

Manuscript Details

Manuscript number	LAND_2019_1218
Title	Research Note: Residential distance and recreational visits to coastal and inland blue spaces in eighteen countries
Article type	Research note

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	Remote Sensing Database, Urban Planning, Landscape Planning
Manuscript category	Human Dimensions
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Suggested reviewers	Matthew Browning, Ulrika Stigsdotter, Camille Perchoux, Dinand Ekkel, Sjerp de Vries

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Dr. Lewis Elliott
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Dear Professor J I Nassauer & Professor P H Verburg
Co-Editors-in-Chief
Landscape and Urban Planning

October 1st 2019

I am pleased to submit a research note entitled “Residential distance and recreational visits to coastal and inland blue spaces in eighteen countries” for consideration for publication in Landscape and Urban Planning.

Across the quantitative literature examining associations between distance to blue spaces and health outcomes, residential distance is often categorised into useful groups. While these are often purported to represent actual, direct, exposure to these environments, the categories are varied and sometimes unsubstantiated, complicating comparisons of meaningful thresholds across studies. In this study, we model relationships between residential distance and reported recreational visits to coasts, lakes, and rivers using data from representative samples of respondents from eighteen countries. Specifically, we used generalised additive mixed models to explore potential distance-decay effects between these two variables and use these to create empirically-derived residential distance categories.

We observed exponential declines in visits with increasing distance to all three blue spaces with plateaus at varying distances. We then derived and demonstrated the usefulness of 5 categories of distance to the coast ($\leq 1\text{km}$, $>1\text{km}$ to $\leq 5\text{km}$, $>5\text{km}$ to $\leq 25\text{km}$, $>25\text{km}$ to $\leq 50\text{km}$, and $>50\text{km}$), 3 categories of distance to a lake ($\leq 1\text{km}$, $>1\text{km}$ to $\leq 5\text{km}$, and $>5\text{km}$), and 3 categories of distance to a river ($\leq 1\text{km}$, $>1\text{km}$ to $\leq 2.5\text{km}$, and $>2.5\text{km}$), in subsequent generalised linear mixed models. As these categories are taken from representative samples of respondents across eighteen countries and reflect underlying recreational visit probability, we argue that they may be useful to researchers investigating associations between residential bluespace and health outcomes internationally, especially where the putative mechanism linking the two is direct, recreational contact.

We believe this article would be of interest to readers of Landscape and Urban Planning because of its international scope, and potential usefulness to scholars of health geographic, environmental epidemiological, and environmental psychological research, all of which is being increasingly well represented in the journal. While we realise we are slightly over the word limit for a Research Note, we believe the article is suitable for publication in this format as it is inherently methodological. We are happy to take editorial advice as to whether we should resubmit as a full-length article, or condense the text if necessary.

I confirm that this manuscript is not published and is not under consideration for publication elsewhere. It also does not duplicate any material already published. All authors have reviewed and approved the content of the manuscript.

We look forward to your consideration of this manuscript.

Sincerely,

Dr. Lewis Elliott

- Varied categories of residential distance to bluespace complicate study comparisons
- Modelled relationships between distance and recreational visits to blue spaces
- Used generalised additive mixed models with survey data from eighteen countries
- Exponential distance-decay relationships for coasts, lakes, and rivers were found
- We develop and demonstrate the utility of resulting general-purpose categorisations

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

Acknowledgements: We thank Ben Butler, Gavin Ellison, and Tom Powell at YouGov for managing the data collection pertaining to this study. We also thank Michelle Tester-Jones, Leanne Martin, Emma Squire, and Theo Economou for their comments on earlier drafts of this study.

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

Funding: This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 666773. Data collection in California was supported by the Center for Conservation Biology, Stanford University. Data collection in Canada was supported by the Faculty of Forestry, University of British Columbia. Data collection in Finland was supported by the Natural Resources Institute Finland (Luke). Data collection in Australia was supported by Griffith University and the

University of the Sunshine Coast. Data collection in Portugal was supported by ISCTE – University Institute of Lisbon. Data collection in Ireland was supported by the Environmental Protection Agency, Ireland. Data collection in Hong Kong was supported by an internal University of Exeter—Chinese University of Hong Kong international collaboration fund.

1 *1. Introduction*

2

3 Investigations of natural environments and population health commonly consider associations
4 between human health outcomes and residential distance to green spaces (e.g. playing fields,
5 parks, woodlands; Browning and Lee, 2017). Although distance is a linear variable, research
6 examining distance to greenspace typically categorises distance into groups (e.g. <300m;
7 >1km etc.). This could be done to circumvent analytical or statistical complexities (e.g.
8 highly skewed distributions); to increase policy relevance or improve communication (e.g.
9 compatibility with the World Health Organisation's 300m urban green space indicator;
10 Annerstedt van den Bosch et al., 2016); to address inherent non-linearity between an
11 exposure and a health outcome (e.g. the capacity of green space to mitigate urban heat may
12 be trivial beyond a certain distance; Shashua-Bar and Hoffman, 2000); or because the
13 categories are purported to represent underlying human behaviour patterns which might also
14 plausibly mediate the health outcome (e.g. typical walkable distances; Smith et al., 2010).
15 Informed by a mixture of these, cross-national research has identified distances of 100m,
16 300m, 500m, and 1km as appropriate for use in a wide range of studies linking exposure to
17 greenspace (using residential distance as a proxy) with a multitude of health outcomes (Smith
18 et al., 2017).

