electronic health record; ESCAPE, European study of cohorts for air pollution effects; GP, general practitioner; LGN, national land use Netherlands; PM, particulate matter; IQR, inter quartile range; LDEN, level day-evening-night; MUPS, medically unexplained physical symptoms; NIVEL, Netherlands Institute for Health Services Research; OR, odds ratio; PC5, five-digit postal code; PCD, primary care database; r_s, Spearman's correlation coefficient; SSND, study on the social networks of the Dutch

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1. Introduction

It is well established that the neighbourhood people live in affects their mental and physical health (Pemberton and Humphris, 2016). The neighbourhood – both in urban and rural areas – comprises a complex mixture of social and physical environmental factors. To date, the influence of these factors on health has typically been studied with a focus on physical or social neighbourhood exposure. For example, research projects have addressed adverse health effects of air pollution (Dimakopoulou et al., 2014), noise (Ising and Kruppa, 2004) or the combination of both (Foraster et al., 2014); others addressed beneficial health effects of greenspace (Hartig et al., 2014), blue spaces (White et al., 2013) or both (Gascon et al., 2015). Other studies have focused on social environments such as social capital (Mohnen et al., 2011; Murayama et al., 2012), social safety (Lovasi et al., 2014) or their interaction (Ruijsbroek et al., 2015). Very few epidemiological studies considered the combination of several physical and social factors (Dzhambov et al., 2018; Groenewegen et al., 2018). This is important since these factors are likely correlated, partly through individual and/or neighbourhood socio-economic status and urbanisation.

A more integrated approach of different social and physical environmental factors in relation to health also helps a proper investigation of the mechanisms of beneficial or adverse health effects of certain factors. For example, several mechanisms have been put forward to explain the observed beneficial effects of greenspace. One of the mechanisms is that more (accessible) greenspace in the neighbourhood enhances social contacts (Hartig et al., 2014), which in turn is positively associated with health (Murayama et al., 2012). However, to date few studies have been able to address this in detail.

The aim of this study was to assess a range of different potentially relevant physical and social environmental characteristics in a representative sample of small neighbourhoods in the Netherlands, to study their mutual correlations and to explore associations with morbidity using routinely collected general practitioners' (GPs') data. Greenspace comprises a complex environmental factor that is currently given much attention in both research and policy making. In our study we considered amount and general type of greenspace in neighbourhoods, as well as the overall land use diversity. We controlled for individual socio-economic status, a potential confounder in the relationship between several social and physical neighbourhood factors and individual health status. Consequently, our research question is to what extent are physical and social aspects of the residential environment associated with GP assessed morbidity in neighbourhoods in the Netherlands? In this exploratory analysis we considered various factors that are relevant from both a scientific and an urban planning point of view, and for which data were available in our setting. This included air pollution, noise, greenspace, land use diversity, social cohesion and collective efficacy.

2. Methods

2.1. Selection of neighbourhoods and study population

The definition of neighbourhood in this study is an area containing residential addresses with the same five-digit postal code (PC5) in the Netherlands. The country consists of in total 32,500 PC5 neighbourhoods within approximately 400 municipalities. A PC5 area typically consists of a few streets, most of them of a surface area of $< 1\ km^2$ with on average 500 inhabitants. However, both area surface and population show a large variation across PC5 neighbourhoods, depending e.g. on urbanisation.

This study is based on individual data from registered patients of Dutch GPs who were living in 2013 in one of the 181 PC5 areas in the Netherlands that were sampling units of the Study on the Social Networks of the Dutch (SSND) (Mollenhorst et al., 2014). The GPs in this study participated in the NIVEL Primary Care Database (Verheij, 2014). The data sources and flows are summarised in Fig. 1 and are elaborated below. The eventual study population with all data available included 4450 participants (Fig. 1) that were representative for the entire country.

2.1.1. Study on the social networks of the Dutch

The overall aims and methods of the longitudinal SSND have been described elsewhere (Mollenhorst et al., 2014). Briefly, a stratified random sample was drawn from 40 Dutch municipalities, representing the various provinces and regions, taking into account the degree of urbanisation and number of residents in these municipalities. In each of these 40 municipalities, four neighbourhoods were randomly selected using the postal code system. Next, per neighbourhood, 25 addresses were randomly selected. At eight of these addresses, the resident between 18 and 65 years of age who had his or her birthday first (counting from the date of the interview) was interviewed in 1999/2000. Follow-up studies in 2006/2007 and 2013/2014 included interviews in the same and new individuals (related to loss to follow-up), while in the last follow-up 20 additional socially disadvantaged neighbourhoods (from 8 municipalities) were added. For the purpose of the present analysis, 181

