Manuscript Details

Manuscript number	UFUG_2018_555_R1
Title	The effects of meteorological conditions and daylight on nature-based recreational physical activity in England
Article type	Research Paper

Abstract

Meteorological conditions affect people's outdoor physical activity. However, we know of no previous research into how these conditions affect physical activity in different types of natural environments – key settings for recreational physical activity, but ones which are particularly impacted by meteorological conditions. Using responses from four waves (2009-2013) of a survey of leisure visits to natural environments in England (n=47613), visit dates and locations were ascribed estimates of energy expenditure (MET-minutes) and assigned meteorological data. We explored relationships between MET-minutes in natural environments (in particular, parks, woodlands, inland waters, and coasts) and the hourly maxima of air temperature and wind speed, levels of rainfall, and daylight hours using generalised additive models. Overall, we found a positive linear relationship between MET-minutes and air temperature; a negative linear relationship with wind speed; no relation with categories of rainfall; and a positive, but non-linear relationship with daylight hours. These same trends were observed for park-based energy expenditure, but differed for visits to other natural environments: only daylight hours were related to energy expenditure at woodlands; wind speed and daylight hours affected energy expenditure at inland waters; and only air temperature was related to energy expenditure at coasts. Natural environments support recreational physical activity under a range of meteorological conditions. However, distinct conditions do differentially affect the amount of energy expenditure accumulated in a range of natural environments. The findings have implications for reducing commonly-reported meteorological barriers to both recreational physical activity and visiting natural environments for leisure, and begin to indicate how recreational energy expenditure in these environments could be affected by future climate change.

Keywords	weather; leisure; energy expenditure; green space; spline

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24th April 2019

Dear Matilda van den Bosch and Cecil Konijnendijk

Re. Manuscript UFUG_2018_555: “The effects of meteorological conditions and daylight on nature-based recreational physical activity in England.”

Thank you for the opportunity to resubmit a revised version of our manuscript for consideration for publication in Urban Forestry and Urban Greening. We are extremely grateful to yourselves and the two reviewers for their careful consideration of the original submission and their constructive and encouraging comments. We have carefully and thoroughly revised the manuscript in line with the suggestions and our responses are provided below in blue typeface.

We hope you agree that our revisions are thorough and compelling and that our efforts have significantly improved the quality and clarity of the article and heightened its potential impact. We look forward to hearing from you in due course pending the reviewers' consideration of this revised manuscript.

Yours sincerely,

The authors

Reviewer 1:

Thank you for the opportunity to review this interesting paper. The subject matter and dataset are novel and very important. The figures are impressive and clear. I had minor comments about the discussion of variables, implications, and clarity of methods, but otherwise enjoyed learning about this line of research.

We thank the reviewer for their positive appraisal of our paper.

Page 8, section 3.3: Why were interaction terms between meteorology and natural environment introduced?

These were added to investigate whether MET-minutes in natural environments were better explained when allowing the impact of weather conditions to differ across environment type (in line with the analysis strategy proposed in section 2.6). To make this clearer we have now added this explanation to the analysis section (2.6):

> *"The adjusted GAM as in (b) but with additional interaction terms between environment type and each meteorological variable. The sample size here was smaller due to the focus on a subset of four (of 16) environments (n=21767).* ***This allowed us to detect whether MET-minutes expended in natural environments were better explained when the impacts of meteorological conditions were allowed to vary with environment type.****"*

And referred back to this at the start of section 3.3:

> *"Adding interaction terms* ***(model c), section 2.6)****…"*

Page 11, section 4.1: The authors mention "targeted strategies" to overcome barriers to physical activity. It might benefit this article to mention and discuss some such relevant strategies.

In line with Reviewer 2's first comment, a new section on implications that devotes a paragraph to expanding on these targeted strategies has now been introduced. Please see our response to Reviewer 2's first comment to see how this has been addressed.

Page 7, section 3.2: Where are the results, adjusting for confounders, reported? Do paragraphs 1 and 2 discuss different analyses? Both reference Fig 3e. for significant associations between temp and MET-minutes.

We thank the reviewer for highlighting this and we agree it can be made clearer. The first paragraph refers to a minimally-adjusted model (model (a); unadjusted for covariates) which we have now further described and linked back to the methods section (2.6). The second paragraph refers to a model additionally adjusted for confounders (model (b); also now explicitly explained in the methods and referred to here).

We realise that reference to the same figure may be confusing for the reader, but this is because we deem it useful to compare the regression lines for both the minimally-adjusted model and the model adjusted for confounders on the same graph. To make this easier to understand, we have now added a legend to this graph which also addresses the reviewer's later comment on Figure 3.

Page 8 "Meterological conditions" paragraph: Many of these include 0 in the 95% confidence interveal – only daylight hours reports significant positive beta coefficients, so this claim is stretched. Also, it appears gender and "further afield" visits are stronger and more consistent predictors than climatic factors.

We agree with the reviewer that we were being overly general with our summation here. We have now clarified that where significant, meteorological conditions are among the strongest predictors across all four stratified models. We have amended the text to reflect this. In line with the reviewer's comment, we additionally now state that both sex and "further afield" visits appear to be the strongest and most consistent predictors of MET-minutes across these stratified models:

> *"Where statistically significant, meteorological conditions and daylight hours represented some of the strongest predictors of MET-minutes across all environments (Fig. 4; standardised coefficients are presented in this figure), although sex and visits "further afield" were generally the strongest and most consistent predictors across these stratified models."*

Have the MENE survey data been used in other peer reviewed publications? Do these discuss the generalizability and potential bias of data? If so, it would be good to include these citations and discuss their implications in Section 2.1

We thank the reviewer for their suggestion to add further literature. In addition to the brief discussion regarding how the sampling strategy minimises biases in section 2.1, we now additionally cite a number of previously peer-reviewed publications which demonstrate the power of this data for making strong inferences at the national level – especially those concerning physical activity. We hope this assures the reviewer of the generalisability of these data:

> *"Data were taken from the repeat cross-sectional Monitor of Engagement with the Natural Environment (MENE) survey. This survey has been used previously to study rates of energy expended in different natural environments (Elliott et al., 2015) and the economic implications this has for public health (White et al., 2016), as well for a variety of further analyses concerning access or contact with natural environments in relation to health outcomes (White et al., 2013, 2014b; M. P. White et al., 2017; White et al., 2018), visit frequencies (Boyd et al., 2018; Elliott et al., 2018) , and cultural ecosystem services (Tratalos et al., 2016)."*

In figure 3 it would be helpful to have a legend that specifies color of line and what type of model it attempts to fit data to.

Following the reviewer's suggestions, a legend has now been added to Figure 3 explaining that the orange line represents the minimally adjusted model and the blue line represents the model adjusted for potential confounds. In addition to this, we have clarified the figure caption to refer back to the analysis strategy section of the text where these models are described. Hopefully this clarifies the figure for the reader.

Formatting of Table 1 does not look standard and is hard to read, for instance, why include Asterix to the left of F-test values? Why include R2 above rather than below results. Please revise formatting to make it more intuitive and standard.

In Tables 1 and 2 in the main manuscript we have now included R^2 statistics at the bottom of the table, transferred the F-test at the top of the maximally-adjusted column in Table 1 to the table caption, and left-aligned all other statistics with asterisks to the right of the numbers following these suggestions. We are mindful of journal guidelines and are happy to revise further at the copyediting stage should this article eventually be accepted.

Why was the maximum chosen for air temperature, daylight, and rainfall? These meteorological factors can be highly variable throughout the day, especially daylight and rainfall. Wouldn't average, or even median, values for these conditions better represent the conditions throughout the entire day?

The reviewer raises an important point about the selection of daily maxima for air temperature and rainfall (daylight hours did not vary over the day) as the operationalisations of our meteorological variables. Given that the MENE does not supply time of visit we were unable to be more precise and felt the best approach would be to adopt that taken in earlier research which focused on the maxima during daylight hours rather than a daily average (e.g. see section 2.2; Wolff & Fitzhugh 2011). Therefore, the selection of daily maxima makes our estimates more comparable with previous research.

Furthermore, the CORDEX temperature projections (used in the appendix) calculate daily averaged temperature using 24 hour temperature measurements. This average can mask diurnal temperature variability—particularly in late winter and early spring when cold nights can be followed by comparatively warm days.

A measure of central tendency can therefore supresses the diurnal variation found across the range of daily temperatures (or indeed rainfall) in different seasons. In other words, an average would roughly approximate seasonality and mask whether a winter day was particularly warm or dry, or a summer day particularly cold or wet (season was already excluded a priori in these analyses due its collinearity with other meteorological/daylight variables). We have thus added the following to the manuscript in section 2.3:

> *"Maxima, as opposed to measures of central tendency, were also preferred so as to not mask diurnal variations found across the ranges of daily temperatures, rainfall rates, or wind speeds in different seasons."*

Reference used in response:

Wolff, D., Fitzhugh, E.C., 2011. The Relationships between Weather-Related Factors and Daily Outdoor Physical Activity Counts on an Urban Greenway. International Journal of Environmental Research and Public Health 8, 579–589).

Using the heat index, or some other measure that assesses apparent (felt) temperature would be more appropriate than maximum unadjusted air temperature.

We agree with the reviewer that the heat index or wind chill factor may have been a more valid measure of temperature than daily maximum air temperature, however we were unable to derive this in the current study. In section 4.2 describing the limitations of this study, we state that humidity data was not attainable using the numerical weather prediction modelled data we were using in this present study, and such humidity data are needed for calculating the heat index. In so doing, we advocate the use of 'felt temperature' metrics in future research. We hope that the discussion of the heat index that is already present in the limitations section is sufficient in justifying why it could not be used here.

More explanation is needed on why the analytical framework used here was chosen. Why start with GAM models, for example?

We decided to start with GAM models because there are several possible limitations with fitting polynomial terms to meteorological data when explaining health outcomes, as has been carried out previously. This is because fitting, for example, a squared (quadratic) term to a meteorological condition assumes: (a) that there is only one change of direction in the mean, and more importantly, (b) that the slope of the curve is of an identical gradient both before and after the apex of the curve. Both assumptions are potentially problematic as has been demonstrated in temperature-related mortality research for example (Gasparrini et al., 2017).

The benefit of using a generalised additive model (especially with the thin-plate regression spline bases we employ) is that it makes neither of these assumptions about the data. Instead, it calculates different regression equations (that may be linear, quadratic, cubic, quartic etc.) for different parts of the exposure-response relationship. These different parts are traditionally defined by "knots" i.e. cut-points in the predictor variables where the estimation of a new regression equation for a new part of the relationship begins. In actual fact, the thin-plate regression splines we use do not define "knots" in the conventional sense and instead use a truncated eigen-decomposition to achieve the effect of reducing the number of regression equations needed to a minimum.

Therefore, the generalised additive model allows a flexible, smooth, exposure-response relationship to be estimated and is appropriate when the research is primarily exploratory and makes few presuppositions about the direction of an exposure-response relationship.

We advocate a shift towards such analytical methods, but only in similarly exploratory research; hypothesising the shape of a relationship in research where the exposure-response relationship is more established is still necessary.

Adding all the above information to the manuscript may be verbose, but in response to the reviewer's comments, we have attempted to expand our explanation of our use of GAMs in our revised manuscript to incorporate some of this information including citing previous research which did describe relationships between meteorological variables and physical activity outcomes with polynomial terms, in order to justify why a generalised additive model may be more beneficial in the present study:

> "A generalised additive model (GAM) predicting MET-minutes from meteorological conditions and daylight hours across all environments. **This model allowed flexible estimation of the shape of these relationships by introducing smoothed terms and therefore does not describe the relationship using degrees of polynomial as has been the case with similar research previously (Chan et al., 2006; Feinglass et al., 2011; Wolff and Fitzhugh, 2011)**. Thin-plate regression splines were chosen for modelling air temperature, wind speed, and daylight hours to avoid arbitrary placement of knots (expected points at which the direction of trend changes), and maximum likelihood parameter estimation was chosen as it has been shown in simulations to avoid occasional under-smoothing (which could affect significance values) (Scheipl et al., 2008)."

