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Nature contact and general health: Testing multiple serial mediation pathways with data from adults in 18 countries

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ABSTRACT

The role of neighbourhood nature in promoting good health is increasingly recognised in policy and practice, but consistent evidence for the underlying mechanisms is lacking. Heterogeneity in exposure methods, outcome measures, and population characteristics, little exploration of recreational use or the role of different types of green or blue space, and multiple separate mediation models in previous studies have limited our ability to synthesise findings and draw clear conclusions. We examined multiple pathways linking different types of neighbourhood nature with general health using a harmonised international sample of adults.

Using cross-sectional survey data from 18 countries (n = 15,917), we developed a multigroup path model to test theorised pathways, controlling for sociodemographic variables. We tested the possibility that neighbourhood nature (e.g. greenspace, inland bluespace, and coastal bluespace) would be associated with general health through lower air pollution exposure, greater physical activity attainment, more social contact, and higher subjective well-being. However, our central prediction was that associations between different types of neighbourhood nature and general health would largely be serially mediated by recent visit frequency to corresponding environment types, and, subsequently, physical activity, social contact, and subjective well-being associated with these frequencies. Several subsidiary analyses assessed the robustness of the results to alternative model specifications as well as effect modification by sociodemographics.

Consistent with this prediction, there was statistical support for eight of nine potential serial mediation pathways via visit frequency which held for a range of alternative model specifications. Effect modification by financial strain, sex, age, and urbanicity altered some associations but did not necessarily support the idea that nature reduced health inequalities.

The results demonstrate that across countries, theorised nature-health linkages operate primarily through recreational contact with natural environments. This provides arguments for greater efforts to support use of local green/blue spaces for health promotion and disease prevention.

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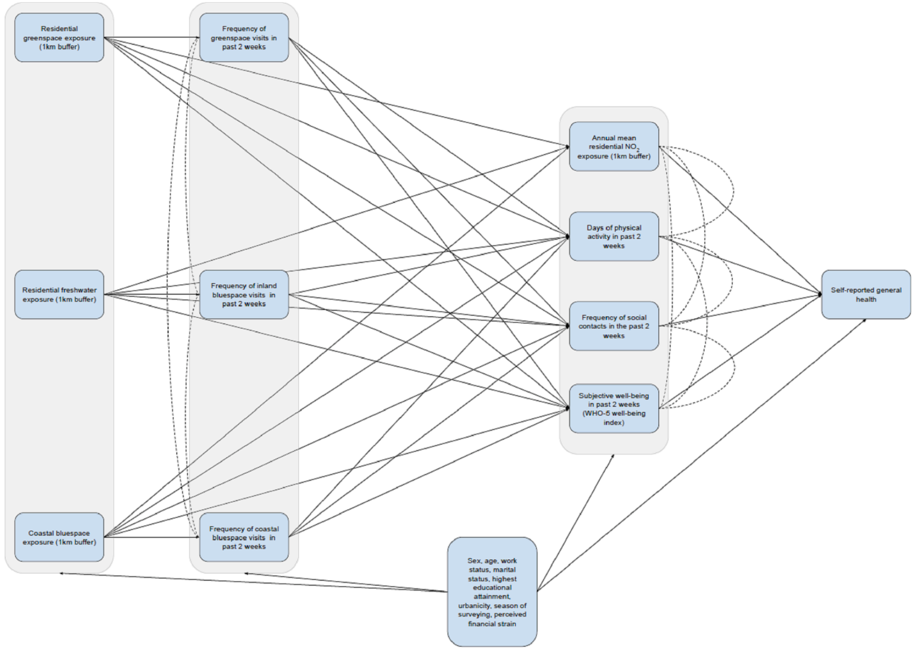

Fig. 1. A diagram of the proposed modelling approach. Direct effects from neighbourhood nature and nature visit frequency variables to general health are not shown for clarity. Solid lines represent direct, indirect, or potential confounding effects. Dotted lines represent residual covariances.

1. Introduction

The pathways underlying the positive impacts of natural environments on public health are complex. Natural environments may promote human health (Frumkin et al. 2017; van den Bosch and Ode Sang, 2017) by mitigating harms such as air pollution (Diener and Mudu 2021), heat reduction (Murage et al. 2020), providing settings for health-enhancing physical activity (Remme et al. 2021), fostering social contact or a sense of community (Francis et al. 2012), and/or positively impacting mental well-being and reducing psychological distress (White et al. 2021). Although several theoretical frameworks have argued that a combination of all these processes may be at play (Bratman et al., 2019; Hartig et al., 2014; Markevych et al., 2017; Marselle et al. 2021; White et al. 2020), to date few studies have tested multiple proposed pathways simultaneously through statistical methods such as structural equation modelling (SEM) and multiple/serial mediation analysis (Dzhambov et al., 2020). Doing so is important because assessing them in isolation obscures the understanding of their individual contributions/effects (Dzhambov et al., 2020).

In one of the few studies to look at several of these possible pathways simultaneously, Dadvand et al. (2016) used data from a random sample of adults from Barcelona, Spain; and found that mental health, social support, and physical activity explained respectively 40%, 10%, and 4% of the variance in the positive association between 'greenness' (measured by normalised difference vegetation index; NDVI) in the 250 m surrounding someone's residence and self-reported general health. Similarly, in a large sample of women from the US-based Nurses' Health Study, James et al. (2016) reported that physician-diagnosed antidepressant use (31%), frequency of social engagement (19%), total physical activity (2%) and modelled fine particulate matter ($PM_{2.5}$) concentrations (4%), all mediated the relationship between NDVI-derived greenness estimates in 250 m and 1,250 m buffers around participants' addresses and key health outcomes. By contrast, in a population-based sample of Belgian adults that considered distance to the coastline, Hooyberg et al. (2020) found no evidence of mediation of the positive association between residential coastal proximity ($\leq$5km vs. >5 km) and self-reported general health through either mental health (GHQ-12), quality of social interactions, physical activity, or observed air pollution concentrations (annual municipal PM_{10} concentrations).

Although these studies were important advances, several limitations remain. First, operationalisations of exposures, mediators, and outcomes across the studies were heterogeneous, which limits comparability of findings. Second, all used multiple single mediator models to determine the significance of mediating pathways, which may obscure intertwined and/or sequential mediating pathways that could instead be investigated with product-of-coefficients or SEM approaches (Dzhambov et al. 2020). This is an important consideration given the serial and intertwined nature of pathways proposed in theoretical frameworks (e.g. Hartig et al. 2014). Third, none of these studies considered both green and blue spaces simultaneously, which is a potentially important oversight given that the relative importance of the hypothesised nature-health pathways may be different for these different types of nature exposure (White et. al., 2020). Finally, samples were from either single cities (Dadvand et al. (2016), individual countries (e.g. Hooyberg et al. 2020), or from only a sub-section of the population (James et al. 2016), limiting generalisability.

Finally, and crucially for the current work, none of these studies considered the role of spending time in green/blue spaces, as opposed to merely living near them. Although many benefits of living in a greener area, such as lower exposure to pollutants, heat reduction, and stormwater management, may be gained within the home setting, benefits such as greater physical activity and social connectedness are assumed to occur outside the home through time spent recreating in accessible green/blue spaces (e.g. van den Berg et al., 2017). While much of this time is spent in the surrounding area (Elliott et al. 2020b; Grahn and Stigsdotter 2003), justifying the standard approach that only uses residential proximity as a metric of nature exposure, time in nature is not restricted to a radius around people's homes and many visits take place beyond such "buffers" (e.g. Elliott et al., 2015; Hillsdon et al., 2015). Indeed, time spent in nature has been shown to be a stronger predictor of mental health and subjective well-being than residential proximity (White et al., 2017, 2019). Understanding how much of the association between where one lives and various pathways to health is mediated through time spent in nature *anywhere* is as yet unexplored.

The present study attempts to address these issues by using cross-sectional survey data from representative samples of adults in 18 countries/territories, with harmonised metrics of exposure, mediation pathways and outcomes. In terms of exposure, we extended previous research by using globally consistent satellite-derived land cover data to measure residential exposure to both greenspace and two categories of bluespace (inland and coastal); and by asking people to recall the frequency of recreational visits to the same three types of nature setting during the last four weeks (our operationalising of *"contact with nature as such"* Hartig et al. 2014). Further building on Hartig et al.'s (2014) conceptual framework (Fig. 1) we explored the pathways of air quality, physical activity, social contacts, and stress (operationalised here, and henceforth referred to, as "*subjective well-being*"). We also extended earlier studies that had explored similar mechanisms (see Dzhambov et al. 2020 for review) by using a path modelling approach to simultaneously explore the many single and serially (via nature visits) mediated proposed pathways.

The main aim of the research was to investigate the relative importance of multiple mediating pathways (air quality, physical activity, social contact, subjective well-being) through which exposure to, and contact with, different types of natural environment may benefit self-reported health across broad segments of 18 diverse populations. We were particularly interested in comparing single-mediator pathways (by which residential exposure may impact health through air quality, physical activity, social contact, and subjective well-being) to serial mediator pathways (by which residential exposures may impact health through *visits* to nature, and subsequently through physical activity, social contact, and subjective well-being; see Fig. 1).

2. Method

This study was approved by the University of Exeter Medical School's Research Ethics Committee (Ref: Aug16/B/099).

2.1. Sample

The BlueHealth International Survey (BIS) was conducted as part of the Horizon 2020 BlueHealth project (Grellier et al. 2017). Its primary aim was to examine the effects of recent recreational visits to blue spaces on health and wellbeing. It was administered in four approximately four-week seasonal waves across 2017–2018 to control for seasonal variation in contact with blue spaces. Adults over the age of 18 were recruited from 14 European countries (Bulgaria, Czech Republic, Estonia, Finland, France, Germany, Greece, Italy, Ireland, Netherlands, Portugal, Spain, Sweden, and the United Kingdom) as well as four further countries or territories (Hong Kong [China], Queensland [Australia], California [USA], and Canada). Samples were targeted to be representative of the adult population in each case based on sex, age group, and, in most cases, region of residence. Tranches of emails were sent daily throughout each four-week wave so as not to complete data collection within a particular geodemographic stratum too quickly and instead have responses which represent the period as a whole. As such, the sampling method can be described as quota sampling based on sex, age, region, and season. This quota sampling combined with the online methodology limits the generalisability over stricter probability sampling. Nonetheless, we recognise similar studies use such sampling to make broad inferences about adult populations across countries/territories when combined in analysis with sampling weights (e.g. Cleary et al. 2020; Gelcich et al. 2014). A total of 18,838 respondents were recruited. Full methodological details can be found online (Elliott and White 2020).

We excluded respondents who displayed response biases (e.g. evidence of straightlining), and likely reported inaccurate home geolocations (e.g. in open water, or outside of the country in which they were a registered panellist), resulting in a final sample of 15,917.

2.2. Measures

2.2.1. General health

Our outcome measure was the SF1 (Ware and Sherbourne, 1992), reflecting participant's assessments of their own general health. Participants were asked: *"How is your health in general? Would you say it is…"*, with response options *"very bad"*, *"bad"*, *"fair"*, *"good"* or *"very good"*. The SF1 correlates with mortality rates (Kyffin et al. 2004), all domains of the SF-36 health survey (physical function, bodily pain, mental health, social function, vitality, and limiting activities due to physical or emotional functioning; Mavaddat et al. 2011); and single items like this were used in previous studies investigating the mechanisms underlying neighbourhood nature and health (Dadvand et al. 2016; de Vries et al. 2013; Hooyberg et al. 2020). Our primary analysis treated this variable as a numeric scale (1–5) following similar treatment in the literature (Hooyberg et al. 2020; Pasanen et al. 2019) based on the argument that linear estimation methods have been found to be robust in large epidemiological samples (Lumley et al. 2002; Norman 2010).