19

20 Residential distance to bluespaces (e.g. coasts, rivers, lakes) may also be an important
21 correlate of a variety of health outcomes (Gascon, Zijlema, Vert, White, & Nieuwenhuijsen,
22 2017), and studies have classified distance in a variety of ways. Regarding distance to the
23 coast, UK studies have used categories of 0-1km, >1-5km, >5-20km, >20-50km, and >50km
24 (Wheeler, White, Stahl-Timmins, & Depledge, 2012) or collapsed versions of these (Pasanen,
25 White, Wheeler, Garrett, & Elliott, 2019; White, Alcock, Wheeler, & Depledge, 2013; White,
26 Wheeler, Herbert, Alcock, & Depledge, 2014), to represent distinct classes of physical
27 coastal access. Research in New Zealand has used distance bands of \leq 300m, 300m-3km, 3-
28 6km, and 6-15km (Nutsford, Pearson, Kingham, & Reitsma, 2016), and, in Australia, greater
29 or less than 800m (Edwards, Giles-Corti, Larson, & Beesley, 2014). Research in Ireland has
30 used quintiles within 10km of the coast (Dempsey, Devine, Gillespie, Lyons, & Nolan,
31 2018). Regarding water bodies and inland waterways, research in the Netherlands and France
32 has considered the availability of blue space in 1km buffers around people's residences (de
33 Vries et al., 2016; Perchoux, Kestens, Brondeel, & Chaix, 2015), and one study in Portugal
34 used distances within and beyond 4km (Burkart et al., 2015). In contrast to green spaces,

35 research investigating blue spaces faces additional complexities in that as well as occupying
36 surface area, they are often nominally narrow linear features (e.g. rivers) which are frequently
37 not featured on land cover maps developed from data with coarse spatial resolution. Further,
38 given that much recreational ‘access’ to bluespace is to beaches, coastal paths, canal towpaths
39 etc., the edges of bluespace are an important facet of access (Pitt, 2018; Vert et al., 2019),
40 rather than the total surface area. Lastly, even in countries with higher availability of
41 bluespace, people are still willing to travel considerable distances to access it (Laatikainen,
42 Piironen, Lehtinen, & Kytta, 2017). Thus distance metrics are often preferred to coverage
43 metrics in research concerning blue spaces.

44

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

59

60 *2. Method*

61

62 Methods were approved by the [ANONYMISED FOR PEER REVIEW] ethics committee
63 (Ref: Aug16/B/099).

64

65 *2.1 Sample*

66

67 The BlueHealth International Survey concerns recreational use of blue spaces and its
68 relationship with human health. It was administered online by YouGov from June 2017 to

69 April 2018 to panellists in 18 countries. In four seasonal stages of data collection,
70 representative samples of 18,838 respondents were sampled from 14 European countries
71 (Bulgaria, the Czech Republic, Estonia, Finland, France, Germany, Greece, Ireland, Italy,
72 Netherlands, Portugal, Spain, Sweden, and the United Kingdom) and four other territories
73 (Hong Kong, Canada, Australia [primarily Queensland], and the USA [state of California
74 only]). Full methodological details are in an accompanying technical report ([http://bit.ly/BIS-
75 Technical-Report](http://bit.ly/BIS-Technical-Report)). Analyses are based on the subset of 15,216 participants (Figure 1) that
76 provided reliable home location information, had no missing data, and that did not exhibit
77 response biases (see technical report for details).

78

79 *2.2 Exposures*

80

81 Participants recorded their home location via a Google Maps application programming
82 interface integrated in the survey. Coordinates (decimal degrees) correct to three decimal
83 places (approximately 75m precision dependent on location) were returned and exposures
84 assigned to these. Residential distance to the coast (n=15,216) was operationalised as the
85 Euclidean distance from the home location to the nearest coast as defined by the highest
86 resolution version of the Global Self-consistent Hierarchical High-resolution Geography
87 shoreline database (Wessel & Smith, 1996). Due to a lack of globally-consistent high-
88 resolution rivers and lakes data, the European Catchments and Rivers Network System
89 (ECRINS) database (European Environment Agency, 2012) was used to assign Euclidean
90 distances from the home location to the nearest lake (n=12,219) and river (or stream, canal,
91 waterway etc.; n=12,255), separately, for the 14 European countries sampled only. ECRINS
92 data are derived from CORINE Land Cover (CLC) data, the EU Water Framework Directive
93 (WFD), and the EU Catchment Characterisation Model (CCM). Rivers are modelled within
94 catchment areas and thus have no minimum width. Lakes have varying minimum mapping
95 units depending on the original data source, spanning 25m² (CCM) to 500m² (CLC).

96

97 *2.3 Outcomes*

98

99 The outcome measure was the probability of respondents reporting visiting a coast, lake, or
100 river, at least weekly within the last four weeks for recreation. Respondents were presented
101 with the names and visual exemplars of 29 different natural environment types and asked to
102 report how often in the last four weeks they had made a recreational visit to each using four

103 categorical response options (not at all in the last four weeks, once or twice in the last four
104 weeks, once a week, several times a week). Responses were dichotomised into the former and
105 latter two response options to denote whether a participant had visited an environment at least
106 weekly or not, consistent with thresholds identified as important in previous research (Garrett
107 et al., 2018; White et al., 2019). We collapsed responses to: (a) eight coastal environments
108 (pier, harbour, promenade, beach, rocky shore, cliff, lagoon, open sea) to denote ‘coastal’
109 visits, and (b) two riverside environments (‘urban’ river or canal [surrounded by buildings]
110 and ‘rural’ river or canal [surrounded by vegetation]) to denote ‘river’ visits. ‘Lake’ visits
111 were represented by a single ‘lake’ environment category.

