Manuscript Details

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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.

Keywords	proximity; water; coast; lake; river; spline
Taxonomy	Urban Planning, Landscape Planning, Remote Sensing Database
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Research Data Related to this Submission

There are no linked research data sets for this submission. The following reason is given:
The data used in this research will be open access in the future under the BlueHealth project's participation in the EU Open Data Pilot (Openaire).

March 5th 2020

Dr Giselle Kolenic
Associate Editor
Landscape and Urban Planning

RE: LAND_2019_1218_R1 Research Note: Residential distance and recreational visits to coastal and inland blue spaces in eighteen countries**.**

Dear Dr Kolenic,

Thank you for the opportunity to resubmit a second revised version of our manuscript for consideration for publication in Landscape and Urban Planning. We are very grateful to Reviewer 1's further comments and careful consideration of this manuscript. We have revised the manuscript in line with these new suggestions and our responses are provided below in blue typeface.

We hope these further revisions are satisfactory and look forward to your consideration in due course.

Yours sincerely,

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Reviewer 1:

- The introduction framing around methodology (rather than health) is clearer and no longer potentially confusing to the reader.

  We are glad the reviewer feels the introduction is now clearer for the reader.

- In specifying what blue space types were used for what countries, a need has arisen for clarifying terms. For instance, "Due to a lack of globally-consistent high-resolution rivers and lakes data, we restricted analysis of these two blue spaces to European countries only" suggests that there are specific rivers and lakes that are THE two blue spaces in these countries. Consider "types" of blue space or another term here.

  We thank the reviewer for pointing out the need for clarification here. We recognise that the way section 2.2 is phrased may be potentially confusing for the reader. We merely mean to say that while our model for coastal proximity used data for all countries, our models for river or lake proximity used only data from European countries (because ECRINS is a European dataset). To clarify this we have rewritten the latter half of this paragraph as such (note the new sentence at the end which hopefully clarifies our method):

  "Due to a lack of globally-consistent high-resolution rivers and lakes data, the ECRINS database 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 25m^2 (CCM) to 500m^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)."***

- L133: I do not believe "the skew of each distance variable" is grammatically correct.

  We agree with the reviewer that this does not appear grammatically correct. In fact, to say we are investigating skew in the method section presupposes we know the shape of the distribution of data points. Therefore, we have rephrased this sentence "the distribution of data for each distance variable (Figure 2)".

- L154: Refresh grammatical use of "which" versus "that" and commas associated with each. The sentence starting with "no model included..." can be improved. Same comment about "which" in L258.

  We thank the reviewer for their careful attention to detail. We have rephrased the sentence starting with "no model included" as such: "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".

We are unsure whether the journal accepts American or British English (or either) and therefore adopted "which" when using restricted and non-restricted (i.e. including commas) clauses which is acceptable for British English. Should this article be accepted for publication, we recognise that the copyeditors would correct such clauses if American English is indeed the standard convention for this journal.

- The results section remains verbose with numerous symbols and numbers. I still believe the article would be more accessible - and therefore likely to be cited and appreciated - by journal readers if the methodological decisions, some of which belong in the methods not in the results, and the actual results were summarized better. The table revisions do help.

  We are glad the reviewer agrees that revisions to the tables aid comprehension of the results.

  In our previous revision, we ensured that section 2.4 alerted the reader to the fact that we proposed to use both policy recommendations and data-driven analysis to create the distance categories: "We combined results from these models with previous research and policy recommendations to identify distances at which the distance-decay relationship changed considerably." As this was a data-driven (as opposed to theory- or hypothesis-driven) analysis, and we could not presuppose our findings, we believe it is appropriate to maintain some narrative in the results section as to how our original additive models were used to inform categorisations.

  With regard to the use of symbols and numbers, we do not agree that this is too burdensome for the reader. Aside from the reporting of six odds ratios in the narrative, the only other numeracy reported refers to frequencies and percentages which we argue are accessible to most readers. In any case the odds ratios reported are not accompanied by confidence intervals, effect sizes, or other test statistics which may confuse the reader; such detail is restricted to tables and supplementary tables only. The only symbols used are less than/greater than (or equal to) symbols which are necessary for explaining the distance categorisations (and would be verbose to write in full), and the equation of a geometric sequence, which again is necessary to explain how the spline informed the categorisations.

