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Research Note: Residential distance and recreational visits to coastal and inland blue spaces in eighteen countries

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ABSTRACT

Varied categorisations of residential distance to bluespace in population health studies make comparisons difficult. Using survey data from eighteen countries, we modelled relationships between residential distance to blue spaces (coasts, lakes, and rivers), and self-reported recreational visits to these environments at least weekly, with penalised regression splines. We observed exponential declines in visit probability with increasing distance to all three environments and demonstrated the utility of derived categorisations. These categories may be broadly applicable in future research where the assumed underlying mechanism between residential distance to a blue space and a health outcome is direct recreational contact.

1. Introduction

Investigations of natural environments and population health commonly consider associations between human health outcomes and residential distance to green spaces (e.g. playing fields, parks, woodlands; Browning & Lee, 2017). Residential distance to natural environments may, in part, be considered a proxy for recreational visits which in turn could determine health impacts (van den Berg et al., 2017). Although distance is a linear variable, research examining distance to greenspace typically categorises distance into groups (e.g. < 300 m; > 1 km etc.). This could be done to circumvent analytical or statistical complexities (e.g. highly skewed distributions); to increase policy relevance or improve communication (e.g. compatibility with the World Health Organisation's 300 m urban green space indicator; Annerstedt van den Bosch et al., 2016); to address inherent non-linearity between an exposure and a health outcome (e.g. the capacity of green space to mitigate urban heat may be trivial beyond a certain distance; Shashua-Bar & Hoffman, 2000); or because the categories are purported to represent underlying human behaviour patterns which might also plausibly mediate the health outcome (e.g. typical walkable distances; Smith, Gidlow, Davey, & Foster, 2010). Informed by a mixture of these, cross-national research has identified distances of 100 m, 300 m, 500 m, and 1 km as appropriate for use in a wide range of studies linking exposure to greenspace (using residential distance as a proxy) with a multitude of health outcomes (Smith et al., 2017).

Residential distance to bluespaces (e.g. coasts, rivers, lakes) may also be an important correlate of a variety of health outcomes (Gascon, Zijlema, Vert, White, & Nieuwenhuijsen, 2017), and studies have

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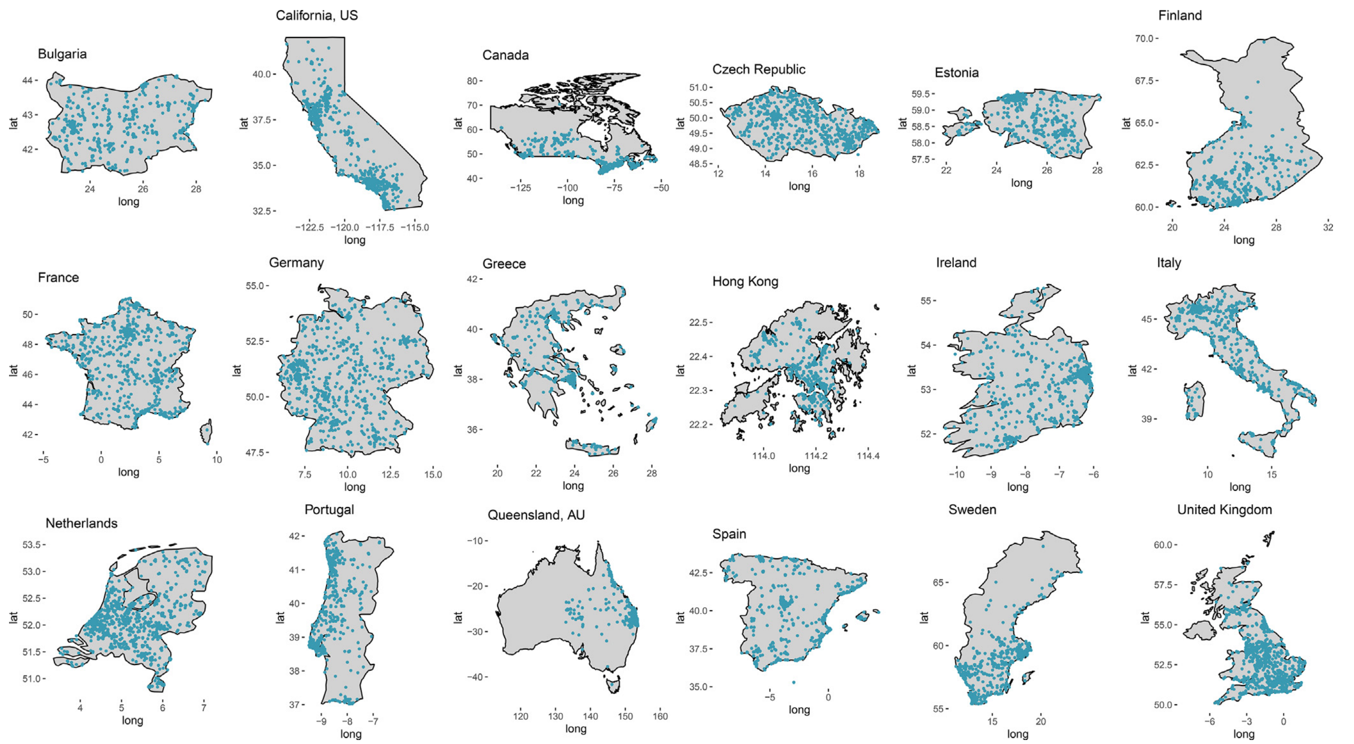

