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Residential greenness and risks of depression: Longitudinal associations with different greenness indicators and spatial scales in a Finnish population cohort

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ABSTRACT

We carried out a longitudinal study on the associations between residential greenness and depression risk in urban areas in Finland. Residential greenness indicators were estimated within various buffer sizes around individuals' home locations (selected n = 14424) using time-series of normalized differential vegetation index (NDVI) and CORINE land cover data (CLC). We estimated individuals' cumulative exposure to residential greenness over a 5-years and 14-years follow-up. We used doctor-diagnosed depression and Beck Depression Inventory for depression assessment. Our multi-logistic model showed an inverse association between residential greenness and depression, implying lowered depression risk for individuals with higher residential greenness. The association was particularly evident when using NDVI-based residential greenness (within a buffer of 100 m radius) and doctor-diagnosis depression data, adjusted with individual-level covariates. The odds ratio was 0.56 (95% CI 0.33 to 0.96) for the 5-years follow-up, and 0.54 (95% CI 0.30 to 0.98) for the 14-years follow-up. The associations between CLC-based total residential green space and depression varied across the different buffer sizes. In general, all the associations depended on the type of depression assessment, quality of greenness indicators, and the spatial scale of analysis. The associations also varied across the socio-demographic groups and neighborhood socioeconomic disadvantage level.

1. Introduction

In the last decade, substantial attention has been paid on the role of urban green spaces for public health (Hartig et al., 2014; Markevych et al., 2017; Houlden et al., 2018). A regular exposure to green natural or semi-natural environments has been linked with various preventive and curative health benefits, and with an active outdoor lifestyle (Bratman et al., 2012; Gascon et al., 2015; Lachowycz and Jones, 2013). Several cross-sectional studies suggest positive associations between increased exposure to green spaces and good mental health, particularly increased green exposure reducing a stress and anxiety (Beyer et al., 2014; Pun et al., 2018), and lowering a risk of depression (Cohen-Cline et al., 2015; South et al., 2018). However, results from longitudinal studies have not shown such evidences. While some studies imply mental health benefits, such as a lower risk for psychiatric disorders (Astell-Burt et al., 2014; Engemann et al., 2019) and depression (Hystad et al., 2019), other studies have not identified such associations (Annerstedt et al., 2012; Noordzij et al., 2020). These studies differ in the spatial and temporal scales of the data analysis, the greenness indicators used, and the applied confounder factors, thus, it is not straightforward to compare or draw conclusions on the role of green spaces for mental health. Therefore, this aspect needs to be further investigated.

Mental health problems, depression in particular, are one of the leading cause for the global disease burden and disability affecting to 4.4% of the global population (WHO, 2017). During the recent COVID-19 pandemics a substantial increase in numbers of lives lost to depression or anxiety has been observed in many countries (Ettman et al., 2022; Santomauro et al., 2021). Finland has the highest estimated incidence rate of mental health problems in the European Union. 20% of the population are affected (OECD/EU, 2018), and 4%–9% of the

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population suffer from a major depression (Lahtinen, 2006). Nordic cities are usually well-connected to natural or semi-natural green environments. The cities have a long tradition of embedding green spaces into the planning and development of urban infrastructures (Löfvenhaft et al., 2002). However, the residents' daily/regular exposure to greenness depends on the greenness qualities of their neighborhoods and how people move and use their local urban environment and various green spaces, such as urban parks, city forests and urban farmlands. Forests are particularly extensive elements in Finnish cities and important areas for recreation and sports activities. Exposure to greenness may also vary according to the neighborhood socioeconomic setting, therefore it is important to take into account the socio-economic status (SES) when studying green space effects on mental health (Sugiyama et al., 2016). To our knowledge only few longitudinal studies have been carried out on the associations between residential greenness and depression risk in the Nordic countries (e.g., Annerstedt et al., 2012; Engemann et al., 2019; Tarkiainen et al., 2021). In Finland, there are good archives of cohort health data, which allow spatio-temporal analyses of the urban green space associations to various mental health outcomes.

Today, vast repositories of open access Earth observation (EO) satellite data allow spatially explicit characterization of green environments and detection of their changes over time (Guo et al., 2017). These resources are vital when linking greenness indicators to longitudinal health data. One of the most widely used satellite-based indices in many health studies is the Normalized Differential Vegetation Index, NDVI (Su et al., 2019), which can be generated from archival EO datasets over many decades as time-series NDVI data. Time-series NDVI is a prominent indicator when estimating cumulative exposure to green spaces over time (Markevych et al., 2017; Engemann et al., 2019). However, NDVI only indicates vegetation greenness intensity (Su et al., 2019), but does not indicate vegetation cover types or vegetation diversity. To represent vegetation types and land cover diversity in urban areas, the use of land cover data, such as CORINE land cover (Büttner, 2014) appears to be useful.

In this paper, we study the associations between residential greenness (NDVI, land cover types, land cover diversity) and depression. We used doctor-diagnosed depression and Beck Depression Inventory data of a Finnish population cohort, with participants from several cities. Various individual- and neighborhood-level confounder factors were included in the analysis. Additionally, we examined how these associations vary when considering the greenness level at various spatial scales around participants' home locations. The results are discussed particularly from the perspective of what role different greenness indicators and spatial scale play when discovering the linkages between mental health and urban green space.

2. Material and methods

2.1. Study population

The health data were derived from the Health and Social Support Study (HeSSup) cohort (24057 individuals, followed up since 1998). It is a longitudinal population study of Finnish adults, men and women (20–54 years) to examine the associations between psychosocial factors, health risk behavior, and subsequent health (Suominen et al., 2012). The HeSSup data collection is based on a completely randomized stratified sampling according to age groups 20–24, 30–34, 40–44, and 50–54 in the year 1998 of the concurrent Finnish population. The data includes three survey years: 1998 (baseline), 2003 (5-years follow-up), and 2012 (14-years follow-up). For this study, we selected all individuals who answered the baseline survey and at least one follow-up survey and had non-missing information on their home locations, including moving dates between 1998 and 2012 (19851 individuals). The home location data (geographic coordinates) was obtained from the Finnish Population Register Center.

2.2. Depression assessment

The HeSSup's depression data consisted of Beck Depression Inventory (BDI) (Beck et al., 1961), a widely used and validated screening tool to detect cases of depression (Beck et al., 1961; Rotenstein et al., 2016; Aalto et al., 2012). The BDI assesses cognitive, affective, somatic, and behavioral symptoms characterizing depression (Aalto et al., 2012). BDI consists of 21 items with points ranging from 0 to 63. The score of 19 or more indicates a moderate to severe depression (Beck et al., 1961). We used 19 as a cutoff point to dichotomize individuals into two groups (depression/no depression). We also used additional depression data from a list of diseases diagnosed by a doctor to the Cohort's participants. This was named herein doctor-diagnosed depression.