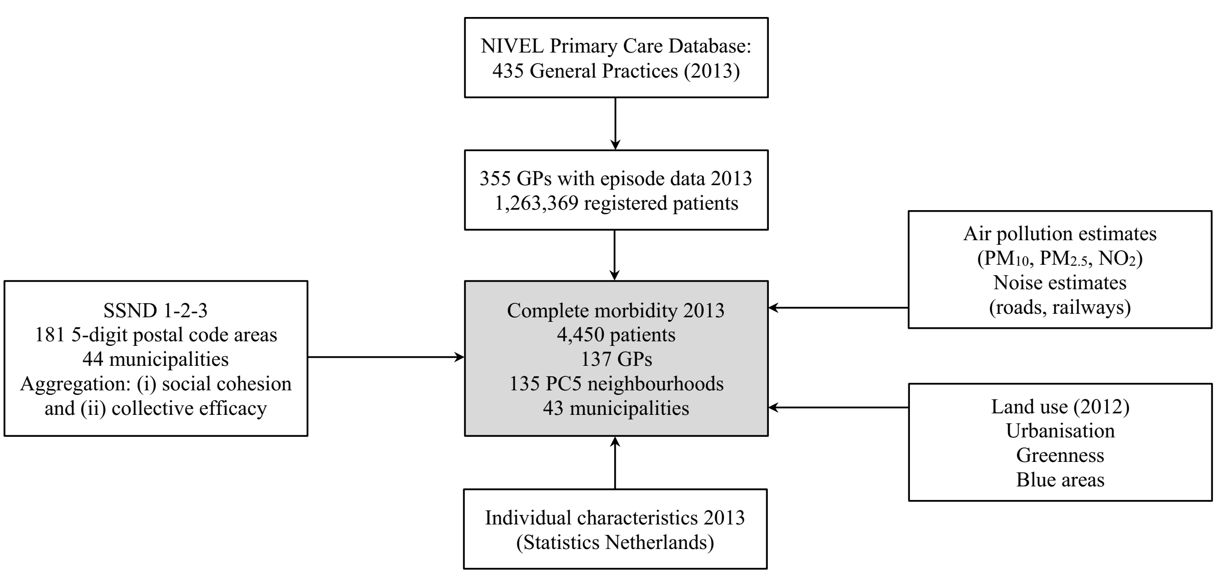

Fig. 1. Overview of data sources and flow of study subjects.

neighbourhoods from 44 municipalities defined by 5-digit postal code were included. In total, data from 3065 interviews from 1885 individuals over the three 3 waves could be used to determine social capital in these neighbourhoods (Supplemental Fig. 1).

2.1.2. NIVEL primary care database

Virtually the whole Dutch population is registered at a particular general practice. GPs are gatekeepers for specialised, secondary health care. Therefore, the electronic health records (EHRs) kept by GPs provide a complete picture of people's health problems and the population registered in general practice can be used as the denominator in epidemiological studies. The NIVEL Primary Care Database (PCD) is a dynamic database containing information of patients from about 10% of GPs in the Netherlands. The practices are representative of the Dutch GP population with respect to age, gender, region and urbanisation. EHRs are being routinely collected together with basic demographic characteristics (sex and age). The NIVEL PCD contains data at the patient level in terms of contacts, morbidity, prescriptions and referrals, with small yearly changes in practice composition. This database is registered with the Dutch Data Protection Authority. Dutch law allows the use of electronic medical records for research purposes under certain conditions. According to this legislation, neither obtaining informed consent from patients nor approval by a medical ethics committee is obligatory for this type of observational studies containing no directly identifiable data. In 2013, 435 GPs participated in the NIVEL PCD.

2.2. Social and physical neighbourhood characteristics

2.2.1. Assessment of social capital

Social cohesion and collective efficacy, as aspects of social capital, were determined in the 181 PC5 neighbourhoods using data obtained from the SSND. Collective efficacy refers to the ability of members of a community to control the behaviour of individuals and groups in the community. Social cohesion was based on the answers to 10 questions from the SSND interviews, while collective efficacy was assessed using five different items (Supplemental Table 1). Variables and the resulting scales were coded so that higher values indicated more social capital (i.e., higher cohesion and collective efficacy). We applied ecometrics (Raudenbush, 2003) to obtain adjusted aggregated measures of social cohesion and collective efficacy to both the municipality and PC5 neighbourhood levels, following the approach described by Mohnen et al. (2011). Briefly, multilevel models predicting the answers to the questionnaire items included municipality and PC5 and were adjusted at the individual level for sex, age (4 categories), educational level and country of birth (Netherlands or elsewhere). By aggregating individual responses to the neighbourhood level by using the ecometric method, we adjusted for differences in the number of respondents per neighbourhood, differences between individuals within neighbourhoods, differences within individuals between study waves, differences in the number of questions answered per individual and individual response patterns on different questions.

2.2.2. Land use, diversity and urbanisation indices

For each of the 181 PC5 neighbourhoods, we collected information on surface area and number of residential addresses from the BAG 2013 database. The degree of urbanisation was expressed as address density (addresses per ha). For descriptive analyses, we also grouped address density into five categories, following the definition used by Statistics Netherlands. Data on land use was obtained from the LGN-7 2012. This database contains the dominant type of land use of each 25×25 m grid cell in the Netherlands (Hazeu, 2014). The LGN-7 database distinguishes 39 types of land use and these were categorised into natural green, agricultural green and blue spaces (Supplemental Table 2). Total green was the sum of natural and agricultural green. The data points (based on grid cells) for each PC5 neighbourhood were identified. We defined the level of different types of greenspace of a PC5 neighbourhood as the percentage of all grid cells within that PC5 belonging to the specific green land use. The same was done for blue (water) areas. The Shannon index (Shannon, 1948), based on all 39 types of land use, was used as diversity score that has been often used in ecology (Morris et al., 2014). It is computed as $-\Sigma p_i \ln(p_i)$ with p_i being the proportion of grid cells belonging to type of land use i.