2.2.2. Neighbourhood nature

Participants were also asked to input their home location via a Google Maps application programming interface. For confidentiality reasons, recorded coordinates were rounded to three decimal degrees on both the longitude and latitude scale. On average, this meant that home locations were around 55 m off their true location, with greater error associated with homes located at more extreme latitudes. The GlobeLand30 data set (a globally-consistent 30 m resolution raster dataset based on remotely-sensed data; Chen et al. 2015) was used to assign indicators of the availability of neighbourhood nature to these coordinates. The data feature ten land cover classes, and congruence with localised land use maps has been demonstrated previously (Brovelli et al. 2015; Chen et al. 2015; Jokar Arsanjani et al. 2016; Wang et al. 2018).

The first two indicators comprised the percentage of 'green' and 'inland blue' space in 1 km buffers. Land classified by GlobeLand30 as "cultivated land" "forests" "shrubland" and "grassland" was collapsed into a 'greenspace' indicator and land classified as "water bodies" or "wetlands" into an 'inland bluespace' indicator. Buffers of 1 km were chosen as they represent an approximate 10–15 min walk from the home; a threshold implemented in cross-national research on the influences of natural environments on a multitude of health outcomes previously (Smith et al. 2017). Percentage of greenspace was operationalised as quintiles in analysis, while we dichotomised the inland bluespace indicator into those who had "some" inland bluespace within 1 km of their residence (36% of the sample participants) and those who had "none" within 1 km of their residence (64% of the sample) due to this variable having a highly positively skewed distribution.

A third indicator assessed residential proximity to the coastline with a Euclidean (as-the-crow-flies) distance metric, consistent with previous research (e.g. Wheeler et al. 2012). We calculated the distance from the home coordinate to the nearest coastline as defined by the highest resolution version of the Global Self-consistent Hierarchical High-resolution Geography shoreline database from the National Oceanic and Atmospheric Administration (Wessel and Smith, 1996). This dataset provides a balance between refinement in capturing a good representation of the land-sea interface, but enough granularity that smaller rivers and other inland waterways are rarely mischaracterised as coastline. To match the 1 km buffers applied to greenspace and inland bluespace indicators, we grouped respondents into two categories representing those that had access to coastline within 1 km of their home versus those who did not.

2.2.3. Nature visit frequency

Participants were presented with names and visual exemplars of 29 different blue and green environment types based on previous taxonomies (Cvejić et al. 2015; Bell et al. 2021) and asked how often in the last four weeks they visited each site for leisure. Here, we focus on a subset of 26 predominantly natural environments that were exemplars of our three categories of neighbourhood nature: green spaces (n = 12 settings, e.g. parks, woodlands); inland blue spaces (n = 6, e.g. lakes, rivers); and coastal (n = 8, e.g. beaches, harbours). The three non-natural excluded settings were ice rinks, pools/spas, and fountains. The last four weeks was chosen as an appropriate recall period due to its use in previous leisure visit surveys (Natural Resources Wales, 2015) and in health questionnaires such as the GHQ-12 (Goldberg and Williams 1988). Consistent with other national surveys (Natural England, 2019), 'leisure time' was described to participants as involving recreation, but not work, and respondents were asked not to report on visits to indoor locations, places they might visit as part of their job, or private locations such as their own garden.

Response options were: "not at all in the last four weeks", "once or twice in the last four weeks", "once a week", "several times a week". We assumed a numerical equivalent of the four response options above to be zero, one, four, and eight visits in the last four weeks respectively following previous research with this dataset (White et al. 2021). We summed responses for the collections of green spaces, inland blue spaces, and coastal blue spaces and capped totals at 56 visits, representing twice a day, every day, in the past four weeks, which might be feasible for dog owners for instance (White et al. 2021). We further divided this total by 2 to give a numeric estimate in the past two weeks for temporal consistency with our metrics of physical activity, social contact, and psychological well-being (see 2.2.5, 2.2.6, and 2.2.7).

2.2.4. Air quality

Air quality was assessed through NO_2 air pollution data derived from a land use regression model with 50 × 50 m^2 resolution (Larkin et al. 2023). This model integrated measurements from 8,250 air pollution monitors with 11 variables which best determined NO_2 concentrations such as the presence of major and minor roads, population density, ozone, temperature, and atmospheric pressure to estimate global annual mean NO_2 concentrations in parts per billion (ppb) along with daily offsets. We assigned values to participants home geolocations by averaging the annual mean NO_2 concentrations in the tiles intersecting a 1 km buffer around the home (to be congruent with the 1 km buffers used for neighbourhood nature indicators). NO_2 is strongly associated with traffic-related air pollution (Beckerman et al. 2008) and has been used previously in studies exploring pathways between nature and mental health in more specific samples and locations (Dzhambov et al. 2018).

2.2.5. Physical activity

Respondents self-reported how many days in the previous week they had achieved at least 30 min of moderate-to-vigorous intensity physical activity through recreation and transport. This item has good test–retest reliability, and modest concurrent validity with comparable international multi-item self-reported physical activity measures (Milton et al. 2011). Relationships between neighbourhood nature and this variable have been demonstrated previously in England (White et al. 2014, 2018). The reported number was multiplied by 2 to represent an estimate of frequency in the past two weeks to maintain temporal consistency with our metric of subjective well-being (see 2.2.7).

2.2.6. Social contact

Frequency of social contacts was measured with the item: *"How often do you meet socially with friends, relatives, or work colleagues? 'Meet socially' implies by choice rather than for reasons of either work or pure duty."* Response options were: *"never"*, *"less than once a month"*, *"once a month"*, *"several times a month"*, *"once a week"*, *"several times a week"*, *"every day"*, and *"do not know"*. The question is taken from the European Social Survey and strong criterion validity has been demonstrated with satisfaction with one's family and social life, and importantly here self-reported health (Eckhard 2018). Following similar treatment in previous analyses (Swader 2019), we assumed numerical equivalents of 0, 6, 12, 24, 52, 104, and 365 respectively with respondents stating "do not know" recoded as missing data. This numeric estimate was divided by 26 to give an estimate of frequency of social contacts in the past two weeks to maintain temporal consistency with our metric of subjective well-being (see 2.2.7).

2.2.7. Subjective well-being

Subjective well-being was operationalised as aggregate scores from responses to the WHO-5 well-being index, a measure of subjective well-being in the past two weeks that has been used in research on nature and mental health previously (Mitchell et al. 2015; White et al. 2021). The WHO-5 has good psychometric validity, as well as validity as a screening tool for depression (Topp et al. 2015). We treated subjective well-being as a mediator rather than an outcome variable given its evidenced influence on physical health markers in previous studies (Boehm and Kubzansky 2012).

Rather than use low WHO-5 scores as an indicator of psychological distress (e.g. see White et al., 2021), here we merely use the scale as originally designed with higher scores reflecting higher subjective well-being. Previous research has operationalised similar mediators as self-reported responses to psychiatric screening tools (Dadvand et al. 2016).

2.3. Theoretical model

Consistent with recommendations on mediation in nature-health literature (Dzhambov et al. 2020), we constructed a model to simultaneously explore all the pathways from neighbourhood green and blue-space exposures to general health proposed in Hartig et al.'s (2014) review (Fig. 1). A total of 12 single mediation pathways (i.e. 3 [neighbourhood nature: greenspace, inland bluespace, coastal bluespace] × 4 [air quality, physical activity, social contact, subjective well-being]) were modelled, as well as 9 serial mediation pathways (i.e. 3 [neighbourhood nature: greenspace, inland bluespace, coastal bluespace] × 1 [nature visit frequency: greenspace visits (for neighbourhood greenspace), inland bluespace visits (for neighbourhood inland bluespace), coastal bluespace visits (for neighbourhood coastal bluespace)] × 3 [physical activity, social contact, subjective well-being]).

Air quality was not considered for serial mediation as we only had NO_2 data surrounding the participant's residence (not in other locations where they may have visited); and it is conceptually problematic to assume that an individual's visits (as opposed to the amount of vegetation near their home) will affect localised air quality.

Hartig et al., (2014) noted that air quality, physical activity, social contact, and stress are "reciprocally related" (p. 213). Therefore, we modelled all possible residual covariances between these mediator variables, as well as residual covariances between the three variables measuring frequencies of visits to green, inland, and coastal blue spaces. All mediators and the outcome were adjusted for sex, age, work status, marital status, highest educational attainment, urbanicity of residence, season of surveying, and reported comfort with current household income. Details of how this information was collected from participants can be found in an accompanying technical report (Elliott and White, 2020).

While Hartig et al., (2014) did not assume single-mediator pathways from neighbourhood nature to health through physical activity and social contact, we nonetheless modelled these, given evidence that access to the natural environment promotes recreational walking in the neighbourhood (Christian et al. 2017) and that access to neighbourhood nature has previously been found to be associated with a sense of community belonging (Rugel et al. 2019).

Lastly, we assume that mediator and outcome variables will naturally vary across countries (i.e. some countries may have higher levels of NO_2 exposure generally because of spatial planning of cities / levels of car use etc.; some respondents may report generally higher levels of subjective well-being due to reporting biases). To account for this, we included country of residence as a grouping variable in our analysis (see

Table 1

Descriptive statistics concerning key variables in the path model, stratified by country (base n = 15,917[a]). For continuous variables, means and standard deviations (in parentheses) are presented. For binary variables (inland bluespace within 1 km of residence, coastal bluespace within 1 km of residence), counts and percentages of participants who had these natural environment types within 1 km of their residence are presented.

