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## Surrounding residential greenness and mental health: Findings from the French CONSTANCES cohort

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### ABSTRACT

This cross-sectional study assessed the association between surrounding greenness and two mental health outcomes according to degree of urbanization in the French CONSTANCES cohort. We included 114,717 participants. Depression in 2018 was evaluated by Center for Epidemiologic Studies Depression Scale (CES-D, from 0 to 60), and psychological distress in 2019 by General Health Questionnaire-12 (GHQ-12, from 0 to 12). Residential surrounding greenness was quantified by the mean of normalized difference vegetation index (NDVI) within 300m circular buffer around residential address. Adjusted negative binomial models were performed to assess the cross-sectional association between a 0.1 increase in NDVI at 300m and each outcome, separately in rural, peri-urban, urban and Paris areas. Stratified analyses by age and sex, and causal mediation models evaluating the role of physical activity were conducted. In 2018, the median age was 48.5, with 54.5 % being women. A 0.1 unit increase of NDVI was associated to lower depressive symptoms in peri-urban areas (incidence rate ratio (IRR) = 0.92; 95 % CI: 0.84–1.00) but higher in Paris (1.21; 1.06–1.38), and no associations were found in urban or rural areas. A 0.1 unit NDVI increase was associated to lower GHQ-12 score in peri-urban (IRR: 0.77; 95 % CI: 0.64–0.93) and urban areas (IRR: 0.79; 95 % CI: 0.65–0.97), with stronger effect size for middle-aged adults in urban areas and men in peri-urban areas. No associations were found in rural or Paris areas. Physical activity showed no mediation role. Surrounding greenness was associated with better mental health in peri-urban and urban but not in rural areas, possibly due to differences in types and uses of greenspaces.

### 1. Introduction

In the 1950s, 70 % of the global population lived in rural areas. This distribution has evolved over time, and is expected to shift dramatically by 2050, with most people moving to urban settings (UN, 2014). Mental illnesses are increasingly recognized as major challenge associated with

urbanization and development, and addressing mental health is a key component of the Sustainable Development Goals for 2030 (WHO, 2018). Mood disorders, and particularly depression, are among the most disabling mental disorders (Batterham et al., 2018). In Europe, the World Health Organization (WHO) reported that mental disorders represent a major public health concern with a prevalence of 12 % of the

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entire population (WHO, 2018), and 5 % of adults globally suffer from depression (WHO, 2023). In France, the cost of mental disorders has surged by 50 % in the last ten years, reaching an economic burden of 163 billion euros in 2018 (Laidi et al., 2023). Therefore, identifying modifiable protective factors for mental health at both the population and individual levels is crucial.

Natural environment exposure including green spaces might be beneficial to mental health through several mechanisms including attenuation of mental fatigue, stress reduction by stimulating the brain and neuroendocrine system and reducing cortisol levels (Roe et al., 2013; Ulrich et al., 1991; Zhou et al., 2022), social cohesion by strengthening the sense of community that include trust, acceptance and belonging (Maas et al., 2009), and promotion of physical activity (Barton and Rogerson, 2017). Several studies found that physical activity does not mediate the relationship between green spaces and mental health (De Vries et al., 2013; Pasanen et al., 2019; Richardson et al., 2013), while a study found that engaging in physical activity in natural environments can reduce the risk of poor mental health (Mitchell, 2013).

A study suggested that the impact of surrounding greenness on mental health may vary between urban and rural contexts (Daghagh Yazd et al., 2019). In our population rural areas were greener and the prevalence of depression and psychological distress was less than in urban areas. Despite this, the restorative role of green spaces in rural areas is less pronounced since rural residents might perceive their natural environment differently than those living in urban areas (Daghagh Yazd et al., 2019). Green spaces in rural areas are often dominated by agricultural lands, whereas, in urban areas green spaces are typically more structured, equipped and ready for use for physical activity or social interactions. All of which might contribute to better mental health (Maas et al., 2009; Pazhouhanfar, 2018). Despite these differences, the literature have predominantly focused on urban areas, with limited studies in other settings such as rural, isolated and peri-urban areas (Ryan et al., 2024).

Using the data of the French CONSTANCES cohort, that includes a large sample of adults living in the metropolitan France, our study aimed to: (1) assess the association between surrounding residential greenness and mental health outcomes, according to the degree of urbanization; and (2) assess the mediating role of non-occupational physical activity on the association between surrounding residential greenness and mental health in each degree of urbanization. We hypothesized that participants with greater exposure to surrounding residential greenness would have lower levels of depressive symptoms and psychological distress, and that these associations, as well as the mediating role of physical activity, would vary depending on degree of urbanization.

## 2. Methods

### 2.1. Study design

The CONSTANCES cohort (Inserm, 2012) is an ongoing population-based study of more than 220,000 French adults aged between 18 and 69 years at inclusion, randomly selected from social security affiliates from 20 French departments over metropolitan France from 2012 to 2021, with different degrees of urbanization (Zins and Goldberg, 2015; 2010). At enrollment, eligible participants completed self-administered questionnaires and underwent a complete medical examination at health screening centres partnering with the cohort. Participants were followed up by annual self-administered questionnaire, and in person health examination every four years. Inclusion and follow-up questionnaires include detailed information on sociodemographic data (e.g., professional situation, education, marital status), lifestyle (e.g., alcohol, tobacco or cannabis smoking, diet, physical activity), life events (e.g., birth, death of a close relative, retirement), occupational factors (e.g., occupational history, stress at work), medical history (e.g., personal and family history, health and quality of life

scales, diseases, disabilities), and long-term illnesses and hospitalizations through linkage to administrative databases. In addition, all residential addresses since inclusion were collected and geocoded.

In this study, we conducted two separate cross-sectional analyses using two different mental health indicators, one collected in the 2018 follow-up questionnaire and another in the 2019 follow-up questionnaire. This study design does not aim to evaluate changes in mental health over time but rather to examine associations between surrounding greenness and two distinct, yet related, mental health outcomes, allowing to test the robustness of the results.

The authors declare that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008. All procedures have been approved by the Institutional review board (IRB) of the French Institute of Health (Inserm) (Opinion n°01-011, then n°21-842), and authorized by the by the French Data Protection Authority ("Commission Nationale de l'Informatique et des Libertés", CNIL) (Authorization #910486). This project obtained authorization from the CNIL (MR004 for the use of the data of this project). A written informed consent was signed by all participants for the use of their data for scientific research, and for each project, they are reminded of their right to object to the use of their data. All information and regulatory authorizations relating to the publication are available on the French version page 'Rights and data protection' ([www.constances.fr](http://www.constances.fr)) (Zins and Goldberg, 2015).

### 2.2. Participants

All the participants who responded to both follow-up questionnaire in 2018 and 2019, with available data on surrounding residential greenness and mental health were included in this analysis.