2.2.3. Air pollution and noise

Exposure to air pollution was estimated on the basis of the ESCAPE model containing long-term average air pollution levels for all home addresses in The Netherlands (Eeftens et al., 2012). From the distribution of all modelled exposures within a neighbourhood, we used the 95-percentile concentration in our analyses. We considered particulate matter (PM) with a diameter $< 10\,\mu m$ (PM_{10}), PM $< 2.5\,\mu m$ ($PM_{2.5}$) and nitrogen dioxide (NO_2).

Two types of noise were considered; from road traffic and from railways. Exposure to road traffic noise and railway noise was estimated by applying the Standard Model Instrumentation for Noise Assessments (STAMINA). This is a model to estimate environmental noise from different sources in the Netherlands (Schreurs et al., 2010). Noise levels (dB) were estimated over a whole period of the day (Lden), which uses penalties for the evening (5 dB(A)) and night (10 dB(A)) and were calculated on a 10×10 m grid covering the whole of the Netherlands. This method is in accordance of the Good Practice Guide for Strategic Noise Mapping (WGAEN, 2007). We assigned each dwelling to the nearest grid point, and for each PC5 neighbourhood we determined the 95-percentile of all modelled long-term average noise levels at address level within that neighbourhood. For exposure to road traffic noise data from 2008 were used, for railways noise data from 2007.

2.3. Socio-economic characteristics

Two different socio-economic indicators at the individual level were obtained from Statistics Netherlands. First, we used the standardised household income. This is defined as the percentile of the household income relative to the whole country. The rationale behind this was that an individual's economic status for most people is probably more determined by his or her household than only by the personal situation. Second, individual socio-economic position was classified into 14 occupational groups that were collapsed into 4 broader categories relevant for the topic under study: occupationally active, social security benefit, retired with pension, and others non-active.

2.4. Morbidity

Electronic health records from the NIVEL Primary Care Database contained diagnosed (co)morbidity and registered symptoms that were coded following the International Classification of Primary Care (ICPC) (Lamberts and Wood, 1987). Patient records of different consultations were combined into episodes of care (Nielen et al., 2016). Data from all four trimesters in one calendar year (2013) were used in order to avoid seasonal influences/differences, and the number of months patients were registered at their GP was taken into account. Chronic disease recorded in previous years (2011 and 2012) was taken into account to minimise misclassification in morbidity, also when patients did not consult their GP for this health problem in 2013. Data from patients of 355 GPs could be used for this purpose (Fig. 1).

We initially considered 24 disease groupings that cover the full range of the most prevalent diseases in general practice and had been used in several studies (Maas et al., 2009). From this list we selected 10 disease groupings with expected influence from one or more of the physical and/or social environmental variables under study, belonging to cardiovascular, mental, respiratory and neurological diseases, diabetes and Medically Unexplained Physical Symptoms (MUPS). The 10 disease groupings were defined on the basis of ICPC codes as previously

Table 1
Distribution of and correlations between social and physical neighbourhood characteristics across 135 five-digit postal code areas in 43 Dutch municipalities.

	Distribution			Correlation (Spearman's *r*)		
	25-percentile	50-percentile	75-percentile	Address density	Social cohesion[a]	Collective efficacy[b]
Address density (addresses/ha)	3.7	22.5	55.5		−0.33	−0.25
Natural green (%)	0.0	0.0	1.9	−0.74	+0.28	+0.29
Agricultural green (%)	0.0	0.0	18.2	−0.78	+0.35	+0.28
Total green (%)	0.0	0.0	32.9	−0.80	+0.36	+0.30
Blue spaces (%)	0.0	0.55	4.5	−0.34	+0.14	+0.04
Shannon index	0.69	1.11	1.53	−0.80	+0.24	+0.26
PM_{10} (μg/m^3)	24.7	25.7	27.2	+0.39	−0.14	−0.06
$PM_{2.5}$ (μg/m^3)	16.5	17.0	17.8	+0.15	−0.08	+0.03
NO_2 (μg/m^3)	22.9	27.5	36.1	+0.62	−0.19	−0.17
Noise road traffic (LDEN)	58.3	61.2	64.0	+0.17	−0.08	−0.09
Noise railway traffic (LDEN)	34.0	40.6	48.7	+0.08	−0.16	−0.08

[a] 25-percentile 3.66; 50-percentile 3.72; 75-percentile 3.77.
[b] 25-percentile 3.86; 50-percentile 3.92; 75-percentile 3.97.

described (Maas et al., 2009) (Supplemental Table 3). Diagnoses were combined with related symptoms in order to decrease variation across general practices/practitioners in diagnostic practices. Not all groupings were mutually exclusive.