	Overall (n = 15,917[a])	Bulgaria (n = 963 [a])	California, US (n = 892 [a])	Canada (n = 787 [a])	Czech Republic (n = 949 [a])	Estonia (n = 831 [a])	Finland (n = 909 [a])	France (n = 953 [a])	Germany (n = 863 [a])	Greece (n = 842 [a])	Hong Kong, CN (n = 750 [a])	Ireland (n = 905 [a])	Italy (n = 868 [a])	Netherlands (n = 951 [a])	Portugal (n = 807 [a])	Queensland, AU (n = 849 [a])	Spain (n = 792 [a])	Sweden (n = 887 [a])	United Kingdom (n = 1,119 [a])
GS	**42.15 (37.56)**	37.26 (38.86)	35.69 (40.41)	39.53 (39.16)	57.26 (36.16)	46.88 (39.38)	35.38 (32.01)	45.53 (38.97)	48.55 (37.93)	32.89 (36.06)	41.33 (29.11)	50.79 (40.71)	42.69 (35.79)	39.43 (35.64)	42.35 (33.48)	47.25 (42.08)	36.58 (36.62)	40.01 (34.90)	38.05 (35.85)
IBS	**5713 (37.56%)**	197 (20.78%)	149 (17.55%)	449 (58.54%)	391 (41.24%)	336 (41.13%)	594 (66.97%)	425 (46.10%)	320 (37.30%)	75 (9.72%)	122 (21.40%)	269 (30.85%)	184 (22.77%)	613 (65.21%)	176 (22.42%)	384 (49.87%)	157 (21.16%)	503 (58.90%)	369 (33.55%)
CBS	**1817 (11.93%)**	29 (3.05%)	31(3.65%)	32 (4.17%)	NA	94 (11.51%)	171 (19.26%)	39 (4.22%)	11 (1.28%)	205 (26.55%)	332 (58.25%)	134 (15.37%)	132 (16.34%)	28(2.98%)	117 (14.89%)	87(11.18%)	108 (14.56%)	150 (17.56%)	117 (10.62%)
GSV	**5.89 (6.15)**	9.05 (6.67)	3.54(4.71)	4.77 (5.88)	8.41 (6.91)	6.87 (6.14)	6.23 (5.62)	3.91 (4.88)	5.65 (5.40)	7.01 (6.42)	4.30 (5.09)	5.50 (5.85)	7.36 (7.11)	5.28(5.75)	6.84 (6.84)	3.82(5.21)	8.02 (7.14)	5.81 (5.70)	3.88 (4.68)
IBSV	**2.07 (3.22)**	2.85 (3.40)	1.25(2.66)	2.28 (3.66)	2.68 (3.46)	2.36 (3.20)	2.17 (3.04)	1.51 (2.54)	2.16 (2.93)	1.23 (2.25)	1.29 (2.70)	2.46 (3.61)	2.30 (3.79)	2.25(3.20)	2.49 (3.73)	1.96(3.35)	2.45 (3.76)	2.22 (3.20)	1.44 (2.50)
CBSV	**2.60 (4.89)**	2.13 (4.72)	1.96(4.12)	1.93 (4.28)	0.70 (2.53)	1.53 (3.27)	2.25 (4.08)	1.78 (4.36)	0.91 (2.98)	6.73 (6.88)	2.64 (3.75)	3.05 (5.22)	4.65 (6.46)	1.46(3.42)	4.53 (6.25)	2.80(4.89)	4.82 (6.66)	2.22 (4.19)	1.76 (3.41)
AQ	**9.39 (5.46)**	7.86 (4.07)	11.53 (5.90)	8.14 (4.93)	7.81 (2.93)	5.83 (3.17)	5.88 (3.30)	9.89 (5.68)	9.55 (3.37)	10.11 (5.87)	19.86 (6.94)	6.25 (3.15)	10.8 (4.49)	11.69 (2.90)	10.38 (4.29)	5.75 (4.68)	10.95 (5.19)	6.37 (3.78)	11.54 (4.32)
PA	**4.86 (4.44)**	5.63 (4.67)	5.58(4.55)	5.24 (4.27)	4.78 (4.39)	4.91 (4.65)	5.80 (4.43)	3.55 (4.22)	4.95 (4.41)	3.41 (3.89)	3.33 (3.48)	5.84 (4.62)	4.13 (3.97)	4.61(4.37)	3.77 (4.17)	5.10(4.46)	5.77 (4.40)	5.77 (4.68)	5.03 (4.59)
SC	**2.84 (3.54)**	5.15 (5.03)	2.28(3.11)	2.49 (3.09)	3.69 (4.17)	1.84 (2.47)	2.73 (3.37)	2.90 (3.58)	2.15 (2.54)	3.18 (3.82)	1.74 (2.53)	2.43 (3.12)	2.70 (3.22)	2.76(3.16)	3.76 (4.33)	2.20(2.91)	3.19 (3.55)	3.47 (3.93)	2.15 (2.70)
SWB	**59.77 (21.65)**	64.20 (23.29)	55.94 (21.45)	61.13 (19.97)	62.13 (21.74)	56.18 (19.65)	60.32 (19.54)	61.59 (22.89)	57.73 (23.32)	63.41 (21.59)	53.56 (21.23)	59.02 (21.55)	60.29 (22.65)	61.07 (20.87)	65.11 (20.33)	56.13 (21.90)	66.69 (18.66)	58.8 (20.67)	53.51 (21.51)
Health	**3.70 (0.84)**	3.98 (0.78)	3.82(0.81)	3.81 (0.79)	3.65 (0.88)	3.43 (0.82)	3.61 (0.79)	3.57 (0.88)	3.41 (0.93)	4.23 (0.72)	3.51 (0.74)	3.81 (0.88)	3.75 (0.77)	3.58(0.75)	3.80 (0.69)	3.63(0.85)	3.77 (0.82)	3.65 (0.90)	3.61 (0.91)

[a] Actual sample sizes upon which these statistics are calculated for each key variable differ due to differing levels of missing data.

Abbreviations:

GS = 'Greenspace' (i.e. % of greenspace in the 1 km surrounding the participant's residence).

IBS = 'Inland bluespace' (i.e. whether the respondent had 'some' [vs. 'none'] inland bluespace within 1 km of their residence).

CBS = 'Coastal blue space' (i.e. whether the respondent had coastal bluespace within 1 km of their residence or not).

GSV = 'Greenspace visits' (i.e. the self-reported number of recreational visits made to green spaces within the last 2 weeks).

IBSV = 'Inland bluespace visits' (i.e. the self-reported number of recreational visits made to inland blue spaces within the last 2 weeks).

CBSV = 'Coastal bluespace visits' (i.e. the self-reported number of recreational visits made to coastal blue spaces within the last 2 weeks).

AQ= 'Air quality' (i.e. modelled annual mean concentration of NO_2 [parts per billion; ppb] at the respondent's residence).

PA = 'Physical activity' (i.e. self-reported number of days in the last 2 weeks on which the participant did at least 30 min of moderate-vigorous intensity physical activity through recreation and transport).

SC = 'Social contact' (i.e. self-reported frequency of days in the past 2 weeks with which the participant meets friends, relatives, or work colleagues socially).

SWB = 'Subjective well-being' (i.e. self-reported subjective well-being in the past 2 weeks as measured by the WHO-5 well-being index [0–100 scale]).Health = 'General health' (i.e. self-reported general health).

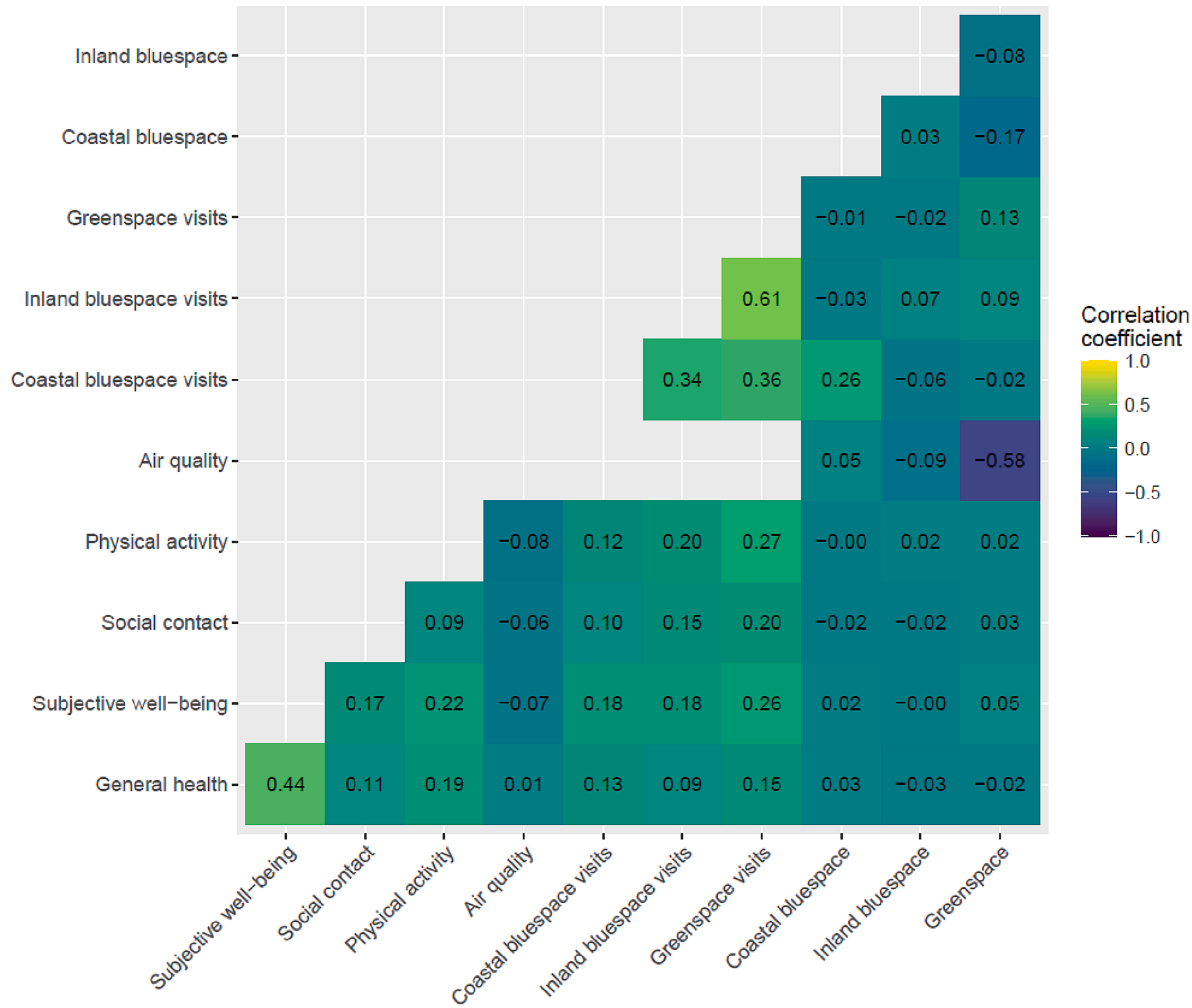

Fig. 2. Correlation matrix of key variables in the present study. N.B n = 14,957; this is lower than the sample size for the modelling due to missing data being excluded here.

2.4).

2.4. Statistical analysis

All analyses were conducted in R version 4.1.3 (R Core Team 2022) using 'lavaan' for path modelling (Rosseel 2012). We fitted a multigroup path model to the data. This is analogous to a multilevel path model in that we could cluster participant data within countries (i.e. the 'groups' in the multigroup path model), but with more flexibility as to which parameters could be 'fixed' across countries, and which could be 'random' (i.e. vary across countries). We allowed intercepts of all outcome and mediator variables (that is, general health, air quality, physical activity, social contact, subjective well-being, and the three nature visit frequency variables) to vary across countries.

We also allowed specific slopes to vary across countries where fixing these would have resulted in large residual terms in several countries; in other words, a fixed slope would have misrepresented the direction and significance of a finding in several countries. This was the case with just four terms in the final model, all concerning air quality.

We weighted participant's responses to ensure estimates were demographically representative of the adult populations of each country and used a full-information maximum likelihood estimator to account for missing data. Indirect effect estimates were calculated using the product-of-coefficients method with statistical significance based on the delta method (Preacher and Hayes 2008) due to computational limitations with using bootstrapping which would otherwise be ideal (Dzhambov et al. 2020). Technical detail regarding model development and estimation is provided in Supplementary File A.

2.4.1. Subsidiary analyses

Since statistical significance can vary depending on the estimator used in multigroup structural equation modelling and given the originally ordered categorical nature of our outcome variable concerning general health, our first subsidiary analysis applied a diagonally-weighted least squares estimator in place of the robust maximum likelihood estimator used in the main model. This model had a reduced sample size (n = 14,761) due to the inability to apply the full-information maximum likelihood technique to account for missing data.