  We appreciate that the statistical methods involved may be unfamiliar to some, but the concepts of frequencies, percentages, odds ratios, and sequences are hopefully accessible to a wide readership of this journal.

- Home distances to coasts, lakes, and rivers were exponentially related to visits
- We develop and demonstrate the utility of resultant general-purpose categorisations
- ≤1km, >1 to 5km, >5 to 25km, >25 to 50km, and >50km suitable for coastal distance
- ≤1km, >1 to 5km, >5km suitable for lake distance
- ≤1km, >1 to 2.5km, >2.5km adequate for river distance

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.

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

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Declarations of interest: none

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Keywords: proximity; water; coast; lake; river; spline

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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 and 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. <300m; >1km 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 300m 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 and 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 et al., 2010). Informed by a mixture of these, cross-national research has identified distances of 100m, 300m, 500m, and 1km 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 classified distance in a variety of ways. Regarding distance to the coast, UK studies have used categories of 0-1km, >1-5km, >5-20km, >20-50km, and >50km (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 ≤300m, 300m-3km, 3-6km, and 6-15km (Nutsford, Pearson, Kingham, & Reitsma, 2016), and, in Australia, greater or less than 800m (Edwards, Giles-Corti, Larson, & Beesley, 2014). Research in Ireland has used quintiles within 10km 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 1km 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 4km (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 [ANONYMISED FOR PEER REVIEW] 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 (Figure 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 75m 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, ~~we restricted analysis of these two blue spaces to European countries only. t~~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 25m^2 (CCM) to 500m^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 ~~skew~~ distribution of data for each distance variable (Figure 2)~~, and likely reasons for this~~. 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 (Figure 3; Supplementary Figure 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. ~~No model included adjustment for f~~Further fixed effects were not included as we did not want ~~want resulting categories~~ distance-decay effects to reflect sociodemographic characteristics which researchers may ~~wish to~~ 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 1,192km, to lakes from 0 to 70km, and to rivers from 0 to 20km. Exposures exhibited high positive skew (Figure 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 (Figure 3; Supplementary Figure 1) with plateaus at varying distances. For coasts, given this decline, and considering 1km 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 50km – the distance at which the European Union considers a residence 'coastal' (Eurostat, 2013) – so a >50km category was also chosen. Between 1km and 50km, categories of >1km to ≤5km, >5km to ≤25km, and >25km to ≤50km 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 ≤1km was also selected for lakes and rivers based on the exponential declines demonstrated and because 1km 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 5km, so two further categories of >1km to ≤5km, and >5km were selected, again representing the exponential decline and maintaining consistency with those categories selected for coasts. For rivers, the relationship plateaued after 2.5km, so two further categories of >1km to ≤2.5km, and >2.5km were selected. Of the analytical samples, 57% (n=8,703) lived within 50km of the nearest coast, 39% (n=4,819) lived within 5km of the nearest lake, and 86% (n=10,502) lived within 2.5km 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 1km 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 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 bluespace 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 Figure 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 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 $25m^2$ 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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Figure captions

Figure 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.