112

113 *2.4 Analysis*

114

115 A distance-decay approach was employed for extracting distance categories for coasts, lakes,
116 and rivers separately. We fitted three generalised additive mixed models with the probability
117 of visiting a bluespace (i.e. coast, river, lake) at least weekly as the outcome variable, the
118 respondent’s country of residence as a random intercept term, and the residential distance to
119 the corresponding bluespace as both a fixed (overall) and random (country-variant) slope
120 term. In all three cases, specification of random slopes yielded better model fit than fixed
121 slopes. Distance was modelled with a thin plate regression spline basis (Wood, 2003). Models
122 were weighted to ensure estimates were representative of the countries’ populations with
123 respect to sex, age, and region of residence. These models were used to identify distances at
124 which the distance-decay relationship changed considerably, and subsequent binomial mixed-
125 effects models of a similar form were run, replacing the smooth function of the exposure with
126 a new categorical variable in order to demonstrate the appropriateness of the categories.
127 Analyses were performed in R v3.6.0 (R Core Team, 2019) using ‘mgcv’ (Wood, 2017) and
128 ‘lme4’ (Bates, Mächler, Bolker, & Walker, 2015) packages.

129

130 *3. Results*

131

132 Residential distance to coast ranged from 0 to 1,192km, to lakes from 0 to 70km, and to
133 rivers from 0 to 20km. Exposures exhibited high positive skew (Figure 2). Outliers for
134 distance to coast included respondents residing in inland Canadian territories, Australia, and
135 the Czech Republic. Outliers for distance to lakes were due to respondents residing in the

136 Greek Islands and the Puglia region of Italy. These are not analytically problematic as the
137 probability of visiting the corresponding environments for recreation is consequently low.

138

139 The probability of visiting all three blue spaces decayed exponentially with increasing
140 distance (Figure 3; Supplementary Figure 1) with plateaus at varying distances. For coasts,
141 given this decline, and considering 1km has been used as a threshold in a number of studies
142 associating distance to coast with health outcomes previously (Pasanen et al., 2019; Wheeler
143 et al., 2012; White et al., 2013, 2014), $\leq 1\text{km}$ was chosen as the most proximal distance
144 category. The relationship appeared to plateau around 50km – the distance at which the
145 European Union considers a residence ‘coastal’ (Eurostat, 2013) – so a $>50\text{km}$ category was
146 also chosen. Between 1km and 50km, categories of $>1\text{km}$ to $\leq 5\text{km}$, $>5\text{km}$ to $\leq 25\text{km}$, and
147 $>25\text{km}$ to $\leq 50\text{km}$ were chosen as they represent an exponential geometric sequence ($\alpha_n =$
148 5^{n-1}) which mirrors the relationship demonstrated by the spline. An initial, most proximal,
149 category of $\leq 1\text{km}$ was also selected for lakes and rivers based on the exponential declines
150 demonstrated and because 1km has been used in literature linking residential distance to
151 inland waterways with health outcomes previously (de Vries et al., 2016; Perchoux et al.,
152 2015). For lakes, the relationship plateaued after 5km, so two further categories of $>1\text{km}$ to
153 $\leq 5\text{km}$, and $>5\text{km}$ were selected, again representing the exponential decline and maintaining
154 consistency with those categories selected for coasts. For rivers, the relationship plateaued
155 after 2.5km, so two further categories of $>1\text{km}$ to $\leq 2.5\text{km}$, and $>2.5\text{km}$ were selected.

156

157 The utility of these categories is evidenced in the subsequent binomial mixed-effects models
158 (Table 1). The odds of visiting the coast increased by 1.44, 2.20, 4.68, and 8.40 for each
159 decreasing category of residential coastal distance and the odds of visiting a lake increased by
160 1.49 and 3.05. The categorisations did not illustrate a distance-decay effect as clearly with
161 rivers with only those respondents living within 1km of a river significantly more likely to
162 visit one.

163

164 *4. Discussion*

165

166 Studies have used a range of residential distance categories to operationalise how far
167 someone lives from their nearest bluespace for the purposes of defining access to, likely use
168 of, or simply general ‘exposure’ to, these environments. This has made comparability across

169 studies and countries difficult. By drawing on data from 18 countries, our aim was to
170 investigate the possibility of developing a more consistent set of distance categories that
171 could be used to aid future comparability. Our outcome variable was whether or not an
172 individual reported visiting the bluespace at least weekly for recreation, and thus these
173 categories are most relevant for research investigating direct, intentional exposure (Keniger,
174 Gaston, Irvine, & Fuller, 2013). Using a distance-decay approach, we demonstrated
175 exponential relationships between residential distance to coasts, lakes, and rivers, and their
176 corresponding recreational use. From this we developed distance categories which can be
177 used in future research to define generic bluespace accessibility.

178

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

192

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

201

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

211

212 We are also mindful that many environment-related aspects of human health may depend on
213 environments which are further away from home. Previous studies have demonstrated city-
214 wide relationships between environment types and individual life satisfaction (Olsen,
215 Nicholls, & Mitchell, 2019), and found that many people tend to visit recreational facilities
216 further away from home for physical activity (Hillsdon, Coombes, Griew, & Jones, 2015).
217 Nonetheless, residential exposure to natural environments remains an important determinant
218 of health behaviours across countries (Sallis et al., 2016; Triguero-Mas et al., 2017; van den
219 Berg et al., 2016). Furthermore, our analyses do not consider blue spaces with a surface area
220 of less than 25m² which may have affected the strength of our observed relationships. Lastly,
221 the data used in this study were mainly from European countries, western societies, and high-
222 income economies, and therefore may not be globally applicable.

223

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

232

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372

373

374 *Figure captions*

375

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

380

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

382

383 Figure 3: Predicted probabilities of reporting recreational visits to the coast, lakes, or rivers at
384 least weekly in the last four weeks as a function of residential distance, derived from our
385 generalised additive mixed models. The x-axis is truncated at distances which better display
386 the exponential relationships. The vertical lines mark the points at which our subsequent
387 categories start/end.