### 2.3. Exposure to surrounding residential greenness

Residential surrounding greenness was quantified using the Normalized Difference Vegetation Index (NDVI), derived from satellite imagery. NDVI is a widely used, unitless indicator of vegetation density and health, based on the differential reflectance of the Earth's surface (Bannari et al., 1995). Healthy vegetation absorbs most visible light and reflects a large portion of near-infrared light, whereas less vigorous vegetation reflects more visible light and less near-infrared light. NDVI values were calculated from Landsat-8 imagery, which is captured every 16 days at a spatial resolution of 30m × 30m. NDVI was computed using the standard formula:  $NDVI = (NIR - Red)/(NIR + Red)$ , where NIR represents near-infrared reflectance and Red represents red visible reflectance. NDVI values range from -1 to +1. Negative values indicate non-vegetated surfaces such as clouds, water, or snow, while positive values represent vegetated areas. Values close to +1 indicate dense green vegetation, and values near 0 indicate bare soil or built environments (Su et al., 2019). Negative NDVI values were set to zero in our analysis (Zare Sakhvidi et al., 2021). To capture peak greenness and minimize cloud interference, we used the maximum NDVI value between May and July from 2013 to 2020. This period corresponds to the greenest season in metropolitan France (Zare Sakhvidi et al., 2021). We calculated average NDVI within 100m, 300m, 500m, and 1000m circular buffers around each participant's geocoded residential address. The 300m buffer was used as our primary exposure metric, in line with the WHO's recommendation to use 300m or less (equating to a 5 min walk) to determine accessibility of green spaces (WHO, 2016). Other buffer sizes were examined in sensitivity analyses. The residential address in 2018 was used for the analyses with CESD as an outcome and the residential address in 2019 was used for the analyses with GHQ-12 as an outcome.

## 2.4. Mental health assessment

Two mental health outcomes including depressive symptoms, and psychological distress were assessed in this study. Depressive symptoms were evaluated using the Centre for Epidemiologic Studies Depression (CES-D) questionnaire available from the 2018 follow-up, while psychological distress was assessed using the 12-items General Health Questionnaire (GHQ-12), available from the 2019 follow-up.

### 2.4.1. Depressive symptoms assessment

The CES-D is a 20-item scale developed by Radloff (1977) to evaluate the frequency of depressive symptoms over the previous week. Respondents choose from four options (0 = “rarely or none of the time”, 1 = “some or little of the time”, 2 = “moderately or much of the time”, 3 = “most or almost all the time”), and the total score can sum up to 60, with higher scores indicating more severe depressive symptoms. The CES-D demonstrated strong internal consistency ( $\alpha = 0.90$  in the CON-STANCES cohort) (Hoven et al., 2019). In addition to the total score, the French version of the CES-D has a well-established four-factor structure, including positive affect (PA; 4 items, e.g., felt happy, enjoyed life), depressive affect (DA; 7 items, e.g., felt sad, depressed), interpersonal problems (IP; 2 items, e.g., people dislike me), and somatic complaints (SC; 7 items, e.g., poor appetite, restless sleep) (Morin et al., 2011). To calculate the total CES-D score, responses for each item were summed (PA items were reverse scored and named less positive affect score), with higher total or dimension-specific scores indicating more severe depression. A CES-D score of  $\geq 19$  was used as a cutoff to identify individuals at risk for clinical depression, based on the validated threshold of the French version (Morin et al., 2011).

### 2.4.2. Psychological distress assessment

The GHQ-12 is a validated instrument developed to assess psychological distress and non-psychotic mental disorders in non-clinical population (those who do not have a diagnosed mental health disorder and are not receiving treatment for a mental health condition) (Goldberg and Blackwell, 1970). The GHQ-12 contains 12-items, six of which are negatively phrased (e.g., “have you been feeling unhappy or depressed”) and six are positively phrased (e.g., “have you been able to enjoy your normal daily activities?”). For each item, the participants had to select one out of four possible responses depending on the frequency “in the last two weeks” comparing to the usual occurrence. In this manuscript, we used the binary scoring method for easier interpretation (Anjara et al., 2020); meaning that “more” and “same as usual” responses to the positively phrased items are coded as zero, and “less” and “much less than usual” to the positively phrased items are coded as one. The reverse coding was applied for the negative items. The coded responses then summed to create a continuous total distress score ranging from zero to 12, with higher total score indicating more severe psychological distress. We further categorized the GHQ-12 continuous score using “one” as a cutoff, to obtain a dichotomous psychological distress outcome: no psychological distress (score of 0 or 1), and psychological distress (score from 2 to 12) (Matta et al., 2023).

## 2.5. Degree of urbanization

We classified each residential address in 2018 and 2019 as follows: rural, peri-urban, urban, and Paris. This classification was adapted from the INSEE (the French National Institute of Statistics and Economic Studies) categories based on the continuity of buildings and population density (central cities, suburban cities, isolated cities, and rural). In this study, central cities were considered as “urban”. Sub-urban and isolated cities were considered as “peri-urban” (due to similar NDVI characteristics and population density). Paris was categorized separately because the NDVI values were low even for participants living near green spaces, probably due to its particular dense urban characteristics (see Figs. S1 and S2 in the supplementary materials).

## 2.6. Covariates

Sex (men/women) was collected from the social security registry. The following variables were obtained from self-administered questionnaires at inclusion: age, education (was initially classified into eight categories based on the ISCED classification (UNESCO, 2017) but for statistical analyses it was categorized into two categories: low education level-including individuals with or less than 12 years of education-, and high education level-including those with more than 12 years of education), smoking status (i.e., non-smokers, smoker, former smoker) and non-occupational physical activity (defined as physical effort with a total score ranging from 0 = “Not at all” to 6 = “Highly active”). The following variables were obtained from the follow-up questionnaires of each year: marital status (single, in a relationship, and separated/or widower), monthly household income (less than 2100 €, from 2100 € to less than 2800 €, from 2800€ to 4200€, and 4200€ and over per month), self-report diagnosis of cardiovascular diseases (CVDs; defined as a yes answer to the question “do you have angina pectoris, myocardial infarction, arthritis of the lower limbs, or other CVDs?”), and body mass index (BMI; categorized into: underweight [ $<18.5$ ], normal weight [ $18.5-24.9$ ], overweight [ $25.0-29.9$ ], and obese [ $\geq 30$ ]) (CDC, 2022).

As mental health and greenness may change according to the period of the year, the season based on the date of completion of the CES-D questionnaire or the GHQ-12 questionnaire was considered. Warm season included spring/summer (March to August) and cold season included fall/winter (September to February).