Reference used in response:

Gasparrini et al., 2017. Projections of temperature-related excess mortality under climate change scenarios. The Lancet Planetary Health 1, e360–e367).

Atmospheric conditions are highly related to one another, and they also might influence or alter natural environments. How were multicollinearity and spatial dependence dealt with in this research? I did not see any discussion regarding either of them.

The reviewer makes another good point here that the team discussed extensively prior to the original submission. In section 3.2, we provide evidence that concurvity (the equivalent of multicollinearity, but for generalised additive models) did not exist in these models.

We do however accept that we did not previously give any evidence of the presence or absence of multicollinearity between meteorological/daylight variables in our stratified models. In our revision, we therefore ran variance inflation factor (VIF) tests on each of the four stratified models which revealed no substantive multicollinearity between any meteorological/daylight variable for any stratified model (which is perhaps not surprising given that, for example, coastal areas in England could often simultaneously experience both high temperatures and high wind speeds).

There was some indication of multicollinearity between work status and age group (VIF=3.57 to 4.72 for work status depending on model). It is likely that age and work status are correlated of course (older people are more likely to be retired), but we also note that inflation of the variance inflation factor is likely among variables which have 3 or more categories (Fox & Monette, 1992), so such an estimate does not concern us greatly.

We have added details of these variance inflation factor estimates to the caption of Table S6 and directed the reader towards these in the main article under section 3.3 (note that variance inflation factors are identical for non-transformed and log-transformed specifications of the models).

Reference used in response:

Fox, J., Monette, G., 1992. Generalized Collinearity Diagnostics. Journal of the American Statistical Association 87, 178–183

The authors briefly touched on the management implications or intervention strategies that might result from this research, most notably in the face of a changing climate. But no specific discussion was offered on what those implications or interventions might be, or how this research could inform them. The authors might consider doing so.

Reviewer 2 makes a similar point so a dedicated implications section (4.2) has now been added to the discussion to facilitate this. Please see our response to Reviewer 2's first comment on how this has been addressed.

What is the abstract and references in the supplementary materials pertaining to?

These pertain to additional analyses that attempted to predict the volume of recreational physical activity that might occur in different natural environments in England in the future under two climate change emissions scenarios. It is referred to in the last paragraph of section 4.2 of the main manuscript.

In line with the suggestion of Reviewer 2 that this supplement may not receive the attention it deserves, this section has now been transferred from the online-only supplementary materials to an appendix of the main manuscript, so hopefully this also clarifies the nature of this supplement for this reviewer as well.

For Table 2 – were the visits log transformed her? This is what you suggest above and it's unclear what variables were transformed for what analyses.

In section 2.2 we highlighted that MET-minutes were log-normally distributed and that non-transformed coefficients are presented in the main manuscript but log-transformed estimates are additionally presented in supplementary materials. However, it is perhaps clearer for this detail to be present in the analysis strategy section so the reader is aware that untransformed coefficients are to be presented throughout the main manuscript. We have now transferred this detail from section 2.2 to section 2.6:

> *"MET-minutes accumulated on visits were log-normally distributed, but to ease interpretation of results, untransformed coefficients are presented throughout the main manuscript (models with log-transformed MET-minutes are presented in supplementary materials, Tables S5 and S6)."*

Reviewer 2

This study describes the association between weather conditions and use of nature based recreational physical activity. The authors use a rich dataset with MET-minutes in natural environments and the hourly weather data and analyse this using generalised additive models. The main conclusion is that energy expenditure is related to certain weather conditions, and that this relationship differs by type natural environments. The study seems to be well executed and the paper is well written, the dataset in interesting. Although I agree with the authors that the research is interesting, I am curious what the implications of this research could be, considering that weather conditions can't be changed. Also, I am not so sure how the outdoor environment could be adapted so that weather conditions have less effect on physical activity (apart from trees providing shade/cooling of an area). The planting of trees to shield from wind might also prevent people from using such an area because of fears of falling branches. I guess my main concern is that I don't fully understand the rationale of the study. Could the authors think of another argument to strengthen the rationale of the paper? I feel that especially the introduction needs a better explanation of the rationale of this study.

We thank the reviewer for their positive reactions to the quality of the research and understand their query regarding the rationale. Notwithstanding a considerable body of earlier published work in this area suggesting it is of interest to a broader audience (section 1 of the main manuscript) we would argue that the rationale for the study can be summarised into its contributions to the literature and to public health in the following ways:

a) Previous literature has not examined how weather conditions might differentially affect physical activity in different types of natural environment; typically described as supportive environments for physical activity attainment (this could be considered the key contribution to the literature).
b) Knowledge of what conditions inhibit or promote more physical activity in certain environments could aid the redesign of those environments if the aim is to encourage more physical activity.
c) Knowledge of what conditions inhibit or promote more physical activity in certain environments could aid so-called "green prescriptions" (one form of social prescribing).
d) The planet is likely to experience substantial variability and extremes in weather patterns if climate warming continues on its current course; knowledge of how 'resilient' (or not) particular environments are to weather patterns affecting their supportiveness for physical activity might help direct future financial resources to their protection and enhancement.

We hope that point (a) is already covered in the manuscript.

However, regarding point (b), we realise the reviewer raises the issue of a limited number of ways in which the environment could be adapted. It is important to realise that often it is not the weather condition itself that is likely to inhibit/facilitate physical activity, but the effect it has on the environment the person is visiting. For example, windy conditions may not be off-putting per se, but may be if the wind causes branches to fall from trees, as the reviewer points out. Shorter daylight hours (a significant effect across parks, woodlands, and inland waters in this study) again may not be off-putting per se, but could mean such areas are perceived as unsafe for physical activity in the dark and therefore, appropriate lighting could be installed to mitigate this. In a similar way, freezing temperatures may discourage physical activity but perhaps not so much if areas are gritted. While rainfall did not emerge as a significant predictor in this study, again, its environmental effects could be mitigated to support physical activity, if, for example, better drainage at an environment (e.g. through more permeable surfaces) is realised.

We contend that there are therefore a number of possible design implications and in response to the reviewer's comments have now made these more explicit in the introduction:

> *"Highlighting how physical activity is inhibited by certain meteorological conditions in different environments could also inform evidence-based landscape design (Ward Thompson, 2013). For example, if shorter daylight hours or more rainfall inhibited park-*

> *based physical activity, then this invites the suggestion that better lighting, shelter, or drainage may facilitate greater physically active use of such spaces (though individual site considerations and public perceptions of such changes would of course still apply)."*

…as well as in a new dedicated implications section (4.2):

> *"Shorter daylight hours (which this study reveals can significantly inhibit physical activity at parks, woodlands, and inland waters) could imply that better lighting in such areas could support more physically active use of these spaces, and in turn potentially impact how safe these environments are perceived to be for physical activity (Pitt, 2019)."*

We do however recognise that many of the design implications may render a natural environment less "natural" which may not be a desirable characteristic for many people. As with any landscape planning project, such design considerations would have to be weighed up against public perceptions of the value of a particular site and its existing features, so we refrain from making definitive recommendations (indeed this is not the aim of this paper), instead favouring possible general solutions which could render an environment more or less supportive of physical activity in the face of differing weather conditions, and recognising that in specific cases, these may not be feasible or realistic. We have added such caveats to the implications section as well:

> *"Nonetheless, promotion of physical activity in a given natural environment might not always be a priority in its redesign, and such changes should always be considered in the context of an individual site and community (e.g. potential disturbances to wildlife or local (human) residents)."*

In contrast to point (b), point (c) refers not to environmental strategies but to individual strategies that can help someone adjust to the potentially inhibitive effects of adverse weather. Previous research suggests adverse weather as a barrier to visiting natural environments especially for the least active (Boyd et al., 2018; Salmon et al., 2003), but promotional efforts often are nonetheless tailored to people who are more experienced with outdoor recreation (Elliott, et al., 2016).

Even simple persuasive strategies to mitigate weather-related barriers may be useful for such groups (e.g. how to access appropriate footwear or clothing, how to avoid slipping, appropriate sun protection / protection from the cold etc.). These may seem like simple strategies with direct instructions, but are nonetheless sometimes what is required in order to overcome barriers to physical activity, as has been demonstrated with much research in physical activity behaviour change (Williams, & French, 2011). Furthermore, these kinds of promotional strategies are often more effective than environmental changes alone (Hunter et al., 2015). Again, in response to the reviewer's comments, more detail on this has now been added to the introduction:

> *"Knowing this could help address widely-reported meteorological barriers to physical activity amongst the least active (Salmon et al., 2003) and to visiting natural environments more generally (Boyd et*

> *al., 2018), and thus support efforts to promote health-enhancing physical activity in these settings* ***(Elliott et al., 2016; Hunter et al., 2015; National Institute for Health and Care Excellence, 2008).****"*

…and implications section:

> *"Previous research has suggested that strategies to encourage physically active use of the natural environment are typically aimed at more active individuals and could be enhanced with simple persuasive behavioural techniques (Elliott et al., 2016). For example, short instructions, shown to be effective at promoting physical activity more generally (Williams and French, 2011), could be introduced into these promotional efforts that target ways in which an individual might counter the inhibitive impact of meteorological conditions on outdoor physical activity (e.g. how to access appropriate clothing, how to avoid slips and falls in wet weather, or how to mitigate the potentially dissuasive effects of extreme temperatures etc.)."*

Regarding point (d), we also recognise that this reviewer comments below that the supplement concerning climatic change perhaps does not get the attention it deserves. Thus, in combination with the suggestion to strengthen the paper's rationale in the introduction, we have transferred this supplement to an appendix (see our response below to this issue). As with the other points raised in this response, more detail has now been added to the introduction:

> *"Furthermore, in the face of changing climate, weather patterns will alter (Meehl et al., 2000). By indicating which natural environment types are less affected by meteorological conditions in terms of supporting physical activity, we can begin to understand how different environments could be viewed, and invested in, as sustainable public health resources in the future."*

…and implications section:

> *"Lastly, the present study could be extended to explore volumes of physical activity that could be supported by a range of natural environments under different climate change scenarios (discussed in Appendix A). Previous research has identified that atmospheric conditions alter preferences for natural environments (Hipp and Ogunseitan, 2011; White et al., 2014a) and could prompt increased participation in outdoor recreational physical activity as a result of climate change (Obradovich and Fowler, 2017), but currently neither how much per-person energy is expended, nor how this might be apportioned across different environments under climate change, has been explored. Such research could explore a range of plausible climate scenarios (Obradovich and Fowler, 2017), account for demographic changes (Perch-Nielsen et al., 2008), control for cumulative effects of climate change on meteorological conditions and environment (e.g. sea level rise, droughts), and use international data*

on leisure visits to natural environments (e.g. Grellier et al., 2017) to gain such an understanding."

References used in response:

Boyd, F., White, M.P., Bell, S.L., Burt, J., 2018. Who doesn't visit natural environments for recreation and why: A population representative analysis of spatial, individual and temporal factors among adults in England. Landscape and Urban Planning 175, 102–113. https://doi.org/10.1016/j.landurbplan.2018.03.016

Salmon, J., Owen, N., Crawford, D., Bauman, A., Sallis, J.F., 2003. Physical activity and sedentary behavior: A population-based study of barriers, enjoyment, and preference. Health Psychology 22, 178–188. https://doi.org/10.1037/0278-6133.22.2.178

Elliott, L.R., White, M.P., Taylor, A.H., Abraham, C., 2016. How do brochures encourage walking in natural environments in the UK? A content analysis. Health Promotion International 33, 299–310. https://doi.org/10.1093/heapro/daw083

Williams, S.L., French, D.P., 2011. What are the most effective intervention techniques for changing physical activity self-efficacy and physical activity behaviour--and are they the same? Health Education Research 26, 308–322. https://doi.org/10.1093/her/cyr005

Hunter, R.F., Christian, H., Veitch, J., Astell-Burt, T., Hipp, J.A., Schipperijn, J., 2015. The impact of interventions to promote physical activity in urban green space: A systematic review and recommendations for future research. Social Science & Medicine 124, 246–256. https://doi.org/10.1016/j.socscimed.2014.11.051

Abstract – is there a simpler way of stating that there is a quartic relationship between MET-minutes and daylight hours? It might not be clear to everyone this means.