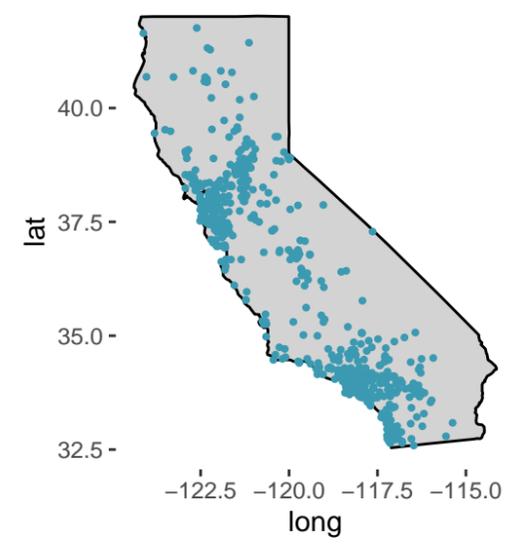
388

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

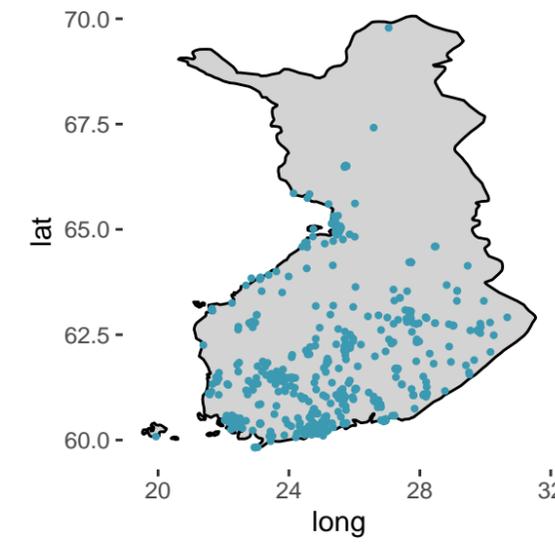
	OR	Lower confidence interval	Upper confidence interval
Coasts (n=15,216)			
Distance (>50km=ref)	/	/	/
0-1km	***8.40	5.32	13.27
>1-5km	***4.68	2.87	7.62
>5-25km	***2.20	1.55	3.10
>25-50km	*1.44	1.04	1.98
(Intercept)	***0.12	0.08	0.16
Conditional R ²	0.23		
Country-level variance	0.44		
0-1km variance	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 control for a random intercept of country and random slopes of distance categorisations. OR=odds ratio; ref=reference category. Conditional R² accounts for both fixed and random effects (Nakagawa, Johnson, & Schielzeth, 2017). *** $p < .001$, ** $p < .01$, * $p < .05$.