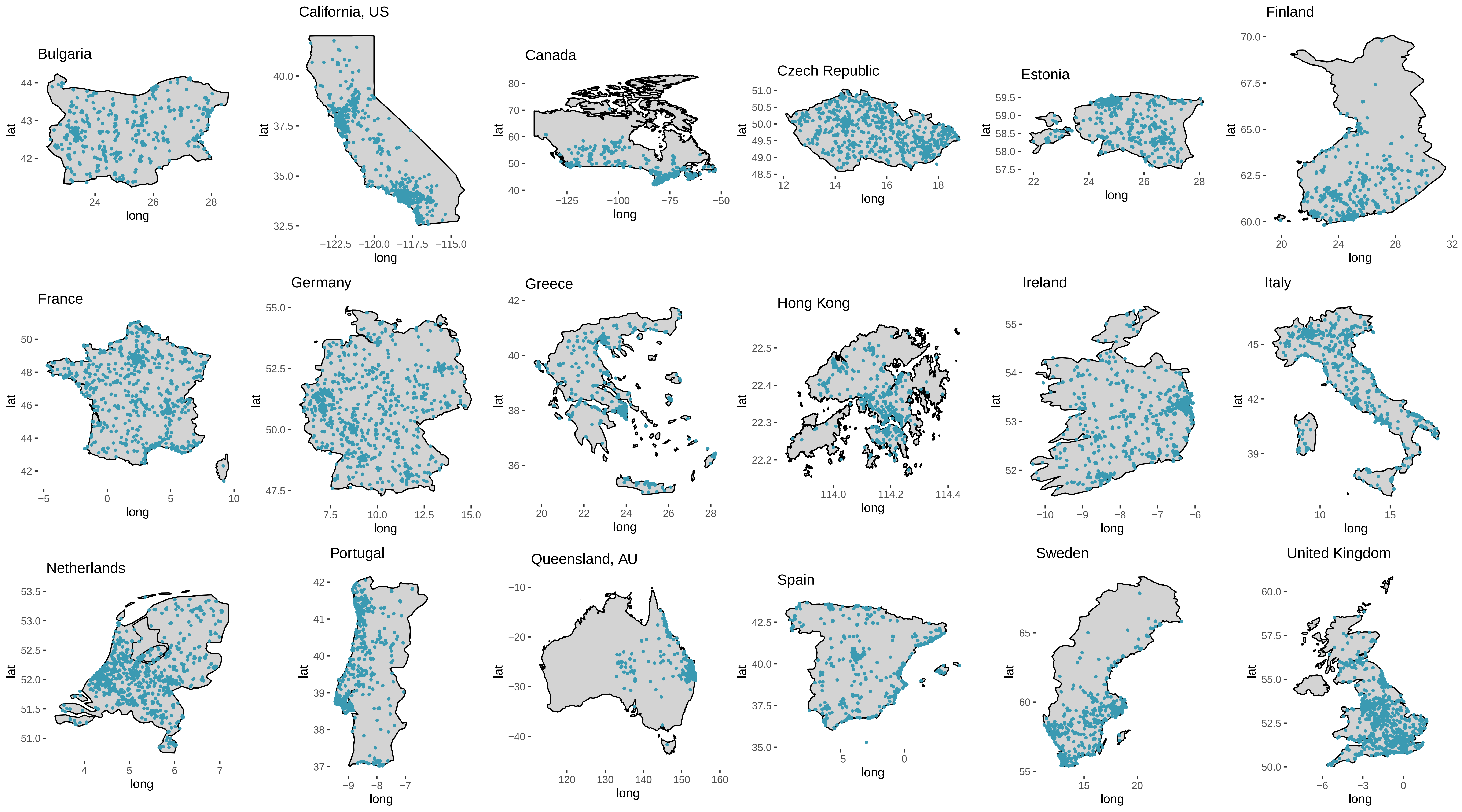
Figure 2: Smoothed distributions of residential distance to coasts, lakes, and rivers.

Figure 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.