Three further subsidiary analyses were conducted which: (a) operationalised neighbourhood nature metrics in 300 m buffers as opposed to 1 km buffers; (b) operationalised neighbourhood greenspace as NDVI levels within a 1 km buffer as opposed to GlobeLand30-derived greenspace land cover classes; and (c) used an indicator of $PM_{2.5}$ around the home (as opposed to NO_2) derived from a 0.1° x 0.1° (approximately 11

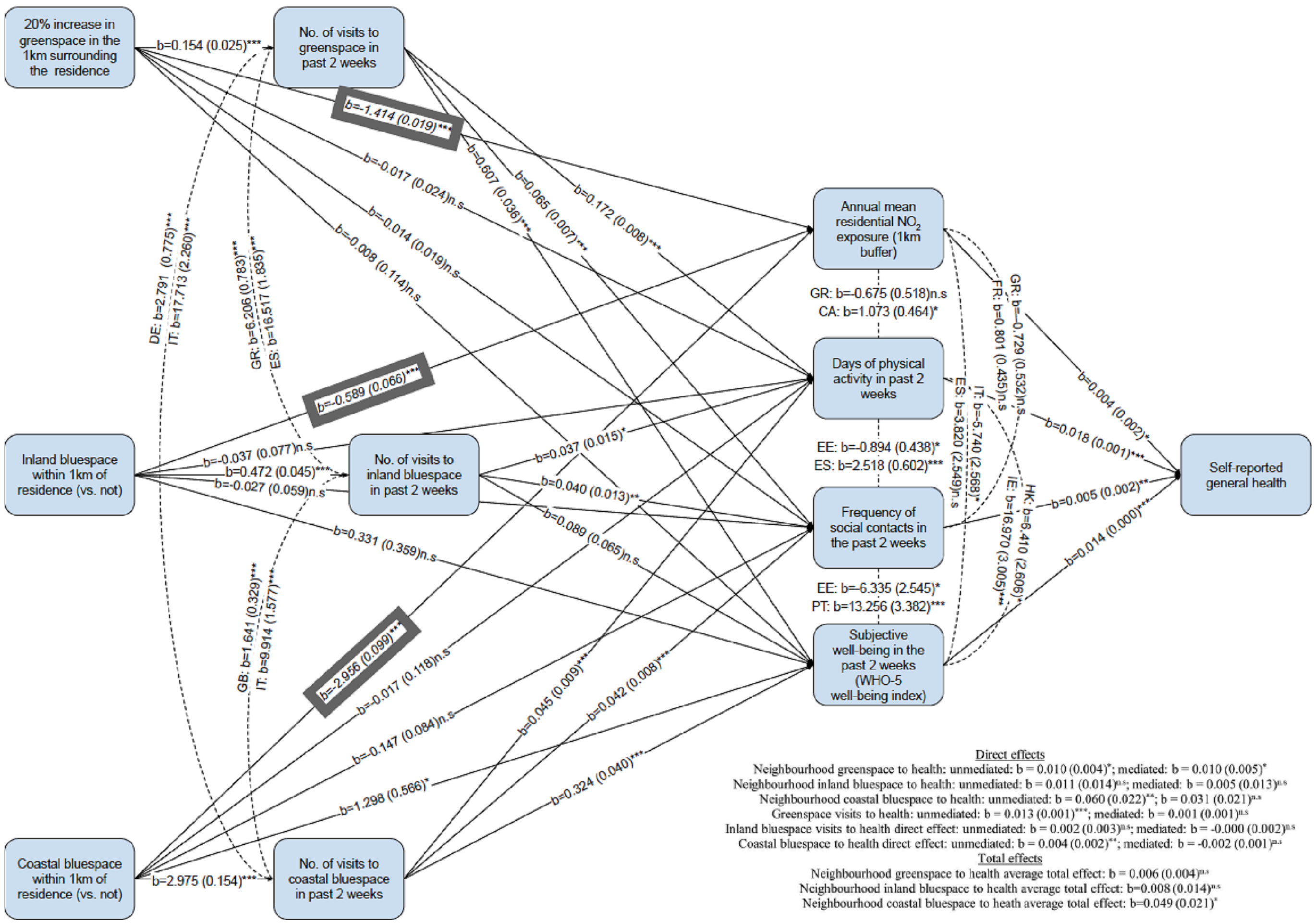

Fig. 3. Path model with unstandardized coefficients and standard errors in parentheses (n = 15,917). Standardised coefficients were not used due the multigroup modelling allowing means/intercepts and variances to vary across countries. Solid lines represent direct and indirect effects. Dotted lines represent residual covariances and ranges between countries and are presented with two-letter ISO codes. Grey shaded boxes refer to paths where the parameters were free to vary across countries; the statistics shown are means across countries with associated standard errors; these values were subsequently used to compute indirect effects for the overall sample. ***=p <.001; **=p <.01; *=p <.05; n.s = not significant.

km^2 at the equator) map (Shaddick et al. 2018).

Eight further subsidiary analyses were conducted to examine whether certain pathways were more or less supported in different sociodemographic groups, with an aim to better understand how neighbourhood nature could reduce health inequalities (Mitchell and Popham 2008; Rigolon et al. 2021; Wheeler et al. 2015). We therefore *a priori* stratified the main model by 'financial strain' (i.e. those who reported 'coping'/'living comfortably' on their present household income vs. 'finding it difficult'/'very difficult'; hereafter referred to as 'coping' vs. 'not coping' respectively), sex (male; female), age group (18–39; 50 and over), and urbanicity (urban; rural) to explore differences in significant mediating pathways across these sociodemographics.

3. Results

3.1. Descriptive statistics

The sample was 51% female and the largest age group was 60yrs+ (27%). Most participants were employed (55%) and the majority were married (59%). Most participants lived in urban areas (69%), and the majority reported 'coping' on their household's current income (75%). Within 1 km of their residence, participants had, on average, 42% (SD = 38%) of the land occupied by greenspace while 38% of participants had access to inland bluespace and 12% had access to the coast. In the past two weeks participants made an average of six visits to greenspace, two visits to inland bluespace, and three visits to coastal bluespace.

Participants lived in areas with an average annual mean NO_2 concentration of 9.4 ppb (this is greater than the WHO's guidance of 5.3 ppb), did five days of physical activity in the past two weeks, met socially with friends, family, or colleagues on three days in the past two weeks, and scored 60 (out of 100) in terms of their subjective well-being. Lastly, self-reported health averaged 3.7, meaning that on average, participants rated their health towards 'good'. There was substantial cross-country variation in these averages which is shown in Table 1.

Bivariate correlations between key variables in this study are displayed in Fig. 2. The strongest correlations existed between neighbourhood greenspace and air quality (r = -0.58), between greenspace visits and inland bluespace visits (r = 0.61) and between general health and subjective well-being (r = 0.44).

3.2. Model estimates

The robust confirmatory fit index (0.93), robust root mean square error of approximation (0.03), and robust standardised root mean squared residual (0.03) were within acceptable limits indicating satisfactory model fit.

Unstandardised regression paths, residual covariances, direct effects, and total effects are shown in Fig. 3. Full model results are given in Supplementary File B; estimates of random intercepts are shown in Fig. 4. Coefficients relating to greenspace in the 1 km surrounding the

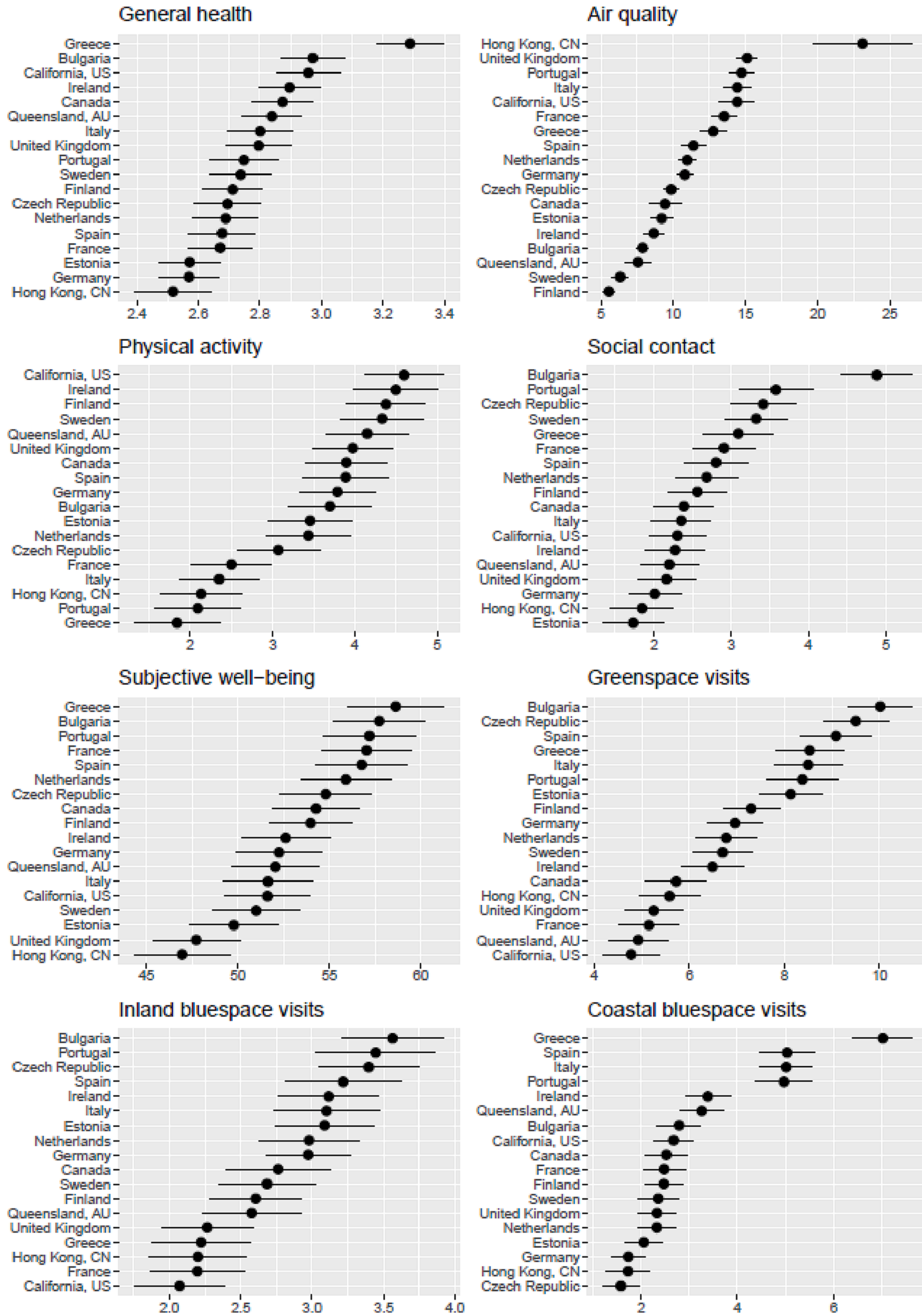

Fig. 4. Plots of random intercept effects from the final model.

Table 2
Estimates of indirect effects from the main path model (n = 15,917). Significant effects are highlighted in bold.

Indirect effect	Unstandardised estimate	LCI	UCI	*p*-value
Single mediations				
GS → AQ → Health	**−0.005682**	**−0.010834**	**−0.000531**	**0.030621**
GS → PA → Health	−0.000301	−0.001130	0.000528	0.477245
GS → SC → Health	0.000070	−0.000123	0.000264	0.476551
GS → SWB → Health	0.000109	−0.003104	0.003322	0.946975
IBS → AQ → Health	**−0.002368**	**−0.004551**	**−0.000186**	**0.033449**
IBS → PA → Health	−0.000663	−0.003339	0.002013	0.627332
IBS → SC → Health	−0.000139	−0.000749	0.000471	0.654482
IBS → SWB → Health	0.004767	−0.005348	0.014883	0.355637
CBS → AQ → Health	**−0.011877**	**−0.022678**	**−0.001077**	**0.031137**
CBS → PA → Health	−0.000295	−0.004397	0.003807	0.887778
CBS → SC → Health	−0.000762	−0.001764	0.000239	0.135787
CBS → SWB → Health	**0.018663**	**0.002694**	**0.034632**	**0.021983**
Serial mediations				
GS → GSV → PA → Health	**0.000471**	**0.000299**	**0.000642**	**0.000000**
GS → GSV → SC → Health	**0.000053**	**0.000012**	**0.000093**	**0.011210**
GS → GSV → SWB → Health	**0.001348**	**0.000884**	**0.001812**	**0.000000**
IBS → IBSV → PA → Health	**0.000309**	**0.000044**	**0.000575**	**0.022372**
IBS → IBSV → SC → Health	**0.000099**	**0.000005**	**0.000192**	**0.038241**
IBS → IBSV → SWB → Health	0.000604	−0.000270	0.001478	0.175339
CBS → CBSV → PA → Health	**0.002400**	**0.001317**	**0.003483**	**0.000014**
CBS → CBSV → SC → Health	**0.000644**	**0.000139**	**0.001149**	**0.012476**
CBS → CBSV → SWB → Health	**0.013881**	**0.010234**	**0.017528**	**0.000000**

Abbreviations:
LCI = lower bound of the 95% confidence interval
UCI = upper bound of the 95% confidence interval
Health = 'General health' (i.e. self-reported general health).
GS = 'Greenspace' (i.e. 20% increase in greenspace in the 1 km surrounding the participant's residence).
IBS = 'Inland bluespace' (i.e. whether the respondent had freshwater within 1 km of their residence or not).
CBS = 'Coastal blue space' (i.e. whether the respondent had coastal bluespace within 1 km of their residence or not).
GSV = 'Greenspace visits' (i.e. the self-reported number of recreational visits made to green spaces within the last 2 weeks).
IBSV = 'Inland bluespace visits' (i.e. the self-reported number of recreational visits made to inland blue spaces within the last 2 weeks).
CBSV = 'Coastal bluespace visits' (i.e. the self-reported number of recreational visits made to coastal blue spaces within the last 2 weeks).
AQ = 'Air quality' (i.e. modelled annual mean concentration of NO_2 [parts per billion; ppb] at the respondent's residence).
PA = 'Physical activity' (i.e. self-reported number of days in the last 2 weeks on which the participant did at least 30 min of moderate-vigorous intensity physical activity through recreation and transport).
SC = 'Social contact' (i.e. self-reported frequency of days in the past 2 weeks with which the participant meets friends, relatives, or work colleagues socially).
SWB = 'Subjective well-being' (i.e. self-reported subjective well-being in the past 2 weeks as measured by the WHO-5 well-being index).

residence are scaled to 20% increases.