2.5. Data linkage and analysis

Analyses were done using Stata version 13 (StataCorp LP, College Station, TX, USA). The different databases were linked and analysed in a protected remote access environment of Statistics Netherlands. Both neighbourhoods and individuals were made unidentifiable by using pseudonym codes. One-to-one linkage of health data, socio-economic data and address information was performed. We selected individuals of all ages who had been living in one of the 181 PC5 neighbourhoods during all 12 months of the year 2013. Finally, we were able to include in the statistical analysis 4450 individuals with complete information on socio-economic status and morbidity, living in 135 PC5 neighbourhoods (Fig. 1).

Correlations between the different neighbourhood characteristics were evaluated using non-parametric Spearman's correlation coefficients. Associations between neighbourhood exposures and morbidity were quantified using multilevel mixed effects logistic regression analyses (*melogit* procedure in Stata). We adjusted all models for a set of potential confounders and established co-variables for the outcomes under study: sex, age (continuous), household income and socio-economic status (individual level) and municipality and neighbourhood (group level). Multilevel logistic regression analysis was performed for each disease grouping separately. These multilevel models had explanatory variables at two levels: Neighbourhood and individual. We modelled the Odds of a morbidity of an individual as function of the neighbourhood characteristic (thus, at the group level), adjusted for several variables at the individual level. Individuals were nested within neighbourhoods, which at their turn were nested within municipalities due to the design of the SSND study. No variables were included at municipal level; the level of municipalities was only added to take the data structure into account because of the correlation between individuals and neighbourhoods within the same municipality. Clustering of morbidity was assessed at neighbourhood and municipality level in models adjusted for individual level variables. Potential effect modification of selected associations by a third variable was evaluated by calculating the *p* value for multiplicative interaction in adjusted models. Associations were expressed as Odds Ratios and 95% confidence intervals related to meaningful changes in the exposure variable under study.

3. Results

3.1. Social cohesion and collective efficacy in neighbourhoods

The influence of the individual characteristics (sex, age, educational level and country of birth) on cohesion and collective efficacy in the ecometrics analyses was limited. The correlations within individuals between the waves were low. For social cohesion, the mean reliability was 0.58 and 0.38 for the municipality and neighbourhood level, respectively. For collective efficacy, the mean reliability was 0.50 and 0.35 for the municipality and neighbourhood level, respectively. The values of reliability for all municipalities and neighbourhoods are listed in Supplemental Table 4.

3.2. Social and physical neighbourhood characteristics

Assessed social cohesion ranged from 3.17 to 3.94 (interquartile range [IQR] 0.21) across municipalities and from 3.55 to 3.91 (IQR 0.11) across PC5 neighbourhoods. Assessed collective efficacy ranged from 3.49 to 4.18 (IQR 0.19) across municipalities and from 3.67 to 4.08 (IQR 0.11) across PC5 neighbourhoods. Thus, the distribution of the social capital variables was relatively narrow; there was only small variation between municipalities, and between neighbourhoods within municipalities. The correlation between these two indicators of social capital was 0.65 at the PC5 neighbourhood level.

Address density and land use variables showed a wide distribution across the neighbourhoods (Table 1). Estimates of ambient air pollution levels of particulate matter PM_{10} and $PM_{2.5}$ showed only small variation between the neighbourhoods, but the variation in NO_2 was somewhat larger. Noise from road traffic did not vary much between PC5 neighbourhoods, while noise from railway traffic showed a wider distribution.

Correlations between address density and most physical neighbourhood characteristics except noise and $PM_{2.5}$ were strong and in the anticipated direction (Table 1 and Supplemental Table 5). As a result, moderately to high negative correlations were also seen between greenspace and air pollution, particularly NO_2. The Shannon index was strongly correlated (r_s = 0.70–0.72) with the different greenspace indicators. A higher address density was moderately correlated with lower social cohesion and lower collective efficacy.

3.3. Characteristics of the study population

Slightly more than half of the population were women, and the

Table 2
Demographic, socio-economic and health[a] characteristics of 4450 residents from 135 neighbourhoods in 43 Dutch municipalities, 2013.

	Number	%
Women	2266	50.9
Men	2184	49.1
Age 0 to 4 years	233	5.2
Age 5 to 12 years	461	10.4
Age 13 to 18 years	328	7.4
Age 19 to 39 years	1032	23.2
Age 40 to 64 years	1663	37.4
Age 65 years and older	733	16.5
Occupationally active[b]	2035	45.7
Social security benefit[c]	384	8.6
Retired with pension[d]	771	17.3
Others non-active[e]	1260	28.3
Very strongly urban (≥25 addresses/ha)	1955	43.9
Strongly urban (15–25 addresses/ha)	598	13.4
Moderately urban (10–15 addresses/ha)	77	1.7
Slightly urban (5–10 addresses/ha)	364	8.2
Non-urban (< 5 addresses/ha)	1456	32.7
High blood pressure	761	17.1
Cardiac disease	278	6.2
Coronary heart disease	191	4.3
Stroke, brain haemorrhage	103	2.3
Depression	202	4.5
Anxiety disorder	178	4.0
Asthma, COPD	504	11.3
Migraine/severe headache	183	4.1
Medically unexplained physical symptoms	1330	29.9
Diabetes	295	6.6