2.3. Confounding factors

Based on previous studies (Kivimäki et al., 2020; Crouse et al., 2021), we considered individual and neighborhood level socioeconomic status to possibly confound or modify residential greenness and depression risk association. Individual-level covariates at the baseline year, such as gender (female, male), age (grouped into 20–30 yr, 31–45 yr, and 46–54 yr), education, employment status (at work or not), chronic disease (yes or no), marital status (yes or no), and body mass index (BMI) were obtained from the survey questionnaires. Individual's reported chronic diseases included bronchiectasis, lung asthma, high blood pressure, hypertension, high cholesterol, diabetes, myocardial infarction, angina pectoris, atrial fibrillation, stroke, cerebrovascular accident, peptic ulcer, liver disease, kidney disease, rheumatoid arthritis, sciatica, fibromyalgia, epilepsy, brain injury, meningitis or encephalitis, malignant tumor, panic disorder, and eating disorder. Education information was based on the self-reported vocational education classified into three categories: low (primary education), intermediate (apprenticeship, vocational school, or college degree), and high (university or polytechnic degree). BMI was estimated as weight (kg) divided by height (m) squared.

Additionally, to control the difference in depression risk related to urban or rural environments, we classified areas of residence as rural and urban, using the Urban-Rural classification of Finnish Environmental Institute (Helminen et al., 2014).

As a neighborhood-level confounding factor, we used the Neighborhood Socioeconomic Disadvantage Index (SEDI), obtained from the Statistics Finland grid database of 250 m × 250 m. The SEDI is a composite indicator derived from the proportion of adults with primary education only, the unemployment rate, and the proportion of people living in rental housing. In SEDI, each variable is standardized as a Z score. The overall SEDI score is the mean value across all three Z scores; the national mean equals 0 with an SD of 1. Values greater than 0 indicate higher neighborhood socioeconomic disadvantage and values less than 0 indicate lower neighborhood socioeconomic disadvantage (Kivimäki et al., 2020). We also obtained population data (in 250 m × 250 m grid) from Statistics Finland.

2.4. Cumulative exposure to residential greenness

We characterized residential greenness in the vicinity of the individuals' homes using two EO-derived datasets: 1) Normalized Difference Vegetation Index (NDVI) and 2) CORINE Land Cover (CLC) data. We estimated NDVI value from the Landsat TM 5 satellite data archive obtained from 1984 to 2012, with spatial resolution of 30 m. NDVI is the normalized ratio of the reflectance differences between the near-infrared (NIR) and visible red bands, ranging from −1 to 1. It is based on the contrasting response of living plants' chlorophyll in red (relatively more absorption) and NIR (relatively more reflectance) wavelengths (Su et al., 2019). To estimate NDVI, seasonal changes in vegetation greenness need to be considered. At the latitudes of Finland, images over the summer period (June–August) are the most useful to maximize the reflectance and to minimize the seasonal greenness variation of living vegetation. We used atmospherically corrected TM images over three consecutive years (1997±1 yr, 2000±1 yr, 2003±1 yr, 2006±1 yr, 2009 ±1 yr, and 2011 ±1 yr) to make a cloud-free Landsat TM image mosaic covering the territory of Finland. Water bodies, represented by negative NDVI-values, were masked out from the images. Thus, areas with NDVI-values approaching 1 represented high greenness. Conversely, areas with values approaching zero indicated low greenness or non-vegetation. TM images were processed in the Google Earth Engine (Gorelick et al., 2017). We also used Corine Land cover (CLC) data (Törmä et al., 2011) of 2000, 2006 (25 m of pixel size) and 2012 (20 m of pixel size) to extract information of the land cover classes. We reclassified the original CLCs data into built-up areas, built-up areas mixed with vegetation (discontinuous urban fabric), agricultural areas, forest areas, shrub and grass areas, bare-surface, wetland, and water bodies.

The residential greenness indicators were estimated as the NDVI mean and the percentage of the land cover classes within a spatial buffer around individuals' home locations (three buffer sizes of 100, 500, and1000 m of radius was used). Total residential green space was estimated by summing up the percentage of built-up areas mixed with vegetation, agricultural areas, forest areas, shrub and grass areas, and wetlands within the spatial buffer. Additionally, using the reclassified CLC data into eight classes, we calculated Simpson's land cover diversity index (LCDI) over the same spatial buffers. LCDI is calculated as $1 - \sum_{i=1}^{m} p_i^2$. Where p_i is the proportion of land cover class i within a specific area (as determined by the size of the buffer area). LCDI ranges from 0 to 1. When the area contains only one land cover class, the index value is 0 (complete uniformity). When the amount and proportion of different land cover classes is more balanced, the value approaches 1 (complete diversity) (Ritsema van Eck and Koomen, 2008). We estimated time-series residential greenness indicators to each individual's home location based on his/her residential history record.

To estimate the cumulative exposure to residential greenness, we considered home address change and residence time in each location for each individual. With this information and the time-series data of the residential greenness indicators, we calculated the time-weighted average of the greenness indicators for each individual. We completed the missing values in the time-series data of the greenness indicators by taking the value from the closest previous or subsequent year with available data. We estimated the time-weighted average of the greenness indicators for two study periods (5-years and 14-years follow-up).

2.5. Data analysis

We analyzed the association of residential greenness with the 1) doctor-diagnosed depression and with the 2) Beck Depression Inventory, by estimating the odds ratio using a multi-logistic model (Sperandei, 2014; Sarkar et al., 2018). To model the effect of residential greenness on depression over the follow-up period, we excluded all participants who presented depression in the baseline year.

In our study design, we examined the association between cumulative exposure to residential greenness and depression as the odds of a depression reported in one of the subsequent surveys (S2 and S3). The first survey was the baseline (S1). When examining the associations between residential greenness and depression over a 5-years follow-up, we used the time-weighted greenness average between the first survey (S1) and the subsequent survey (S2) as the exposure. When examining the associations between residential greenness and depression over a 14-years follow-up, we used the time-weighted greenness average between the first survey (S1) and the third survey (S3) as the exposure. The time after the measurement of the outcome was not taken into account when defining the exposure. All participants who had responded S1–S2 and S1–S3 were included in the 5-years and 14-years follow-up analyses, respectively. The participants who had responded to the three surveys were included in the 5-years as well as the 14-years follow-up analyses. Fig. 1 illustrates this approach.

Equations from 1 to 2 represent the different logistic models we used in this study.

$$\log(D_i) = \alpha_i + \beta_0 \text{Greenness} + \varepsilon_i \tag{1}$$

$$\log(D_i) = \alpha_i + \beta_0 \text{Greenness} + \beta_1 \text{Sex} + \beta_2 \text{Age} + \beta_3 \text{Education} + \beta_4 \text{BMI} + \beta_5 \text{AtWork} + \beta_6 \text{Spouse} + \beta_7 \text{Disease} + \varepsilon_i \tag{2}$$

Where log(Di) is the depression occurrence log-odds ratio, defined by the natural logarithm of the ratio between the probability that the event will occur (p) to the probability that it will not occur (1-p). The symbol α is the model intercept, β is a parameter to be estimated for each covariable, and ε_i is the error term.