We agree with the reviewer that this may be less clear and have changed the abstract to read "positive, non-linear relationship" as opposed to "quartic".

Hypothesis/Research question: physical activity in natural environments may be sensitive to meteorological conditions, but it's unclear how. Could the authors specify what the hypotheses were for the different environments?

We agree with the reviewer and have added the following to the end of the introduction section regarding our initial hypotheses:

"Consistent with previous research, we hypothesised that energy expenditure on recreational visits to natural environments would demonstrate: (a) quadratic relationships with increasing air temperature (e.g Wolff and Fitzhugh, 2011), (b) quadratic relationships with increasing wind speeds (e.g Chan et al., 2006), (c) positive linear relationships with increasing daylight hours (e.g. Wu et al., 2017b), and (d) negative linear relationships with increasing rainfall (e.g. Feinglass et al., 2011). However, we were agnostic about how the strength or significance of these relationships might vary with environment type as comparable previous research has only focused

> *on single natural environments in North American climates (Patrolia et al., 2017; Wolff and Fitzhugh, 2011) or has not concentrated on the locations of physical activity under different meteorological conditions (Chan et al., 2006; Feinglass et al., 2011; Klenk et al., 2012; Tucker and Gilliland, 2007; Wu et al., 2017b, 2017a), which is also why we decided to initially apply additive models rather than constrain the data using quadratic terms (section 2.6).”*

We hope the reviewer understands our desire to be agnostic about how these relationships differ with environment type as we feel there is insufficient evidence to assert strong hypotheses about this from the outset.

Furthermore, we now state at the start of section 4.1 that our hypotheses were, broadly speaking, disconfirmed (i.e. we did not find quadratic relationships for air temperature nor wind speed; the relationship with daylight hours was positive but not linear, and there were no relationships with categories of rainfall):

> *“Our hypotheses concerning the shape of relationships between meteorological conditions or daylight hours and physical activity for all natural environments collectively were mostly disconfirmed.”*

Was there any information about the amount of sunshine during the sampled days?

The data from the Met Office’s numerical weather prediction models do include data on estimated sunlight hours i.e. number of hours in daylight when the sun is not obscured by cloud. We have now included a graph of sunshine hours across the sampling period as a supplementary figure in the online supplementary materials (Figure S1) and referred to it in the caption of Figure 3 in the main manuscript.

However, sunlight hours are closely related to daylight hours (as longer days are summer days and thus also often characterised by more sunlight hours; as evidenced by comparing the new supplementary figure with Figure 3d). We therefore decided it was inappropriate to model both in these analyses (see Reviewer 1’s comment on multicollinearity). To be consistent with previous research on this topic we opted to explore the influence of daylight hours on physical activity as opposed to sunlight hours.

Quite some observations were excluded from the analyses, as the authors report that MET minutes could not be reliably calculated. Could this have affected the results? Please comment on that a bit more.

We agree with the reviewer that the large number of observations excluded from analysis could have affected the results. As the largest exclusion concerns people reporting multiple visit activities, we judge that this may have affected the results the most. Of course we can only speculate as to how people reporting multiple visit activities may have proportioned their time engaging in these activities.

However, a look at the data prior to exclusions reveals that the most common combinations were walking (without a dog) in combination with either eating or drinking (MET rate 1.75), playing with children (3.58), or visiting an attraction (3.50). Considering that two of these three activities are ascribed almost identical MET rates to walking itself (3.5), we do not judge that this would have unduly affected our results. Averages of meteorological conditions also appear to be similar across excluded and included visits. However, the mean duration of a visit that was excluded from analysis was substantially longer (224 minutes) than those which remained in analysis (127 minutes), potentially reflecting engagement with multiple activities, so this may mean that we are underestimating energy expenditure across all natural environments.

Though the data are not shown, in response to the reviewer's comments, we have added this new information to the limitations section:

> "Secondly, MET-minutes could not be calculated for a large number of participants who reported multiple visit activities as we could not ascertain the relative time spent engaging in these different activities. The most common two-way activity combinations were walking without a dog in combination with either eating or drinking, playing with children, or visiting an attraction; the latter two activities are ascribed almost identical MET rates to walking so we do not expect this to have affected our estimates unduly. Included and excluded visits also did not appear to be substantially different in terms of meteorological conditions or daylight hours. However, visits excluded from analyses were substantially longer in duration (M=224 minutes) than those included (M=127), potentially reflecting the fact that these visits included multiple activities, so our results could represent underestimations of actual energy expenditure."

Was there information about dog ownership? Might have been good to adjust the analyses for dog ownership. Also, the authors talk about dog ownership a few times in the discussion, and one might wonder why this has not been done in the current study. The lack of these data is not discussed as a potential limitation.

The reviewer is right to raise dog ownership as a potential oversight considering the literature we evidence that it might buffer against any negative impact of adverse weather on physical activity. The MENE dataset does contain data on dog ownership so we have now additionally conducted sensitivity analyses which interact each meteorological/daylight variable with dog ownership (yes/no) across our four stratified models. Thus, this builds on the work of, for example, Wu and colleagues (Wu, et al., 2017) and White and colleagues (White, et al., 2018) by demonstrating how dog ownership might buffer against the impact of adverse weather on physical activity in four different types of natural environment.

These analyses are now stated in section 2.6, described in a new results section (3.4), discussed in section 4.1 where we have edited the current discussion of similar relevant papers, and reported in a new supplementary table (S7).

In short, perhaps somewhat surprisingly, these analyses reveal no clear indication that dog ownership moderates relationships between meteorological conditions/daylight and energy expenditure across the four types of natural environment. Longer day length appears to be associated with *less* MET-minutes at woodlands for dog owners but not non-dog-owners and moderate/heavy rain appears to be associated with *more* MET-minutes at woodlands for dog owners but not non-dog-owners (i.e. dog ownership buffers the negative impacts of rain on physical activity – consistent with Wu et al). However, neither of these associations hold for log-transformation of MET-minutes. Furthermore, longer day length is positively associated with energy expenditure at coastal environments for dog owners but not non-dog-owners, but only in the log-transformed model. Thus it is difficult to make definitive conclusions about the moderating effect of dog ownership on the associations between meteorological conditions/daylight and energy expenditure in different natural environments.

References used in response:

Wu, Y.-T., Luben, R., Jones, A., 2017. Dog ownership supports the maintenance of physical activity during poor weather in older English adults: cross-sectional results from the EPIC Norfolk cohort. Journal of Epidemiology and Community Health 71, 905–911. https://doi.org/10.1136/jech-2017-208987

White, M.P., Elliott, L.R., Wheeler, B.W., Fleming, L.E., 2018. Neighbourhood greenspace is related to physical activity in England, but only for dog owners. Landscape and Urban Planning 174, 18–23. https://doi.org/10.1016/j.landurbplan.2018.01.004

I am no expert in these type of statistical techniques, but they seem to be appropriately executed.

We thank the reviewer for their positive appraisal and along with comments from Reviewer 1 we have added some more explanation as to why the initial generalised additive models were conducted to section 2.6.

How was the fit of the GAM with interaction term (environment type*meteorological variable) evaluated? Please add to page 6, section 2.6c/d.

This was evaluated with an analysis of deviance, the results of which can be found in Table S5. In response to this comment, we have now added this point to section 2.6d:

> *"c) The adjusted GAM as in (b) but with additional interaction terms between environment type and each meteorological variable. The sample size here was smaller due to the focus on a subset of four (of 16) environments (n=21767).* ***This allowed us to detect whether MET-minutes expended in natural environments were better explained when the impacts of meteorological conditions were allowed to vary with environment type.***
>
> *d) If, as predicted, (c) significantly improved the fit of the model* ***(as demonstrated by an analysis of deviance)****, the above GAM stratified by environment type. Sample sizes for these models would be further reduced (park=11988, woodland=2947, inland waters=2561, coast=4271)."*

In the final results' paragraph (p. 8-9), Please say that these are standardized coefficients so that the reader knows these estimates are indeed comparable.

The statistics quoted in this paragraph are actually unstandardized coefficients, but we present standardised coefficients in the Figure in order to fairly demonstrate the strength of association between variables which are operationalised continuously (e.g. the meteorological variables) and those which are operationalised categorically (e.g. social grade). In response to this comment, we have however added that standardised coefficients are presented in Figure 4 inside the parentheses referring to this Figure within this paragraph:

> "Meteorological conditions and daylight hours represented some of the strongest predictors of MET-minutes across all environments (Fig. 4; **standardised coefficients are presented in this figure)**"

We have also added more explanation about this in the figure caption:

> *"Standardised coefficients are presented in order to fairly demonstrate the strength of association between variables which are operationalised continuously (e.g. the meteorological variables) and those which are operationalised categorically (e.g. social grade)."*

Figures and tables look very nice – well done.

We thank the reviewer for this positive appraisal. We have slightly reformatted tables in line with suggestions from Reviewer 1. We are aware that these may receive further copyediting by the journal.

Discussion – when comparing results to other research, please explain a bit more about the other study (location/type of environment/climate type), so that the reader understands the context better.

We agree with the reviewer and have revised section 4.1 of the discussion thoroughly to ensure we mention the setting of studies which we cite. Note that a lot of the research cited in this section is not specific to certain types of natural environments so we refrain from mentioning environment types (indeed, one of the main contributions of the present study is the ability to speak about the effects of meteorological conditions/daylight on physical activity in different natural environments).

I appreciate the Supplement with the subsidiary analysis attempted to predict the volume of recreational PA the future under two climate change emissions scenarios. But to be honest I was a bit surprised finding this in the Discussion and Supplement, as it seems like it could be a separate study. Not sure what the considerations were, but I am not sure whether these findings get their full attention when presenting it like this, which is a pity.

We understand the reviewers point. It was originally envisaged that a stronger rationale for this study might be to investigate the current patterns regarding the impact of weather and daylight on energy expenditure in natural environments and then to project the estimates we have observed for present day data into the future using the two temperature scenarios we describe in this supplement.

The temperature data used in the supplement are robust in themselves, and represent the most precise resolution of predicted modelled temperature data currently available. However, a number of limitations and complications to doing this effectively (and more importantly, validly), existed. Firstly, we are only able to examine temperature projections and not how other weather conditions may change under future scenarios.

Secondly, we are unable to detect whether our observed data for the present day, for each case, represent an extreme high, low, or moderate temperature for that time of year; appropriate future projections require knowledge of, for example, the percentile of temperature where that reading falls (according to some arbitrary selection of time period e.g. month, or season). If these data were available, it would permit Monte Carlo simulation, whereby distributions of possible future temperatures could be generated, across which average (or median) values could be drawn which would more robustly estimate potential energy expenditure at that location in the future. As it is, we are only able to use the one temperature estimate per case in our observed data which may or may not be characteristic of that time of year and location. Consequently, we can only multiply coefficients from our present day models by future temperature estimates which leads to confidence intervals that are wider if either the coefficient or the average future temperature for those locations is greater; this is likely not valid.

Thirdly, we collapse projected temperature data for all visits to the four types of natural environment which overlooks regional variation in future temperature change.