The French Deprivation Index (FDep) was available at municipality level. The FDep used in this study corresponds to the municipality of the residential address of participants in 2018 for CES-D outcome, and in 2019 for GHQ-12 outcome. The FDep is calculated based on median household income, percentage of bachelor’s graduates, percentage of blue-collar workers, and unemployment rate in order to characterize the socio-economic situation of families and to account for territorial disparities (Rey et al., 2009). The FDep variable in our study was categorized into tertiles (low FDep ( $-6.4, -1.19$ ]; middle FDep ( $-1.19, 0.0139$ ]; high FDep ( $0.0139, 5.07$ ]).

## 2.7. Statistical analyses

We applied imputation by means (Shrive et al., 2006) for participants with one missing response out of the 12 questions (10 %) for the GHQ-12 and two out of 20 questions (10 %) for the CES-D; otherwise participants with more missing outcome data were excluded from the analysis. The percentage of missing values of the covariates ranged between 0 % and 14 %, with the highest for monthly household income. Multiple imputation for missing covariates for each outcome was performed using R and the mice package, with five imputed data sets (Buuren and Groothuis-Oudshoorn, 2011). The following variables were used as predictors in multiple imputation: monthly household income, marital status, education, physical activity, BMI, and smoking status. In the subsequent analyses we used these five datasets, and model-based estimates were pooled using Rubin Rules (Rubin, 1987).

To assess the association between NDVI within the 300 m buffer around residential addresses and the continuous total scores of the CES-D and GHQ-12, we employed negative binomial statistical models for both outcomes. The CES-D and GHQ-12 scores showed skewed distributions with high frequencies of low values and overdispersion; therefore, negative binomial regressions were chosen for modelling these continuous count-like scores (see Figs. S3 and S4 in supplementary materials). We reported crude and adjusted incidence rate ratios (IRRs) with 95 % confidence intervals (CIs) for a 0.1 unit increase in NDVI exposure at residential address (according to NDVI at 300m buffer). All analyses were conducted separately based on the degree of urbanization as the type, with the assumption that use of green spaces may differ in each classification as explained above.

Adjustment of statistical models were based on a priori knowledge

based on previous literature (Geneshka et al., 2021; Geoffroy et al., 2014; Horesh et al., 2020; Tebeka et al., 2018). The covariates included in the main model were: age, sex, health center of inclusion (except for analyses in Paris), education, season, marital status, and FDep. Several variables may modify the association between exposure to surrounding greenness and mental health (Fernández et al., 2022), therefore interaction by sex, age (recategorized into 3 age categories: 18–45, 45–60 and 60+) and seasons (warm and cold seasons) were tested. To minimize the number of statistical tests performed, the stratified analyses were done only when the p-value of interaction was below 0.5.

Several sensitivity analyses were performed in order to evaluate the robustness of our findings: 1) using the dichotomized total score instead of the continuous total score of each outcome (GHQ-12 and CES-D) and running logistic regression models with adjusted odds ratios (ORs) and 95 % CI reported for a 0.1 unit increase in NDVI exposure; 2) using NDVI within 100m, 500m, 700m and 1000m buffer sizes; 3) using a complete case dataset (i.e. data set without imputation of covariates); 4) removing each of the following adjustment variables one by one: FDep, marital status, season, and education (to assess the impact of each adjustment variable); 5) further adjustment on monthly household income instead of education (Household income had the highest missing data and was measured at the household level, unlike education, which is an individual-level variable. Since both are highly correlated indicators of socioeconomic status, we selected education for the main models and replaced education with household income in sensitivity analyses to avoid over-adjustment); 6) model with further adjustments on CVDs and BMI that were not included in the main model as they are potential mediators (to avoid risk of overadjustment) but are often used in the literature as adjustment covariates (Keith et al., 2024; Song et al., 2023; Zhang et al., 2022); 7) excluding the participants who have moved since the inclusion into the CONSTANCES cohort (to decrease exposure misclassification risk); and 8) running the analysis in the population with available CES-D data and surrounding greenness for 2018 (N = 170,537), regardless of GHQ-12 availability, and vice versa for 2019 (N = 117,447), to assess potential selection bias.

The mediating role of physical activity was evaluated using the causal mediation model in separate analyses for the CES-D and the GHQ-12 continuous total scores. The mediation model was adjusted for age, sex, health center of inclusion (except for analyses in Paris), education, season, marital status, and FDep same as the main analysis. To address potential unmeasured confounding and assess the plausibility of mediation and IV assumptions, we constructed a directed acyclic graph (DAG) (see Fig. S5 in the supplementary materials). The DAG guided our covariate selection to satisfy the assumptions of no unmeasured confounding for the exposure–outcome, exposure–mediator, and

mediator–outcome relationships. The hypothesized causal mediation model of the association between surrounding greenness (the exposure) and mental health (the outcome), with physical activity as a mediator, is shown in Fig. 1. In our study, we used the function “mediate\_zi” from the “maczic” package of R (Cheng et al., 2018), which is designed for causal mediation analysis with count data such as CESD and GHQ-12 scores (Cheng et al., 2023). The results of the mediation analyses were reported as: average causal mediation effects (ACME) representing the indirect effect on mental health (CES-D or GHQ-12 total score) while considering the effect of the mediator (physical activity); average direct effect (ADE) representing the average direct effect of exposure to surrounding greenness on mental health (CES-D or GHQ-12 total score) while physical activity is held constant; the total effect of surrounding greenness on CES-D or GHQ-12 total score representing the sum of ADE and ACME; and the proportion of mediation representing the ratio of ACME to the total effect in order to explain the extent to which the total effect is accounted for by the pathway through physical activity. The  $\beta$ 's represents effect estimates for direct, indirect, and total effect derived from causal mediation analysis. All statistical analyses have been done using R software v4.4.1.

### 2.8. Role of the funding source

The funders of this study had no role in study design, data collection, data analysis, data interpretation, or writing of the report.

## 3. Results

### 3.1. Population description

The final study population included in this analysis consisted of 114,717 participants with both CES-D measured in 2018, and GHQ-12 measured in 2019 (see flow-chart in Fig. 2). In 2018, the median age at inclusion was 48.5 years, with 54.5 % (n = 62,362) being women (A detailed description of participants during the 2019 follow-up is provided in Table S1; Description showed similar characteristics). Table 1 presents a detailed description of participants during the 2018 follow-up. The majority of participants lived in peri-urban areas (41.0 %), followed by urban areas (25.0 %), rural areas (19.0 %), and Paris (15.0 %). Participants from more urbanized areas tended to have higher levels of education and income. The prevalence of depressive symptoms was lower in rural areas (16.7 %) and in peri-urban areas (16.5 %), compared to non-Parisian and non-Parisian urban areas (17.7 % and 18.0 % respectively). Similarly, GHQ-12 data indicated the lowest prevalence of psychological distress in rural areas (34.5 %), followed by