[a] Definitions of disease clusters on the basis of ICPC codes are given in Table 1 of the online supplement.
[b] Employee company; civil servant; managing director; self-employed; others active.
[c] Any type of social security benefit; disabled.
[d] Retired with pension younger or older than 65 years.
[e] Student; others non-active; without income.

mean age was 40.5 years (Table 2). Related to the selection of PC5 neighbourhoods in the SSND, three quarters of the study population lived in either the most urban (that is, ≥25 addresses/ha) or the most rural areas (< 5 addresses/ha), and 88% were born in The Netherlands (data not shown). Forty-five per cent were working and the distribution of the standardised household income was close to that of the entire country. The correlations of the latter socio-economic variable with neighbourhood factors was in general low; only for collective efficacy ($r_s = 0.25$) and for the three indices of greenspace ($r_s = 0.20$–0.21), correlation coefficients exceeded 0.2. The correlation between standardised household income and NO_2 was -0.16.

3.4. Prevalence and determinants of disease groupings

The prevalence of health problems ranged from 2 to 30% across the different groupings (Table 2). The Odds for all groupings clusters increased with higher age and lower household income (Supplemental Table 6). The difference in prevalence between men and women was different for different conditions. Occupationally non-active individuals tended to have less often high blood pressure, while for other conditions this varied by type of unemployment or retirement.

Variance between municipalities (adjusted for individual level variables) was very low for most disease groupings (Supplemental Table 7). The variance at the neighbourhood level was for several outcomes somewhat higher, which justified the exploration of the role of the explanatory neighbourhood variables that were determined in the framework of this study. For stroke/brain haemorrhage, basically all variance at neighbourhood and municipality level was explained by the individual factors.

3.4.1. Neighbourhood characteristics and disease groupings

Adjusted associations between neighbourhood characteristics and the prevalence of disease clusters are presented in Table 3. A higher address density was associated with higher morbidity of all conditions under study, particularly apparent for migraine/severe headache and diabetes. Associations between the social capital variables (social cohesion and collective efficacy) and morbidities were mostly unstable with large confidence intervals. Nevertheless, a higher social cohesion at the municipal level coincided with a lower prevalence of depression, migraine/severe headache and Medically Unexplained Physical Symptoms (MUPS). A higher percentage of both natural and agricultural greenspace in the neighbourhood was weakly associated with less morbidity for all conditions. Significant inverse association (pointing towards beneficial effects) was found for anxiety and migraine/severe headache. The amount of blue space was not apparently associated with most morbidities, only significantly associated with a lower prevalence of high blood pressure and diabetes.

Consistent associations between a higher Shannon index and lower morbidity were found for most conditions, suggesting a beneficial health effect of land use diversity (Table 3). Particulate air pollution (PM_{10} and $PM_{2.5}$) levels were not consistently associated with morbidity, although higher levels coincided with higher prevalences of coronary heart disease and depression. Levels of NO_2 tended to be related to higher morbidity of all conditions, being most apparent for diabetes. Noise levels in the neighbourhood were not related to the conditions under study.

The models presented in Table 3 were repeated with additional adjustment for address density (Supplemental Table 8). In general the estimates did not change much, only the association between NO_2 and diabetes attenuated from 1.30 to 1.14 (95% CI: 0.90–1.46). For associations with the Shannon index, statistical significance was lost for most outcomes but Odds Ratios were in most cases only slightly attenuated. For cardiac disease the association became stronger (OR 0.60, 95% CI 0.42–0.86) while for MUPS and diabetes, the OR became close to 1 after adjustment for address density.

As land use diversity had the clearest pattern of association with the morbidity clusters, we explored the idea that these associations would be stronger among people presumably more exposed to neighbourhood influences, and/or with lower socio-economic status. Thus, the associations between the Shannon index and morbidities were stratified by occupational activity and by standardised household income. The inverse associations between a higher diversity and prevalence of most disease groupings were stronger or only apparent in non-occupationally active individuals (Table 4). This was most pronounced for high blood pressure, cardiac disease, anxiety disorder and MUPS. For some conditions (depression, anxiety and MUPS), the inverse association between Shannon index and morbidity tended to be stronger among those with a lower household income. For other conditions such as coronary heart disease and diabetes, the association with land use diversity was similar for the different income strata. Similar results were found when these stratified models were additionally adjusted for address density (results not presented).

4. Discussion

In this multilevel analysis of a representative sample of inhabitants from small neighbourhoods in the Netherlands we observed that a larger diversity of land use in the neighbourhood was related to lower morbidities of various physical and mental conditions. These associations were only partly explained by the degree of urbanisation, and were more pronounced among groups with lower socio-economic status, and among occupationally non-active people. In addition to degree of urbanisation and surrounding greenspace, the variety in

Table 3
Associations (odds ratios and 95% confidence intervals) between neighbourhood characteristics and the prevalence of 10 disease groupings. N = 4450 individuals nested in 135 neighbourhoods in 43 municipalities. Multilevel models adjusted for sex, age, household income and socio-economic status.