3.2.1. Direct effects

When exploring only direct effects between neighbourhood nature exposures and general health (adjusted for covariates, but not including mediators), we observed a positive association between neighbourhood greenspace and general health (for a 20% increase in neighbourhood greenspace $b = 0.01$, [0.00 – 0.02]) and between coastal proximity and general health (living within 1 km of the coast, compared to further away $b = 0.06$, [0.02 – 0.10]), but not between inland bluespace and general health ($b = 0.01$ [-0.02 – 0.04]). Given that similar previous research has demonstrated that the lack of a direct effect can be due to competing indirect effect pathways (i.e. via different mediators) engendering both better and poorer health simultaneously (Dzhambov et al. 2018), we did not change our modelling approach. Once mediating pathways were included, direct effects between neighbourhood nature variables and general health were partially attenuated (see Fig. 3), indicative of potential mediation.

3.2.2. Effects of neighbourhood nature variables on corresponding nature visit frequencies

Living near a specific type of nature was positively associated with visiting that type of nature more often in the last two weeks in all cases. A 20% increase in neighbourhood greenspace within 1 km was associated with significantly more visits to greenspace ($b = 0.154$ [0.105 – 0.203]). The presence of inland bluespace within 1 km of the home was associated with significantly more visits to inland bluespace ($b = 0.472$ [0.384 – 0.561]). This association was also positive but far stronger for the presence of coastal bluespace within 1 km of the home ($b = 2.975$ [2.674 – 3.277]).

3.2.3. Effects of neighbourhood nature and nature visit frequency on air quality, physical activity, social contact, and subjective well-being

With respect to air quality (with no hypothesised mediation path through visits), a 20% increase in greenspace in the surrounding 1 km was associated with a 1.414 ppb decrease in annual mean NO_2 concentrations (-1.452 – −1.377). The presence of inland bluespace within 1 km of home was associated with a 0.589 ppb decrease (-0.719 – −0.460), and living with 1 km of the coast was associated with a 2.956 ppb decrease (-3.151 – −2.762). See Supplementary File C for description regarding cross-country variation with respect to these associations.

For those pathways where visits were modelled as a potential mediator (physical activity, social contact, subjective well-being), the only significant direct association between neighbourhood nature and physical activity, social contact, or subjective well-being was between coastal proximity and subjective well-being ($b = 1.298$ [0.189 – 2.406]).

By contrast all but one of the associations between nature visit frequency and physical activity/social contact/subjective well-being were significant. The number of days of physical activity in the past two weeks was positively associated with recreational visits to green spaces ($b = 0.172$ [0.155 – 0.188]), inland blue spaces ($b = 0.037$ [0.007 – 0.067]), and coastal blue spaces ($b = 0.045$ [0.027 – 0.064]). Days of social contact in the past two weeks was also positively associated with visits to green spaces ($b = 0.065$ [0.052 – 0.079]), inland blue spaces ($b = 0.040$ [0.015 – 0.065]), and coastal blue spaces ($b = 0.042$ [0.025 – 0.058]). Finally, subjective well-being was positively associated with the frequency of visits to green spaces ($b = 0.607$ [0.537 – 0.678]) and coastal blue spaces ($b = 0.324$ [0.247 – 0.402]) but not inland blue spaces.

3.2.4. Effects of air quality, physical activity, social contact, and subjective well-being on general health

Supporting previous models, days of physical activity in the past two weeks ($b = 0.018$ [0.015 – 0.021]), days of social contact in the past two weeks ($b = 0.005$ [0.002 – 0.009]), and subjective well-being in the past two weeks ($b = 0.014$ [0.014 – 0.015]) were all positively associated with general health. Counterintuitively, annual mean NO_2 concentrations were weakly *positively* associated with general health ($b = 0.004$ [0.000 – 0.008]).

3.2.5. Indirect effects - testing key theorised pathways

Our main investigation was whether the majority of theorised pathways linking neighbourhood nature to general health would involve serial mediation whereby the relationship between neighbourhood exposure to nature (of a particular type) and general health would be serially mediated by: (a) self-reported frequency of visits to those same types of nature for recreation; and subsequently (b) either more days of adequate physical activity in the past two weeks, more days of social contact with friends, family, or colleagues in the past two weeks, or better self-reported subjective well-being in the past two weeks. As noted above, air quality was not considered to be plausibly affected by visit frequency.

Supporting our theory, eight of the nine proposed serial mediation pathways were statistically significant (Table 2). The relationship between greenspace within 1 km of the residence and general health was serially mediated by a greater frequency of greenspace visits in the past two weeks and: (a) more days of physical activity in the past two weeks (*Effect* = 0.00047 [0.00030 – 0.00064]); (b) more days of social contact in the past two weeks (*Effect* = 0.00005 [0.00001 – 0.00009]); and (c) better subjective well-being in the past two weeks (*Effect* = 0.00135 [0.00088 – 0.00181]). The relationship between the presence of inland bluespace within 1 km of the residence and general health was serially mediated by a greater frequency of inland bluespace visits in the past two weeks and: (a) more days of physical activity in the past two weeks (*Effect* = 0.00031 [0.00004 – 0.00058]), and (b) more days of social contact in the past two weeks (*Effect* = 0.00010 [0.00001 – 0.00019]). Lastly, the relationship between the presence of coastal bluespace within 1 km of the residence and general health was serially mediated by a greater frequency of coastal bluespace visits in the past two weeks and: (a) more days of physical activity in the past two weeks (*Effect* = 0.00240 [0.00132 – 0.00348]), (b) more days of social contact in the past two weeks (*Effect* = 0.00064 [0.00014 – 0.00115]), and (c) better subjective well-being in the past two weeks (*Effect* = 0.01388 [0.01023 – 0.01753]).

In contrast, only one of a possible 12 single mediation pathways was statistically significant in the expected direction. Living nearer the coast was associated with better subjective well-being which was in turn associated with better general health (*Effect* = 0.01866 [0.00269 – 0.03464]), but this was not simply due to more frequent visits to the coast. Three further single mediation pathways concerning air quality were also statistically significant but counterintuitive to predictions: air quality was a statistically significant mediator of the relationship between all three types of neighbourhood nature and general health (greenspace: *Effect* = -0.00568 [-0.01083 – −0.00053]; inland bluespace: *Effect* = -0.00237 [-0.00455 - −0.00019]; coastal bluespace: *Effect* = -0.01188 [-0.02268 – −0.00108]), but the effects counterintuitively imply that the presence of NO_2 negates the positive effects of exposure to these types of neighbourhood nature on general health.

3.3. Subsidiary analyses

Mediation results pertaining to the 12 subsidiary analyses are shown in appendices (Table A.1) with full model results in Supplementary File B.

In the model employing a diagonally-weighted least-squares estimator and ordered categorical general health outcome (n = 14,761), all significant mediation pathways in the main model were observed again, apart from the pathway linking inland bluespace with general health through more inland bluespace visits and more days of physical activity in the last two weeks. In the three further subsidiary analyses utilising alternative model specifications, all statistically significant serial mediation pathways observed in the main model were observed again. Additionally: (a) in the 300 m model, subjective well-being significantly mediated the relationship between inland bluespace within 300 m of the residence and general health, and (b) in the NDVI and $PM_{2.5}$ models, like the main model, subjective well-being mediated the relationship between coastal proximity and general health. None of the single mediation pathways concerning air quality were significant in these three models.

When examining only those respondents who reported ‘coping’ or ‘living comfortably’ with their present income (n = 11,860), all statistically significant serial mediation pathways found in the main model were again observed, except for the pathway from inland blue space to general health via inland bluespace visits and social contacts. Additionally, the single mediation pathway from coastal blue space to general health via subjective well-being was non-significant. In contrast, for those who reported finding it ‘difficult’ or ‘very difficult’ on their present income (n = 3,843), only four pathways observed in the main model were statistically significant: these were the pathways linking greenspace to general health through more greenspace visits and both physical activity and subjective well-being, and the pathways linking coastal proximity to health through more coastal bluespace visits and both physical activity and subjective well-being.

When examining only male respondents (n = 7,746), only the six serial mediation pathways linking greenspace or coastal proximity to general health through more recreational visits and, separately, physical activity, social, contact, and subjective well-being were observed. When examining only female respondents (n = 8,171), the single mediation pathway linking coastal proximity to general health through subjective well-being was observed, and four serial mediation pathways linking greenspace or coastal proximity to general health through more recreational visits and, separately, physical activity and subjective well-being were observed.

When examining only respondents aged 18–39 (n = 5,788), the four single mediation pathways observed in the main model were observed again. Five out of eight serial mediation pathways were also observed: the pathways linking greenspace to general health through physical activity, social contact, and subjective well-being, and the pathways linking coastal proximity to health through social contact and subjective well-being. When examining only respondents aged 50 or older (n = 7,154), no single mediation pathways found in the main model were observed. Five out of eight serial mediation pathways found in the main model were observed again: pathways linking greenspace to general health through more recreational visits and more physical activity and higher subjective well-being, the pathway linking inland bluespace to general health through more inland bluespace visits and more physical activity, and the pathways linking coastal proximity to general health through more coastal bluespace visits and more physical activity and higher subjective well-being.

These same five serial mediation pathways were the only significant ones when examining only respondents living in urban areas (n = 11,038). In addition, the only single mediation pathway observed in the main model which was significant was the pathway linking coastal proximity to general health through higher subjective well-being. When examining only respondents living in rural areas, four out of eight serial mediation pathways observed in the main model were significant: pathways linking greenspace or coastal proximity to health through more recreational visits and, separately, more physical activity and higher subjective well-being. For this group, we also observed a significant serial mediation pathway linking inland bluespace to general health through more inland bluespace visits and higher subjective well-being which was not observed in the main model.