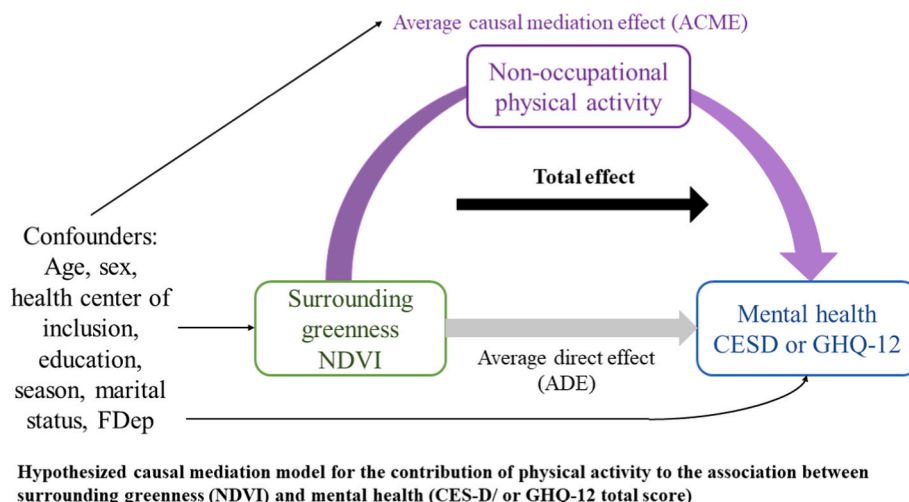
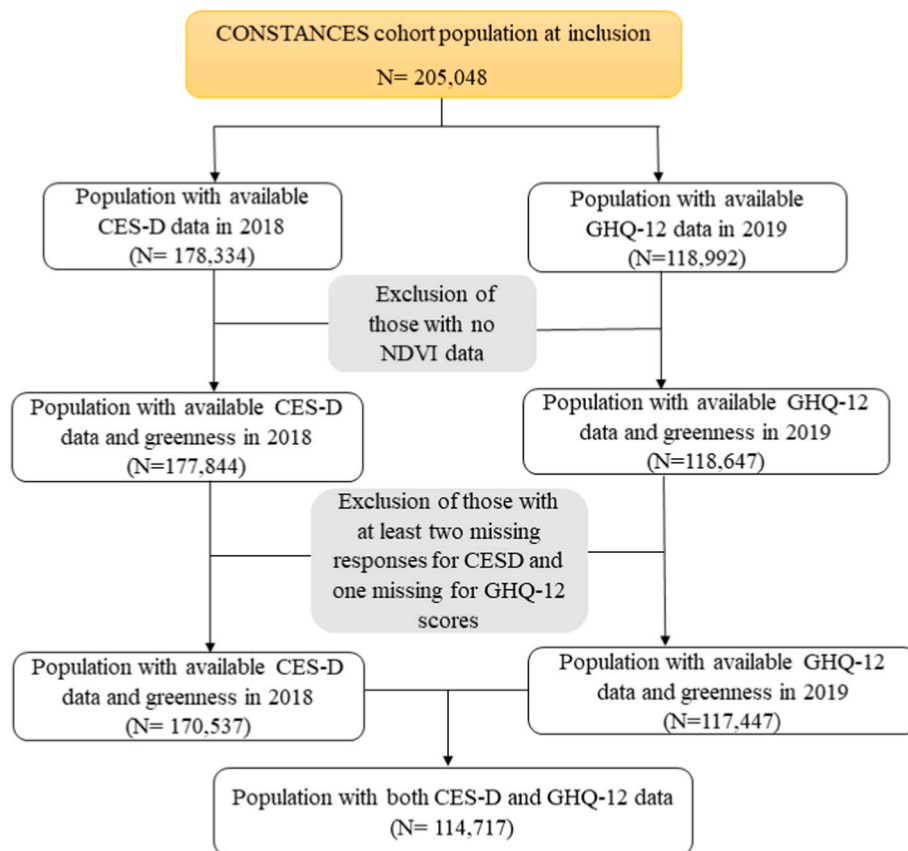


Fig. 1.



**Flow chart of participants included in the study**

Fig. 2.

peri-urban areas at (34.9 %), non-Parisian urban areas at (35.9 %), and the highest in Paris (38.0 %) (see Table 2).

### 3.2. Main findings

#### 3.2.1. CES-D

No association was found between NDVI and CES-D in rural areas, either for the total CES-D score (IRR = 1.02; 95 % CI: 0.85–1.22), or the sub-scores (Fig. 3). In peri-urban areas, adjusted analyses showed that a 0.1 unit increase in NDVI exposure within a 300m buffer was associated with 8 % decrease in CES-D total score (lower depressive symptoms) (IRR = 0.92; 95 % CI: 0.84–1.00), 15 % decrease in depressed affect (IRR = 0.85; 95 % CI: 0.72–0.99), and 9 % in somatic complaints (IRR = 0.91; 95 % CI: 0.83–0.99) sub-scores (Fig. 3). In urban areas, no association was found between NDVI within a 300m buffer and the total CES-D score (IRR = 1.00; 95 % CI: 0.92–1.10) (Fig. 3). For sub-scores, a 0.1 increase in NDVI exposure within a 300m buffer was associated with risk of less positive affect sub-scores (IRR = 1.13; 95 % CI: 1.02–1.24). In contrast, in Paris, a 0.1 unit increase in NDVI exposure within a 300m buffer was associated with an increased CES-D total score (IRR = 1.21; 95 % CI: 1.06–1.38) and higher risk of less positive affect (IRR = 1.34; 95 % CI: 1.17–1.53) (Fig. 3).

#### 3.2.2. GHQ-12

In rural area and in Paris, the IRR for the association between NDVI and GHQ-12 scores (higher psychological distress) was above 1, although not statistically significant (see Fig. 4). A 0.1 increase in NDVI within the 300m buffer was associated with a lower GHQ-12 score (less psychological distress) in peri-urban (IRR = 0.77; 95 % CI: 0.64–0.93) and urban areas (IRR = 0.79; 95 % CI: 0.65–0.97).

### 3.3. Stratified models

For CESD, no statistically significant interaction has been found across the four degrees of urbanization. For GHQ-12, interaction with age (categories: 18–44, 45–59, 60+) was found only in urban ( $p = 0.03$ ) and peri urban areas ( $p = 0.04$ ), while interaction with sex (men/women) was found only in peri-urban areas ( $p < 0.01$ ) (details of the p-value of interaction in Table S4).

In urban areas, the protective effect of surrounding residential greenness on psychological distress has been found among middle-aged adults (45–60 years old) (IRR = 0.64; 95 % CI = 0.44–0.95) but not among the youngest nor the elderly within an NDVI at 300-m buffer (Fig. 5).

In peri-urban areas, the protective effect of surrounding greenness increased with age, reaching (IRR = 0.63; 95 % CI = 0.40–1.00) for those aged over 60 years. This protective effect was also higher among men (IRR = 0.65; 95 % CI = 0.49–0.87) compared to women within a 300m NDVI buffer (Fig. 5).