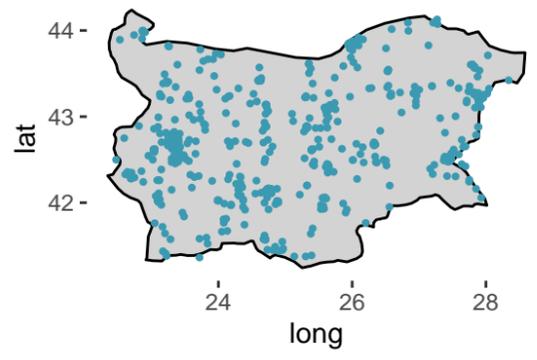
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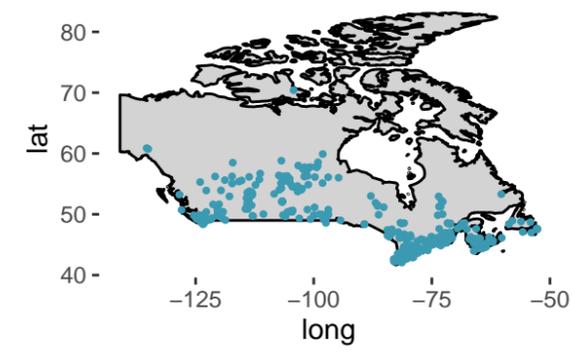
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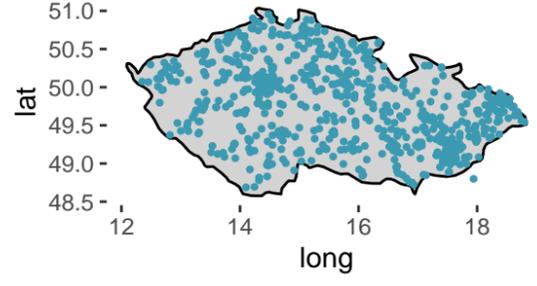
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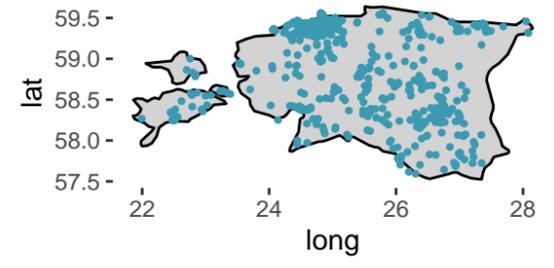
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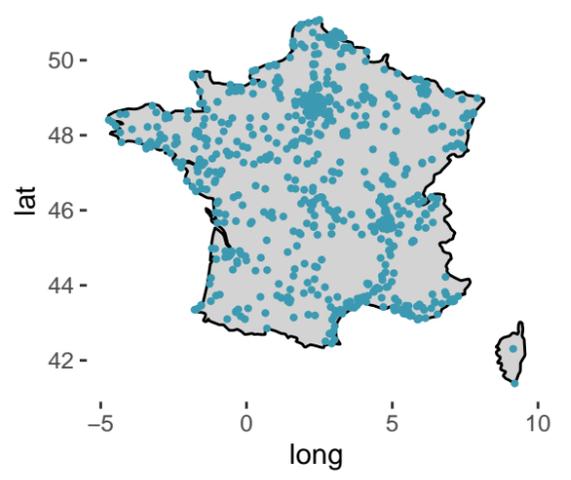
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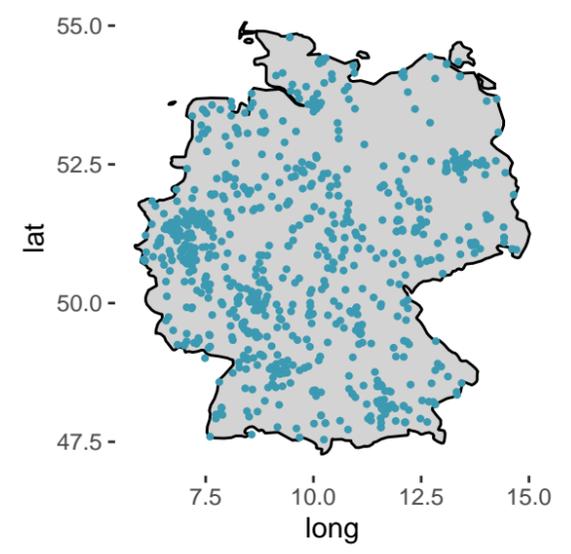
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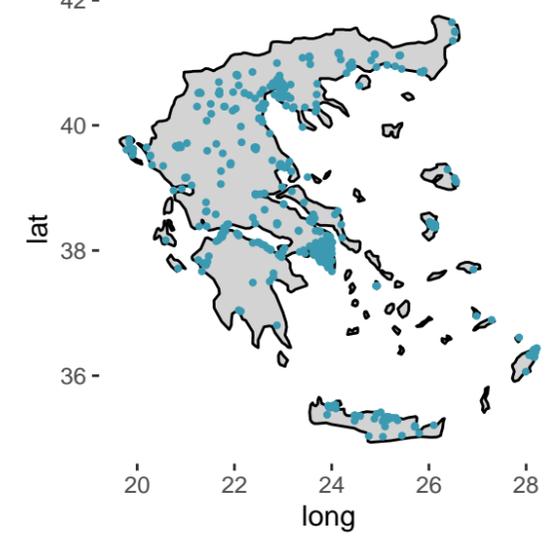
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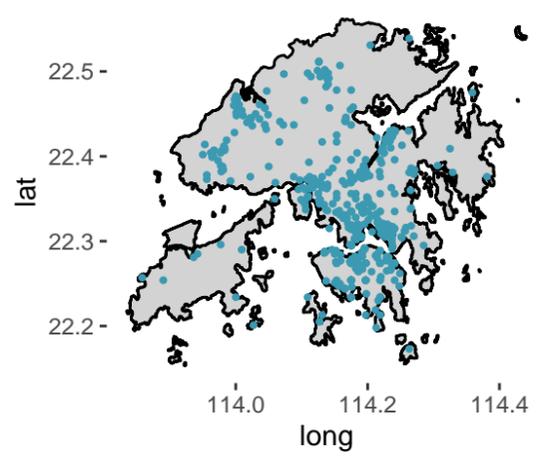
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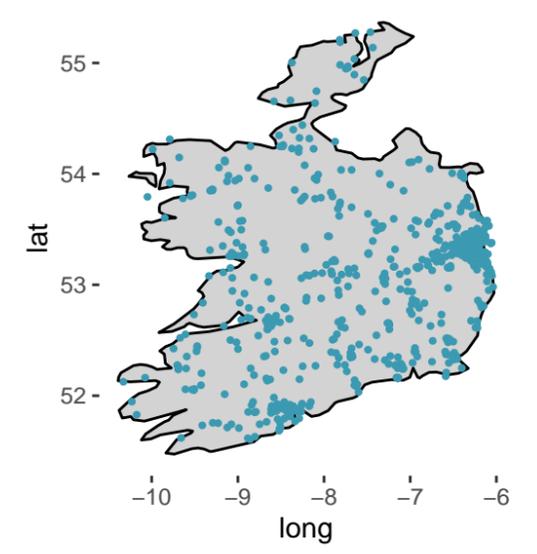
Greece