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


Bulgaria
California, US
Canada
Czech Republic
Estonia
Finland
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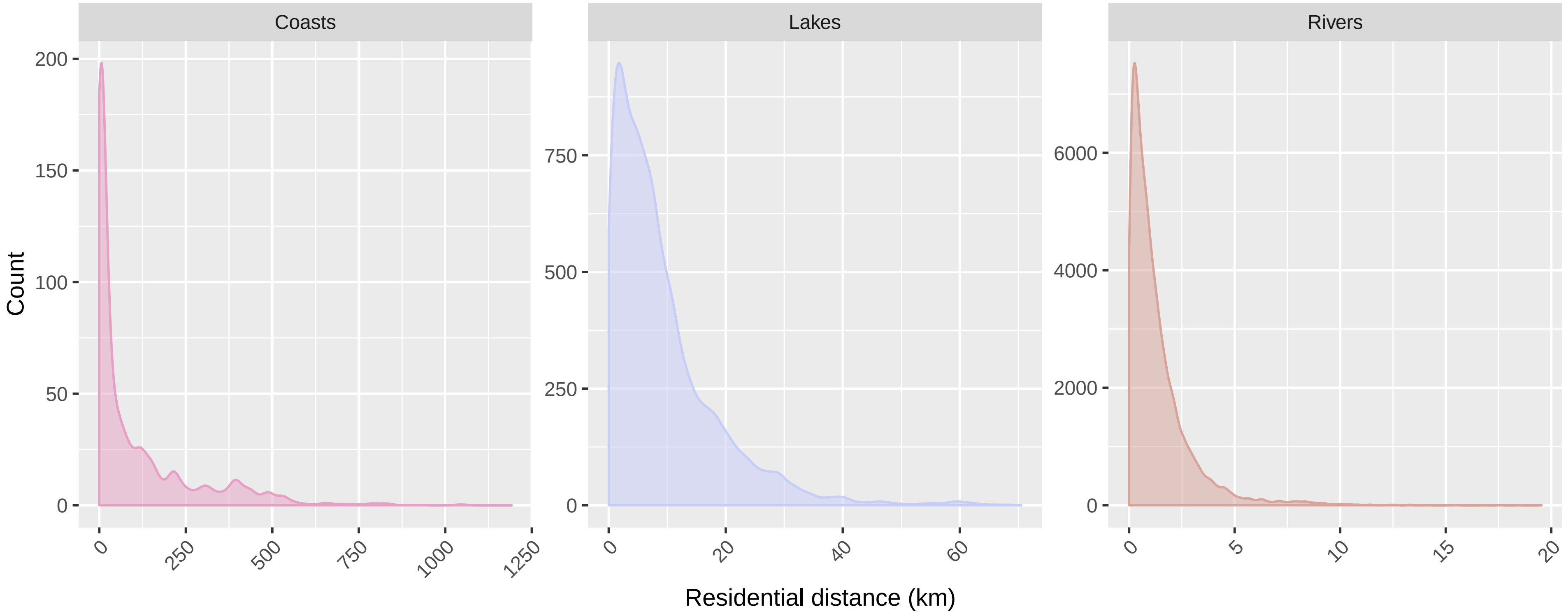
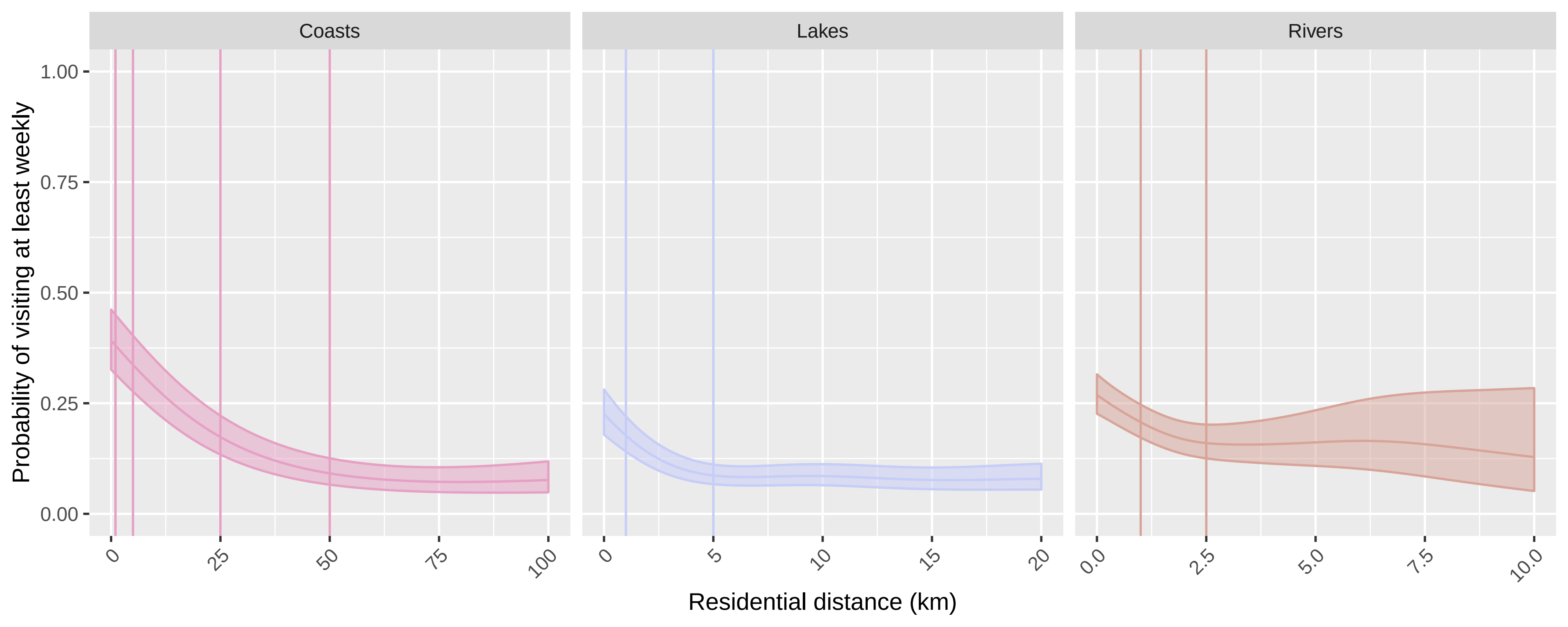