### 3.4. Mediation analyses

When assessing the impact of exposure to surrounding residential greenness on depressive symptoms (CES-D) (Table S5) and psychological distress (GHQ-12) (Table S6) within a 300m NDVI buffer, no mediating effect of non-occupational physical activity was found in any of the four area types. The direct effect, unmediated by non-occupational physical activity, was consistent with the total effect across all degrees of urbanization (Tables S5 and S6).

**Table 1**  
 Characteristics of the included participants in 2018 across the different degree of urbanization (N = 114,717).

		Rural areas (N = 21,724)	Peri-urban (N = 46,788)	Urban areas§ (N = 29,570)	Paris (N = 16,635)	Total (N = 114,717)
Age at inclusion (years old), Mean ( $\pm$ SD)		48.5 ( $\pm$ 12.9)	48.9 ( $\pm$ 13.1)	47.9 ( $\pm$ 13.5)	46.8 ( $\pm$ 13.6)	48.3 ( $\pm$ 13.3)
Sex, n (%)	Women	12073 (55.6 %)	25257 (54.0 %)	16035 (54.2 %)	8997 (54.1 %)	62362 (54.4 %)
Educational level, n (%)	No diploma	489 (2.3 %)	774 (1.7 %)	527 (1.8 %)	208 (1.3 %)	1998 (1.7 %)
	General education certificate, Primary education certificate, School-leaving certificate	1425 (6.6 %)	2547 (5.4 %)	1355 (4.6 %)	427 (2.6 %)	5754 (5.0 %)
	Certificate of professional competence, vocational training certificate	4571 (21.0 %)	7428 (15.9 %)	3697 (12.5 %)	676 (4.1 %)	16372 (14.3 %)
	Baccalaureate or equivalent diploma	4250 (19.6 %)	7995 (17.1 %)	4362 (14.8 %)	1435 (8.6 %)	18042 (15.7 %)
	Baccalaureate + 2 or 3 years	6501 (29.9 %)	13387 (28.6 %)	8180 (27.7 %)	2976 (17.9 %)	31044 (27.1 %)
	Baccalaureate + 4 years	1513 (7.0 %)	4166 (8.9 %)	3009 (10.2 %)	1991 (12.0 %)	10679 (9.3 %)
	Baccalaureate + 5 and more	2905 (13.4 %)	10410 (22.2 %)	8380 (28.3 %)	8885 (53.4 %)	30580 (26.7 %)
Monthly household income (euros), n (%)	Other	70 (0.3 %)	81 (0.2 %)	60 (0.2 %)	37 (0.2 %)	248 (0.2 %)
	Less than 2100 €	2860 (13.2 %)	5605 (12.0 %)	4596 (15.5 %)	1818 (10.9 %)	14879 (13.0 %)
	From 2100 € to less than 2800 €	4503 (20.7 %)	7811 (16.7 %)	5456 (18.5 %)	2283 (13.7 %)	20053 (17.5 %)
	From 2800€ to 4200€	9253 (42.6 %)	17494 (37.4 %)	10007 (33.8 %)	3999 (24.0 %)	40753 (35.5 %)
Smoking status, n (%)	4200€ and over	5108 (23.5 %)	15878 (33.9 %)	9511 (32.2 %)	8535 (51.3 %)	39032 (34.0 %)
	Non-smoker	10354 (47.7 %)	23451 (50.1 %)	14282 (48.3 %)	7649 (46.0 %)	55736 (48.6 %)
CVDs, n (%)	Yes	1586 (7.3 %)	3478 (7.4 %)	2040 (6.9 %)	927 (5.6 %)	8031 (7.0 %)
Season, n (%)	Responses in warm season	16980 (78.2 %)	36718 (78.5 %)	23227 (78.5 %)	12907 (77.6 %)	89832 (78.3 %)
BMI (kg/m <sup>2</sup> ), n (%)	Underweight	433 (2.0 %)	1086 (2.3 %)	926 (3.1 %)	681 (4.1 %)	3126 (2.7 %)
	Normal weight	10693 (49.2 %)	25621 (54.8 %)	16929 (57.3 %)	10785 (64.8 %)	64028 (55.8 %)
	Overweight	7450 (34.3 %)	14686 (31.4 %)	8663 (29.3 %)	3995 (24.0 %)	34794 (30.3 %)
	Obese	3148 (14.5 %)	5395 (11.5 %)	3052 (10.3 %)	1174 (7.1 %)	12769 (11.1 %)
Non-occupational physical activity, Mean ( $\pm$ SD)		3.55 ( $\pm$ 1.52)	3.62 ( $\pm$ 1.53)	3.62 ( $\pm$ 1.49)	3.46 ( $\pm$ 1.39)	3.58 ( $\pm$ 1.50)
Marital Status, n (%)	Single	3437 (15.8 %)	8149 (17.4 %)	7553 (25.5 %)	6338 (38.1 %)	25477 (22.2 %)
	Relationship	15788 (72.7 %)	32602 (69.7 %)	17618 (59.6 %)	8251 (49.6 %)	74259 (64.7 %)
	Separated	2499 (11.5 %)	6037 (12.9 %)	4399 (14.9 %)	2046 (12.3 %)	14981 (13.1 %)
French Deprivation Index (FDep), n (%)	Low	2664 (12.3 %)	15970 (34.1 %)	4807 (16.3 %)	15428 (92.7 %)	1.99 (0.815)
	Middle	6680 (30.7 %)	16957 (36.2 %)	13633 (46.1 %)	1206 (7.2 %)	2.00 [1.00, 3.00]
	High	12380 (57.0 %)	13861 (29.6 %)	11130 (37.6 %)	0 (0.0 %)	1.99 (0.815)
NDVI, Mean ( $\pm$ SD)	100-m buffer	0.779 (0.0804)	0.695 (0.113)	0.638 (0.135)	0.441 (0.117)	0.659 (0.153)
	300-m buffer	0.824 (0.0608)	0.722 (0.105)	0.653 (0.129)	0.450 (0.0933)	0.684 (0.153)
	500-m buffer	0.843 (0.0516)	0.735 (0.103)	0.660 (0.128)	0.455 (0.0845)	0.696 (0.153)
	700-m buffer	0.855 (0.0462)	0.744 (0.101)	0.666 (0.127)	0.458 (0.0800)	0.703 (0.154)
	1000-m buffer	0.865 (0.0417)	0.754 (0.0996)	0.674 (0.127)	0.462 (0.0760)	0.712 (0.155)

SD: standard deviation; CVDs: cardiovascular diseases; NDVI: Normalized difference vegetation index; BMI: Body mass index; CESD: Center for epidemiologic studies depression scale, § urban areas excluding Paris city. The percentage of men, smokers, and individuals without CVDs correspond to the complementary percentages of women, non-smokers, and individuals with CVDs, respectively, summing to 100 % in each category.