Fig. 1. Given residential locations (correct to three decimal degrees) of the 15,216 respondents included in analysis. The map of Spain includes respondents resident in the autonomous city of Melilla. Respondents resident in the Canary Islands, Azores, and Madeira are not displayed.

classified distance in a variety of ways. Regarding distance to the coast, UK studies have used categories of 0–1 km, > 1–5 km, > 5–20 km, > 20–50 km, and > 50 km (Wheeler, White, Stahl-Timmins, & Depledge, 2012) or collapsed versions of these (Pasanen, White, Wheeler, Garrett, & Elliott, 2019; White, Alcock, Wheeler, & Depledge, 2013; White, Wheeler, Herbert, Alcock, & Depledge, 2014), to represent distinct classes of physical coastal access. Research in New Zealand has used distance bands of ≤300 m, 300 m–3 km, 3–6 km, and 6–15 km (Nutsford, Pearson, Kingham, & Reitsma, 2016), and, in Australia, greater or less than 800 m (Edwards, Giles-Corti, Larson, & Beesley, 2014). Research in Ireland has used quintiles within 10 km of the coast (Dempsey, Devine, Gillespie, Lyons, & Nolan, 2018). Regarding water bodies and inland waterways, research in the Netherlands and France has considered the availability of blue space in 1 km buffers around people's residences (de Vries et al., 2016; Perchoux, Kestens, Brondeel, & Chaix, 2015), and one study in Portugal used distances within and beyond 4 km (Burkart et al., 2015). In contrast to green spaces, research investigating blue spaces faces additional complexities in that as well as occupying surface area, they are often nominally narrow linear features (e.g. rivers) which are frequently not featured on land cover maps developed from data with coarse spatial resolution. Further, given that much recreational 'access' to bluespace is to beaches, coastal paths, canal towpaths etc., the edges of bluespace are an important facet of access (Pitt, 2018; Vert et al., 2019), rather than the total surface area. Lastly, even in countries with higher availability of bluespace, people are still willing to travel considerable distances to access it (Laatikainen, Piiroinen, Lehtinen, & Kyttä, 2017). Thus distance metrics are often preferred to coverage metrics in research concerning blue spaces.