Greenness is the cumulative exposure to residential greenness (NDVI, percentage of total green space, percentage of forest area, or LCDI), estimated over a 5-years and 14-years follow-up. Individual-level covariates at baseline year are sex (2 groups), age (3 groups), education (3 levels), BMI (Body Mass Index), AtWork (the employment status, 2 groups), Spouse (the marital status, 2 groups), and Disease (indicates if the individual have a chronic diseases, 2 groups).

The logistic models were fitted using the maximum likelihood method in the R program (R core team, 2018). The odds ratio (OR) is the exponentiated β coefficient. OR range from 0 to positive infinity. OR less than 1 indicates lower risk, OR equal to 1 indicates no association between two variables, and OR greater than 1 indicates higher risk.

Additionally, we examine what level of residential greenness associates mostly with depression. We classified the cumulative exposure to residential greenness into four levels. For NDVI, we used more biophysical meaningful cutoff values as follows. Low greenness (NDVI $\leq$0.3), lower-medium greenness (NDVI $>$0.3 and $\geq$0.5), upper-medium greenness (NDVI $>$0.5 and $\leq$0.7), and high greenness (NDVI $>$0.7). With the categorized residential greenness, we re-ran the multi-logistic model. We proceeded similarly with the total green space percentage. In addition, to examine differences of greenness benefit between sex and age groups, we ran the multi-logistic model for each of these groups.

For a further sensitivity analysis, we examined the association between residential greenness and depression by stratifying participants neighborhood socioeconomic disadvantage index (SEDI) into three levels using terciles (low neighborhood disadvantage, medium neighborhood disadvantage, and high neighborhood disadvantage). Similarly, we also examined the association between residential greenness and depression across neighborhood population density, by grouping participants' neighborhood population density into three groups using terciles. We ran the multi-logistic model for each of these groups.

3. Results

3.1. Characteristics of the study sample

The preliminary sample included 19851 individuals having home location and moving history data at the baseline year (1998). From these, 14424 individuals resided in urban areas; 47% in Southern Finland, 25% in Southwest Finland and Åland, 8% in Western and Central Finland, 15% in Eastern Finland, and 5% in Northern Finland and Lapland. From the urban individuals, 13261 (92%) reported control data in 1998 and 2003 (5-years follow-up), and 9238 (64%) reported control data in 1998 and 2012 (14-years follow-up). Finally, after excluding individuals with missing values in covariates and presenting depression in the baseline year, we ended up with an analytical sample of 11794 individuals for BDI-based depression in 5-years follow-up, 8201 individuals for BDI-based depression in 14-years follow-up, 11945 individuals for doctor-diagnosed depression in 5-years follow-up, and 8248 individuals for doctor-diagnosed depression in 14-years follow-up. Table A1 in the appendix presents the sample size at the

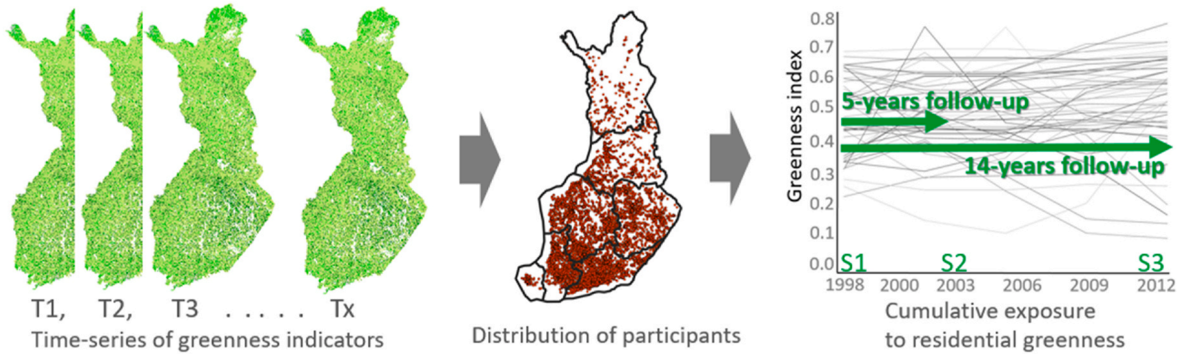

Fig. 1. Study design and extraction of time-series residential greenness indicators (based on NDVI and CORINE land cover data) within different buffer sizes around the participants' home location (100 m, 500 m, and 1000 m of radius). The cumulative exposure to residential greenness was estimated as time-weighted average greenness in each follow-up period. S1, S2, and S3 are the Cohort's survey years.

baseline year and the follow-up periods. Table 1 shows the selected population characteristic at the baseline year. In our data, Doctor Diagnosis and BDI-based depression showed fair agreement using Cohen's Kappa coefficient in the baseline year (0.22, $p < 0.001$).

3.2. *Relationship between NDVI- and CLC-based residential greenness indicators*

The estimated cumulative exposure (over a 5-years and 14-years follow-up) to residential greenness based on NDVI- and CLC-data showed moderate to strong correlation in the different buffer sizes (Table 2). CLC- total residential green space correlated strongly with NDVI-based residential greenness (up to 0.70, $p < 0.001$, in all cases). Residential forest correlation with NDVI-based residential greenness in the small buffer size (100 m of radius) was moderate (0.29 and 0.37, with $p < 0.001$, in 5-years and 14-years follow-up, respectively). The correlation of this variables increased when the buffer size increased and the forest area became larger. However, in GIS analysis, NDVI and CLC differed in representing urban green space. For example, CLC data included areas with both non-vegetation and vegetation in the same land-use class (discontinuous urban fabric), particularly in low-density residential areas. Generally, NDVI seemed to better represent the spatial variation of residential greenness than CLC data. Fig. 2 shows an example of the spatial data comparison for the Turku city area. LCDI exposure was moderately correlated with NDVI-based greenness exposure in all cases (Spearman rho <0.5, $p < 0.001$).

Table 1
Descriptive statistic of the study population at the baseline year. The number of individuals with "No depression" and "Depression" is based on doctor-diagnosed depression data. NDVI is the residential NDVI mean, and Green space is the percentage mean of total residential green space estimated from CORINE land cover data. The residential NDVI and Green space was estimated in a buffer of 100 m radius around the individuals' home.