### 3.5. Sensitivity analyses

Crude models within 300m supported results of the main adjusted models for both outcomes (Table S7).

When using the dichotomized score of each outcome instead of the continuous score, we also found that exposure to surrounding greenness was associated with lower depression in peri urban areas and higher depression in Paris. Additionally, lower psychological distress in urban

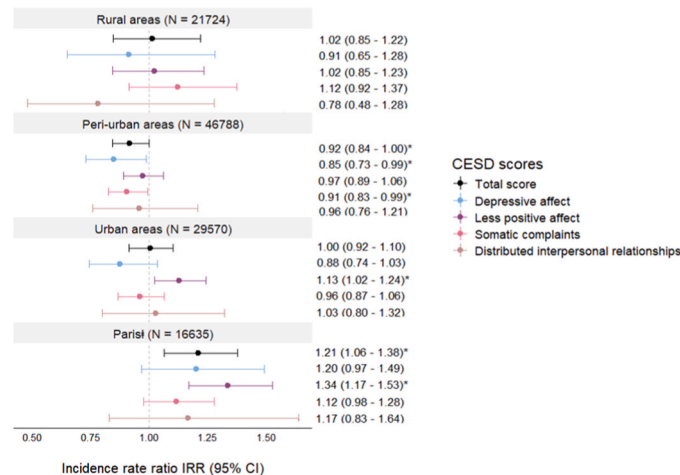
and peri urban areas. However, this association did not reach statistical significance except in Paris for CES-D and in peri-urban areas for GHQ-12 (Table S7).

Findings for both outcomes using different NDVI exposures (i.e., within 100m, 500m, 700m, and 1000m buffers) were consistent with the results found for the 300m NDVI buffer. However, these associations did not reach statistical significance for depression at other NDVI buffer sizes, except in Paris. In contrast, for psychological distress, the results

**Table 2**  
CESD (available in 2018) and GHQ-12 (available in 2019) scores across the different degree of urbanization (N = 114,717).

In 2018		Rural areas (N = 21,724)	Peri-urban (N = 46,788)	Urban areas§ (N = 29,570)	Paris (N = 16,635)	Total (N = 114,717)
CESD continuous total score (0 to 60)	Mean (SD)	11.1 (8.56)	11.0 (8.65)	11.3 (8.97)	11.4 (8.87)	11.2 (8.75)
	Median [Q1-Q3]	9.00 [5.00–15.0]	9.00 [5.00–15.0]	9.00 [5.00–15.0]	9.00 [5.00–16.0]	9.00 [5.00–15.0]
Dichotomized CESD total score, n(%)	Depression	3622 (16.7 %)	7729 (16.5 %)	5230 (17.7 %)	3000 (18.0 %)	19581 (17.1 %)
CESD depressed affect sub-score (0 to 21)	Mean (SD)	2.45 (3.34)	2.49 (3.39)	2.67 (3.56)	2.84 (3.54)	2.58 (3.45)
	Median [Q1-Q3]	1.00 [0.0–4.0]	1.00 [0.0–4.0]	1.00 [0.0–4.0]	2.00 [0.0–4.0]	1.00 [0.0–4.0]
CESD less positive affect sub-score (0 to 12)	Mean (SD)	4.32 (3.17)	4.18 (3.14)	4.16 (3.13)	3.96 (2.99)	4.17 (3.12)
	Median [Q1-Q3]	4.00 [2.0–6.0]	4.00 [2.0–6.0]	4.00 [2.0–6.0]	4.00 [1.0–6.0]	4.00 [2.0–6.0]
CESD somatic complains sub-score (0 to 21)	Mean (SD)	3.91 (3.31)	3.93 (3.31)	4.04 (3.39)	4.10 (3.32)	3.98 (3.33)
	Median [Q1-Q3]	3.00 [1.0–6.0]	3.00 [1.0–6.0]	3.00 [1.0–6.0]	3.00 [2.0–6.0]	3.00 [1.0–6.0]
CESD disturbed interpersonal relationship sub-score (0 to 6)	Mean (SD)	0.463 (0.914)	0.444 (0.910)	0.462 (0.928)	0.484 (0.948)	0.458 (0.921)
	Median [Q1-Q3]	0 [0.0–1.0]	0 [0.0–1.0]	0 [0.0–1.0]	0 [0.0–1.0]	0 [0.0–1.0]
In 2019		Rural areas (N = 21,879)	Peri-urban (N = 47,174)	Urban areas* (N = 29,486)	Paris (N = 16,178)	Total (N = 114,717)
GHQ-12 continuous total score (0 to 12)	Mean (SD)	1.80 (2.78)	1.82 (2.81)	1.91 (2.87)	1.96 (2.82)	1.86 (2.82)
	Median [Q1-Q3]	0 [0.0–3.0]	0 [0.0–3.0]	0 [0.0–3.0]	1.00 [0.0–3.0]	0 [0.0–3.0]
Dichotomized GHQ-12 total score, n(%)	Psychological distress	7556 (34.5 %)	16,467 (34.9 %)	10,584 (35.9 %)	6148 (38.0 %)	40,755 (35.5 %)

Q1: first quartile; Q3: third quartile; SD: standard deviation; CESD: Center for epidemiologic studies depression scale; GHQ-12: General health questionnaire 12 items, § urban areas excluding Paris city.



**Incidence Rate Ratio (IRR) (95% CI) of the association between NDVI within a 300-m buffer and CES-D (in 2018) total and sub-scores stratified by different degrees of urbanization.**  
Urban areas excluding Paris city; † not adjusted on Health center of inclusion; \*Statistically significant p value (p<0.05)

**Fig. 3.**

remained statistically significant across other NDVI buffer sizes in urban and peri-urban areas (Tables S2 and S3).

Further adjustments for CVDs and BMI supported the main findings for both outcomes CES-D and GHQ-12 across all four degrees of urbanization (Table S7).

Replacing education with monthly household income as a covariate in the models showed similar results for GHQ-12. For CESD, results were also consistent, but losing statistical significance in peri-urban area (Table S7).

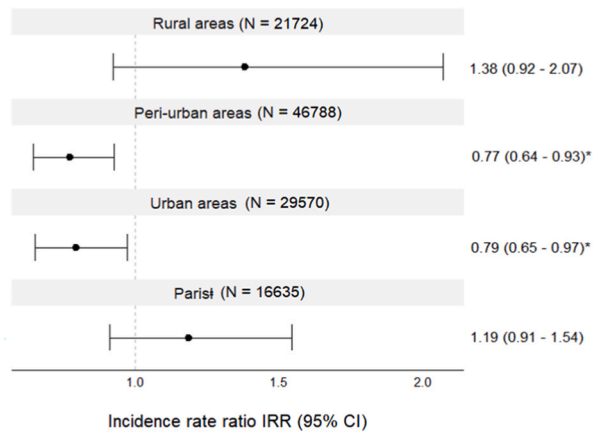
Analyses using complete case datasets or excluding participants who had moved or using main population showed also consistent results (Table S7).