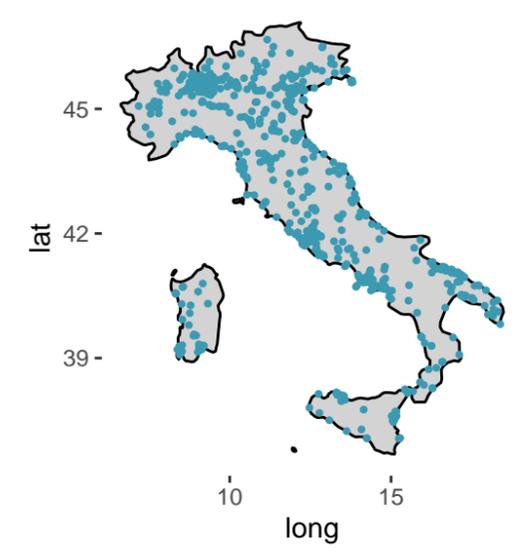
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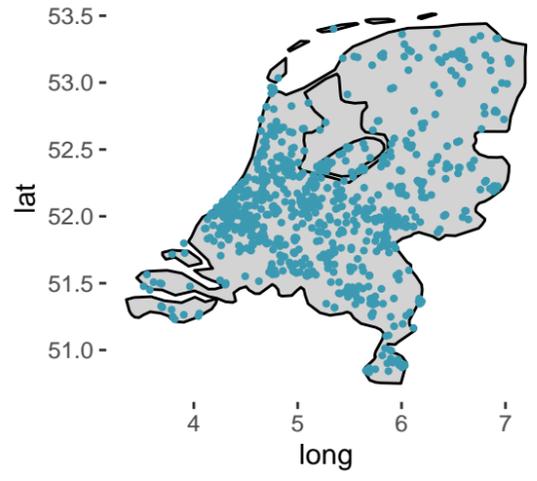
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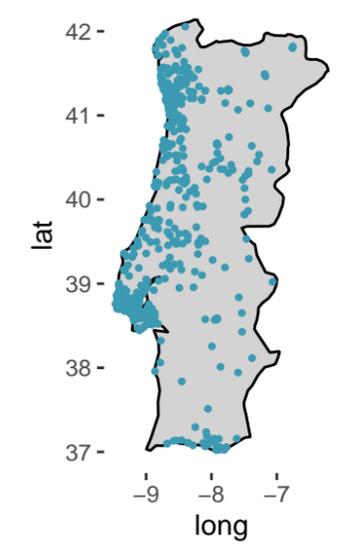
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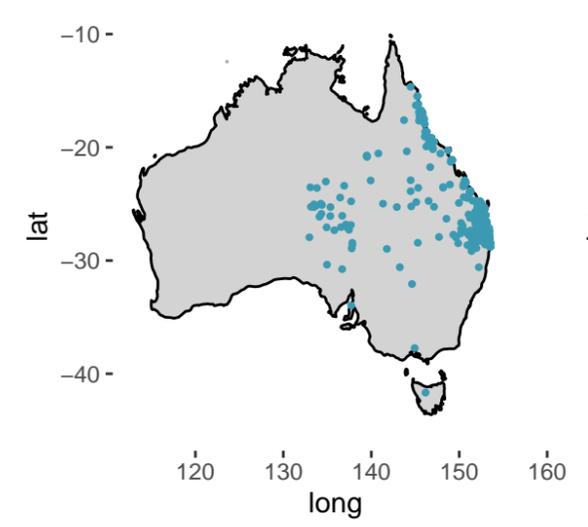
Netherlands



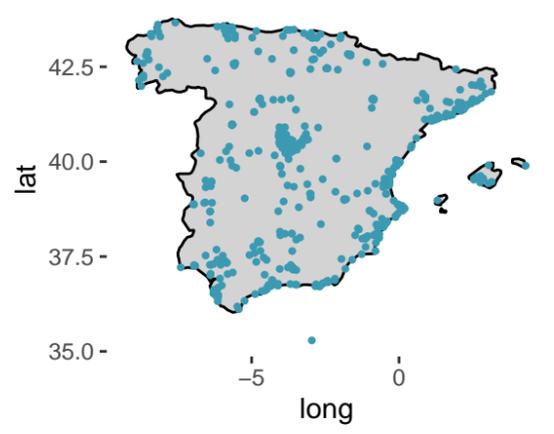
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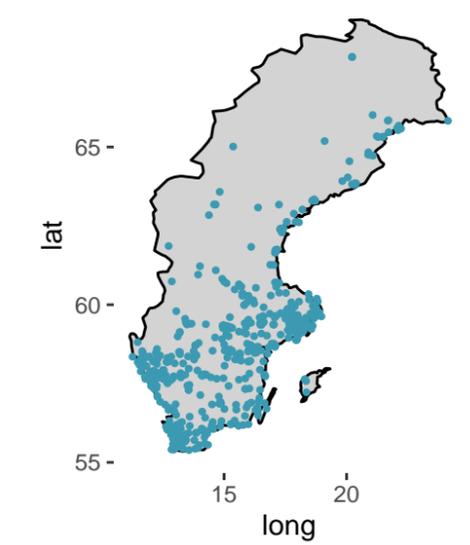
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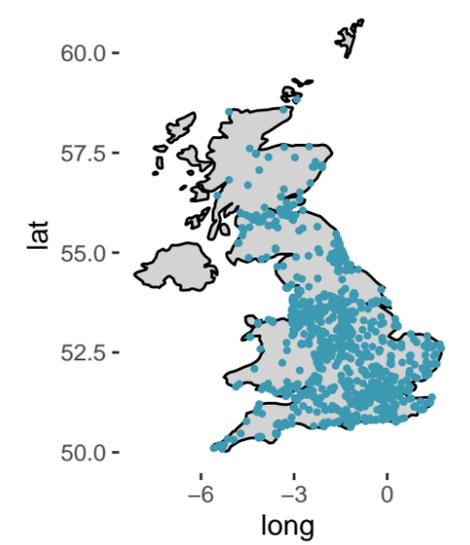
Spain