Confounding factors	Total	%	No depression			Depression		
			n	NDVI (SD)	Green space % (SD)	n	NDVI (SD)	Green space % (SD)
Sex: Male (%)	5496	38.1	4952	0.52 (0.13)	60 (34)	536	0.50 (0.14)	54 (35)
Sex: Female (%)	8928	61.9	7770	0.50 (0.13)	56 (34)	1144	0.48 (0.14)	49 (34)
Age group 1 (20–30)	4642	32.2	4294	0.46 (0.13)	45 (29)	344	0.44 (0.13)	39 (28)
Age group 2 (31–45)	5978	41.4	5239	0.53 (0.13)	63 (34)	731	0.50 (0.14)	54 (35)
Age group 3 (46–55)	3804	26.4	3189	0.53 (0.13)	63 (36)	605	0.51 (0.14)	53 (36)
Education level: Low (%)	7248	50.2	6284	0.50 (0.13)	55 (33)	954	0.49 (0.14)	49 (34)
Education level: Intermediate (%)	4309	29.9	3881	0.52 (0.13)	62 (34)	424	0.51 (0.13)	55 (35)
Education level: High (%)	2714	18.8	2428	0.50 (0.14)	57 (35)	282	0.47 (0.15)	50 (35)
Education level: Missing	153	1.1	–	–	–	–	–	–
Body mass index (< 25)	9056	62.8	8078	0.50 (0.13)	55 (34)	968	0.48 (0.14)	48 (34)
Body mass index (≥ 25 < 30)	4072	28.2	3574	0.52 (0.13)	61 (35)	492	0.51 (0.13)	54 (35)
Body mass index (≥ 30)	1225	8.5	1009	0.52 (0.13)	59 (34)	213	0.52 (0.13)	55 (35)
Body mass index: Missing	71	0.5	–	–	–	–	–	–
Employment status (No at work)	4933	34.2	4202	0.48 (0.13)	49 (32)	722	0.48 (0.13)	46 (33)
Employment status (At work)	9442	65.5	8480	0.52 (0.13)	61 (35)	951	0.50 (0.14)	55 (35)
Employment status: Missing	49	0.3	–	–	–	–	–	–
Spouses (no)	4907	34.0	4145	0.46 (0.13)	42 (30)	752	0.45 (0.13)	39 (30)
Spouses (yes)	9510	65.9	8572	0.53 (0.13)	64 (34)	927	0.52 (0.13)	60 (35)
Spouses: Missing	7	0.0	–	–	–	–	–	–
Chronic Diseases (no)	11545	80.0	10597	0.51 (0.13)	57 (34)	948	0.49 (0.14)	51 (34)
Chronic Diseases (yes)	2857	19.8	2125	0.51 (0.13)	57 (34)	732	0.49 (0.14)	50 (35)
Chronic Diseases: Missing	22	0.2	–	–	–	–	–	–
Low neigborhood disadvantage (1st terciles)	4333	30.0	3922	0.54 (0.12)	75 (31)	407	0.52 (0.15)	69 (35)
Medium neighborhood disadvantage (2nd terciles)	4281	29.7	3794	0.47 (0.13)	49 (33)	480	0.46 (0.14)	45 (33)
High neighborhood disadvantage (3rd terciles)	3874	26.9	3279	0.47 (0.12)	40 (30)	587	0.46 (0.11)	35 (27)
Neighborhood disadvantage: Missing	1936	13.4	–	–	–	–	–	–
Low population density (1st terciles)	2660	18.4	2395	0.64 (0.08)	87 (17)	262	0.64 (0.07)	88 (16)
Medium population density (2nd terciles)	5317	36.9	4726	0.55 (0.09)	73 (26)	582	0.55 (0.09)	69 (28)
High population density (3rd terciles)	6341	44.0	5509	0.41 (0.12)	30 (25)	822	0.40 (0.12)	26 (22)
Population density: Missing	106	0.7	–	–	–	–	–	–

Table 2
Spearman correlation of CLC-based residential greenness with NVDI-based residential greenness, estimated within different buffer sizes and two study periods (5-years and 14-years follow-up). CLC (CORINE land cover), NDVI (Normalized difference vegetation index). LCDI (Land Cover Diversity Index).

	5-year follow-up	14-year follow-up
	rho (p-value)	rho (p-value)
100 m buffer		
Forest	0.29 (<0.001)	0.37 (<0.001)
Total green space	0.74 (<0.001)	0.72 (<0.001)
LCDI	0.44 (<0.001)	0.48 (<0.001)
500 m buffer		
Forest	0.58 (<0.001)	0.61 (<0.001)
Total green space	0.81 (<0.001)	0.80 (<0.001)
LCDI	0.50 (≤0.001)	0.46 (<0.001)
1000 m buffer		
Forest	0.71 (<0.001)	0.71 (<0.001)
Total green space	0.80 (<0.001)	0.79 (<0.001)
LCDI	0.40 (<0.001)	0.32 (<0.001)

3.3. Association between NDVI-based residential greenness and depression

We found associations between doctor-diagnosed depression and NDVI-based cumulative exposure to residential greenness, in the 5-years and 14-years follow-up. Here the multi-logistic modeling was significant in all unadjusted models (Model 1) within all buffer sizes (odds ratio ranged from 0.35 to 0.50; Table 3). The association remained significant within 100 m and 500 m buffer sizes, in 5-years follow-up, after adjusting for individual-level covariates (Model 2), odds ratio of 0.56 (95% CI 0.33 to 0.96) and 0.50 (95% CI 0.28 to 0.88), respectively, and within buffer size of 100 m of radius in the 14-years follow-up, with an odds ratio of 0.54 (95% CI 0.30 to 0.98). However, these associations were not found when using BDI-based depression (Table 3).

Additionally, modeling the association between doctor-diagnosed depression and NDVI-based cumulative exposure levels (low, lower-medium, upper-medium, and high) to residential greenness shows a significant association for the upper-medium greenness exposure (OR 0.71, 95% CI 0.57 to 0.90) and high greenness exposure (OR 0.60, 95% CI 0.38 to 0.91) with the unadjusted model in 5-years follow-up, within a buffer size of 100 m of radius. The association remained significant after adjusting with individual-level covariates for upper-medium greenness exposure (OR 0.76, 95% CI 0.60 to 0.98). Over a 14-years follow-up, only the unadjusted model for upper-medium greenness exposure was significant (OR of 0.73, 95% CI 0.56 to 0.97). When modeling these associations using BDI-based depression, no significant associations were found in any of the models. (Table A2, Appendix).

3.4. Association between CLC-based residential greenness and depression

The associations between doctor-diagnosed depression and cumulative exposure to residential total green space, based on CORINE land cover (CLC), were significant with the unadjusted models in 5 years follow-up within all buffer sizes (100 m, 500m, and 1000 m of radius), odds ratio being 0.73 (95% CI 0.60 to 0.89), 0.63 (95% CI 0.48 to 0.84), and 0.64 (95% CI 0.47 to 0.88), respectively (Table 4). The associations remained significant after adjusting with individual-level covariates within buffer sizes of 500 m of radius (OR 0.71, 95% CI 0.52 to 0.96) and 1000 m of radius (OR 0.70, 95% CI 0.50 to 0.99). Similarly, in 14 years follow-up, the unadjusted models showed significant associations within the three buffer sizes, odds ratio being 0.56 (95% CI 0.45 to 0.70), 0.56 (95% CI 0.41 to 0.76) and 0.59 (95% CI 0.42 to 0.83), respectively. The associations remained significant when adjusting with individual-level covariates (Model 2) within a buffer size of 100 m of radius (OR 0.65, 95% CI 0.51 to 0.83) and 500 m of radius (OR 0.68, 95% CI 0.49 to 0.96).