Empirically derived categorisations of distance can be useful in defining generic levels of accessibility. In the greenspace literature, "distance-decay" effects between residential distance and recreational use of green spaces have long been used as a basis for ascertaining distance categories which represent direct exposure in health geography research (Grahn & Stigsdotter, 2003). In this article we use similar distance-decay relationships across 18 countries to propose general distance categories to three prominent blue spaces – coasts, lakes, and rivers. Using international survey data collected as part of the BlueHealth project (Grellier et al., 2017), the aim of this article is to provide researchers with meaningful categories of residential distance to these three types of bluespace which are useful in defining accessibility where the putative mechanism linking distance with the health outcome is direct recreational use. Given the heterogeneity in previous distance categories used in blue space research, the use of an 18-country dataset might help define clearer thresholds that could be used across multiple countries in future which would enable greater comparability across studies.

2. Method

Methods were approved by the University of Exeter Medical School Research Ethics Committee (Ref: Aug16/B/099).

2.1. Sample

The BlueHealth International Survey concerns recreational use of blue spaces and its relationship with human health. It was administered online by YouGov from June 2017 to April 2018 to panellists in 18 countries. In four seasonal stages of data collection, it used stratified sampling to collect representative samples of 18,838 respondents from 14 European countries (Bulgaria, the Czech Republic, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, and the United Kingdom) and four other territories (Hong Kong, Canada, Australia [primarily Queensland], and the USA [state of California only]). Stratified sampling designs differed depending on country/territory and full methodological details concerning this are in an accompanying technical report (http://bit.ly/BIS-Technical-Report). Analyses are based on the subset of 15,216 participants (Fig. 1) that provided reliable home location information, had no missing data, and that did not exhibit response biases (see technical report for details).

2.2. Exposures

Participants recorded their home location via a Google Maps application programming interface integrated in the survey. Coordinates (decimal degrees) correct to three decimal places (approximately 75 m precision dependent on location) were returned and residential distances to the nearest coast, lake, and river, were assigned to these coordinates. Residential distance to the coast (n = 15,216) was operationalised as the Euclidean distance from the home location to the nearest coast as defined by the highest resolution version of the Global Self-consistent Hierarchical High-resolution Geography shoreline database (Wessel & Smith, 1996).

Due to a lack of globally-consistent high-resolution rivers and lakes data, the European Catchments and Rivers Network System (ECRINS) database (European Environment Agency, 2012) was used to assign Euclidean distances from the home location to the nearest lake (n = 12,219) and river (or stream, canal, waterway etc.; n = 12,255). ECRINS data are derived from CORINE Land Cover (CLC) data, the EU Water Framework Directive (WFD), and the EU Catchment Characterisation Model (CCM). Rivers are modelled within catchment areas and thus have no minimum width. Lakes have varying minimum mapping units depending on the original data source, spanning 25 m^2 (CCM) to 500 m^2 (CLC). As ECRINS data were only available for Europe, we only included survey data from European countries in the two regression models investigating distances to lakes and rivers (Section 2.4).

2.3. Outcomes

The outcome measure was the probability of respondents reporting visiting a coast, lake, or river, at least weekly within the last four weeks for recreation. Respondents were presented with the names and visual exemplars of 29 different natural environment types and asked to report how often in the last four weeks they had made a recreational visit to each using four categorical response options (not at all in the last four weeks, once or twice in the last four weeks, once a week, several times a week). Responses were dichotomised into the former and latter two response options to denote whether a participant had visited an environment at least weekly or not; a threshold associated with good self-reported health, high wellbeing, and a lower risk of depression in previous studies (Garrett et al., 2018; White et al., 2019). These environment types included 'urban' green spaces (e.g. local parks, playgrounds), 'rural' green spaces (e.g. farmland, mountains), 'urban' coastal blue spaces (e.g. piers, harbours), 'rural' coastal blue spaces (e.g. beaches, cliffs), 'urban' inland blue spaces (e.g. urban rivers, fountains), and 'rural' inland blue spaces (e.g. lakes, waterfalls). See the accompanying technical report for more details. We collapsed responses to: (a) eight coastal environments (pier, harbour, promenade, beach, rocky shore, cliff, lagoon, open sea) to denote 'coastal' visits, and (b) two riverside environments ('urban' river or canal [surrounded by buildings] and 'rural' river or canal [surrounded by vegetation]) to denote 'river' visits. 'Lake' visits were represented by a single 'lake' environment category.