Fourthly, the projections presented, while built from models of observed data that control for other demographic and visit-related factors, cannot in themselves control for changes in demography or behaviour that might result under future climate change scenarios. Accounting for demographic changes is possible using other projected demographic data but was deemed too complex for the present study, and as the reviewer suggests, could form the focus of a different paper.

In spite of these limitations, we contend that the supplement helps give the paper a stronger rationale, which is one of the issues raised earlier by the reviewer i.e. despite not being able to ‘change’ the weather, the results can help inform how physical activity behaviour in natural environments might alter with future climate change. It also hopefully provides researchers with an interesting avenue for future research.

As a compromise we have edited this supplement so it is no longer present in online supplementary materials but instead will be included as an appendix which we understand would appear in both the online and print versions of the journal article should it be accepted for publication. We hope this addresses the reviewers concern that it may not get full attention but hope they also understand our reluctance for it to be included in the main manuscript due to its methodological limitations. We are prepared however to take editorial advice on whether this should be included as an appendix or within online supplementary materials.

Highlights

- Meteorological conditions and daylight hours affect recreational physical activity
- Research has not explored how these affect physical activity in different environments
- Park-based physical activity associated with temperature, wind speed, and daylight
- Unique associations for physical activity at woodlands, inland waters, and coasts
- Implications for ‘green prescriptions’ and future climate change are discussed

The effects of meteorological conditions and daylight on nature-based recreational physical activity in England

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Declaration of interest

The authors have no conflicts of interest to disclose.

Abstract

Meteorological conditions affect people's outdoor physical activity. However, we know of no previous research into how these conditions affect physical activity in different types of natural environments – key settings for recreational physical activity, but ones which are particularly impacted by meteorological conditions.

Using responses from four waves (2009-2013) of a survey of leisure visits to natural environments in England (n=47613), visit dates and locations were ascribed estimates of energy expenditure (MET-minutes) and assigned meteorological data. We explored relationships between MET-minutes in natural environments (in particular, parks, woodlands, inland waters, and coasts) and the hourly maxima of air temperature and wind speed, levels of rainfall, and daylight hours using generalised additive models.

Overall, we found a positive linear relationship between MET-minutes and air temperature; a negative linear relationship with wind speed; no relation with categories of rainfall; and a positive, but non-linear relationship with daylight hours. These same trends were observed for park-based energy expenditure, but differed for visits to other natural environments: only daylight hours were related to energy expenditure at woodlands; wind speed and daylight hours affected energy expenditure at inland waters; and only air temperature was related to energy expenditure at coasts.

Natural environments support recreational physical activity under a range of meteorological conditions. However, distinct conditions do differentially affect the amount of energy expenditure accumulated in a range of natural environments. The findings have implications for reducing commonly-reported meteorological barriers to both recreational physical activity and visiting natural environments for leisure, and begin to indicate how recreational energy expenditure in these environments could be affected by future climate change.

Keywords

Weather; leisure; energy expenditure; green space; spline

Highlights

- Meteorological conditions and daylight hours affect recreational physical activity
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1. Introduction

Many adults worldwide do not achieve recommended levels of physical activity (Hallal et al., 2012), potentially undermining physical and mental health (Nocon et al., 2008; R. L. White et al., 2017). However, factors outside of an individual's control, such as meteorological conditions, can affect levels of physical activity (Tucker and Gilliland, 2007). In a US sample, accelerometer-measured physical activity was higher on days with moderate as opposed to cold (<-6°C) or hot (>23°C) temperatures and on dry as opposed to rainy days (Feinglass et al., 2011). Similarly, a Canadian study found clement (vs. inclement) meteorological conditions were associated with an additional 2000 steps per day with mean daily temperatures, total daily rainfall, and maximum wind speeds playing a role (Chan et al., 2006). Seasonal effects such as daylight hours, have also been associated with physical activity. For instance, a study of older English adults found that each quartile of daylight hours was associated with significantly more minutes of daily physical activity than the preceding quartile (Wu et al., 2017b).

Separately, physical environments in which people live and recreate substantially influence physical activity (Bauman et al., 2012; Sallis et al., 2006). In particular, greater availability of natural environments (e.g. parks, woodlands, inland waters, coasts) has been shown to support health-enhancing levels of leisure-time physical activity such as walking and cycling (Elliott et al., 2015; National Institute for Health and Care Excellence, 2008) with considerable implications for health promotion and disease prevention (White et al., 2016). Nevertheless, levels of physical activity in natural environments may be particularly sensitive to meteorological conditions (Wolff and Fitzhugh, 2011). However, we know of no prior research which has disaggregated the relationships between meteorological conditions and different types of natural environment. Parks, woodlands, inland waters, and coasts provide different physical properties and affordances (Ward Thompson, 2013), as well as temperature-regulating properties (Völker et al., 2013), and therefore it cannot be assumed that physical activity in each setting is affected by meteorological conditions in the same way.

Knowing this could help address widely-reported meteorological barriers to physical activity amongst the least active (Salmon et al., 2003) and to visiting natural environments more generally (Boyd et al., 2018), and thus support efforts to promote health-enhancing physical activity in these settings (Elliott et al., 2016; Hunter et al., 2015; National Institute for Health and Care Excellence, 2008). Highlighting how physical activity is inhibited by certain meteorological conditions in different environments could also inform evidence-based landscape design (Ward Thompson, 2013). For example, if shorter daylight hours or more rainfall inhibited park-based physical activity, then this invites the suggestion that better lighting, shelter, or drainage may facilitate greater physically active use of such spaces (though individual site considerations and public perceptions of such changes would of course still apply). Furthermore, in the face of changing climate, weather patterns will alter (Meehl et al., 2000). By indicating which natural environment types are less affected by meteorological conditions in terms of supporting physical activity, we can begin to understand how different environments could be viewed, and invested in, as sustainable public health resources in the future.

This study therefore explored whether meteorological conditions (air temperature, wind speed, and rainfall) and daylight hours were associated with physical activity differently in a range of natural environments. Consistent with previous research, we hypothesised that energy expenditure on recreational visits to natural environments would demonstrate: (a) quadratic relationships with increasing air temperature (e.g Wolff and Fitzhugh, 2011), (b) quadratic relationships with increasing wind speeds (e.g Chan et al., 2006), (c) positive linear relationships with increasing daylight hours (e.g. Wu et al., 2017b), and (d) negative linear relationships with increasing rainfall (e.g. Feinglass et al., 2011). However, we did not hypothesise about how the strength or significance of these relationships might vary with environment type as comparable previous research has only focused on single natural environments in North American climates (Patrolia et al., 2017; Wolff and Fitzhugh, 2011) and/or has not concentrated on the locations of physical activity under different meteorological conditions (Chan et al., 2006; Feinglass et al., 2011; Klenk et al., 2012; Tucker and Gilliland, 2007; Wu et al., 2017b, 2017a). This is also why we decided to initially apply additive models rather than constrain the data using quadratic terms (section 2.6).

2. Method

2.1 Sample

Data were taken from the repeat cross-sectional Monitor of Engagement with the Natural Environment (MENE) survey. This survey has been used previously to study rates of energy expended in different natural environments (Elliott et al., 2015) and the economic implications this has for public health (White et al., 2016), as well for a variety of further analyses concerning access or contact with natural environments in relation to health outcomes (White et al., 2013, 2014b; M. P. White et al., 2017; White et al., 2018), visit frequencies (Boyd et al., 2018; Elliott et al., 2018), and cultural ecosystem services (Tratalos et al., 2016). The survey forms part of the UK Government's National Statistics and is conducted across the whole of England and throughout the year to reduce potential geographical and seasonal biases. A design sampling frame ensures a high degree of representativeness to the adult population with minimal clustering effects (Natural England, 2017). Participants are interviewed about their leisure visits to natural environments in the previous week using in-home face-to-face interviews with responses recorded using Computer Assisted Personal Interviewing (CAPI). For people who reported making ≥1 visit in the previous week (≈42% of the total sample), a visit is randomly selected by the CAPI software for further questions. Pooling data from the first four waves of MENE (February 2009 to March 2013) produced a total of 62238 randomly-selected visits.

2.2 Physical activity

Our primary outcome was the estimated energy expended on these visits defined as the metabolic equivalent of task (MET) rate of the primary visit activity, multiplied by visit duration (in minutes), to provide "MET-minutes," an internationally used measure of physical activity (Ainsworth et al., 2011). MET-minutes were derived from two questions which concerned the participant's randomly-selected visit: (a) "which of these activities did you undertake?" with a possible list of 20 activities that have previously been ascribed MET rates (Elliott et al., 2015); and, (b) "how long did this visit last altogether - from the time you left to when you returned?" Although this question implies two-way travel time, previous research suggests participants respond as though they only reported time spent in the natural environment (Elliott et al., 2015).

2.3 Meteorological conditions and daylight

Our key predictor variables were three meteorological conditions and daylight hours. In line with previous research, maximum air temperature during daylight hours (°C) and maximum wind speed during daylight hours (m/s) were used as continuous variables (Wolff and Fitzhugh, 2011), and maximum rainfall during daylight hours was categorised into "no rain," "light rain" (>0 to 0.5mm/hour), and "moderate/heavy rain" (>0.5mm/hour) (Feinglass et al., 2011; Met Office, 2007). Maxima, as opposed to measures of central tendency, were also preferred so as to not mask diurnal variations found across the ranges of daily temperatures, rainfall rates, or wind speeds in different seasons. The hourly maxima of air temperature, wind speed, and rainfall are the values for these meteorological conditions on the hour when their maximum occurred on the day of the visit. All three meteorological variables were derived from the Met Office's Numerical Weather Prediction (NWP) model data for the UK (https://www.metoffice.gov.uk/research/modelling-systems/unified-model/weather-forecasting), processed into hourly weather "nowcasts" for each postcode district, and applied to the coordinates of each specific visit location in MENE by selecting the postcode district with the closest centroid. These data used observed data from weather stations and other sources and modelled these meteorological conditions in cases where there were no available direct observations, offering the best estimate of the weather at any given location and time (https://www.metoffice.gov.uk/research/weather/data-assimilation/data-assimilation-methods). Daylight hours were computed using the 'suncalc' R package (Agafonkin and Thieurmel, 2017) by subtracting dawn from dusk (i.e. including civil twilight time).

2.4 Type of natural environment

Along with exact coordinates of the visit location, participants self-reported the general type of natural environment they visited. Participants were asked: "Which of the following list of types of place best describe where you spent your time during this visit?" Four (of 16) key settings were selected based on distinct recreational patterns found in earlier work (Elliott et al., 2018): "a park in a town or city" (hereafter 'park'), "a woodland or forest" (hereafter 'woodland'), "a river, lake, or canal" (hereafter 'inland waters'), and "a beach" or "other coastline" collectively (hereafter 'coast'; White et al., 2013).

2.5 Covariates

Analyses controlled for sex, age, ethnicity, social grade, disability, marital status, work status, number of children in the household, days of sufficient physical activity in the past week, whether the visit was on a weekday or weekend, and whether the visit was "local" (<1 mile from home). These factors have all been found to influence physical activity in natural environments (Elliott et al., 2015). Details on these variables' measurement and implementation in analyses are included in supplementary materials (Table S1).

2.6 Analyses

The following types of visit were excluded as MET-minutes could not be reliably calculated for them: (i) visits where "any other outdoor activity" or "none of these activities" were reported (n=2689); (ii) visits which involved more than one activity (n=11182); (iii) visits without complete meteorological data (n=588); and (iv) visits with duration <1 minute (n=14). This left 47613 visits for analysis (Fig. 1).