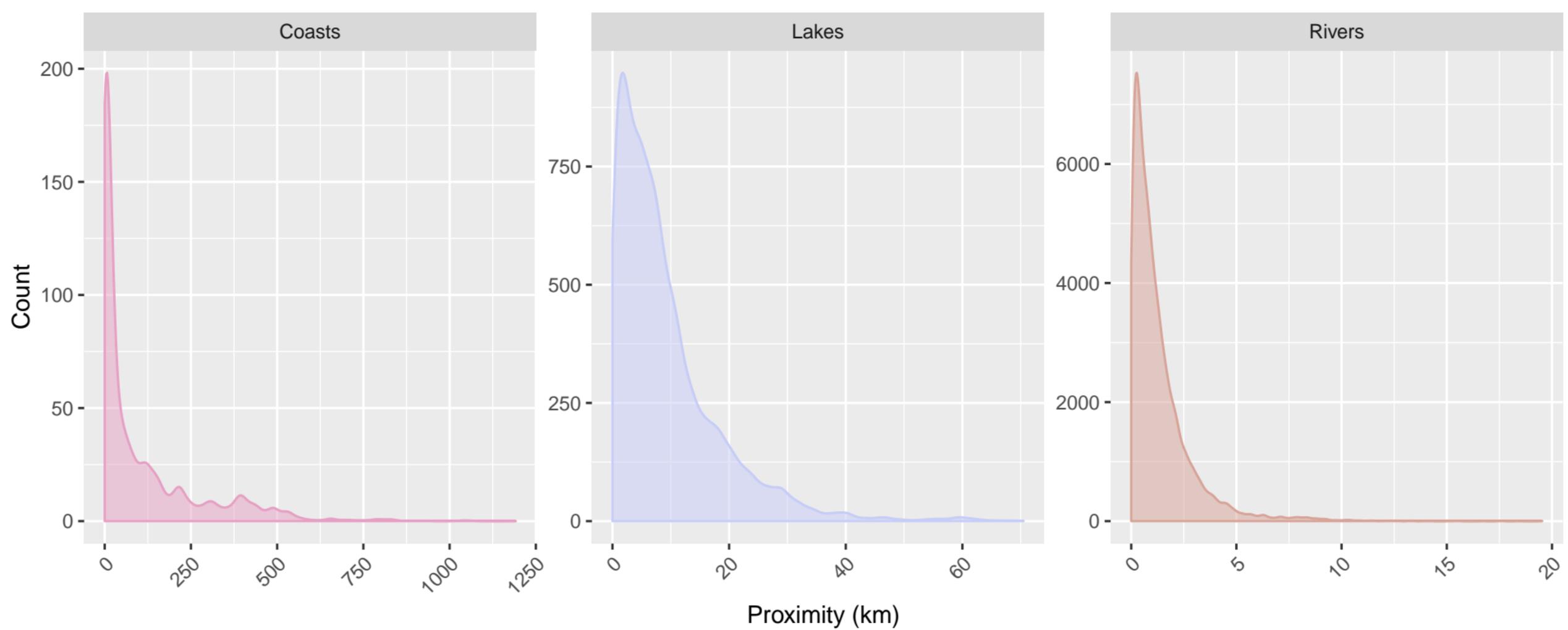


Sweden



United Kingdom





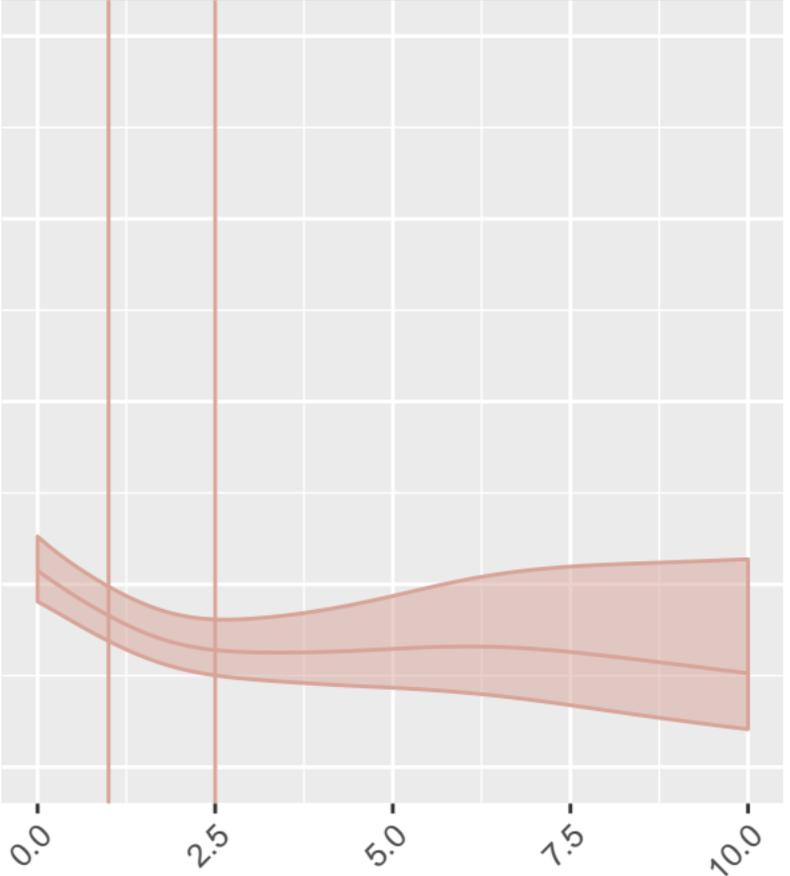
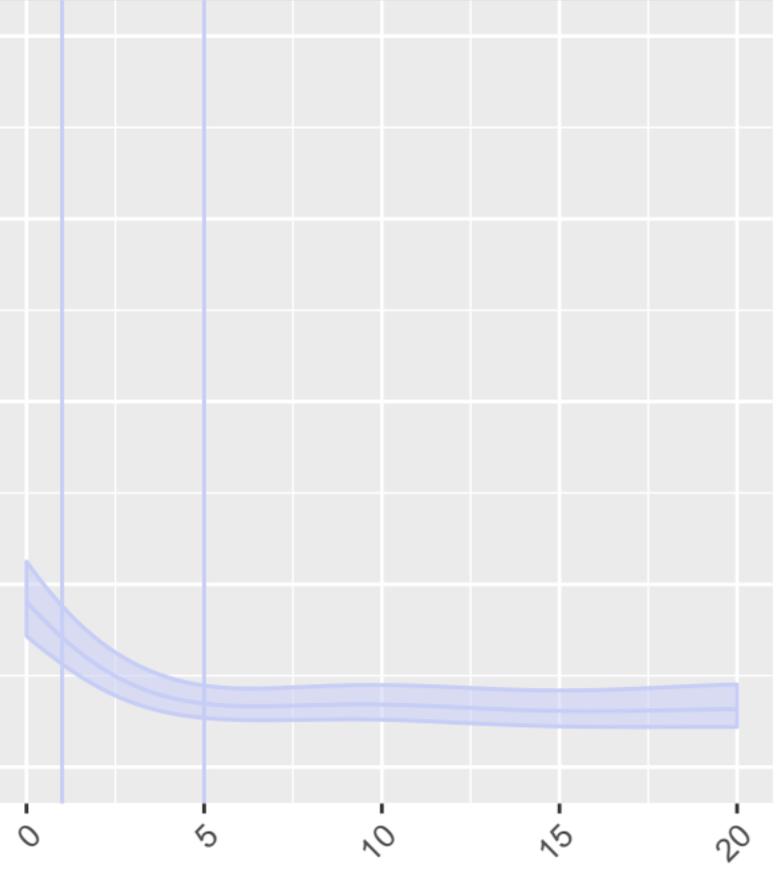
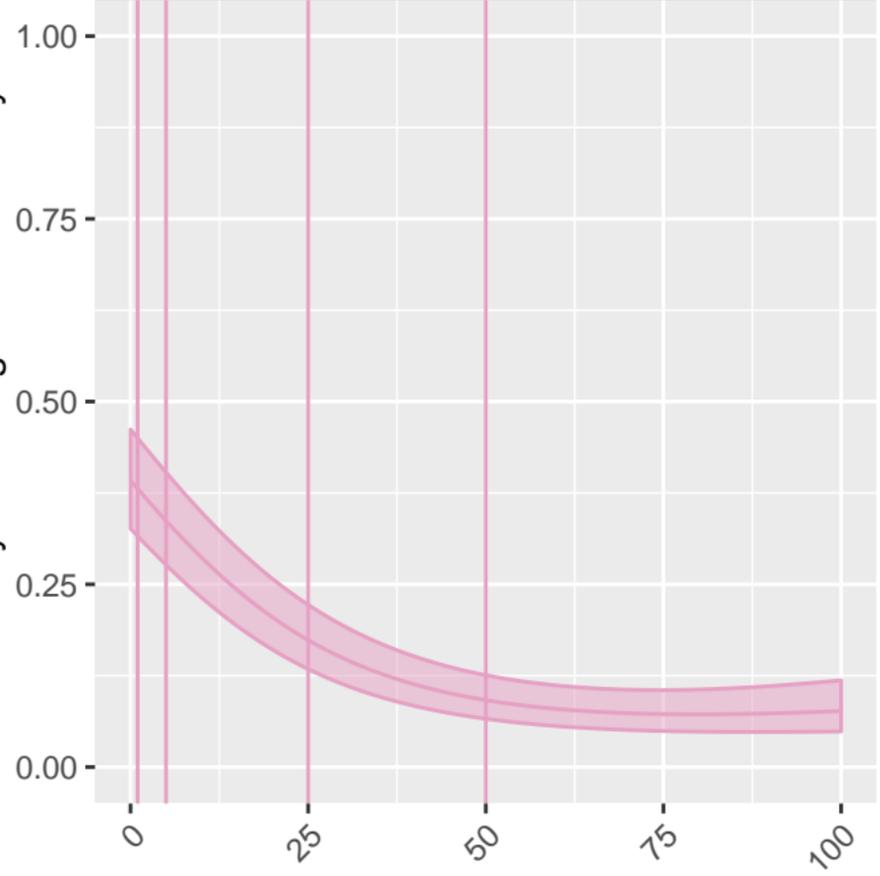
Probability of visiting at least weekly