We did not find statistical significant association between CLC-based cumulative exposure to residential forest areas and doctor-diagnosed in any models. Also, land cover diversity index (LCDI) was significant only in an unadjusted model (within buffer size of 1000 m of radius, in 14-years follow-up), odds ratio 0.42 (95% CI 0.18 to 0.98) (Table 4).

The association between CLC-based cumulative exposure to total green space and BDI-based depression was significant in the unadjusted model (OR 0.55, 95% CI 0.40 to 0.78) in 5-years follow-up and within 100 m of buffer size, and in the model adjusted with individual-level covariates (OR 0.62, 95% CI 0.43 to 0.90) (Table 4). Over a 14-years follow-up, the association was significant in the unadjusted model (OR 0.50, 95% CI 0.34 to 0.75) within buffer size of 100m of radius. Similar to doctor-diagnosed depression, we found no significant association between BDI-based depression and CLC-based residential forest area or LCDI in any of the models or buffer sizes (Table 4).

Results of the associations between depression and CLC-based greenness cumulative exposure levels (low, lower-medium, upper-medium, and high), estimated within a buffer size of 100 m of radius, shows a significant association between the doctor-diagnosed depression and high total green space in the unadjusted model in 5-years follow-up (OR 0.75, 95% CI 0.62 to 0.90), and remained significant after adjusting with individual-level covariates (OR 0.82, 95% CI 0.68 to 1). In the 14-years follow-up, the unadjusted model shows a significant association with lower-medium total green space (OR 1.26, 95% CI 1.02 to 1.57) and high total green space (OR 0.74, 95% CI 0.60 to 0.92). However, these associations did not remain significant after adjusting with individual-level covariates. Instead, the upper-medium total green space was significant in the adjusted model (OR 0.78, 0.62 to 0.98).

In case of the BDI-based depression, the unadjusted model was

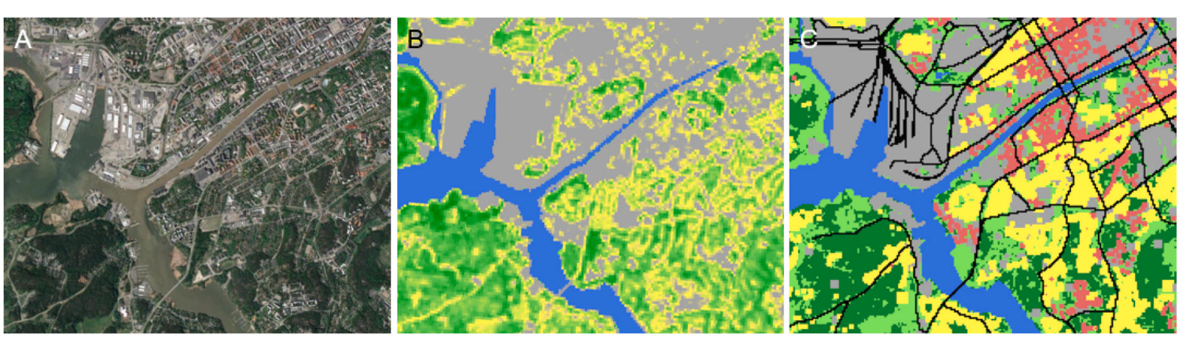

Fig. 2. Example of the spatial data used in estimating residential greenness. A. Aerial orthophoto of Turku city, Finland, from Google Map. B. Normalized Difference Vegetation Index based on Landsat TM 5 (30 m). In NDVI data, the water bodies (blue) were masked out, and the NDVI values range from 0 (grey, non-vegetation) to 1 (dark green, high vegetation). C. Reclassified CORINE land cover data. Grey represents industrial and commercial areas, black main roads and streets, red residential areas (all these were reclassified as built-up area), yellow discontinues urban fabric (built-up area mixed with vegetation), light-green shrub and grass and wetland, dark-green forest, and blue the water bodies. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 3
Longitudinal association between NDVI-based residential greenness and depression. The cumulative exposure to residential greenness was estimated within different buffer sizes around individuals' home (100, 500, and 1000 m of radius). OR is the odd ratio and 95% CI is 95% confidence interval. The p-values in bold indicate statistical significant associations (< 0.05).

	Model 1	Model 2
	OR (95% CI), p-value	OR (95% CI), p-value
Doctor-diagnosed depression		
Cumulative exposure to residential greenness in 5-years fellow-up		
NDVI greenness (100 m buffer)	0.45 (0.28–0.74), **<0.001**	0.56 (0.33–0.96), **0.04**
NDVI greenness (500 m buffer)	0.41 (0.24–0.69), **<0.001**	0.50 (0.28–0.88), **0.02**
NDVI greenness (1000 m buffer)	0.47 (0.27–0.81), **0.01**	0.57 (0.31–1.03), 0.06
Cumulative exposure to residential greenness in 14-years fellow-up		
NDVI greenness (100 m buffer)	0.35 (0.21–0.60), **<0.001**	0.54 (0.30–0.98), **0.04**
NDVI greenness (500 m buffer)	0.47 (0.26–0.83), **0.01**	0.70 (0.37–1.31), 0.26
NDVI greenness (1000 m buffer)	0.50 (0.28–0.92), **0.02**	0.75 (0.39–1.44), 0.38
Beck Depression Inventory		
Cumulative exposure to residential greenness in 5-years fellow-up		
NDVI greenness (100 m buffer)	0.43 (0.19–1.01), 0.05	0.51 (0.21–1.26), 0.14
NDVI greenness (500 m buffer)	0.50 (0.21–1.24), 0.13	0.52 (0.20–1.37), 0.18
NDVI greenness (1000 m buffer)	0.71 (0.28–1.89), 0.48	0.70 (0.26–1.99), 0.50
Cumulative exposure to residential greenness in 14-years fellow-up		
NDVI greenness (100 m buffer)	0.38 (0.14–1.03), 0.05	0.61 (0.21–1.85), 0.38
NDVI greenness (500 m buffer)	0.93 (0.32–2.87), 0.90	1.41 (0.44–4.79), 0.58
NDVI greenness (1000 m buffer)	1.12 (0.36–3.73), 0.85	1.52 (0.44–5.54), 0.52

Model 1: with no covariates (unadjusted).
Model 2: adjusted with individual-level covariates (sex, age groups, education, BMI, the employment status, the marital status, and chronic diseases).

significant for the upper-medium total green space (OR 0.58, 95% CI 0.40 to 0.83) and for the high total green space (OR 0.64, 95% CI 0.47 to 0.86) in case of the 5-years follow-up, and the associations remained significant after adjusting with individual-level covariates (Model 2) (OR 0.63, 95% CI 0.43 to 0.91 for upper-medium total green space, and OR 0.71, 95% CI 0.51 to 0.98 for high total green space). Over a 14-years follow-up, the only significant model was the unadjusted model for high total green space (OR of 0.59, 95% CI 0.40 to 0.87) (Table A3, Appendix).