We fitted the following models:

a) A generalised additive model (GAM) predicting MET-minutes from meteorological conditions and daylight hours across all environments. This model allowed flexible estimation of the shape of these relationships by introducing smoothed terms and therefore does not describe the relationship using degrees of polynomial as has been the case with similar research previously (Chan et al., 2006; Feinglass et al., 2011; Wolff and Fitzhugh, 2011). Thin-plate regression splines were chosen for modelling air temperature, wind speed, and daylight hours to avoid arbitrary placement of knots (expected points at which the direction of trend changes), and maximum likelihood parameter estimation was chosen as it has been shown in simulations to avoid occasional under-smoothing (which could affect significance values) (Scheipl et al., 2008).
b) An adjusted GAM which additionally controlled for the covariates known to influence MET-minutes.
c) The adjusted GAM as in (b) but with additional interaction terms between environment type and each meteorological variable. The sample size here was smaller due to the focus on a subset of four (of 16) environments (n=21767). This allowed us to detect whether MET-minutes expended in natural environments were better explained when the impacts of meteorological conditions were allowed to vary with environment type.
d) If, as predicted, (c) significantly improved the fit of the model (as demonstrated by an analysis of deviance), the above GAM stratified by environment type. Sample sizes for these models would be further reduced (park=11988, woodland=2947, inland waters=2561, coast=4271).

Analyses were performed in R (R Core Team, 2018) using the 'mgcv' package (Wood, 2018).

MET-minutes accumulated on visits were log-normally distributed, but to ease interpretation of results, untransformed coefficients are presented throughout the main manuscript (models with log-transformed MET-minutes are presented in supplementary materials, Tables S5 and S6). In England, dog ownership has been shown to moderate relationships between greenspace availability and physical activity (White et al., 2018) as well as buffer the impact of adverse weather on physical activity (Wu et al., 2017a). Therefore subsidiary analyses tested whether dog ownership moderated any associations between meteorological conditions or daylight on energy expenditure in the four stratified models outlined in (d) above by introducing interaction terms into the models.

3. Results

3.1 Descriptive statistics

The percentage of respondents making at least one recreational visit to a natural environment varied seasonally (Fig. 2) with 45% of respondents, on average, reporting at least one visit in August versus 29% in December (Table S2). Towards the end of the sampling period, seasonal variation reduces with decreases in visits in April-August 2012 (vs. 2011) and increases in December 2012-February 2013 (vs. 2011-2012).

The mean maximum air temperature on visits was 14°C (SD=6°C), mean maximum wind speed was 6 m/s (SD=2 m/s), mean maximum rainfall was 0.5 mm/hour (SD=1.1 mm/hour) and mean daylight hours were 14 (SD=3) with seasonal variations accounting for much of this variability (Fig. 3a–d). These averages were largely consistent across all four key environments (Table S3). A median of 300 MET-minutes (SD=528) were expended on visits to natural environments, but these median values varied with environment (park=266; woodland=270; inland waters=360; coast=420).

3.2 MET-minutes as a function of meteorological conditions and daylight

In our first model (model a); unadjusted for covariates), we observed significant associations between MET-minutes and smoothed terms for air temperature, wind speed and daylight hours (Table 1). MET-minutes steadily increased with air temperature until ≈23°C, after which the direction of the relationship was less clear (Fig. 3e). MET-minutes declined linearly with increasing wind speed (Fig. 3f). MET-minutes increased with daylight hours with a plateau around 11–13 hours, followed by an increase and further plateau after 15 hours (Fig. 3h). There were no significant associations between the categories of rainfall and MET-minutes in the untransformed model, but the model in which MET-minutes were log-transformed (Table S5) suggested that visits taken on days of moderate/heavy rain were associated with fewer MET-minutes than days of no rain (b=-0.03, 95% CI -0.05, -0.01). Concurvity (similar to multicollinearity but for smoothed terms (Morlini, 2006)) was not excessively high for any variable (air temperature=0.46, wind speed=0.11, rainfall=0.67, daylight hours=0.56).

After adjustment for covariates (Table S5; model (b)), categories of rainfall were no longer associated with MET-minutes in the log-transformed model, and our results indicated a positive linear relationship between air temperature and MET-minutes (Fig. 3e). Associations with MET-minutes for wind speed and daylight hours remained similar to the minimally-adjusted model. Significant associations between covariates and MET-minutes included: being male versus female (b=92.62, 95% CI 83.01, 102.25); visiting 'further afield' versus 'locally' (b=280.64, 95% CI 271.13, 290.15); visiting at a weekend versus on a weekday (b=28.16, 95% CI 18.71, 37.61); and being in education versus not working (b=31.47, 95% CI 7.60, 55.34). Older age and lower socioeconomic grades were also associated with fewer MET-minutes.

3.3 MET-minutes as a function of meteorological conditions, daylight, and environment

Adding interaction terms (model c), section 2.6) between the meteorological/daylight variables and the types of natural environment significantly improved the prediction of MET-minutes (F(18,21726)=25.31, p<.001; Table S5). To better understand these complex interactions, the adjusted GAM was stratified by environment type. However, after stratifying, all relationships between MET-minutes and smoothed terms, in all environments, were penalised to 1 degree of freedom (suggesting entirely linear relationships). Therefore, the proposed stratifications (model (d); stratified by environment type) were re-run as least-squares linear regressions (Table 2 and Table S6). There was no evidence of multicollinearity between meteorological/daylight variables in these stratified models (Table S6).

For a given park visit, a 1°C increase in air temperature was associated with 3.08 additional MET-minutes (95% CI 1.50, 4.66); a 1 m/s increase in wind speed was associated with 5.14 fewer MET-minutes (95% CI -8.26, -2.02); and a 1 hour increase in daylight was associated with 3.20 additional MET-minutes (95% CI 0.12 6.27). For woodland visits, neither air temperature nor wind speed were related to MET-minutes, but a 1 hour increase in daylight was associated with 12.61 additional MET-minutes (95% CI 4.81, 20.40). For visits to inland waters, air temperature was unrelated to MET-minutes; but a 1 m/s increase in wind speed was associated with 13.43 fewer MET-minutes (95% CI -25.83, -1.04); and a 1 hour increase in daylight was associated with 16.99 additional MET-minutes (95% CI 4.27, 29.72). For coasts, a 1°C increase in air temperature was associated with 12.22 additional MET-minutes (95% CI 6.94, 17.50), but neither wind speed nor daylight hours were associated with MET-minutes. Across all stratified models, no relationships existed between categories of rainfall and MET-minutes.

Where statistically significant, meteorological conditions and daylight hours represented some of the strongest predictors of MET-minutes across all environments (Fig. 4; standardised coefficients are presented in this figure), although sex and visits "further afield" were generally the strongest and most consistent predictors across these stratified models. Many covariates showed fairly consistent relationships across environments, but there were exceptions. For example, White British respondents expended significantly fewer MET-minutes at parks (b=-22.95, 95% CI -38.00, -7.90) and coasts (b=-89.93, 95% CI -173.65, -6.01) compared to all other ethnicities, but significantly more MET-minutes at inland waters (b=122.59, 95% CI 24.14, 221.04). Each extra day of sufficient physical activity in the past week was associated with 3 additional MET-minutes on park visits (b=2.92, 95% CI 0.44, 5.41), but 14 fewer MET-minutes on visits to inland waters (b=-14.29, 95% CI -24.47, -4.12).

3.4 Subsidiary analyses

Subsidiary analyses tested whether dog ownership moderated the relationships between meteorological conditions or daylight and energy expenditure across these four natural environments. In short, there was no clear indication that dog ownership moderated these relationships. Longer daylight hours appeared to be associated with fewer MET-minutes expended at woodlands for dog owners (b=-22.36, 95% CI -37.48, -7.24) and moderate/heavy rain appeared to be associated with more MET-minutes at woodlands for dog owners (*b*=96.86, 95% CI 4.44, 189.27); that is, owning a dog appeared to buffer the negative impact of rain on energy expenditure at woodlands. However, neither of these associations held for log-transformation of MET-minutes (Table S7) and the large confidence interval for the latter finding indicates a lack of statistical power to detect this effect. Furthermore, longer daylight hours were positively associated with energy expenditure at coastal environments for dog owners, but only in the log-transformed model (*b*=0.03, 95% CI 0.00, 0.05).

4. Discussion

To our knowledge, this is the first study to examine how meteorological conditions and daylight hours affect recreational physical activity in different natural environments. Using a large sample of recreational visits in England, this study found that higher air temperatures, lower wind speeds, and more daylight hours were associated with greater energy expenditure in all types of natural environment. This pattern was also found for park-based energy expenditure. However, only higher air temperatures predicted greater energy expenditure at coastal environments; decreases in wind speed and more daylight hours predicted greater energy expenditure at inland waters; and more daylight hours predicted greater energy expenditure at woodlands. We additionally observed seasonal variations in the proportion of respondents visiting natural environments at least once in the last week (Fig. 2). While these variations appear to be diminishing in latter sampling years, these changes do not correspond with any obvious climatic differences (Met Office, 2018).

4.1 Explanation of findings

Our hypotheses concerning the shape of relationships between meteorological conditions or daylight hours and physical activity for all natural environments collectively were mostly disconfirmed. Unlike previous studies in which quadratic relationships between air temperature and physical activity were found (e.g. Feinglass et al., 2011), we found a linear relationship. This linear trend could be due to the larger sample size in the present study, the different range of covariates controlled for, or that respondents chose not to visit natural environments on days that were overly hot. It could also be that currently in England, air temperatures are often not high enough to provoke the attenuation of physical activity evident in literature concerning populations from different countries and climates (Feinglass and colleagues' study was based in Chicago, USA for example). Other evidence from England has found linear relationships between daily maximum air temperature and accelerometer-measured physical activity (Wu et al., 2017a).

Similarly, the quadratic relationship between physical activity and wind speed found in a previous study of a smaller sample of adults from Prince Edward Island, Canada (Chan et al., 2006) was also not evident here. This could be because respondents chose not to visit natural environments on days that were particularly windy. In a previous analysis of six waves of the MENE data (n=16812), such inclement conditions were a key barrier to visiting natural environments for leisure (Boyd et al., 2018).

We categorised rainfall into three categories as over a third of respondents did not visit natural environments on days where it rained, consistent with stated barriers in previous research in England (Boyd et al., 2018). The lack of association between rainfall and energy expenditure could be explained by people who *are* willing to visit natural environments during inclement meteorological conditions being those who are prepared to endure these conditions for longer (e.g. dog-walkers in England; Wu et al., 2017a); this is consistent with the tentative findings of our subsidiary analysis of the moderating effect of dog ownership on these associations at woodland environments (section 3.4).

We observed a nuanced relationship between MET-minutes and daylight hours that contrasts with previous studies conducted in Chicago, USA, Southern Germany, and England (Feinglass et al., 2011; Klenk et al., 2012; Wu et al., 2017b, 2017a). The change in MET-minutes between 13 and 15 hours of daylight corresponds with: (a) the change to daylight savings time in the UK, and, in the latter half of the year, (b) the end of school summer holidays in the UK. Both could therefore be indicative of a change in how people use their time. It has been demonstrated before that children, at least, tend to conduct more physical activity in the late afternoon and early evening following a change to daylight savings time (Goodman et al., 2014).

After stratifying models by the type of natural environment visited, the lack of significant associations was salient. For example, only one meteorological condition was significantly related to energy expenditure at woodlands (daylight hours) and coasts (temperature). Such results suggest natural environments can promote recreational physical activity under a range of clement and inclement weather conditions in England. Indeed, woodlands can mitigate extreme temperatures, and provide shelter from wind and rainfall (Tyrväinen et al., 2005), potentially rendering them suitable settings for recreational physical activity promotion (Moseley et al., 2017). Coasts afford a range of recreational activities, both land- and sea-based, and their different relationships with different weather conditions found previously (Patrolia et al., 2017), albeit in Rhode Island, USA, may help explain the null associations found here (e.g. some water sports may be facilitated by windier conditions, but fishing may be impeded).