In summary, most serial mediation pathways remained significant in the four former subsidiary analyses employing alternative model specifications, but single mediation pathways varied across these models. Notable differences in models concerning those not coping' on their present income, females, and older adults included the lack of serial mediation pathways concerning social contact compared with their more affluent, male, and younger counterparts. A notable difference between younger and older respondents included two additional pathways linking neighbourhood nature to health through more visits and more physical activity for the older age group only. A notable difference between urban and rural participants was the serial mediation pathway not observed in the main model linking inland bluespace to general health through more inland bluespace visits and higher subjective well-being for rural respondents. Across all 12 subsidiary analyses, only three pathways were consistently observed from the main model: the pathways linking greenspace to general health through more greenspace visits and, separately, more physical activity and higher subjective well-being, and the pathway linking coastal proximity to health through more coastal bluespace visits and higher subjective well-being.

4. Discussion

The aims of this study were to investigate commonly theorised pathways between neighbourhood nature and general health in an international sample and compare how these differed by environment type. In so doing, we addressed several limitations of previous research such as the focus on single countries, single environment types and exposures, the tendency to overlook recreational contact with natural environments, and separate mediation modelling. Essentially, we were testing Hartig et al.'s (2014) theoretical framework which implied partial serial mediation from neighbourhood nature exposure to health, first through contact with nature directly (including recreational visits), and then through air quality, physical activity, social contact, and stress (here expressed as 'subjective well-being').

Supporting the framework, eight of nine possible serial mediation pathways were statistically significant, and largely robust to four alternative model specifications, with constituent stepwise paths typically in the hypothesised direction. Taken together, these findings provide good empirical support for Hartig et al.'s (2014) theoretical framework. Our eight additional stratified models were subject to reduced power with significant pathways differing across sociodemographic strata, but their results still provide further support for the robustness of serial mediation pathways through recreational visits to green and coastal environments in particular and through physical activity and subjective well-being as relatively consistent mechanisms.

4.1. Interpretation of results

It is perhaps unsurprising that eight of nine potential serial mediation paths – where associations between neighbourhood nature and general health were sequentially mediated by nature visit frequency and either physical activity, social contact, or subjective well-being – emerged as statistically significant in our results, as well as in multiple subsidiary analyses given previous research demonstrating the importance of recreational visits to green and blue spaces for greater physical activity attainment (Elliott et al. 2015; Flowers et al. 2016), social contact (Ashbullby et al. 2013; de Bell et al. 2017; Kaźmierczak 2013), and greater subjective well-being (van den Berg et al., 2016; White et al. 2017, 2019) independent of residential location. Earlier studies that explored some of the pathways but did not take visits into account (e.g. Dadvand et al., 2016; James et al., 2016; Dzhambov et al., 2018) concluded, for example, that policies to increase vegetation would support physical activity, social contact, and well-being. However, the present findings suggest that mere neighbourhood exposure may not be enough to facilitate these benefits; they may only result from recreational visits to natural environments (though we note we only look at recreational visits here and not other types of contact with nature).

The present findings therefore support the conclusions of previous reviews of interventions suggesting that efforts to promote the use of greenspace must accompany any greening intervention to have successful implications for certain facets of health like physical activity, social contact, or mental well-being (Hunter et al. 2019). They may include supporting and promoting social programmes of events (van den Bogerd et al. 2021) or carefully designed promotional materials (Elliott et al. 2020a). Moreover, given that people often visit recreational destinations that are further than 1 km from their home (Hillsdon et al. 2015), it is not clear from these or previous findings, whether neighbourhood natural environments are the same ones being most often used by residents for recreational purposes (Pyky et al. 2019); although the much stronger association between coastal proximity and coastal visits than the equivalent associations for green spaces and inland waters, suggests that local visits may be especially high among coastal communities. More detailed exploration of this issues is warranted in future research.

The only potential serial pathway involving recreational visits that was not statistically significant (albeit positive) was the association between neighbourhood inland bluespace and general health via recreational visits to inland blue spaces and subjective well-being. Previous research in Pennsylvania, USA has revealed that frequency of visits to freshwater bluespace is related to perceived stress and psychological restoration, but not mental health nor life satisfaction (Poulsen et al. 2022). These latter constructs are perhaps more indicative of what the WHO-5 well-being index measures, and therefore our findings are partially consistent with this work. Other research from Scotland, for instance, has revealed associations between frequency of visits to certain types of inland bluespace and the WHO-5 well-being index (McDougall et al. 2022); and in our own subsidiary analysis, this pathway was observed but only for respondents living in rural areas. Therefore, the relationship between inland waters and well-being may be country- and location-specific, depending on the amount and quality of its inland lakes and rivers. If confirmed in future studies, it suggests that there could be more nuanced cultural and cross-country variation in such a pathway, something that has been posited in qualitative research previously (Pitt 2018). More generally, we recognise that the availability of nature for recreation may vary according to biophysical conditions, cultural acceptability, and historical landscape planning practices (Kabisch et al. 2016) and our results only speak to absolute differences in availability across the international sample, not differences within countries relative to the resources which are prevalent nationally. Further research with much larger within-country samples would be needed to explore these possibilities robustly.

Regarding single mediation pathways, results concerning air quality were counterintuitive and we are sceptical of these for several reasons. Firstly, the unadjusted correlation between NO_2 and general health was non-significant (Fig. 2). That this association becomes significant once other mediators (which largely act as hypothesised) are accounted for could indicate either residual confounding, or that other confounds (e.g. aspects of the residential environment) should have been accounted for. Furthermore, the significant mediation estimates indicate that NO_2 partially offsets the positive associations between neighbourhood nature variables and health. This 'suppressor'-like effect could indicate that NO_2 is more likely a moderator of these nature – health linkages, as opposed to a mediator (i.e. rather than these forms of nature removing or dispersing pollutants, it may be that more space for nature in the neighbourhood equates to less space for traffic or other pollution-generating activity). Given limited evidence of NO_2 removal by greenspace at least (Nemitz et al. 2020), this is plausible. Lastly, given that these effects do not hold for several subsidiary analyses (Table A.1) it is difficult to make firm conclusions.

In addition to the single mediation pathways involving air quality, the only other significant single mediation pathway (i.e. not involving recreational visits) was the pathway where subjective well-being mediated the association between the presence of coastal bluespace within 1 km of the residence and general health. Previous research has revealed that a view of coastal bluespace from the home is associated with less psychological distress in urban dwellers in New Zealand (Nutsford et al. 2016) and with lower depression scores amongst older adults in Ireland (Dempsey et al. 2018). This may explain why this pathway was observed independently of recreational interactions with coastal bluespace. However, we are conscious that in our subsidiary analysis using 300 m buffer as opposed to 1 km buffers, this mediation pathway was not observed (while all serial mediation pathways remained) suggesting that this result may be sensitive to model specifications.

The four subsidiary analyses which used different model specifications are testament to the robustness of the serial mediation pathways found overall – only one such pathway was rendered non-significant in one of these additional models. The eight further subsidiary analyses which stratified by various sociodemographic factors both support and diverge from previous research. It was notable that serial mediation pathways concerning social contact were non-significant for those 'not coping' on their present income, females, and older adults; groups who are typically less likely to access nature for recreation anyway (Boyd et al. 2018). While this could be due to reduced power or explained by variations in the type of social contact typically experienced (Aartsen et al. 2017), it presents a challenge to the idea that nature can be used to mitigate income-, sex-, or age-related health inequalities (Mitchell et al. 2015; Sillman et al. 2022), an idea supported by recent research revealing that residential coastal proximity supports better health but does not reduce inequalities (Geiger et al. 2023). The stratification by age though supports the idea of nature as an aid to physically active ageing – while greenspace was linked to general health sequentially through more visits and more physical activity for both age groups, inland and coastal bluespace was similarly linked to general health through this pathway for older adults only. This may reflect the propensity of older people to use such environments for walking (e.g. coastal bluespace; Elliott et al. 2018) and extends previous research demonstrating associations between nature and health-enhancing physical activity in older populations (e.g. Astell-Burt et al. 2014) by demonstrating the importance of recreational visits to these spaces. While it is difficult to make firm conclusions about differences by urban/rural residence (especially given the reduced sample size and poorer model fit for rural areas), these differences deserve further research given, for example, the much larger effect size for the pathway linking inland bluespace to general health through more visits and better subjective well-being in rural respondents – the only serial mediation pathway not observed in the main model. Studies taking such a 'whole country' approach or studying rural areas specifically are relatively scarce compared to those focused on urban areas (Fian et al. 2023).

4.2. Strengths and limitations

The main strength of the study is its recognition of, and attempt to model, the complexity of the relationships between nature contact and health. Thousands of studies have now emerged showing associations between one type of exposure and a single or multiple health outcomes, but these tend to underplay the fact that we encounter many different types of nature in our everyday lives and that our interactions with it vary from relatively passive home-bound encounters to more active encounters during recreational visits. A few studies have started to look at multiple mediating pathways to explain such relationships, but these have tended to explore the pathways in isolation rather than simultaneously which fails to account for the ways in which they may interact (e.g. going for a walk in nature with friends involves multiple interacting mechanisms).

By including three different types of nature, both home and recreational exposure to each type, and four potential pathways, our study makes a novel contribution by simultaneously testing all the main single and serial mediation pathways proposed in Hartig et al.'s (2014) influential conceptual model. Broadly speaking our data largely support the model, the generalisability of which is enhanced by our use of data spanning 18 different countries.

We also acknowledge several limitations. Our data are cross-sectional and therefore despite evidence of indirect effects, we cannot be sure of the direction of those effects. For example, while an association may exist between greenspace and general health that is serially mediated by frequency of recreational visits to greenspace and physical activity, it is not necessarily true that those visits are supporting physical activity attainment. It could be that more physically active people choose to visit greenspace more often and those visits in turn support health in other ways. Mediation testing with cross-sectional data is certainly not uncommon in this field (Dzhambov et al. 2020), and our modelling is consistent with proposed theoretical frameworks (Hartig et al. 2014). However, we realise that cross-sectional designs can yield evidence of an indirect effect when none may be present with a comparable longitudinal study design (Mitchell and Maxwell 2013). Longitudinal designs themselves may be able to better address problems of reverse causality.

Some mediators may precede others in a putative causal pathway. For example, a previous study identified that neighbourhood green and blue space promoted mental health through higher perceived restorativeness, and in turn, greater physical activity among a sample of city-dwelling students (Dzhambov et al. 2018). While we controlled for residual covariance of mediators, we did not model such possibilities in the present study. We also recognise that we were unable to test multiple other mechanisms which may better reflect the direct benefits of neighbourhood exposure to nature, independent of recreational visits. These include many regulating ecosystem services such as heat reduction (Murage et al. 2020), noise pollution (Van Renterghem 2019), regulation of the immune system through exposure to biodiversity (Rook 2013), sleep quantity and quality (Shin et al. 2020), or appetitive behaviours (Martin et al. 2020), which were not considered here. In most cases, these alternatives were not feasible to study given the nature of available data (e.g. noise maps are only available for large conurbations; Eriksson et al. 2013). It is promising therefore, to see recent studies looking at such alternatives with bespoke data collection (Allard-Poesi et al. 2022).

We appreciate that other operationalisations of the underlying theoretical framework are possible. We used frequency of social contacts to conceptualise the 'social' pathway in our chosen framework (Hartig et al. 2014), but other studies have evidenced links between neighbourhood nature and a sense of community belonging (Rugel et al. 2019) or social cohesion (Weinstein et al. 2015); both alternative candidates for conceptualising this pathway. In terms of measurement, we realise that, for example, single-item measures of physical activity, while not without precedent (Milton et al. 2011), do not necessarily capture physical activity attainment as comprehensively as multi-item measures (Craig et al. 2003). Similarly, the WHO-5 well-being index, here used to represent the inverse of Hartig et al's (2014) 'stress' pathway, considers mostly positive aspects of recent subjective well-being.