3.5. Association between residential greenness and depression by sex and age groups

The sub-group analysis of the association between cumulative greenness exposure and depression is based on NDVI-based residential greenness within a 100 m buffer size. The associations differed between sexes (Table A4, Appendix). The doctor-diagnosed depression associations were significant for the women in the unadjusted models (OR 0.47, 95% CI 0.26 to 0.85 in 5-years follow-up, and OR 0.33, 95% CI 0.18 to 0.64 in 14-years follow-up). The 14-years follow-up was also significant in adjusted model (OR 0.48, 95% CI 0.24 to 0.98). Nevertheless, when using the BDI-based depression in the modeling, in 5-years follow-up, significant associations appeared for men with the unadjusted model (OR 0.16, 95% CI 0.04 to 0.68), and adjusted model (OR 0.20, 95% CI 0.05 to 0.97).

Similarly, modeling the association between NDVI-based residential greenness and depression by age groups (group1: 20–30 yr, group2: 31–45 yr, and group3: 46–54 yr), the association differed between the groups (Table A5, Appendix). The doctor-diagnosed depression association was significant in the age group 1 and 2 in 5-years follow-up with Model 1 (OR 0.22, 95% CI 0.09 to 0.54, and OR 0.35, 95% CI 0.16 to 0.77, respectively). The association remained significant only for age

Table 4
Longitudinal association between CORINE land cover (CLC)-based residential greenness and depression. The CLC-based residential greenness indicators are the forest area (%), total green space (%), and the land cover diversity index (LCDI). The cumulative exposure to CLC-based residential greenness indicators were estimated within different buffer sizes around the individuals' home locations (100, 500, and 1000 m of radius). OR is Odds ratio and 95% CI is 95% confidence interval. The p-values in bold indicate statistical significant associations (< 0.05).

	Model 1	Model 2
	OR (95% CI), p-value	OR (95% CI), p-value
Doctor-diagnosed depression		
Cumulative exposure to residential greenness in 5-years follow-up		
Total green space (100 m)	0.73 (0.60–0.89), **<0.001**	0.82 (0.66–1.01), 0.07
Forest (100 m)	1.16 (0.53–2.46), 0.71	1.19 (0.53–2.57), 0.66
LCDI (100 m)	1.12 (0.79–1.60), 0.52	1.09 (0.76–1.57), 0.63
Total green space (500 m)	0.63 (0.48–0.84), **<0.001**	0.71 (0.52–0.96), **0.03**
Forest (500 m)	0.70 (0.37–1.31), 0.27	0.74 (0.38–1.40), 0.36
LCDI (500 m)	0.69 (0.40–1.19), 0.18	0.78 (0.44–1.38), 0.39
Total green space (1000 m)	0.64 (0.47–0.88), **0.01**	0.70 (0.50–0.99), **0.04**
Forest (1000 m)	0.69 (0.36–1.27), 0.24	0.74 (0.38–1.40), 0.35
LCDI (1000 m)	0.69 (0.32–1.51), 0.35	0.88 (0.39–2.01), 0.76
Cumulative exposure to residential greenness in 14-years follow-up		
Total green space (100 m)	0.56 (0.45–0.70), **<0.001**	0.65 (0.51–0.83), **<0.001**
Forest (100 m)	1.11 (0.52–2.30), 0.79	1.24 (0.56–2.66), 0.59
LCDI (100 m)	1.06 (0.72–1.57), 0.77	1.11 (0.74–1.68), 0.61
Total green space (500 m)	0.56 (0.41–0.76), **<0.001**	0.68 (0.49–0.96), **0.03**
Forest (500 m)	1.04 (0.56–1.91), 0.90	1.19 (0.621–2.25), 0.60
LCDI (500 m)	0.77 (0.42–1.43), 0.40	1.01 (0.53–1.95), 1.00
Total green space (1000 m)	0.59 (0.42–0.83), **<0.001**	0.73 (0.50–1.06), 0.09
Forest (1000 m)	0.83 (0.44–1.53), 0.55	0.98 (0.51–1.86), 0.95
LCDI (1000 m)	0.42 (0.18–0.98), **0.04**	0.66 (0.27–1.63), 0.37
Beck Depression Inventory		
Cumulative exposure to residential greenness in 5-years follow-up		
Total green space (100 m)	0.55 (0.40–0.78), **<0.001**	0.62 (0.43–0.90), **0.01**
Forest (100 m)	0.33 (0.07–1.37), 0.14	0.31 (0.06–1.30), 0.13
LCDI (100 m)	1.05 (0.57–1.94), 0.88	0.90 (0.48–1.68), 0.74
Total green space (500 m)	0.64 (0.40–1.04), 0.07	0.68 (0.40–1.14), 0.14
Forest (500 m)	0.79 (0.26–2.28), 0.68	0.77 (0.25–2.28), 0.65
LCDI (500 m)	0.90 (0.36–2.37), 0.83	0.85 (0.33–2.28), 0.75
Total green space (1000 m)	0.82 (0.48–1.43), 0.48	0.80 (0.45–1.45), 0.46
Forest (1000 m)	0.93 (0.32–2.63), 0.90	0.85 (0.28–2.50), 0.78
LCDI (1000 m)	0.67 (0.19–2.60), 0.56	0.67 (0.18–2.65), 0.55
Cumulative exposure to residential greenness in 14-years follow-up		
Total green space (100 m)	0.50 (0.34–0.75), **<0.001**	0.67 (0.41–1.05), 0.08
Forest (100 m)	0.99 (0.97–1.00), 0.18	0.29 (0.05–1.37), 0.13
LCDI (100 m)	0.89 (0.42–1.86), 0.75	0.73 (0.38–1.57), 0.42
Total green space (500 m)	0.63 (0.35–1.13), 0.12	0.80 (0.41–1.52), 0.50
Forest (500 m)	1.00 (0.99–1.01), 0.80	0.90 (0.25–3.04), 0.87
LCDI (500 m)	1.87 (0.57–6.47), 0.31	1.99 (0.58–7.21), 0.29
Total green space (1000 m)	0.77 (0.40–1.49), 0.43	0.92 (0.46–1.88), 0.81
Forest (1000 m)	1.00 (0.98–1.01), 0.44	0.67 (0.19–2.27), 0.52
LCDI (1000 m)	1.48 (0.29–8.16), 0.64	2.01 (0.37–12.09), 0.43

Total green space was estimated by summing up the percentage of built-up areas mixed with vegetation, agricultural areas, forest areas, shrub and grass, and wetland.
Model 1: with no covariates (unadjusted).
Model 2: adjusted with individual-level covariates (sex, age groups, education, BMI, the employment status, the marital status, and chronic diseases).

group 1 after model adjustment with the individual-level covariates (OR 0.35 95% CI 0.13 to 0.90). In 14-years follow-up, the unadjusted model showed a significant association for the age group 1 (OR 0.34, 95% CI 0.13 to 0.92). With the adjusted model (Model 3), the association became significant for the age group 3 (OR 0.11, 95% CI 0.02 to 0.73). In the case of BDI-based depression, the unadjusted model showed a significant association in the age group 2 (OR 0.19, 95% CI 0.06 to 0.64) in 5-years follow-up. A similar result was found for 14-years follow–up (OR 0.18, 95% CI 0.05 to 0.72).