2.4. Analysis

For descriptive statistical analysis, the range of data concerning residential distance from each blue space was explored, along with the distribution of data for each distance variable (Fig. 2). For inferential analysis, a distance-decay approach was employed for extracting distance categories for coasts, lakes, and rivers separately. We fitted three generalised additive mixed models (Wood, 2017) with the probability of visiting a bluespace (i.e. coast, river, lake) at least weekly as the outcome variable, the respondent's country of residence as a random intercept term, and the residential distance to the corresponding bluespace as both a fixed (overall) and random (country-variant) slope term. In all three cases, generalised likelihood ratio tests demonstrated that specification of random slopes yielded better model fit than fixed slopes (Supplementary Table 1). Distance was modelled with a thin plate regression spline basis (Wood, 2003). Models were weighted to ensure estimates were representative of the countries' populations with respect to sex, age, and region of residence. We combined results from these models (Fig. 3; Supplementary Fig. 1; Supplementary Table 2) with previous research and policy recommendations to identify distances at which the distance-decay relationship changed considerably, and subsequent binomial mixed-effects models of a similar form (Table 1) were run, replacing the smooth function of the exposure with a new categorical variable in order to demonstrate the appropriateness of the categories. Further fixed effects were not included as we did not want distance-decay effects to reflect sociodemographic characteristics which researchers may adjust for in future analyses. Analyses were performed in R v3.6.0 (R Core Team, 2019) using 'mgcv' (Wood, 2017) and 'lme4′ (Bates, Mächler, Bolker, & Walker, 2015) packages.

3. Results

Residential distance to coast ranged from 0 to 1,192 km, to lakes from 0 to 70 km, and to rivers from 0 to 20 km. Exposures exhibited high positive skew (Fig. 2). Outliers for distance to coast included respondents residing in inland Canadian territories, Australia, and the Czech Republic. Outliers for distance to lakes were due to respondents residing in the Greek Islands and the Puglia region of Italy. These are not analytically problematic as the probability of visiting the corresponding environments for recreation is consequently low.

The probability of visiting all three blue spaces decayed exponentially with increasing distance (Fig. 3; Supplementary Fig. 1) with plateaus at varying distances. For coasts, given this decline, and considering 1 km has been used as a threshold in a number of studies associating distance to coast with health outcomes previously (Pasanen et al., 2019; Wheeler et al., 2012; White et al., 2013, 2014), ≤1km was chosen as the most proximal distance category. The relationship appeared to plateau around 50 km – the distance at which the European Union considers a residence 'coastal' (Eurostat, , 2013) – so a > 50 km category was also chosen. Between 1 km and 50 km, categories of > 1 km to ≤5 km, > 5km to ≤25 km, and > 25 km to ≤ 50 km were chosen as they represent an exponential geometric sequence ($\alpha_n = 5^{n-1}$) which mirrors the relationship demonstrated by the spline. An initial, most proximal, category of ≤ 1 km was also selected for lakes and rivers based on the exponential declines demonstrated and because 1 km has been used in literature linking residential distance to inland waterways with health outcomes previously (de Vries et al., 2016; Perchoux et al., 2015). For lakes, the relationship plateaued after 5 km, so two further categories of > 1 km to ≤5 km, and > 5 km were selected, again representing the exponential decline and maintaining consistency with those categories selected for coasts. For rivers, the relationship plateaued after 2.5 km, so two further categories of > 1 km to ≤2.5 km, and > 2.5 km were selected. Of the analytical samples, 57% (n = 8703) lived within 50 km of the nearest coast, 39% (n = 4819) lived within 5 km of the nearest lake, and 86% (n = 10,502) lived within 2.5 km of the nearest river (counts per country are displayed in Supplementary Table 3).

The utility of these categories is evidenced in the subsequent binomial mixed-effects models (Table 1). The odds of visiting the coast increased by 1.44, 2.20, 4.68, and 8.40 for each decreasing category of residential coastal distance and the odds of visiting a lake increased by 1.49 and 3.05. The categorisations did not illustrate a distance-decay effect as clearly with rivers with only those respondents living within 1 km of a river significantly more likely to visit one.