Coasts

Lakes

Rivers

Residential proximity (km)



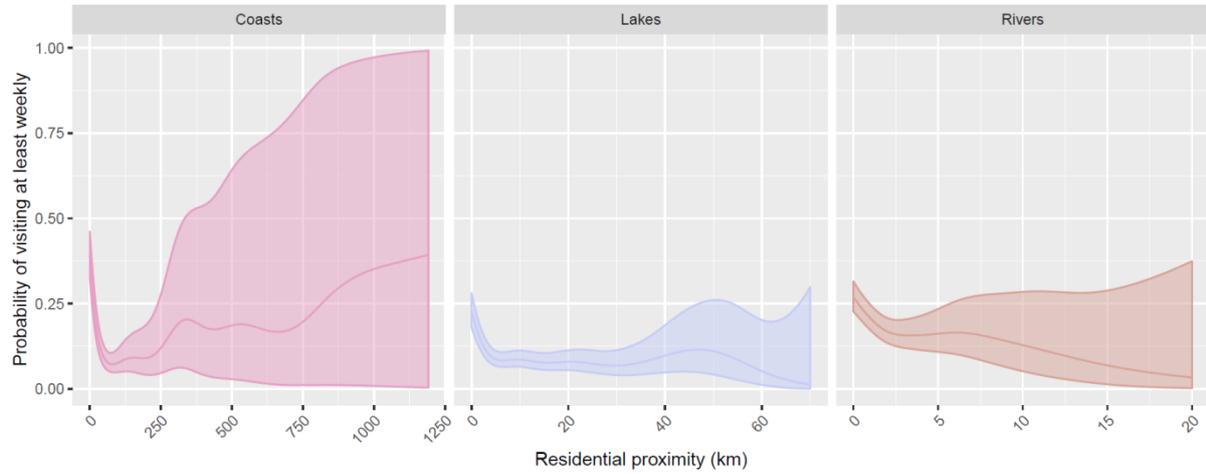
Supplementary Materials

Supplementary Table 1. 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-level variance	0.35	
Distance variance	0.00	
Lakes		
Distance	7.01	***134.75
Tjur's R ²	0.04	
Country-level variance	0.23	
Distance variance	0.00	
Rivers		
Distance	4.24	***43.66
Tjur's R ²	0.04	
Country-level variance	0.16	
Distance variance	0.02	

N.B Models apply survey weights and control for a random intercept of country and random slopes of residential distance to each environment. Tjur's R² 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 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.



Supplementary Figure 2. Country-level distance-decay effects derived from the random effect components of our generalised additive mixed models.