4.2 Implications

Such insights may be useful in addressing meteorological barriers to visiting natural environments for physical activity found in England previously (Boyd et al., 2018), especially if tailored to those who are less active (Salmon et al., 2003). For example, at a population level, dog ownership has been shown to mitigate temperature-related barriers to physical activity in Canada and England (Temple et al., 2011; Wu et al., 2017a), and thus could support maintenance of energy expenditure at parks and coasts (where temperature significantly affected MET-minutes in this study). However, our subsidiary analyses concerning dog ownership, while partially consistent with this research, do not offer great support for such strategies. Nonetheless, dog ownership may still buffer against the negative impact of weather on physical activity for some demographic groups (e.g. older people, (Wu et al., 2017a)).

At an individual-level, these results could aid the growing application of social prescribing as 'green prescriptions' (Van den Berg, 2017), where health professionals can use promotional strategies to encourage patients to spend time in natural environments. Previous research has suggested that strategies to encourage physically active use of the natural environment are typically aimed at more active individuals and could be enhanced with simple persuasive behavioural techniques (Elliott et al., 2016). For example, short instructions, shown to be effective at promoting physical activity more generally (Williams and French, 2011), could be introduced into these promotional efforts that target ways in which an individual might counter the inhibitive impact of meteorological conditions on outdoor physical activity (e.g. how to access appropriate clothing, how to avoid slips and falls in wet weather, or how to mitigate the potentially dissuasive effects of extreme temperatures etc.).

In terms of landscape design, strategies could be implemented to shelter from higher wind speeds at parks or inland waters (where higher wind speeds appear to be a barrier to energy expenditure in this study), such as the planting of trees (Tyrväinen et al., 2005). Shorter daylight hours (which this study reveals can significantly inhibit physical activity at parks, woodlands, and inland waters) could imply that better lighting in such areas could support more physically active use of these spaces, and in turn potentially impact how safe these environments are perceived to be for physical activity (Pitt, 2019). Nonetheless, promotion of physical activity in a given natural environment might not always be a priority in its redesign, and such changes should always be considered in the context of an individual site and community (e.g. potential disturbances to wildlife and/or local (human) residents).

Lastly, the present study could be extended to explore volumes of physical activity that could be supported by a range of natural environments under different climate change scenarios (discussed in Appendix A). Previous research has identified that atmospheric conditions alter preferences for natural environments (Hipp and Ogunseitan, 2011; White et al., 2014a) and could prompt increased participation in outdoor recreational physical activity as a result of climate change (Obradovich and Fowler, 2017). However, currently neither how much per-person energy is expended, nor how this might be apportioned across different environments under climate change, has been explored. Such research could explore a range of plausible climate scenarios (Obradovich and Fowler, 2017), account for demographic changes (Perch-Nielsen et al., 2008), control for cumulative effects of climate change on meteorological conditions and environment (e.g. sea level rise, droughts), and use international data on leisure visits to natural environments (e.g. Grellier et al., 2017) to gain such an understanding.

4.3 Strengths and limitations

To our knowledge, this is the largest study to date concerning the effects of meteorological conditions on outdoor energy expenditure and the first to do so for a range of natural environments. However, a number of limitations and opportunities for future research exist. Firstly, MET-minutes were ascribed to self-reported activities without regard to factors that affect energy expenditure (e.g. body mass, terrain). Future research could combine geolocation (e.g. GPS on a smartphone) with topography to objectively assess physical activity (Jansen et al., 2017), thereby better accounting for these factors. Secondly, MET-minutes could not be calculated for a large number of participants who reported multiple visit activities as we could not ascertain the relative time spent engaging in these different activities. The most common two-way activity combinations were walking without a dog in combination with either eating or drinking, playing with children, or visiting an attraction; the latter two activities are ascribed almost identical MET rates to walking so we do not expect this to have affected our estimates unduly. Included and excluded visits also did not appear to be substantially different in terms of meteorological conditions or daylight hours. However, visits excluded from analyses were substantially longer in duration (M=224 minutes) than those included (M=127), potentially reflecting the fact that these visits included multiple activities, so our results could represent underestimations of actual energy expenditure.

Thirdly, low air temperature and high wind speed likely explain energy expenditure better when interacted with each other (wind chill; Bluestein and Zecher, 1999). However, although we could have calculated wind chill for temperatures below 10°C, the equivalent heat index measure for conditions above 10°C requires humidity to also be accounted for and these data were not available. Fourthly, the models did not explain much variance in MET-minutes. However, models with log-transformed MET-minutes explained up to twice the variance of untransformed models (Tables S5 and S6) and key relationships between meteorological conditions/daylight hours held.

4.4 Conclusions

Meteorological conditions and daylight can affect physical activity, especially when undertaken in natural environments. The current research suggested that in England, distinct meteorological conditions differentially affect the amount of energy expenditure accumulated in a range of natural environments. Park-based activity was affected by air temperature, wind speed, and daylight hours, whereas coastal activity was only significantly affected by air temperature. Activity at inland waters was sensitive to both wind speed and hours of daylight, while activity at woodlands was only significantly affected by hours of daylight. Knowledge of how different meteorological conditions affect physical activity across a range of natural environments may help address place-specific meteorological barriers to physical activity and begin to indicate how distinct environments may support different levels of energy expenditure under climatic changes. Promisingly though, physical features and affordances mean that natural environments support recreational physical activity in spite of inclement weather conditions for a considerable proportion of the population, which underlines their importance as resilient public health resources.

5. Appendix A

Introduction

Considering climate change will affect future meteorological conditions (Meehl et al., 2000) and thus the amount of PA conducted in different environments in the future (Obradovich and Fowler, 2017), this subsidiary analysis attempted to predict the volume of recreational PA that might occur in different natural environments in England in the future under two climate change emissions scenarios.

Method

In this analysis, future climate projections are based on data from a set of simulations carried out by regional climate models (RCMs) participating in the last EURO-CORDEX initiative. The EURO-CORDEX experiment aims to downscale CMIP5 simulations over Europe (www.euro-cordex.net) in a multi-model framework. Results from four RCMs are considered at the highest spatial resolution available, covering the UK domain at about 10 km as horizontal resolution. Two different Representative Concentration Pathways (RCPs) are used to investigate potential changes induced by moderate (RCP4.5;(Thomson et al., 2011) to business as usual (RCP8.5;(Riahi et al., 2011) emissions to the end of the current century.

Specifically, re-runs of the stratified models presented in Table 2 and Figure 4 were conducted which estimated MET-minutes on recreational visits to different natural environments in England for the years 2040 and 2090 based on estimated temperatures for low (RCP4.5) and high (RCP8.5) emissions scenarios across 20 year periods (2031 to 2050 and 2081-2100, respectively). To do this, estimated ensemble mean daily maximum temperatures for the location of every visit were retrieved from 20km grid-square raster images over England to produce MET-minutes estimates for each environment type for the two time periods and two scenarios. Following earlier research (Obradovich and Fowler, 2017), our projections focused only on predicted changes in daily maximum temperatures.

Results

Daily maximum temperatures in England show modest increases under both scenarios to 2040. Differences between the two scenarios become more pronounced in 2090 (Figure A1) with increases under high emissions scenarios approximating 2°C to 2.5°C compared to modelled 2012 data. Accordingly, these modest increases predicted only small changes in MET-minutes across the four natural environment types (Figure A2). Even under the high-emissions scenario in 2090, only an extra 7 MET-minutes per visit were projected at parks, 6 extra MET-minutes at inland waters, and a decrease of 3 MET-minutes at woodlands. Coastal environments showed the most considerable increases: both scenarios predicted increases of around 5 to 6 MET-minutes in 2040, but in 2090 this increased to around 13 MET-minutes in the low emissions scenario, and 28 MET-minutes in the high emissions scenario. For context, this latter value could be equivalent to around 8 extra minutes of walking without a dog (3.5 METs).

Discussion

Consistent with projections over a similar time period elsewhere (Obradovich and Fowler, 2017), we find that recreational physical activity in natural environments could increase in most types of natural environment as a result of temperature changes. The appropriateness of using statistical models created from recent historical data to predict the future is questionable, since, for example, patterns of migration to different areas (with different quantities and qualities of natural environment) are likely to change under different climate futures (Perch-Nielsen et al., 2008). Nonetheless, it does appear that coasts in particular could support small amounts of more physical activity in the future in England. Such modest increases are perhaps not surprising as climatic changes are not predicted to be as extreme in England as they may be in, for example, southern Europe (Scoccimarro et al., 2017). Of course in areas such as this, extreme temperatures will likely discourage outdoor recreational PA (Townsend et al., 2003).

In addition to migration patterns changing with climate, the future projections presented are based on a number of other assumptions, for example that: (a) this sample of visits is representative of the behaviour of the population, (b) a linear temperature term is best for explaining associations with energy expenditure in the future, (c) covariates' associations will remain the same in the future, and (d) the two selected scenarios are most appropriate for projecting future estimates. The scope of this appendix was only ever to explore volumes of physical activity that could be supported by different environments if all else remains constant. Section 4.2 details ways in which some of these limitations could be overcome in future research.

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Figure legends

Figure 1: Map of the locations of the 47613 leisure visits to natural environments in England (2009-2013) included in analyses and their environments.

Figure 2: Percentage of respondents reporting at least one recreational visit to a natural environment in the previous week as a function of month of interview.

Figure 3: Monthly averaged (a) daily maximum temperature during daylight hours, (b) wind speed during daylight hours, (c) rainfall during daylight hours, and (d) daylight hours, for the leisure visits to natural environments in England (2009-2013) included in analyses. See supplementary materials for additional information on sunlight hours on visits from this same sampling period (Figure S1). Minimally (orange; section 2.6a) and maximally (blue; section 2.6b) adjusted thin plate regression spline smoothed terms with 95% Bayesian credible intervals predicting MET-minutes expended on a visit by (e) temperature, (f) wind speed, and (h) daylight hours, together with parametric terms and 95% confidence intervals for (g) categories of rainfall, for the leisure visits to natural environments in England (2009-2013) included in analyses.

Figure 4: Standardised coefficients and 95% confidence intervals showing the relative strength of all variables in adjusted least-squares linear regression models stratified by type of environment visited for selected leisure visits to natural environments in England (2009-2013). Standardised coefficients are presented in order to fairly demonstrate the strength of association between variables which are operationalised continuously (e.g. the meteorological variables) and those which are operationalised categorically (e.g. social grade).

Figure A1. Change (from modelled 2012 data) in mean daily maximum temperature in the four regional climate models.

Figure A2. Projected changes in MET-minutes expended parks, woodlands, indland waters, and coasts, as a function of the four regional climate models. Point estimates and confidence intervals simply reflect multiplying coefficients and confidence intervals in the original regressions presented in Table 2 and Figure 4 by the projected temperautre increase in the 20km grid square where the visit was located. Thus, these, especially confidence intervals, should be interpreted with caution.

Table 1. MET-minutes on leisure visits to natural environments in England (2009-2013) as a function of meteorological conditions and daylight in minimally and maximally (all covariates) adjusted models (n=47613).

	Minimally-adjusted model			Maximally-adjusted model		
	edf	res df	*F*-test	edf	res df	*F*-test
Max. temperature during daylight	4.50	5.58	10.06***	1.02	1.03	46.76***
Max. wind speed during daylight	1.01	1.03	4.33*	1.01	1.01	11.66***
Daylight hours	6.17	7.33	12.41***	5.63	6.78	12.02***
	b	LCI	UCI	*b*	LCI	UCI
(Intercept)	457.14	448.90	465.38	265.60	241.10	290.09
Rainfall (No rainfall=ref)	/	/	/	/	/	/
Light rain (>0mm to 0.5mm)	-5.65	-16.88	5.57	-0.08	-10.74	10.58
Moderate/heavy rain (>0.5mm)	-12.46	-26.42	1.50	5.96	-19.06	7.14
R^2	.01			.09		

Maximally adjusted model controls for sex, age, ethnicity, disability, marital status, work status, number of children in the household, days of physical activity in the last week, whether the visit was on a weekday or weekend, and whether the visit was "local". Comparison with the minimally adjusted model revealed a significantly better fit (F=380.76, p<.001).