4. Discussion

Studies have used a range of residential distance categories to operationalise how far someone lives from their nearest bluespace for the

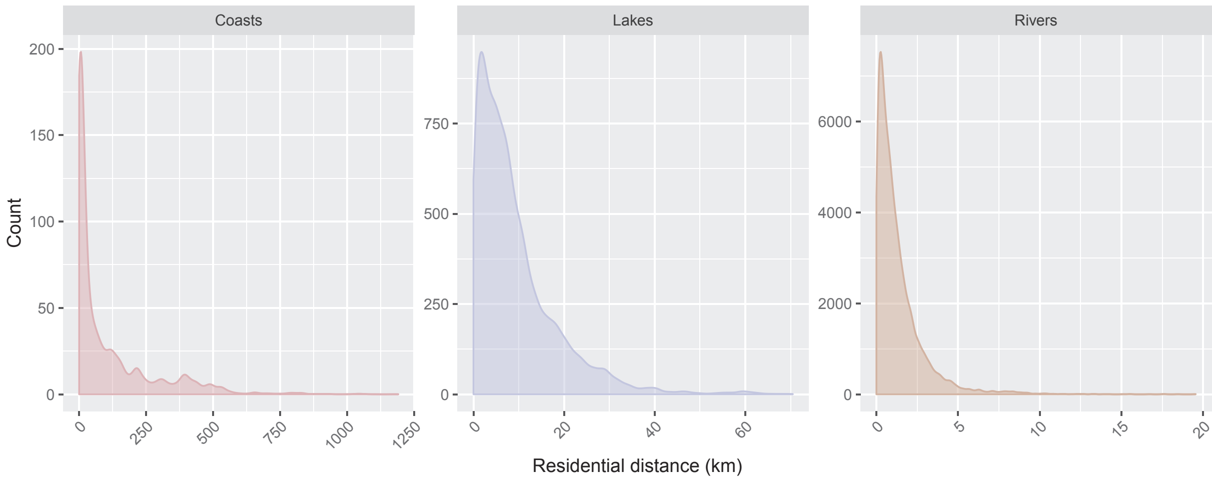

Fig. 2. Smoothed distributions of residential distance to coasts, lakes, and rivers.

Table 1
Odds ratios and 95% confidence intervals concerning the probability of visiting each environment for recreation at least once a week in the last month as a function of distance categories.

	OR	Lower bound	Upper bound
Coasts (n = 15,216)			
Distance (> 50 km = ref)	/	/	/
0–1 km	***8.40	5.32	13.27
> 1–5 km	***4.68	2.87	7.62
> 5–25 km	***2.20	1.55	3.10
> 25–50 km	*1.44	1.04	1.98
(Intercept)	***0.12	0.08	0.16
Conditional R^2	0.23		
Country-level variance	0.44		
0–1 km variance	0.83		
> 1–5 km variance	0.97		
> 5–25 km variance	0.43		
> 25–50 km variance	0.27		
Intraclass correlation coefficient	0.11		
Lakes (n = 12,219)			
Distance (> 5km = ref)	/	/	/
0–1 km	***3.05	2.17	4.28
> 1–5 km	**1.49	1.16	1.91
(Intercept)	***0.09	0.07	0.11
Conditional R^2	0.10		
Country-level variance	0.17		
0–1 km variance	0.30		
> 1–5 km variance	0.15		
Intraclass correlation coefficient	0.07		
Rivers (n = 12,255)			
Distance (> 2.5 km = ref)	/	/	/
0–1 km	**1.56	1.19	2.03
> 1–2.5 km	1.05	0.85	1.31
(Intercept)	***0.20	0.15	0.28
Conditional R^2	0.06		
Country-level variance	0.28		
0–1 km variance	0.16		
> 1–2.5 km variance	0.07		
Intraclass correlation coefficient	0.05		