Coasts
Lakes
Rivers
Count
200
150
100
50
0
0
250
500
750
1000
1250
750
500
250
0
0
20
40
60
6000
4000
2000
0
0
5
10
15
20
Residential distance (km)


Coasts
Lakes
Rivers
Probability of visiting at least weekly
1.00
0.75
0.50
0.25
0.00
0
25
50
75
100
0
5
10
15
20
0.0
2.5
5.0
7.5
10.0
Residential distance (km)

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

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Supplementary Table 1. Results of likelihood ratio tests comparing the fit of generalised additive mixed models which included a random intercept of country and a fixed slope of residential distance, with those which additionally included a random slope of residential distance.

	Residual degrees of freedom	Residual deviance	Degrees of freedom	Deviance	*p* value	AIC
Coasts						
Model without a random slope	15189	13529	-	-	-	13985.77
Model with a random slope	15173	13347	15.54	182.25	>0.001	13817.45
Lakes						
Model without a random slope	12196	7877	-	-	-	12717.82
Model with a random slope	12186	7852	10.37	25.20	0.006	12692.87
Rivers						
Model without a random slope	12235	12446	-	-	-	8067.78
Model with a random slope	12223	12404	11.93	41.77	>0.001	8055.82

N.B Models apply survey weights. As random effect terms have a zero-dimensional null space (i.e. they can be penalised to zero), *p* value approximation can be poor for these generalised likelihood ratio tests; the value can often be substantially too low. Nonetheless, in all three cases better fit is still indicated by the lower AIC values.

Supplementary Table 2. Results of initial generalised additive mixed models predicting the probability of visiting each environment for recreation at least weekly in the last four weeks from an unknown smooth function of residential distance to each environment (modelled with thin-plate regression splines).