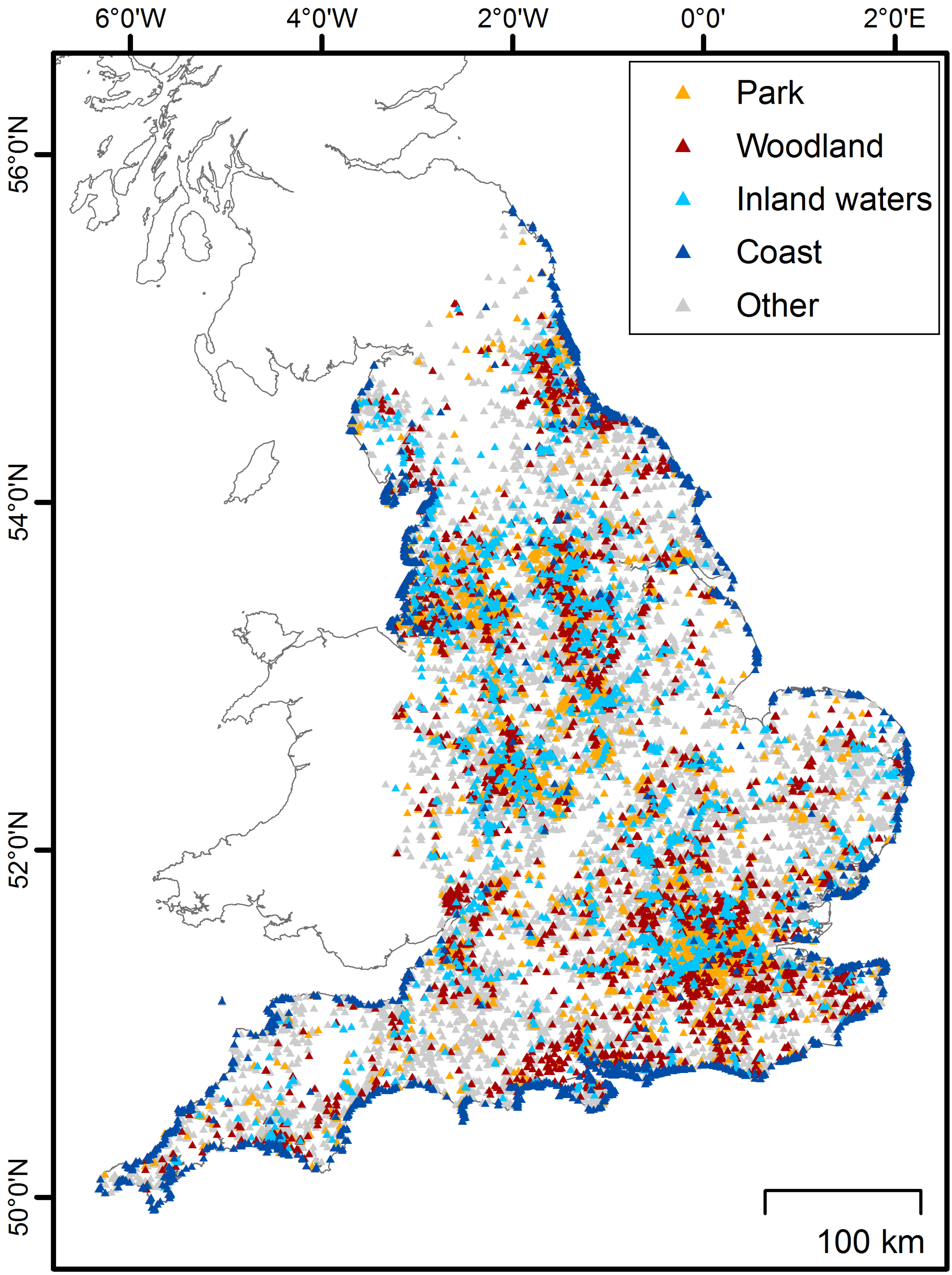
N.B Temperature, wind speed, and daylight hours are smooth terms fitted with thin plate regression splines. Estimated degrees of freedom roughly approximate the degree of polynomial in the smooth (see Fig. 3). edf=Estimated degrees of freedom; res df=residual degrees of freedom; LCI=lower bound of 95% confidence interval; UCI=upper bound of 95% confidence interval; ***=p<.001; *=p<.05.

Table 2. MET-minutes on leisure visits to natural environments in England (2009-2013) as a function of meteorological conditions and daylight in maximally adjusted models stratified by environment type.

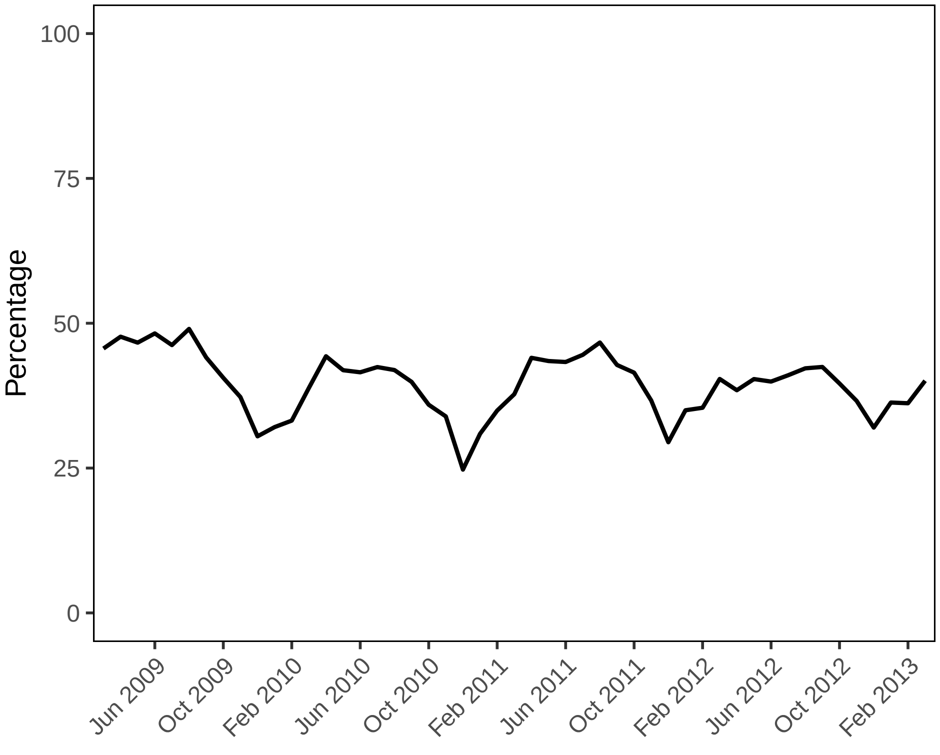
	Park n=11988			Woodland n=2947			Inland waters n=2561			Coast n=4271		
	b	LCI	UCI	*b*	LCI	UCI	*b*	LCI	UCI	*b*	LCI	UCI
(Intercept)	-598.60	-1024.39	-172.81	86.54	-42.25	215.34	-135.74	-346.82	75.34	117.38	-51.71	286.46
Max. temperature during daylight (°C)	3.08***	1.50	4.66	-1.16	-5.18	2.85	2.73	-3.96	9.42	12.22***	6.94	17.50
Max. wind speed during daylight (m/s)	-5.14**	-8.26	-2.02	-4.03	-11.26	3.20	-13.43*	-25.83	-1.04	-4.26	-13.52	5.00
Hours of daylight	3.20*	0.12	6.27	12.61**	4.81	20.40	16.99**	4.27	29.72	4.15	-5.86	14.16
Rainfall (No rainfall=ref)	/	/	/	/	/	/	/	/	/	/	/	/
Light rain (>0mm to 0.5mm)	-2.76	-17.72	12.20	4.24	-34.06	42.52	37.66	-23.76	99.08	39.22	-8.84	87.28
Moderate/heavy rain (>0.5mm)	-3.17	-21.67	15.33	-25.24	-72.70	22.23	37.99	-38.81	114.78	13.96	-45.40	73.33
R^2	.08			.08			.10			.06		

N.B Models run as least-squares linear regressions after GAMs penalised smooth terms to approximately 1 degree of freedom for all relevant terms in all environments. Adjusted for sex, age, ethnicity, disability, marital status, work status, number of children in the household, days of physical activity in the last week, whether the visit was on a weekday or weekend, and whether the visit was "local".

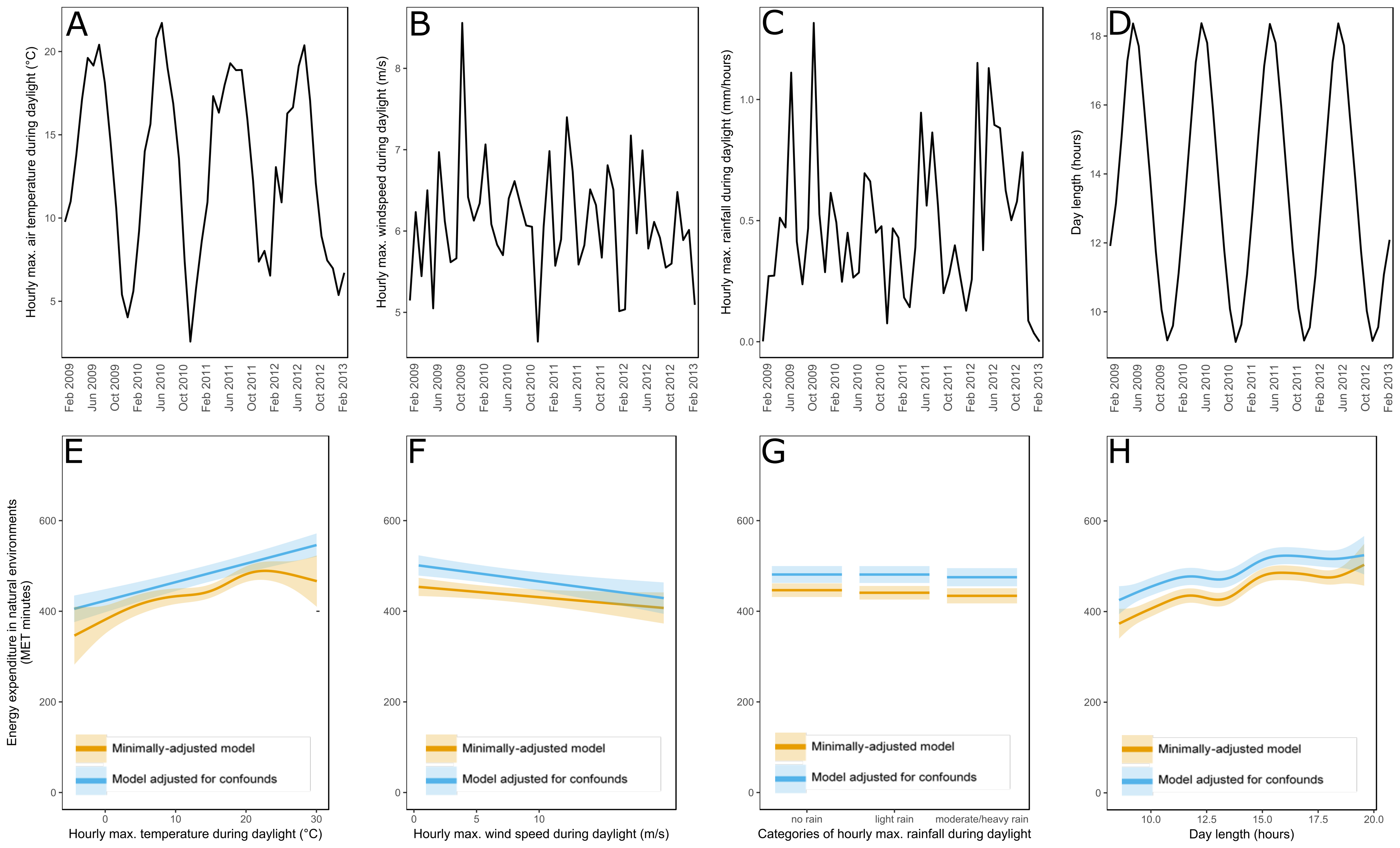
LCI=lower bound of 95% confidence interval; UCI=upper bound of 95% confidence interval