N.B Models apply survey weights and include a random intercept of country and random slopes of distance categorisations. OR = odds ratio; ref = reference category. Conditional R^2 accounts for both fixed and random effects (Nakagawa, Johnson, & Schielzeth, 2017). $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

purposes of defining access to, likely use of, or simply general ‘exposure’ to, these environments. This has made comparability across studies and countries difficult. By drawing on data from 18 countries, our aim was to investigate the possibility of developing a more consistent set of distance categories that could be used to aid future comparability. Our outcome variable was whether or not an individual reported visiting the bluespace at least weekly for recreation, and thus these categories are most relevant for research investigating direct, intentional exposure (Keniger, Gaston, Irvine, & Fuller, 2013). Using a distance-decay approach, we demonstrated exponential relationships between residential distance to coasts, lakes, and rivers, and their corresponding recreational use. From this we developed distance categories which can be used in future research to define generic blue-space accessibility.

Despite using data from eighteen countries and a completely different approach to categorising distance to coasts, these categories closely resemble those used previously in the UK (Wheeler et al., 2012), and therefore bolster the author’s original claim that they represent “comparative geographical accessibility and…frequency/intensity of ‘exposure’ to coastal environments” (p. 1199). Across different blue spaces, differences in the distance at which the relationships plateaued are likely due to a combination of their relative availability, as well as the types of visits they attract and people’s motivations for visiting them (Elliott et al., 2018). As our additive models included random effects, we were able to identify countries in which distance-decay relationships are more or less prominent (Supplementary Fig. 2). For example, countries bordering the Mediterranean Sea appear to have more pronounced distance-decay relationships regarding distance to coasts, suggesting that climatic or cultural factors interact with these distance-decay relationships, although a detailed discussion of these issues is beyond the scope of this short communication.

For rivers, our categorisations did not perform as well which is unsurprising given the exponential relationship we found in the initial model was neither as strong as coasts or lakes, nor as confident (wider confidence intervals were observed throughout the spectrum of distances). This perhaps owes to the narrower range of distances the respondents resided from rivers, variations in river size, or because access may be compromised by culverts, privatised land, or other features. This latter finding is consistent with previous research which found weaker associations between perceived walking distance to rivers and the frequency of their use compared to other types of blue space in two German cities (Völker et al., 2018).

A strength of the study is that our categorisations do not necessarily result in the loss of information associated with percentile categorisation, and using splines to inform the development of the categories means that we can be confident they represent the true relationship between the continuous exposure and the outcome (Lamb & White, 2015). Nonetheless, these categories cannot replace considerations of previous research or theory when deciding the distance within which a natural environment might plausibly affect a health outcome. Researchers should also be aware of the impact on statistical power that categorisations may have, and should ensure that there are appropriate sample sizes for making robust inferences when including these