**4. Discussion**

Among more than 114,000 adults from the large French cohort CONSTANCES, we investigated the association between residential surrounding greenness and two distinct, yet related, measures of mental health according to the degree of urbanization. Our findings showed that

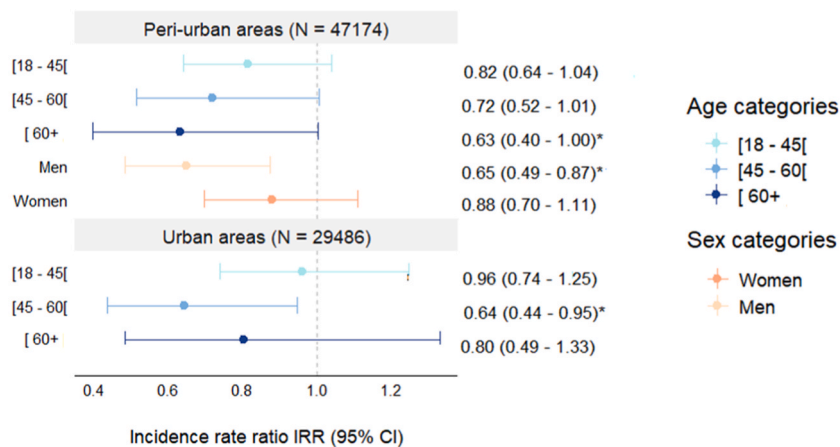
higher exposure to surrounding greenness was associated with less depressive symptoms in peri-urban areas and less psychological distress in both urban and peri-urban areas. Stratified analyses also indicated that the association between surrounding greenness and psychological distress was stronger among men in peri-urban areas, and middle-aged adults in urban areas.

Our findings align with previous studies, suggesting a protective role of surrounding greenness on mental health in urban dwellers (Dadvand et al., 2016; Song et al., 2019). However, this association was not observed in rural areas in our study. A cross-sectional study conducted in Korea with more than 65,000 participants found that higher exposure to surrounding greenness among adults in urban areas was associated with lower rates of depressive symptoms, as measured using the CES-D scale (Song et al., 2019). Similarly, cross-sectional studies in England and Spain reported that proximity to greenness among adults in urban areas was associated with less psychological distress, assessed with the GHQ-12 scale (Dadvand et al., 2016; White et al., 2013). Authors hypothesized that natural environments in cities allow residents to have more interaction with nature, which could lead to improved feeling of



**Incidence Rate Ratio (IRR) (95% CI) of the association between NDVI within a 300m buffer and GHQ-12 (in 2019) total score stratified by different degrees of urbanization.**  
 Urban areas excluding Paris city ; † not adjusted on Health center of inclusion ; \*Statistically significant p value (p<0.05)

Fig. 4.



**Incidence Rate Ratio (IRR) (95% CI) of the stratified analysis by age and sex pertaining to GHQ-12 (in 2019) total score, stratified by degree of urbanization.**  
 Urban areas excluding Paris city ; † not adjusted on Health center of inclusion ; \*Statistically significant p value (p<0.05)

Fig. 5.

belonging, and enhancing mental health (Maas et al., 2009; Pazhouhanfar, 2018).

Regarding CES-D sub-scores, our results suggested that residential surrounding greenness may have a protective role on depressed affect and somatic complaints in peri-urban areas, but not on less positive affect in urban areas and Paris city. The protective role of surrounding greenness on mental health has been discussed above and may explain the beneficial role on depressed affect and somatic complaints. However, the higher risk of less positive affect particularly in urban areas and Paris city could have various explanations. A previous study indicated that higher NDVI levels are associated with a greater intensity of positive emotions (Zhu et al., 2021). Since peri-urban areas in our study had higher NDVI values compared to urban areas and Paris, the lower NDVI levels in urban settings might contribute to reduce the protective role of greenness to buffer against less positive affect. Additionally, our population description showed that the prevalence of depression was highest in urban areas and Paris, where parks tend to be smaller and more crowded, this might reduce the protective role of greenness against less positive affect.

Paris was treated as a separate category in our analysis due to its distinct urban and socio-demographic characteristics. The city's high population density and competing land uses could result in limited

availability and accessibility of green spaces, even though such spaces may still hold social or psychological value. Most of green areas in Paris consist of small squares or courtyards (Fig. S1). Therefore, residing near a town square may still have a very low NDVI value, especially if in an area generally lacking vegetation in general such as trees, green roofs and private gardens. These pocket green spaces may support social cohesion and psychological restoration, but they are often minimally vegetated and surrounded by densely built environments. Therefore, the average NDVI within a residential buffer may underestimate actual greenness exposure. In addition, the socio-economic profile of Parisian residents differs significantly from the rest of regions in the CONSTANCES cohort: they are, on average, more affluent and better educated. These differences may influence not only the availability and use green spaces but also their perceived value. Taken together, these factors and results of our study for Paris, we believe surrounding residential greenness measured by NDVI may not be an optimal metric for assessing green space exposure in highly dense, urbanized contexts like Paris. Alternative or complementary measures, such as land use mapping, accessibility-based metrics, perceived greenness, or green space use may be more appropriate in such settings.

Regarding rural areas, although greenness is more abundant, its restorative role may be less pronounced due to generally lower baseline

stress levels compared to urban settings, as suggested by our descriptive data (Table 2). Moreover, the type of greenness common in rural environments, often consisting of agricultural land (Daghagh Yazd et al., 2019), may not offer the same psychological or physical benefits as structured, accessible green spaces typically found in urban areas (though not measured by NDVI). Urban parks, for instance, are often equipped with walking paths, seating, playgrounds, and sports facilities that encourage both physical activity and social interaction (Cohen et al., 2016). In contrast, rural green areas are frequently farmland for livelihood not explicitly designed (Daghagh Yazd et al., 2019) for recreational use. Additionally, rural residents may face contextual stressors that modify or counteract the potential mental health benefits of surrounding greenness (Jeong et al., 2022). These include exposure to agricultural pollutants such as pesticides (Daghagh Yazd et al., 2019; Houlden et al., 2017), as well as reduced access to healthcare, cultural amenities, and public transport (Jeong et al., 2022). Rural communities may also experience lower levels of social cohesion (Houlden et al., 2017). These factors can interact with green space exposure in complex ways, potentially diluting or altering greenspace influence on mental well-being. However, we cannot rule out our study limitations such as lack of metrics for measuring accessibility, use, or quality of green spaces, which are likely important to the greenness–mental health relationship in rural contexts.