The 30 m resolution of our neighbourhood nature data may mean that nature in urban areas (e.g. pocket parks), which may be important for particular mechanisms, is underestimated. Likewise, our study was not able to account for the quality of neighbourhood and visit-related nature which may more strongly predict the health benefits associated with natural environments than quantity (Yang et al. 2021). We also recognise that there is the potential for crossover between what is considered greenspace and bluespace (both with regards to our neighbourhood nature variables and recreational visits frequency variables). However, to not distinguish these environment types in analysis would make unjustified assumptions that all types of nature offer similar affordances and health benefits which much previous research has shown not to be the case.

4.3. Conclusion

By simultaneously studying multiple serial pathways linking neighbourhood nature to general health, this study has uncovered which theorised pathways are supported by evidence and how they vary with environment type, and ultimately underlined the importance of neighbourhood nature in supporting recreational visits to potentially facilitate a range of health-related and overall health benefits. Such findings may improve the effectiveness of public health interventions that involve the creation, improvement, or promotion of green and blue spaces by encouraging focus on evidence-based mechanisms. Furthermore, given the international nature of the present research, we can begin to understand which mechanisms could be broadly transferable across diverse national contexts.

CRediT authorship contribution statement

Lewis R. Elliott: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Tytti Pasanen:** Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Mathew P. White:** Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing. **Benedict W. Wheeler:** Funding acquisition, Investigation, Writing – original draft, Writing – review & editing. **James Grellier:** Investigation, Project administration, Writing – original draft, Writing – review & editing. **Marta Cirach:** Methodology, Resources. **Gregory N. Bratman:** Funding acquisition, Writing – original draft, Writing – review & editing. **Matilda van den Bosch:** Funding acquisition, Writing – original draft, Writing – review & editing. **Anne Roiko:** Funding acquisition, Writing – original draft, Writing – review & editing. **Ann Ojala:** Funding acquisition, Writing – original draft, Writing – review & editing. **Mark Nieuwenhuijsen:** Funding acquisition, Writing – original draft, Writing – review & editing. **Lora E. Fleming:** Funding acquisition, Project administration, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: [Lewis R Elliott reports financial support was provided by EU Framework Programme for Research and Innovation Societal Challenges. Mathew P White reports financial support was provided by EU Framework Programme for Research and Innovation Societal Challenges. Benedict W Wheeler reports financial support was provided by EU Framework Programme for Research and Innovation Societal Challenges. James Grellier reports financial support was provided by EU Framework Programme for Research and Innovation Societal Challenges. Marta Cirach reports financial support was provided by EU Framework Programme for Research and Innovation Societal Challenges. Matilda van den Bosch reports financial support was provided by EU Framework Programme for Research and Innovation Societal Challenges. Mark Nieuwenhuijsen reports financial support was provided by EU Framework Programme for Research and Innovation Societal Challenges. Lora E Fleming reports financial support was provided by EU Framework Programme for Research and Innovation Societal Challenges. Co-author Mark Niewenhuijsen is co-Editor-in-Chief of Environment International.].

Data availability

A subset of the data is available at: (Elliott, LR, White, MP. 2022. BlueHealth International Survey Dataset, 2017-2018. [data collection]. UK Data Service. SN: 8874, doi: 10.5255/UKDA-SN-8874-2).

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Appendix A

See Table A1.

Table A1
Indirect effect results pertaining to subsidiary analyses (mediation estimates with standard errors in parentheses and *p*-values in square brackets). Statistically significant mediation effects are highlighted in bold.

Indirect effect	Using a diagonally-weighted least-squares estimator (n = 14,761) CFI = 0.90 RMSEA = 0.03 SRMR = 0.05	Using 300 m neighbourhood nature metrics as opposed to 1 km metrics (n = 15,917) CFI = 0.93 RMSEA = 0.03 SRMR = 0.03	Using NDVI (1 km) instead of GlobeLand30 greenspace (n = 15,917) CFI = 0.93 RMSEA = 0.03 SRMR = 0.03	Using $PM_{2.5}$ instead of NO_2 (n = 15,917) CFI = 0.91 RMSEA = 0.03 SRMR = 0.03
Single mediations				
GS → AQ → Health	**−0.009349 (0.004490) [0.037329]**	−0.002899 (0.001552) [0.061822]	−0.002145 (0.002284) [0.347793]	−0.000549 (0.000688) [0.425094]
GS → PA → Health	0.000348 (0.000709) [0.623915]	0.000095 (0.000359) [0.790899]	−0.000927 (0.000560) [0.097691]	−0.000247 (0.000430) [0.566436]
GS → SC → Health	0.000280 (0.000181) [0.122298]	0.000038 (0.000081) [0.637860]	−0.000143 (0.000135) [0.289608]	0.000064 (0.000099) [0.513946]
GS → SWB → Health	0.001258 (0.002682) [0.639076]	−0.000325 (0.001386) [0.814458]	−0.002334 (0.002114) [0.269608]	0.000227 (0.001657) [0.890953]
IBS → AQ → Health	**−0.003642 (0.001799) [0.042912]**	−0.002376 (0.001312) [0.070004]	−0.000759 (0.000812) [0.349924]	0.000346 (0.000450) [0.442084]
IBS → PA → Health	−0.000465 (0.002151) [0.828884]	−0.001504 (0.001892) [0.426791]	−0.000705 (0.001363) [0.605145]	−0.000587 (0.001366) [0.667530]
IBS → SC → Health	−0.000270 (0.000473) [0.568444]	0.000287 (0.000445) [0.518972]	−0.000181 (0.000314) [0.565142]	−0.000180 (0.000313) [0.566138]
IBS → SWB → Health	0.011497 (0.008291) [0.165536]	**0.015513 (0.006926) [0.025097]**	0.004297 (0.005141) [0.403273]	0.004708 (0.005158) [0.361321]
CBS → AQ → Health	**−0.019522 (0.009408) [0.037988]**	−0.009292 (0.004992) [0.062694]	−0.004146 (0.004424) [0.348689]	−0.002303 (0.002886) [0.424820]
CBS → PA → Health	0.003028 (0.003349) [0.365908]	0.003291 (0.002993) [0.271577]	−0.000533 (0.002096) [0.799207]	−0.000327 (0.002096) [0.876049]
CBS → SC → Health	−0.000708 (0.000794) [0.372416]	0.000109 (0.000646) [0.866288]	−0.000895 (0.000535) [0.094403]	−0.000684 (0.000496) [0.167870]
CBS → SWB → Health	**0.028503 (0.013099) [0.029550]**	0.022405 (0.012135) [0.064852]	**0.017470 (0.008147) [0.031992]**	**0.018263 (0.008137) [0.024800]**
Serial mediations				
GS → GSV → PA → Health	**0.001374 (0.000230) [0.000000]**	**0.000393 (0.000075) [0.000000]**	**0.000411 (0.000105) [0.000090]**	**0.000488 (0.000089) [0.000000]**
GS → GSV → SC → Health	**0.000125 (0.000051) [0.014168]**	**0.000044 (0.000018) [0.011834]**	**0.000046 (0.000020) [0.020669]**	**0.000055 (0.000022) [0.010745]**
GS → GSV → SWB → Health	**0.004228 (0.000613) [0.000000]**	**0.001120 (0.000204) [0.000000]**	**0.001173 (0.000293) [0.000063]**	**0.001396 (0.000239) [0.000000]**
IBS → IBSV → PA → Health	0.000357 (0.000285) [0.211003]	**0.000345 (0.000150) [0.021061]**	**0.000315 (0.000138) [0.022195]**	**0.000305 (0.000135) [0.023469]**
IBS → IBSV → SC → Health	**0.000157 (0.000077) [0.041375]**	**0.000109 (0.000053) [0.039222]**	**0.000099 (0.000048) [0.038782]**	**0.000098 (0.000047) [0.037728]**
IBS → IBSV → SWB → Health	−0.000363 (0.001064) [0.732718]	0.000604 (0.000485) [0.213598]	0.000621 (0.000453) [0.170018]	0.000623 (0.000443) [0.158864]
CBS → CBSV → PA → Health	**0.003264 (0.000915) [0.000360]**	**0.001720 (0.000420) [0.000042]**	**0.002391 (0.000552) [0.000015]**	**0.002445 (0.000557) [0.000011]**
CBS → CBSV → SC → Health	**0.001235 (0.000488) [0.011417]**	**0.000441 (0.000183) [0.016100]**	**0.000653 (0.000260) [0.012197]**	**0.000631 (0.000254) [0.013058]**
CBS → CBSV → SWB → Health	**0.025844 (0.003497) [0.000000]**	**0.010575 (0.001597) [0.000000]**	**0.013938 (0.001859) [0.000000]**	**0.014285 (0.001866) [0.000000]**

Abbreviations:
Health = 'General health' (i.e. self-reported general health).
GS = 'Greenspace' (i.e. quintile increase of greenspace in the 1 km surrounding the participant's residence).
IBS = 'Inland bluespace' (i.e. whether the respondent had freshwater within 1 km of their residence or not).
CBS = 'Coastal blue space' (i.e. whether the respondent had coastal bluespace within 1 km of their residence or not).
GSV = 'Greenspace visits' (i.e. the self-reported number of recreational visits made to green spaces within the last 2 weeks).
IBSV = 'Inland bluespace visits' (i.e. the self-reported number of recreational visits made to inland blue spaces within the last 2 weeks).
CBSV = 'Coastal bluespace visits' (i.e. the self-reported number of recreational visits made to coastal blue spaces within the last 2 weeks).
AQ = 'Air quality' (i.e. modelled annual mean concentration of NO_2 [parts per billion; ppb] at the respondent's residence). N.B $PM_{2.5}$ concentrations in $\mu g/m^3$ in the $PM_{2.5}$ model.
PA = 'Physical activity' (i.e. self-reported number of days in the last 2 weeks on which the participant did at least 30 min of moderate-vigorous intensity physical activity through recreation and transport).
SC = 'Social contact' (i.e. self-reported frequency of days in the past 2 weeks with which the participant meets friends, relatives, or work colleagues socially).
SWB = 'Subjective well-being' (i.e. self-reported subjective well-being in the past 2 weeks as measured by the WHO-5 well-being index).

(*continued on next page*)

Table A1 (*continued*)