3.6. Association between residential greenness and depression by neighborhood disadvantage levels and neighborhood population density levels

The stratified analysis showed differences in the association between depression and cumulative exposure to residential greenness between neighborhood disadvantage levels, using NDVI-based residential greenness within a 100 m buffer size (Table A6, Appendix). Only the medium neighborhood disadvantage level had a significant association between doctor-diagnosed depression and NDVI-based residential greenness in 5-years follow-up (OR 0.37, 95% CI 0.16 to 0.87 in the unadjusted model) and 14-years follow-up (OR 0.28, 95% CI 0.11 to 0.74 in the unadjusted model, and OR 0.34, 95% CI 0.13 to 0.96 in the adjusted model). When modeling with BDI-based depression, none of the modeling cases showed statistical significance.

Similarly, modeling of the association between NDVI-based residential greenness (within 100 m buffer size) and depression by neighborhood population density levels showed differences between the population density levels (Table A7, Appendix). The association was significant only in the medium level of population density in 14-years follow-up (OR 0.11, 95% CI 0.03 to 0.40 in the unadjusted model, and OR 0.17, 95% CI 0.05 to 0.66 in the adjusted model).

4. Discussion

In this longitudinal study, we found a lowered depression risk for individuals exposed to high residential greenness. Our results coincide with the previous studies, which are primarily cross-sectional (Cohen-Cline et al., 2015; Beyer et al., 2014; Sarkar et al., 2018), and also with some longitudinal ones (Alcock et al., 2014; Hystad et al., 2019; Engemann et al., 2019), claiming a positive association between green exposure and good mental health, including a lower risk of depression. Additionally, we found that the longitudinal association between residential greenness and depression is sensitive to the type of depression assessment, residential greenness indicators, and the spatial scale of analysis. The strength of our study lays in the high-quality longitudinal health data with accurate geographic coordinates of participants' home locations and moving history, and several individual- and neighborhood-level confounder factors used, and time-series greenness indicators from two different sources. These dataset has allowed us to model not only the effects of general greenness but also of the vegetation cover types, greenness categories, and land cover diversity. The findings contribute to a better understanding of the association between residential greenness and depression risk, particularly in Nordic environments.

The role of the greenness indicators. Concerning to the use of different greenness indicators, we found differences in the associations between residential greenness and depression when using NDVI- and CLC-based greenness indicators. The significance of the association was more evident when using doctor-diagnosed and NDVI-based residential greenness. Doctor-diagnosed depression was also associated with CLC total green space, but mostly when using bigger buffer sizes around individual's home locations. These differences can be linked to the differences in the greenness indicators to represent the characteristics of residential greenness. Urban and residential green areas are complex and mixed patches of diverse vegetation types (natural and artificial), making it challenging to map them accurately. The cumulative exposure to residential greenness based on NDVI and CLC total green space was moderate to strongly correlated, indicating that both indicators represent similar residential green space characteristics. However, some urban vegetation areas were not well represented in CLC, particularly in low-density residential areas (a mix of buildings and vegetation areas). Overall, NDVI represented better the spatial variation of residential greenness than CLC. However, Landsat-based NDVI also has some limitations. It tends to overestimate NDVI values compared to NDVI estimated from higher resolution satellite data (Su et al., 2019). Although, Landsat-based NDVI still appears to be a strong predictor of several health parameters, including mental health (Su et al., 2019; Hystad et al., 2019; Engemann et al., 2019).

In our modeling, only the associations between depression and residential greenness indicators representing general level of greenness and all vegetation cover types (NDVI and CLC total green space) were significant. This may suggest that vegetation composition and distribution in the residential area are relevant, producing a preventive effect on depression. We did not find evidence of the association between the depression estimates and CLC-based forest areas, as found in some previous studies (Astell-Burt and Feng, 2019; Marselle et al., 2020). However, forest areas are an important component of urban green spaces, providing several ecosystem services and health benefit (Roeland et al., 2019). A finer representation of urban trees and canopy density in residential areas might be needed to reduce uncertainties related to the data, Our data did not represent well residential and street tree distribution and density. Recent studies also suggest the importance of eye-level greenness in mental health and greenness associations, rather than overhead-view provided by the satellite data (Larkin and Hystad, 2019; Labib et al., 2020). We did not find an association between land cover diversity index (LCDI) and depression estimates, although some previous studies have highlighted the role of the spatial configuration and diversity of land cover on mental health (Sarkar et al., 2013). LCDI is highly sensitive to spatial land cover data quality and the number of land-cover classes considered to calculate it (Kallimanis and Koutsias, 2013). This makes it challenging to reproduce similar results with different data and land-cover settings.

The role of the spatial scale. The association between residential greenness and depression was also affected by the spatial scale of the residential greenness estimate, particularly after adjusting the model by individual-level covariates (Tables 3 and 4). Models using data of small buffer sizes (100–500 m of radius) had more significant associations. Similar findings have also been found in other studies (Banay et al., 2019; Paul et al., 2020). Some previous studies also show no effect of buffer sizes on the association between residential greenness and mental health (Klompmaker et al., 2019; Engemann et al., 2019; Crouse et al., 2021), and some even show that bigger buffer sizes (e.g. 3 km) are better associated with mental health than smaller ones (van den Berg et al., 2010). Thus, it is not clear what buffer size provides more meaningful insights about the effect of residential greenness on mental health. The buffer size effect might also be site-specific. For example, in urban areas with low and dispersed vegetation cover, the estimated NDVI mean is similar within different buffer sizes, but in areas with high vegetation cover, the estimated NDVI mean increases as the buffer size increases because the vegetation extent increases (Su et al., 2019). Finnish cities are higher in greenness compared to central European cities (Kabisch et al., 2016). Therefore, a small buffer might better capture the greenness exposure variability between the individuals. More careful consideration of the scale effect and spatial data quality is required to better understand what extent of residential green spaces influences mental health and depression risk reduction (Labib et al., 2020).

The role of the depression assessment type. The associations between residential greenness and depression risk were also sensitive to the type of depression assessment. We found a significant association of the residential greenness to the doctor-diagnosed depression in several model settings, but not to the BDI-based depression. In our data, depression prevalence based on the BDI-data was also lower (4%) than the prevalence estimated from the doctor-diagnosed depression data (12%), and these two dataset were fairly agreed according to Cohen's kappa index. Although the BDI is helpful for depression screening (Aalto et al., 2012), the limitation is that it can either minimize or exaggerate depressive symptoms, and self-reporting also seems to differ by sex (Hunt et al., 2003). According to our sensitivity analyses (Table A8, Appendix), the models were sensitive to the BDI cut-off score selection to identify depression. For example, increasing or decreasing the reference cut-off score (19) by three resulted in a 20% lower value of the odds ratio in both cases, but did not change the direction nor significance of the association. Currently most of the studies associating greenness and mental health are based on self-reported health questionnaires (e.g., Sarkar et al., 2018; Crouse et al., 2021; Abraham Cottagiri et al., 2022), and more studies using medical records would be needed to better clarify the association between greenness and depression risk.