In our stratified results by age and sex, the association between NDVI and psychological distress score was particularly found among men in peri-urban areas and among middle aged adults in urban areas. This aligns with the findings of Maas and colleagues, showing a positive impact of surrounding greenness, measured as percentage of green spaces within 1000m and 3000m buffer at residential address, on older people mental health across areas with different urbanity levels (Maas et al., 2006). Regarding sex differences, our results align with those from a British study, indicating a protective role of exposure to greenness expressed by the percentage of total land cover of green and natural environment per administrative ward on the total GHQ-12 score among men but not women (Astell-Burt et al., 2014). Overall, these results are consistent with the well-established lower vulnerability of both men and older people regarding psychological distress. They may also differ regarding how and why they use it.

Contrary to our initial hypothesis, we did not observe a mediating role of physical activity in the association between residential surrounding greenness and mental health outcomes, regardless of the degree of urbanization. This finding aligns with that of Pasanen et al. (2019) who also reported no mediating role of physical activity in the relationship between green spaces and psychological distress (using GHQ-12). They attributed the lack of mediation to limitations in their exposure assessment, particularly the absence of information on green space access and typology. In contrast, Zuo et al. (2024) found that physical activity (assessed through a single-item question on regular exercise in the past month) mediated the association between green space and depressive symptoms. This heterogeneity in findings across studies may reflect methodological differences, including potential measurement error in exposure (NDVI greenness vs. green space from land use mapping), mediator, and outcome variables, as well as issues related to the temporal alignment of exposure, mediator and outcome required in mediation analysis. In our study, physical activity was measured at the time of participant inclusion, while mental health was assessed in 2018 and 2019, introducing a time lag of up to seven years. While this sequencing respects the principle of temporality between the mediator and outcome, it may not adequately capture the relevant time window during which physical activity influences mental health. Furthermore, we lacked contextual information on where physical activity occurred (e.g., indoors vs. outdoors), as greater overall physical activity does not necessarily mean that it was performed in green or natural environments. Additionally, using NDVI as a measure of residential surrounding greenness does not capture all influential characteristics of green space such as visual aspect, type, quality, or

accessibility, which may be important to their mental health benefits and relevance for supporting physical activity.

We acknowledge several limitations in our study. The cross-sectional study design had a limited capability to infer causality regarding our evaluated associations. The CES-D and GHQ-12 are self-reported questionnaires; therefore, the accuracy and reliability of the self-reported data may be limited compared to clinical diagnosis. These tools do not allow for diagnosing specific mental disorders, while being a sensitive measure of altered mental health. Additionally, we acknowledge that mental health status may vary over time, and collecting CES-D and GHQ-12 in different years could introduce temporal heterogeneity. However, the one-year gap between measurements is relatively short, as descriptive comparisons showed similar sociodemographic characteristics across the two waves, suggesting that the analytic samples are largely comparable. We also recognize that limiting the analysis to participants with both CES-D and GHQ-12 data could introduce selection bias, especially if missingness is non-random. However, to address this concern, we conducted sensitivity analyses on participants with CES-D or GHQ-12 data separately, without requiring overlap. These analyses yielded results consistent with the main findings, indicating that our conclusions are robust to different assumptions about missing data and timing.

Regarding the exposure metric, we used the NDVI measured by the greenest pixels between May and July/2013–2020 for a long-term average based on the address at inclusion, whereas the outcomes were measured in 2018/19 thus exposure misclassification due to potentially moving cannot be ruled out. However, in our sensitivity analysis excluding those who have moved since inclusion, we have found similar results. Moreover, and as mentioned previously, NDVI does not take into account quality, size and use of green spaces. This limitation is particularly relevant in Paris, where green spaces are often small and embedded within a dense urban building so Parisian may perceive and use the green spaces differently. Although we adjusted for several indicators such as socioeconomic status, residual confounding cannot be entirely ruled out, particularly given the complex interplay between urbanization, social factors, and mental health outcomes.

This study has several strengths. First, the stratification by degree of urbanization—shown to be relevant in our study since different exposures and associations were found in type of area—has rarely been done in previous studies. Secondly, it represents one of the largest studies on the association between surrounding greenness and mental health on a study population of 114,717 participants randomly sampled from the French general population, with individual residential exposure data and mental health outcomes. Additionally, we were able to adjust our results for several potential covariates, and check the robustness of our findings. We used the CES-D and the GHQ-12 which are validated instruments for the evaluation of mental health outcomes in the general population, thereby increasing the comparability of our findings with other studies worldwide, and allows us to study two distinct aspects of mental health. However, exposure to surrounding greenness was estimated only based on participants' residential addresses, meaning that this approach may not fully capture individual exposure as it does not take into consideration exposures at other locations, such as work, or during commuting. Future studies incorporating time-weighted exposure assessments could provide a more accurate exposure estimation. Also, longitudinal analyses using appropriate methodology are needed to better understand the directionality of the relationship and to more robustly assess causality.

In conclusion, exposure to surrounding residential greenness was associated with less depression in peri urban areas and with less psychological distress in urban and peri-urban areas. Given the current prevalence of mental disorders and the increase in urbanization worldwide, the incorporation of greenness in the infrastructure of communities and urban areas should be maintained or increased to promote better mental health in these areas. In addition to the health benefits, surrounding greenness provides also provides environmental

benefits, such as biodiversity which promote physical and mental health.

### CRedit authorship contribution statement

**Zeinab Bitar:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Mohammad Javad Zare Sakhvidi:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Emeline Lequy:** Writing – review & editing, Methodology, Conceptualization. **Antoine Lafontaine:** Writing – review & editing, Formal analysis. **Cédric Lemogne:** Writing – review & editing, Methodology, Conceptualization. **Kees de Hoogh:** Writing – review & editing. **Marcel Goldberg:** Writing – review & editing, Resources, Methodology, Investigation, Conceptualization. **Franck Schürhoff:** Writing – review & editing. **Danielle Vienneau:** Writing – review & editing. **Marie Zins:** Writing – review & editing, Resources, Methodology, Investigation, Conceptualization. **Baptiste Pignon:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Emilie Burte:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Bénédicte Jacquemin:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

### Data sharing

All the data in this study is collected in the framework of the CONSTANCES cohort. The authors do not have permission to share the study data, which are under the protection of health data regulation set by the French National Commission on Informatics and Liberty (*Commission Nationale de l'Informatique et des Libertés*, CNIL). However, they may be accessible providing authorizations from the CNIL and the CONSTANCES' international scientific council. The procedure to access data is available on the web page: <https://www.constances.fr/en/scientific-area/access-to-constances/> and with agreement of the steering committee of the CONSTANCES cohort.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.envres.2025.122253>.

### Data availability

The authors do not have permission to share data.

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