Indirect effect	Restricted only to those reporting 'not coping' with their present income (n=3,843) CFI=0.87 RMSEA=0.04 SRMR=0.05	Restricted only to those reporting 'coping' with their present income (n=11,860) CFI=0.92 RMSEA=0.03 SRMR=0.03	Restricted only to males (n=7,746) CFI=0.92 RMSEA=0.04 SRMR=0.04	Restricted only to females (n=8,171) CFI=0.92 RMSEA=0.03 SRMR=0.04
Single mediations				
GS → AQ → Health	−0.005589 (0.005955) [0.347961]	**−0.005930 (0.002922) [0.042415]**	−0.005446 (0.003529) [0.122812]	−0.004830 (0.003884) [0.213637]
GS → PA → Health	0.000118 (0.000787) [0.880399]	−0.000445 (0.000488) [0.361319]	−0.000835 (0.000741) [0.259675]	−0.000082 (0.000462) [0.859883]
GS → SC → Health	−0.000091 (0.000182) [0.618228]	0.000237 (0.000147) [0.107545]	0.000035 (0.000159) [0.824789]	0.000155 (0.000143) [0.279590]
GS → SWB → Health	−0.002096 (0.003753) [0.576392]	0.000951 (0.001823) [0.601721]	−0.001150 (0.002404) [0.632466]	0.000558 (0.002237) [0.802913]
IBS → AQ → Health	−0.002735 (0.002988) [0.359909]	**−0.002476 (0.001242) [0.046200]**	−0.002525 (0.001665) [0.129327]	−0.001881 (0.001526) [0.217749]
IBS → PA → Health	0.002887 (0.002565) [0.260437]	−0.002172 (0.001590) [0.171750]	0.000071 (0.002398) [0.976382]	−0.000932 (0.001492) [0.532295]
IBS → SC → Health	0.000102 (0.000294) [0.727673]	−0.000383 (0.000409) [0.348997]	−0.000447 (0.000533) [0.401680]	0.000107 (0.000369) [0.771989]
IBS → SWB → Health	0.018032 (0.011708) [0.123541]	−0.000644 (0.005730) [0.910525]	0.010849 (0.007545) [0.150438]	−0.000332 (0.007039) [0.962430]
CBS → AQ → Health	−0.011982 (0.012812) [0.349660]	**−0.012246 (0.006058) [0.043224]**	−0.011381 (0.007403) [0.124237]	−0.010183 (0.008201) [0.214358]
CBS → PA → Health	−0.002099 (0.003761) [0.576742]	0.000613 (0.002462) [0.803213]	0.000130 (0.003511) [0.970422]	−0.000701 (0.002408) [0.770891]
CBS → SC → Health	0.000246 (0.000553) [0.656720]	−0.001065 (0.000675) [0.114791]	−0.001238 (0.000866) [0.153004]	−0.000204 (0.000555) [0.713257]
CBS → SWB → Health	0.030055 (0.018238) [0.099364]	0.012899 (0.009096) [0.156147]	0.012290 (0.011556) [0.287545]	**0.022853 (0.011529) [0.047458]**
Serial mediations				
GS → GSV → PA → Health	**0.000503 (0.000186) [0.006689]**	**0.000451 (0.000098) [0.000004]**	**0.000648 (0.000150) [0.000016]**	**0.000341 (0.000101) [0.000752]**
GS → GSV → SC → Health	0.000019 (0.000034) [0.582720]	**0.000059 (0.000025) [0.017060]**	**0.000064 (0.000031) [0.039835]**	0.000042 (0.000027) [0.119621]
GS → GSV → SWB → Health	**0.001764 (0.000586) [0.002600]**	**0.001244 (0.000255) [0.000001]**	**0.001506 (0.000341) [0.000010]**	**0.001240 (0.000332) [0.000188]**
IBS → IBSV → PA → Health	0.000146 (0.000194) [0.451066]	**0.000365 (0.000165) [0.026789]**	0.000387 (0.000266) [0.146191]	0.000227 (0.000133) [0.087811]
IBS → IBSV → SC → Health	0.000051 (0.000094) [0.590980]	0.000072 (0.000050) [0.147260]	0.000176 (0.000099) [0.075181]	0.000045 (0.000040) [0.268143]
IBS → IBSV → SWB → Health	0.001474 (0.000838) [0.078639]	0.000397 (0.000524) [0.448631]	0.000569 (0.000731) [0.436412]	0.000643 (0.000541) [0.235081]
CBS → CBSV → PA → Health	**0.002281 (0.000995) [0.021879]**	**0.002547 (0.000647) [0.000083]**	**0.002709 (0.000961) [0.004805]**	**0.002148 (0.000636) [0.000729]**
CBS → CBSV → SC → Health	0.000177 (0.000327) [0.586889]	**0.000824 (0.000339) [0.015188]**	**0.000746 (0.000377) [0.047610]**	0.000535 (0.000345) [0.120722]
CBS → CBSV → SWB → Health	**0.008827 (0.003616) [0.014645]**	**0.016035 (0.002193) [0.000000]**	**0.013304 (0.002727) [0.000001]**	**0.014531 (0.002582) [0.000000]**

Abbreviations:

Health = 'General health' (i.e. self-reported general health).
GS = 'Greenspace' (i.e. quintile increase of greenspace in the 1km surrounding the participant's residence).
IBS = 'Inland bluespace' (i.e. whether the respondent had freshwater within 1km of their residence or not).
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IBSV = 'Inland bluespace visits' (i.e. the self-reported number of recreational visits made to inland blue spaces within the last 2 weeks).
CBSV = 'Coastal bluespace visits' (i.e. the self-reported number of recreational visits made to coastal blue spaces within the last 2 weeks).
AQ = 'Air quality' (i.e. modelled annual mean concentration of NO_2 [parts per billion; ppb] at the respondent's residence). N.B $PM_{2.5}$ concentrations in μg/m^3 in the $PM_{2.5}$ model.
PA = 'Physical activity' (i.e. self-reported number of days in the last 2 weeks on which the participant did at least 30 min of moderate-vigorous intensity physical activity through recreation and transport).
SC = 'Social contact' (i.e. self-reported frequency of days in the past 2 weeks with which the participant meets friends, relatives, or work colleagues socially).
SWB = 'Subjective well-being' (i.e. self-reported subjective well-being in the past 2 weeks as measured by the WHO-5 well-being index).

Indirect effect	Restricted only to those aged 18 to 39[a] years old (n=5,788) CFI=0.94 RMSEA=0.04 SRMR=0.05	Restricted only to those aged 50[a] years old and over (n=7,154) CFI=0.93 RMSEA=0.04 SRMR=0.05	Restricted only to those living in urban areas (n=11,038) CFI=0.92 RMSEA=0.03 SRMR=0.03	Restricted only to those living in rural areas (n=4,878) CFI=0.85 RMSEA=0.04 SRMR=0.05
Single mediations				
GS → AQ → Health	**−0.011846 (0.004187) [0.004667]**	−0.000112 (0.004245) [0.978873]	−0.006181 (0.003368) [0.066500]	−0.003427 (0.003521) [0.330502]
GS → PA → Health	0.000581 (0.000627) [0.353951]	−0.001109 (0.000781) [0.155661]	−0.000640 (0.000532) [0.229245]	0.000977 (0.000819) [0.232620]
GS → SC → Health	−0.000215 (0.000322) [0.504589]	−0.000149 (0.000151) [0.326321]	−0.000009 (0.000105) [0.928282]	0.000549 (0.000363) [0.130122]

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Table A1 (*continued*)

Indirect effect	Restricted only to those aged 18 to 39[a] years old (n=5,788) CFI=0.94 RMSEA=0.04 SRMR=0.05	Restricted only to those aged 50[a] years old and over (n=7,154) CFI=0.93 RMSEA=0.04 SRMR=0.05	Restricted only to those living in urban areas (n=11,038) CFI=0.92 RMSEA=0.03 SRMR=0.03	Restricted only to those living in rural areas (n=4,878) CFI=0.85 RMSEA=0.04 SRMR=0.05
GS → SWB → Health	−0.002252 (0.002734) [0.410154]	−0.000118 (0.002641) [0.964238]	0.001329 (0.001939) [0.493100]	−0.003680 (0.003340) [0.270609]
IBS → AQ → Health	**−0.004084 (0.001614) [0.011376]**	−0.000049 (0.001864) [0.978870]	−0.002004 (0.001121) [0.073697]	−0.001880 (0.002317) [0.417177]
IBS → PA → Health	−0.001334 (0.002057) [0.516527]	−0.001492 (0.002459) [0.544108]	0.000053 (0.001697) [0.975095]	−0.001039 (0.002359) [0.659595]
IBS → SC → Health	−0.000324 (0.000999) [0.745673]	−0.000176 (0.000295) [0.551139]	0.000046 (0.000316) [0.884450]	−0.000917 (0.000870) [0.291963]
IBS → SWB → Health	0.001612 (0.008700) [0.852976]	0.007780 (0.008296) [0.348364]	0.009707 (0.006039) [0.107995]	−0.010065 (0.010103) [0.319129]
CBS → AQ → Health	**−0.025288 (0.009028) [0.005095]**	−0.000243 (0.009177) [0.978873]	−0.011636 (0.006356) [0.067172]	−0.011733 (0.011702) [0.316048]
CBS → PA → Health	0.003263 (0.003046) [0.284061]	−0.003967 (0.003899) [0.308931]	−0.000187 (0.002472) [0.939748]	−0.000016 (0.004381) [0.997032]
CBS → SC → Health	−0.000951 (0.001382) [0.491094]	0.000498 (0.000570) [0.382014]	−0.000749 (0.000559) [0.180531]	−0.000105 (0.001299) [0.935269]
CBS → SWB → Health	**0.032443 (0.012899) [0.011899]**	0.007269 (0.013271) [0.583881]	**0.020489 (0.008973) [0.022407]**	0.010656 (0.018468) [0.563931]
Serial mediations				
GS → GSV → PA → Health	**0.000422 (0.000114) [0.000213]**	**0.000638 (0.000185) [0.000551]**	**0.000456 (0.000106) [0.000018]**	**0.000540 (0.000166) [0.001133]**
GS → GSV → SC → Health	**0.000135 (0.000054) [0.012956]**	−0.000029 (0.000026) [0.256028]	0.000048 (0.000025) [0.057587]	0.000073 (0.000042) [0.078882]
GS → GSV → SWB → Health	**0.002025 (0.000465) [0.000014]**	**0.001284 (0.000364) [0.000428]**	**0.001373 (0.000303) [0.000006]**	**0.001437 (0.000416) [0.000549]**
IBS → IBSV → PA → Health	0.000183 (0.000194) [0.344658]	**0.000634 (0.000271) [0.019487]**	**0.000578 (0.000203) [0.004381]**	0.000017 (0.000150) [0.908295]
IBS → IBSV → SC → Health	0.000154 (0.000115) [0.178427]	−0.000043 (0.000046) [0.348960]	0.000051 (0.000046) [0.262228]	0.000161 (0.000098) [0.100809]
IBS → IBSV → SWB → Health	−0.000570 (0.000754) [0.449763]	0.001274 (0.000789) [0.106568]	0.000170 (0.000580) [0.769793]	**0.001306 (0.000649) [0.044239]**
CBS → CBSV → PA → Health	0.000479 (0.000623) [0.441541]	**0.004853 (0.001195) [0.000049]**	**0.002815 (0.000706) [0.000067]**	**0.002151 (0.000985) [0.028883]**
CBS → CBSV → SC → Health	**0.001210 (0.000509) [0.017476]**	−0.000424 (0.000367) [0.248189]	0.000640 (0.000334) [0.055508]	0.000726 (0.000468) [0.120705]
CBS → CBSV → SWB → Health	**0.006423 (0.002498) [0.010150]**	**0.026697 (0.003707) [0.000000]**	**0.014661 (0.002102) [0.000000]**	**0.013075 (0.004054) [0.001260]**

[a] For these models, work status was removed as a covariate on account of some categories having no variance within those age groups in several countries (e.g. 'retired' work status in those aged 18–39).

Abbreviations:
Health = 'General health' (i.e. self-reported general health).
GS = 'Greenspace' (i.e. quintile increase of greenspace in the 1km surrounding the participant's residence).
IBS = 'Inland bluespace' (i.e. whether the respondent had freshwater within 1km of their residence or not).
CBS = 'Coastal blue space' (i.e. whether the respondent had coastal bluespace within 1km of their residence or not).
GSV = 'Greenspace visits' (i.e. the self-reported number of recreational visits made to green spaces within the last 2 weeks).
IBSV = 'Inland bluespace visits' (i.e. the self-reported number of recreational visits made to inland blue spaces within the last 2 weeks).
CBSV = 'Coastal bluespace visits' (i.e. the self-reported number of recreational visits made to coastal blue spaces within the last 2 weeks).
AQ = 'Air quality' (i.e. modelled annual mean concentration of NO_2 [parts per billion; ppb] at the respondent's residence). N.B $PM_{2.5}$ concentrations in μg/m^3 in the $PM_{2.5}$ model.
PA = 'Physical activity' (i.e. self-reported number of days in the last 2 weeks on which the participant did at least 30 min of moderate-vigorous intensity physical activity through recreation and transport).
SC = 'Social contact' (i.e. self-reported frequency of days in the past 2 weeks with which the participant meets friends, relatives, or work colleagues socially).
SWB = 'Subjective well-being' (i.e. self-reported subjective well-being in the past 2 weeks as measured by the WHO-5 well-being index).

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2023.108077.

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