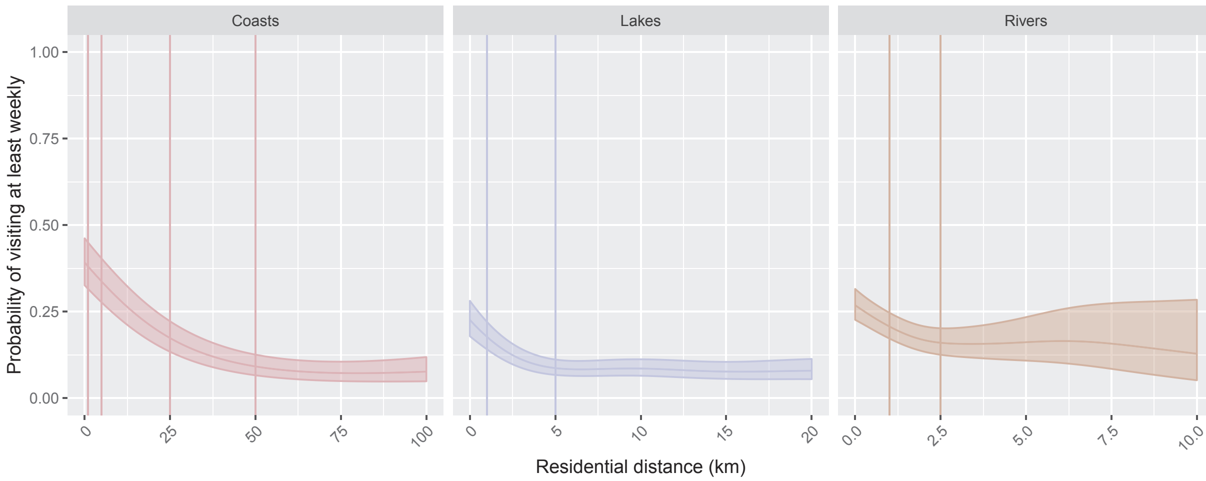

Fig. 3. Predicted probabilities of reporting recreational visits to the coast, lakes, or rivers at least weekly in the last four weeks as a function of residential distance, derived from our generalised additive mixed models. The x-axis is truncated at distances which better display the exponential relationships. The curved line represents the main spline term and the shaded region represents the 95% confidence interval. The vertical rules mark the points at which our subsequent categories start/end.

categories in regression models.

We are also mindful that many environment-related aspects of human health may depend on environments which are further away from home. Previous studies have demonstrated city-wide relationships between environment types and individual life satisfaction (Olsen, Nicholls, & Mitchell, 2019), and found that many people tend to visit recreational facilities further away from home for physical activity (Hillsdon, Coombes, Griew, & Jones, 2015). Such findings may be due to selective daily mobility biases (i.e. people with certain characteristics could also be the people who tend to visit more remote destinations; Chaix et al., 2012). Nonetheless, proximal residential exposure to natural environments remains an important determinant of health behaviours across countries (Sallis et al., 2016; Triguero-Mas et al., 2017; van den Berg et al., 2016). Furthermore, our analyses do not consider blue spaces with a surface area of less than 25 m^2 which may have affected the strength of our observed relationships. In a similar way, metadata on the minimum mapping unit of each lake feature in ECRINS were not available which could have led to bias in the results if there were systematic differences in the minimum mapping unit applied to different geographies (e.g. different countries, or urban vs. rural areas). Lastly, the data used in this study were mainly from European countries, western societies, and high-income economies, and therefore may not be globally applicable.

In conclusion, we have demonstrated marked distance-decay effects concerning residential distance to bluespace and recreational use across eighteen countries. We recommend our categories for future research which attempts to associate residential distance to blue space with a health outcome, where the assumed underlying mechanism is recreational contact with those environments. The categorisation of continuous exposure metrics like these in modelling sacrifices statistical power for the sake of improving the communication of results. Researchers should be aware of this and other methodological and theoretical considerations when deciding upon appropriate distance categories.

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CRediT authorship contribution statement

Lewis R. Elliott: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Mathew P. White:** Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Supervision, Project administration, Funding acquisition. **James Grellier:** Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization, Project administration. **Joanne K. Garrett:** Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization. **Marta Cirach:** Methodology, Formal analysis, Data curation. **Benedict W. Wheeler:** Methodology, Formal analysis, Writing - original draft, Writing - review & editing, Funding acquisition. **Gregory N. Bratman:** Writing - original draft, Writing - review & editing, Funding acquisition. **Matilda A. van den Bosch:** Writing - original draft, Writing - review & editing, Funding acquisition. **Ann Ojala:** Writing - original draft, Writing - review & editing, Funding acquisition. **Anne Roiko:** Writing - original draft, Writing - review & editing, Funding acquisition. **Maria L. Lima:** Writing - original draft, Writing - review & editing, Funding acquisition. **Aisling O'Connor:** Writing - original draft, Writing - review & editing, Funding acquisition. **Mireia Gascon:** Conceptualization, Writing - original draft, Writing - review & editing. **Mark Nieuwenhuijsen:** Writing - original draft, Writing - review & editing, Funding acquisition. **Lora E. Fleming:** Writing - original draft, Writing - review & editing, Supervision, Project administration, Funding acquisition.

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

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