	High blood pressure	Cardiac disease	Coronary heart disease	Stroke, brain haemorrhage	Depression	Anxiety disorder	Asthma, COPD	Migraine/severe headache	MUPS	Diabetes
Address density [per 50 addresses/ha]	1.07 (0.92–1.25)	1.03 (0.87–1.22)	1.32 (0.98–1.78)	1.01 (0.80–1.28)	**1.19 (1.03–1.38)**	1.03 (0.86–1.25)	1.12 (0.98–1.29)	**1.27 (1.05–1.52)**	**1.15 (1.03–1.28)**	**1.33 (1.12–1.58)**
Social cohesion municipality	1.27 (0.59–2.71)	0.85 (0.38–1.88)	0.34 (0.08–1.47)	1.30 (0.37–4.53)	**0.37 (0.16–0.86)**	0.59 (0.22–1.57)	0.80 (0.39–1.63)	**0.37 (0.14–0.99)**	**0.42 (0.20–0.88)**	0.40 (0.12–1.30)
Social cohesion neighbourhood	0.55 (0.11–2.85)	**6.51 (1.36–31.1)**	23.6 (0.79–709)	0.90 (0.09–9.32)	1.28 (0.22–7.30)	0.98 (0.12–8.08)	0.28 (0.05–1.49)	0.38 (0.04–3.65)	1.24 (0.38–4.03)	0.46 (0.06–3.70)
Collective efficacy municipality	1.69 (0.65–4.43)	0.95 (0.30–2.99)	0.29 (0.04–1.90)	2.29 (0.41–12.7)	0.37 (0.11–1.21)	1.07 (0.31–3.73)	0.73 (0.30–1.78)	0.36 (0.10–1.25)	0.46 (0.18–1.16)	0.69 (0.13–3.74)
Collective efficacy neighbourhood	0.47 (0.09–2.47)	1.49 (0.20–10.8)	17.5 (0.43–719)	0.81 (0.05–12.6)	0.74 (0.11–5.06)	0.16 (0.02–1.31)	0.22 (0.05–1.06)	0.31 (0.03–2.86)	0.55 (0.17–1.74)	0.88 (0.10–8.06)
Natural green [per 10%]	0.96 (0.86–1.07)	**0.90 (0.81–0.99)**	0.80 (0.62–1.03)	1.01 (0.89–1.14)	1.02 (0.91–1.14)	0.98 (0.84–1.14)	0.92 (0.81–1.04)	**0.81 (0.65–1.00)**	0.98 (0.89–1.07)	0.96 (0.83–1.11)
Agricultural green [per 10%]	0.99 (0.95–1.04)	1.00 (0.95–1.05)	0.98 (0.89–1.09)	0.96 (0.89–1.05)	0.96 (0.89–1.03)	**0.94 (0.88–1.00)**	0.98 (0.94–1.03)	0.96 (0.90–1.03)	0.98 (0.95–1.02)	0.96 (0.90–1.03)
Total green [per 10%]	0.99 (0.95–1.03)	0.98 (0.94–1.03)	0.96 (0.88–1.05)	0.98 (0.91–1.05)	0.98 (0.92–1.03)	**0.94 (0.89–1.00)**	0.97 (0.94–1.02)	0.95 (0.89–1.01)	0.98 (0.95–1.02)	0.96 (0.91–1.02)
Blue spaces [per 1%]	**0.96 (0.94–0.98)**	1.00 (0.98–1.03)	0.97 (0.92–1.03)	1.00 (0.96–1.04)	1.00 (0.97–1.03)	1.00 (0.97–1.04)	1.00 (0.97–1.02)	0.98 (0.95–1.02)	0.99 (0.97–1.01)	**0.94 (0.91–0.98)**
Shannon index	0.87 (0.68–1.12)	**0.75 (0.59–0.96)**	**0.53 (0.33–0.84)**	1.02 (0.70–1.47)	**0.68 (0.51–0.91)**	0.88 (0.64–1.21)	**0.77 (0.61–0.97)**	**0.65 (0.47–0.90)**	0.84 (0.70–1.01)	**0.66 (0.49–0.90)**
PM_{10} [per 10 $\mu g/m^3$]	0.98 (0.45–2.12)	0.82 (0.32–2.11)	3.71 (0.78–17.7)	0.65 (0.16–2.68)	2.33 (0.73–7.44)	1.12 (0.40–3.12)	1.05 (0.49–2.25)	1.45 (0.51–4.15)	0.96 (0.43–2.13)	1.90 (0.46–7.82)
$PM_{2.5}$ [per 10 $\mu g/m^3$]	1.10 (0.29–4.11)	0.40 (0.08–2.01)	9.58 (0.67–138)	0.19 (0.02–1.94)	**6.42 (1.39–29.7)**	0.32 (0.05–1.92)	0.73 (0.20–2.75)	1.89 (0.30–11.8)	0.79 (0.26–2.45)	0.63 (0.08–5.16)
NO_2 [per 10 $\mu g/m^3$]	1.00 (0.86–1.16)	1.04 (0.87–1.25)	1.29 (0.95–1.75)	1.01 (0.77–1.32)	1.15 (0.95–1.39)	1.10 (0.91–1.33)	1.05 (0.90–1.21)	1.15 (0.95–1.41)	1.04 (0.89–1.21)	**1.30 (1.03–1.64)**
Noise road traffic [per 10 LDEN]	1.04 (0.73–1.47)	0.93 (0.61–1.42)	1.57 (0.75–3.26)	0.88 (0.49–1.59)	1.17 (0.72–1.91)	0.94 (0.59–1.52)	0.98 (0.69–1.38)	0.92 (0.55–1.54)	0.88 (0.64–1.21)	1.11 (0.59–2.12)
Noise railway traffic [per 10 LDEN]	1.00 (0.86–1.16)	0.99 (0.83–1.17)	0.89 (0.64–1.23)	0.89 (0.70–1.14)	0.94 (0.76–1.18)	1.06 (0.87–1.29)	1.01 (0.87–1.17)	0.85 (0.69–1.06)	0.95 (0.83–1.08)	1.01 (0.81–1.27)