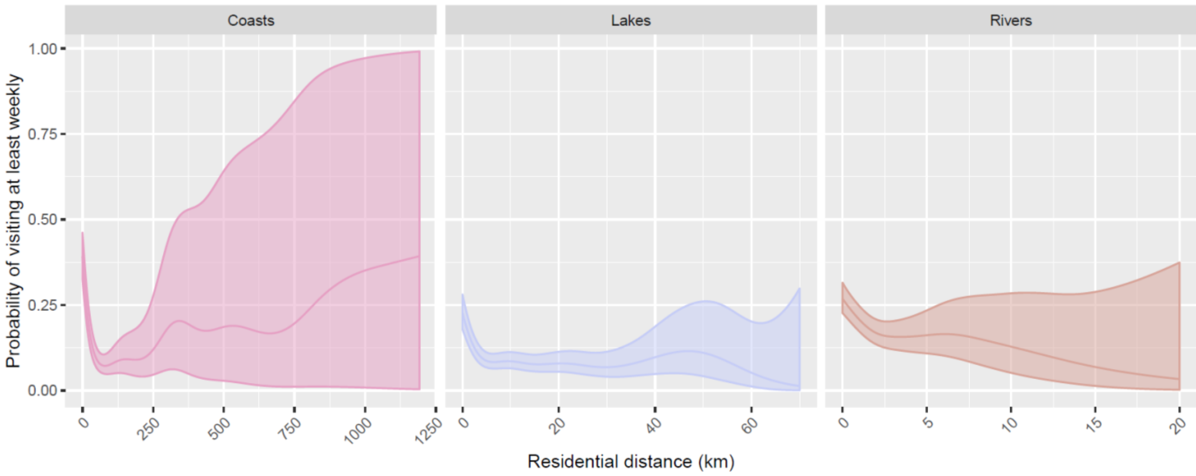
	Effective degrees of freedom	Chi-squared test
Coasts		
Distance	8.58	***392.98
Tjur's R^2	0.16	
Country/territory-level variance	0.35	
Distance variance	0.00	
Lakes		
Distance	7.01	***134.75
Tjur's R^2	0.04	
Country/territory-level variance	0.23	
Distance variance	0.00	
Rivers		
Distance	4.24	***43.66
Tjur's R^2	0.04	
Country/territory-level variance	0.16	
Distance variance	0.02	

N.B Models apply survey weights and include a random intercept of country/territory and random slopes of residential distance to each environment. Tjur's R^2 represents the difference between the averages of fitted values for successes (i.e. visited in the last week) and failures (i.e. did not visit in the last week), respectively (Tjur, T., 2009. Coefficients of Determination in Logistic Regression Models—A New Proposal: The Coefficient of Discrimination. The American Statistician 63, 366–372. https://doi.org/10.1198/tast.2009.08210). *** $p<.001$

Supplementary Table 3. Numbers of respondents per country/territory who reside within the various distance categorisations created for each type of bluespace.

	Coasts					Lakes			Rivers		
	0-1km	>1-5km	>5-25km	>25-50km	>50km	0-1km	>1-5km1	>5km	0-1km	>1-2.5km	>2.5km
Bulgaria	29	75	25	20	801	58	296	595	630	277	42
California, US	31	127	291	100	301	-	-	-	-	-	-
Canada	32	42	52	10	631	-	-	-	-	-	-
Czech Republic	0	0	0	0	949	59	371	519	652	275	22
Estonia	94	216	144	50	313	71	295	451	444	287	86
Finland	171	158	104	54	401	306	291	290	452	261	174
France	39	59	97	77	653	51	278	593	523	313	86
Germany	11	19	42	17	771	69	273	517	509	248	102
Greece	205	236	245	38	48	24	25	722	450	261	60
Hong Kong, CN	326	206	22	1	1	-	-	-	-	-	-
Ireland	134	277	264	105	92	55	213	604	531	261	80
Italy	132	117	184	82	293	39	100	669	506	233	69
Netherlands	28	156	376	181	199	146	516	278	249	214	477
Portugal	117	249	228	101	91	18	82	673	387	287	112
Queensland, AU	87	128	322	84	157	-	-	-	-	-	-
Spain	108	148	97	51	338	35	98	585	407	240	94
Sweden	150	206	218	75	205	262	345	247	412	281	161
United Kingdom	117	164	276	276	269	41	402	657	521	391	188

Supplementary Figure 1. Predicted probabilities of visiting 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. These are the same relationships that are depicted in Figure 3 of the main manuscript, but including the entire spectrum of distances in the data. The curved lines represent the main spline term and the shaded areas represent the 95% confidence interval.



Supplementary Figure 2. Country/territory-level distance-decay effects derived from the random effect components of our generalised additive mixed models. The curved lines represent the main spline term and the shaded areas represent the 95% confidence interval. Note the Czech Republic is omitted from the residential coastal distance plot (top) as all participants resided over 50km from the nearest coastline.