Variations by sex and age groups. The association between residential greenness and depression risk also varied between sex and ages categories. We found a significant association for women, as was also found in other studies (Annerstedt et al., 2012; Roe et al., 2013; Sarkar et al., 2018; Triebner et al., 2022). Also a social study by Braçe et al. (2021) shows that women give higher value on urban green spaces than men. Other studies in the Scandinavian context also found that women use more actively urban green spaces and show higher well-being benefit linked to green spaces than men (Ode Sang et al., 2016).But there are also studies showing greenness benefit for both men and women (Abraham Cottagiri et al., 2022). Age is another factor causing variation in associations between residential greenness and depression. In our study, the residential greenness was associated with a lower depression risk only for individuals less than 30 years. Some other studies have also found protective effect of greenness in younger adult groups, probably due to high outdoor and physical activity of these age groups (Reece et al., 2021; Dzhambov et al., 2018). On the other hand, it has also been shown that older age groups value more the green spaces and benefit more from them than younger age groups (Astell-Burt et al., 2014; Ode Sang et al., 2016; Abraham Cottagiri et al., 2022). Overall, the relationship between greenness and mental health can vary across the life course, being more pronounced at some stages of life (Astell-Burt et al., 2014).

Possible mechanisms underlying the association between residential greenness and depression. The mechanisms of the association between residential greenness and depression is complex. Experimental studies show psychological preventive and restorative benefits of green space, such as recovery from stress and mental fatigue (Grahn and Stigsdotter, 2010; Ojala et al., 2019; Pasanen et al., 2018). The benefits depend on the duration, frequency, and intensity of the exposure (Shanahan et al., 2016). Even short-time green space exposure (30–120 min) can reduce stress (Ojala et al., 2019; Pasanen et al., 2018; White et al., 2019) and lower stress hormone levels, such as adrenaline, noradrenaline, and cortisol (Roe et al., 2013; Hunter et al., 2019). Thus, daily exposures to residential greenness can have a high potential to prevent depression (Shanahan et al., 2016). Additionally, the residential green view is an important benefit for mental health, as it lowers the risk of anxiety and depression (Honold et al., 2016; Song et al., 2019; Braçe et al., 2020). The residential green space benefit can also be meaningful in the winter period in Nordic countries. Snow accumulation is substantially higher in green spaces than in built-up areas (Kremsa et al., 2015), which improves the quality of the residential environment and provides recreational opportunities. This aspect might be particularly relevant for preventing seasonal affective disorder (SAD) in the winter months (Melrose, 2015). Green spaces also encourage people for physical activities (Mytton et al., 2012; Hunter et al., 2015; Persson et al., 2019), and this will in turn lead to a healthy balance of neurotransmitters (Wipfli et al., 2011; Lin and Kuo, 2013). Residential greenness also protects from traffic noise (Mueller et al., 2020), and urban heat (Ziter et al., 2019; Astell-Burt and Feng, 2020), and promotes a regular sleep-wake cycle (Shin et al., 2020), therefore contributing to a good mental health condition.

Variations by neighborhood socioeconomic disadvantage levels and population density. Neighborhood socioeconomic disadvantage (SED) and population density are important risk factors for mental health and depression (Rautio et al., 2018; Kivimäki et al., 2020, Tarkiainen et al., 2021). We conducted a stratified SED analysis of the associations between residential greenness and doctor-diagnosed depression for different SED groups. We found a significant greenness-depression association only in the medium SED group. Our data show higher depression prevalence and low residential greenness for individuals with high SED, but the greenness-depression association was not significant. We also observed lower depression prevalence and considerably higher residential greenness for individuals with low SED, but the greenness-depression association was not significant. Studies show that the potential associations between greenness and health outcomes are often affected and suppressed by socio-economic and socio-demographic confounders (Kabisch, N., 2019). For example, the variables related to participants' lower socio-economic status explain more negative health outcomes (Lakey and Cronin, 2008). Nevertheless, other studies have also found a higher greenness benefit for the high SED group (Sugiyama et al., 2016; Abraham Cottagiri et al., 2022).

Similarly, our stratified analysis by neighborhood population density level showed a significant association between residential greenness and depression only in the medium level of population density. In high and low population densities, other factors such as different stresses, discomfort and feeling of isolation, can impact greater than greenness on depression, whereas in medium population density areas people can find a good community support without these stresses (Lakey and Cronin, 2008; Lee, 2014; Sariaslan et al., 2015).

Overall, results from studies including SED levels and socio-demographic factors in mental health are not consistent (Kabisch, N., 2019, James et al., 2015), and these factors are highly variable and challenging to represent in linear models. The inter-linkages of these factors and greenness affecting depression risk need to be further investigated.

Limitations of the study. Although we used time-series residential greenness indicators (30 m of spatial resolution), uncertainty linked to the spatial data quality is still present. Another limitation is that we only adjusted the model with the commonly used, individual-level covariates. The study could have benefitted from using more covariates, such as smoking, alcohol consumption, individual income, and social interaction. Climate-related covariates are also important in the Nordic context. Variables such as neighborhood temperature and sunlight duration can be relevant to investigate further the greenness-depression association, particularly under the present climate change conditions. Our data also had a gender imbalance, with 62% of female participants, and a considerable loss of follow-ups, particularly in the 14-years follow-up (46%). Also, the cohort participant age ranged from 20 to 54 years old in the baseline year, missing a significant group of adults more than 54 years old. The were not possible to carry out in a particular season of the year, as the number of participants is large. Therefore, we did not have information about the time of the year the surveys were conducted to adjust the effect of seasonality.

Notwithstanding these limitations, our study provides evidence of longitudinal associations on the role of residential green space in lowering depression risk in the Nordic environment. We also highlight a need to better understand the interlink between residential greenness and neighborhood socioeconomic status. A comprehensive understanding of this linkage can lead to a better urban planning policy, considering the importance of the both elements on the health and wellbeing of all city dwellers.

5. Conclusions

We found inverse longitudinal associations between depression and residential greenness in the study carried out for the adult population in the Nordic environment, in Finland. These associations indicate lower depression risk for individuals with higher residential greenness. The associations varied depending on the type of the depression assessment, the spatial data quality of residential greenness indicators, and the spatial scale of the analysis. The greenness indicators within small buffer sizes around the individuals' home location showed stronger associations. The associations also varied across socio-demographic and neighborhood disadvantage levels. Further studies are needed especially on the interactions between residential greenness and neighborhood socioeconomic status to better understand the role of urban green spaces in lowering the depression risk and promoting good public health.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2022.102760.

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