MUPS: medically unexplained physical symptoms.
Statistically significant ($p < 0.05$) associations are given in bold.

greenspace and built-up area may affect health of people living in the neighbourhoods.

We considered a variety of environmental factors that were to a smaller or larger extent mutually correlated, partly through degree of urbanisation. Most of the associations of these factors with the prevalence of various disorders were consistent with findings from other studies. Interestingly, a higher social cohesion at the municipal level − rather than the small neighbourhood level − coincided with a lower prevalence of depression, migraine/severe headache and MUPS. Another study from the Netherlands (Mohnen et al., 2011) observed a

Table 4
Associations (odds ratios and 95% confidence intervals) between the *Shannon index diversity score* and the prevalence of 10 disease groupings, broken down by individual socio-economic indicators. Multilevel models adjusted at the individual level for sex, age, household income (where applicable) and socio-economic status (where applicable). N = 4450 individuals nested in 135 neighbourhoods in 43 municipalities.

	Occupationally active		Standardised household income		
	Yes	No	0–35 percentile	36–70 percentile	71–99 percentile
Individuals (n)	2035	2415	1497	1620	1333
Neighbourhoods (n)	124	113	106	99	104
Municipalities (n)	41	38	35	34	35
High blood pressure	1.05 (0.78–1.42)	**0.71 (0.52–0.97)**[*]	0.87 (0.56–1.33)	**0.72 (0.53–0.99)**	1.01 (0.71–1.43)
Cardiac disease	1.47 (0.88–2.46)	**0.64 (0.46–0.89)**	0.69 (0.46–1.04)	**0.61 (0.37–0.99)**	1.06 (0.67–1.70)
Coronary heart disease	0.53 (0.28–1.00)	**0.48 (0.29–0.80)**	**0.62 (0.38–0.99)**	**0.31 (0.14–0.70)**[†]	**0.45 (0.23–0.89)**
Stroke, brain hemorrhage	2.68 (0.91–7.93)	0.85 (0.57–1.26)[†]	0.89 (0.50–1.61)	1.07 (0.60–1.90)	0.84 (0.36–2.00)
Depression	0.67 (0.43–1.05)	**0.56 (0.39–0.81)**	**0.39 (0.25–0.62)**	0.83 (0.51–1.35)[*]	0.67 (0.38–1.19)
Anxiety disorder	1.09 (0.66–1.80)	**0.66 (0.44–0.98)**	0.66 (0.41–1.05)	1.09 (0.62–1.93)	0.80 (0.43–1.50)
Asthma, COPD	**0.72 (0.53–0.98)**	0.76(0.57–1.01)	**0.57 (0.42–0.79)**	0.79 (0.57–1.11)	0.85 (0.60–1.21)
Migraine/severe headache	0.68 (0.43–1.07)	**0.60 (0.40–0.90)**	**0.56 (0.33–0.95)**	0.78 (0.47–1.27)	0.61 (0.31–1.21)
MUPS	1.00 (0.80–1.25)	**0.67 (0.54–0.83)**	**0.62 (0.47–0.82)**	0.93 (0.72–1.22)[†]	0.92 (0.70–1.20)[*]
Diabetes	0.66 (0.40–1.09)	**0.62 (0.44–0.87)**	**0.57 (0.39–0.84)**	**0.52 (0.30–0.90)**	0.87 (0.53–1.44)

MUPS: medically unexplained physical symptoms.
Statistically significant ($p < 0.05$) associations are given in bold.
[*] $p < 0.05$.
[†] $p < 0.10$ for multiplicative interaction.

better self-rated general health related to more social capital at the 4-digit postal code level, which size is between the PC5 and the municipal level. Our findings are also consistent with several international studies (Murayama et al., 2012), including similar findings for social capital and depression.

Particulate air pollution (PM_{10} and $PM_{2.5}$) levels at the PC5 neighbourhood level were not consistently related to the health outcomes under study. This may partly be due to the small variation in assessed exposure levels between the neighbourhoods. Ambient levels of NO_2 showed a wider distribution across the neighbourhoods, and were generally associated with increased prevalences of various disorders. The interesting finding of a positive association with diabetes is consistent with other studies (Strak et al., 2017), in particular for type 2 diabetes (Butalia et al., 2016; Thiering and Heinrich, 2015).

We found indications for beneficial health effects of greenspace, which is consistent with a growing body of evidence (Tzoulas et al., 2007; Hartig et al., 2014). In addition, a fairly consistent pattern of lower morbidity coinciding with a higher Shannon index, indicating increased land use diversity, was observed for most disease groupings. The Shannon index in our study reflects the diversity of all types of land use, natural and built-up areas together. Most considered types of land use (27 out of 39 types) regarded green, and some categories included in built areas could actually also be perceived as green, such as grass and forest within built-up areas (Supplemental Table 2). Thus, the diversity of green in the neighbourhood is part of the Shannon index as explored in this analysis. The correlation between the Shannon index and greenspace was around 0.7, suggesting that about half of the land use variability is explained by variability in the amount of greenspace.

The inverse associations between the Shannon index and morbidities were more pronounced among people who were not occupationally active. This suggests that beneficial effects of land use diversity are stronger among those who likely spend more time in the neighbourhood around their own homes. Not surprisingly, the Shannon index was strongly correlated with the degree of urbanisation. Nevertheless, the associations between a higher Shannon index and lower prevalences of most health problems remained present after controlling for address density. To our knowledge this has not been reported often. Recently, one study from New Zealand found inverse associations between vegetation diversity and childhood asthma (Donovan et al., 2018). This study, however, did not consider the total land use mix, that is, the combination of natural and built-up areas. It has been well recognised that diversity is an important indicator of ecosystem health (Hartig et al., 2014). Recently, (microbial) biodiversity has been put forward as a possible new mechanism for the beneficial health effects of greenspace, although to date evidence for this is limited (Nieuwenhuijsen et al., 2017). Among different possible mechanisms, we speculate that the pathway through stress reduction (Hartig et al., 2014) may provide a possible explanation of land use diversity coinciding with lower morbidity of some health problems.

Given an Odds Ratio of 0.7 and an interquartile range of the Shannon Index of 0.84, it can be estimated that a change of land use diversity in our study population from the 25th to the 75th percentile is associated with a 25% reduction of the prevalence of various physical and mental conditions. This is substantial at the population level. Although it is difficult to translate this directly to practical recommendations, it may help giving input for the development of healthy planning and design of (urban) neighbourhoods.

A limitation of this study that needs to be considered was that the aggregation of the social capital variables to neighbourhood level had limited reliability. Three or four PC5 neighbourhoods were nested within a municipality, and limited variability of social cohesion or collective efficacy was left between PC5 neighbourhoods within municipalities. No strong associations with health were observed at this level, and the unstable coefficients made additional adjustment or stratification not feasible. Nevertheless, correlations with degree of urbanisation and other environmental factors were in the anticipated direction. The operationalisation of social cohesion is comparable with that in other studies into the association between social capital and health. However, collective efficacy was operationalised in terms of norms regarding disorderliness and not in terms of unhealthy behaviours. Another limitation was that only few potential confounders at the individual levels, such as lifestyle factors, were available for this analysis.

For the complete set of exposure variables we could only consider the own neighbourhood, since data on social cohesion and collective efficacy were not available for surrounding neighbourhoods. Health status could also be affected by environmental factors outside the own neighbourhood. Nevertheless, we were able to consider municipality for the social capital variables. Finally, we explored associations between a large number of neighbourhood exposure variables (15) and health outcomes (10). We did not apply strict statistical criteria to identify (isolated) significant associations, but rather looked at consistency of findings across different health outcomes and thus avoided the over-interpretation of spurious findings.

Strengths of this study included the objective assessment of health done by the own general practitioner. It can also be considered both conservative and relevant since health problems for which people did not contact their GP are not considered. In addition, it is more specific than self-rated general health as used in other studies. A second strength was that the source of the data for the health assessment was different from the source of the interview data in the framework of the SSND study leading to the assessment of social capital. Third, many small neighbourhoods were included and the study population was large and included all ages. The size of neighbourhoods is a source of huge variation between studies. We used rather small areas, nested within municipalities. Especially for exposure to air pollution and noise, even these small areas are perhaps not homogeneous enough. In this study we improved over previous studies in the Netherlands, which used the four digit postal codes as their spatial scale (Groenewegen et al., 2018), but still, exposure to air pollution and noise should perhaps be included at the level of individual addresses rather than small areas. Finally, the population was representative of the entire country, indicated by the distribution of the individual socio-economic variable that followed exactly the percentiles relative to the whole country.

In conclusion, a high diversity in land use of neighbourhoods may be beneficial for physical and mental health of the inhabitants. We recommend further study of this hypothesis. If confirmed, this may be incorporated into urban planning, in particular regarding the diversity of greenspace.

Competing interests

None declared.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2018.09.008.

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