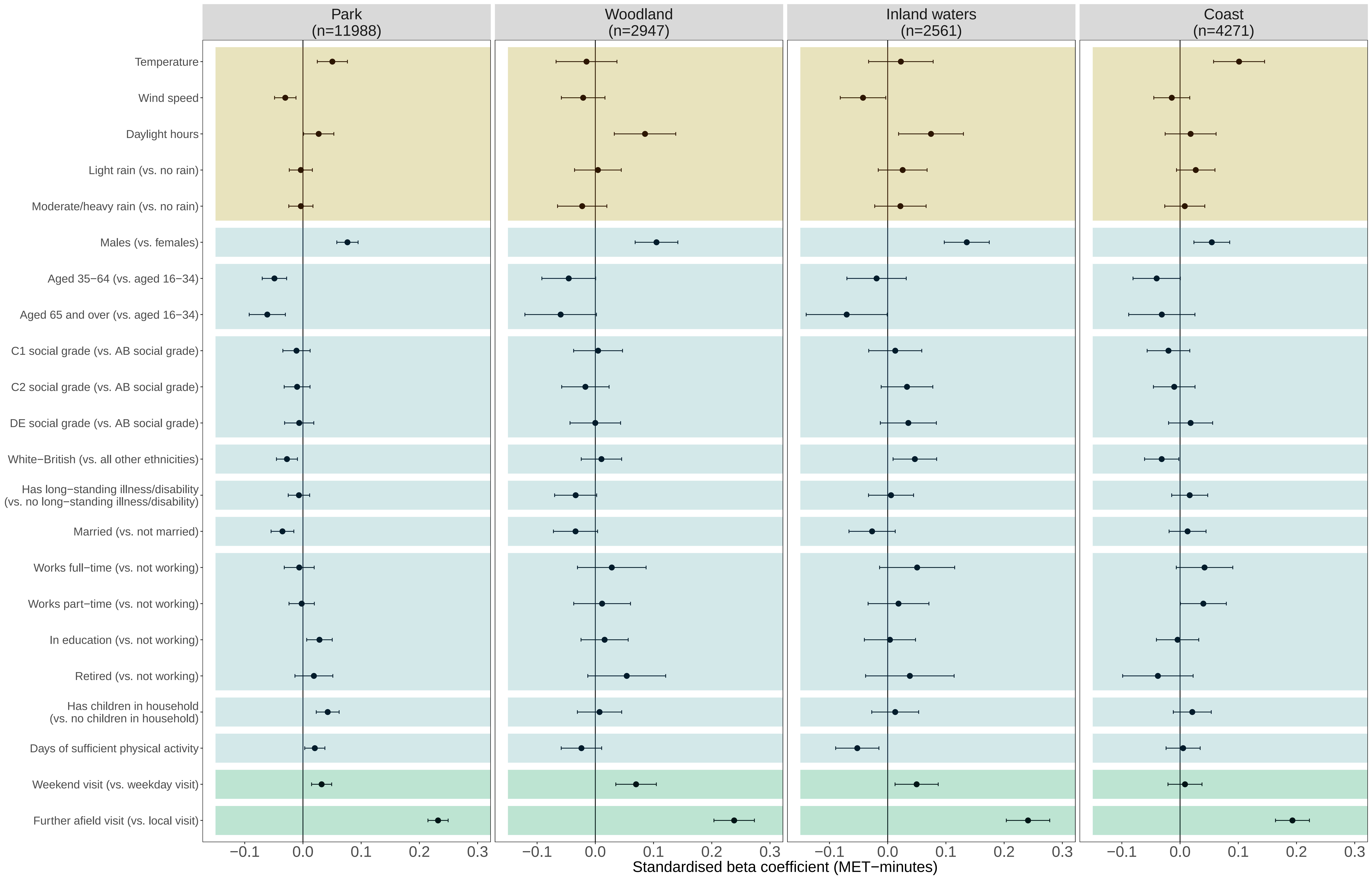


6°0'W
4°0'W
2°0'W
0°0'
2°0'E
56°0'N
54°0'N
52°0'N
50°0'N
Park
Woodland
Inland waters
Coast
Other
100 km



100
75
50
25
0
Percentage
Jun 2009
Oct 2009
Feb 2010
Jun 2010
Oct 2010
Feb 2011
Jun 2011
Oct 2011
Feb 2012
Jun 2012
Oct 2012
Feb 2013


A
Hourly max. air temperature during daylight (°C)
B
Hourly max. windspeed during daylight (m/s)
C
Hourly max. rainfall during daylight (mm/hours)
D
Day length (hours)
Feb 2009
Jun 2009
Oct 2009
Feb 2010
Jun 2010
Oct 2010
Feb 2011
Jun 2011
Oct 2011
Feb 2012
Jun 2012
Oct 2012
Feb 2013
E
F
G
H
Energy expenditure in natural environments (MET minutes)
Minimally-adjusted model
Model adjusted for confounds
Hourly max. temperature during daylight (°C)
Hourly max. wind speed during daylight (m/s)
no rain
light rain
moderate/heavy rain
Categories of hourly max. rainfall during daylight
Day length (hours)



Park (n=11988)
Woodland (n=2947)
Inland waters (n=2561)
Coast (n=4271)
Temperature
Wind speed
Daylight hours
Light rain (vs. no rain)
Moderate/heavy rain (vs. no rain)
Males (vs. females)
Aged 35−64 (vs. aged 16−34)
Aged 65 and over (vs. aged 16−34)
C1 social grade (vs. AB social grade)
C2 social grade (vs. AB social grade)
DE social grade (vs. AB social grade)
White−British (vs. all other ethnicities)
Has long−standing illness/disability (vs. no long−standing illness/disability)
Married (vs. not married)
Works full−time (vs. not working)
Works part−time (vs. not working)
In education (vs. not working)
Retired (vs. not working)
Has children in household (vs. no children in household)
Days of sufficient physical activity
Weekend visit (vs. weekday visit)
Further afield visit (vs. local visit)
−0.1
0.0
0.1
0.2
0.3
Standardised beta coefficient (MET−minutes)

Table S1. A description of how covariates were derived and operationalised in analysis.

Covariate	Question(s) in MENE pertaining to covariate	Operationalisation in analysis	Reference category (if applicable)
Individual-level covariates			
Sex	Interviewer self-assessed whether the respondent appeared male or female.	Two categories: Male and female.	Females
Age	"What was your age last birthday?" Interviewer then enters age in one of eight age brackets: 16-17, 18-24, 25-34, 35-44, 45-54, 55-64, 65-74, or 75 and over.	Collapsed into three categories: 16-34, 35-64, and 65 and over.	16-34
Ethnicity	"Which of these best describes your ethnic group?" (*Prompt:* "By this I mean your cultural background"). White-British, White-Irish, Any other White background, White & Black Caribbean, White & Black African, White & Asian, Any other mixed background, Indian, Pakistani, Bangladeshi, Any other Asian Background, Caribbean, African, Any other Black background, Chinese, Any other.	Dichotomised into "White-British" and "All other ethnicities". This is both to create more uniform sample sizes, and is also consistent with previous work on the MENE dataset which analyses physical activity in natural environment (Elliott et al., 2015).	All other ethnicities
Social grade	Participants are classified in line with the Ipsos-MORI classification: A, B, C1, C2, D, and E.	Four categories are used: AB, C1, C2, and DE. These have revealed distinct patterns with physical activity attainment in this data set previously (White et al., 2014).	AB

Disability	"Do you have any long standing illness, health problem or disability that limits your daily activities or the kind of work you can do?" Yes, No.	Two categories: Yes and No.	No
Marital status	Interviewers ask participants to classify themselves into one of three categories: Married/living as married, Single, Widowed/divorced/separated.	Dichotomised into "Married" (i.e. married/living as married) and "Not married" (i.e. single or widowed/divorced/separated).	Married
Work status	Interviewers ask participants to classify themselves into one of eight possible options: Full-time paid work (30+ hours per week), Part-time paid work (8-29 hours per week), Part-time paid work (under 8 hours per week), Retired, Still at school, In full time higher education, Unemployed (seeking work), Not in paid employment (not seeking work).	Five categories are used: "Not working" (i.e. unemployed or not in paid employment), "Full-time" (i.e. full-time paid work), "Part-time" (i.e. either part-time option), "In education" (i.e. still at school or in full time higher education), "Retired" (i.e. retired).	Not working
Number of children in the household	"And how many children under the age of 16 are there in the household?" N.B this is contingent on the respondent answering more than "1" to the previous question: "How many people are there in your household altogether, including any children and yourself?"	Dichotomised into "None" and "At least one".	None

Physical activity attainment	"In the past week, on how many days have you done a total of 30 minutes or more of physical activity, which was enough to raise your breathing rate? This may include sport, exercise, and brisk walking or cycling for recreation or to get to and from places, but should not include housework or physical activity that may be part of your job." The respondent answers with a number between 0 and 7.	This was entered into regression models as a continuous variable.	Not applicable
Visit-level covariates			
Whether the visit was on a weekend or a weekday	The CAPI device that interviewers used randomly selects one visit that the respondent mentions embarking on in the last seven days. In the MENE dataset this visit is ascribed a date.	We used date extraction functions to deduce whether the visit was on a weekday (Monday-Friday) or weekend (Saturday-Sunday).	Weekday

Whether the visit was "local" or "further afield".	This covariate was created from two questions in MENE. The first asks: "And did this journey start from…" Your home, Someone else's home, Work, Holiday accommodation, Somewhere else. The second question asks: "Approximately how far, in miles, did you travel to reach this place? By that I mean the one way distance from where you set off to the place visited." Less than 1 mile 1 or 2 miles 3 to 5 miles 6 to 10 miles 11 to 20 miles 21 to 40 miles 41 to 60 miles 61 to 80 miles 81 to 100 miles More than 100 miles	Two categories were created: Visits which started from "your home" and were "less than 1 mile" away were classified as "local". All other combinations of start point and distance travelled were classified as "further afield".	Local

Table S2. Percentage of respondents making recreational visits to natural environments at least once a week as a function of month (of interview)

Month of interview (pooled)	%	Month and year of interview	%
January	33.71	Mar-09	45.63
February	34.94	Apr-09	47.68
March	40.73	May-09	46.65
April	43.64	Jun-09	48.24
May	43.25	Jul-09	46.23
June	43.42	Aug-09	49.02
July	43.47	Sep-09	44.10
August	44.92	Oct-09	40.58
September	42.38	Nov-09	37.26
October	39.44	Dec-09	30.48
November	36.12	Jan-10	32.07
December	29.02	Feb-10	33.19
		Mar-10	38.83
		Apr-10	44.30
		May-10	41.89
		Jun-10	41.54
		Jul-10	42.44
		Aug-10	41.92
		Sep-10	39.88
		Oct-10	35.93
		Nov-10	33.92
		Dec-10	24.73
		Jan-11	30.91
		Feb-11	34.93
		Mar-11	37.75
		Apr-11	44.03
		May-11	43.48
		Jun-11	43.31
		Jul-11	44.55
		Aug-11	46.68
		Sep-11	42.80
		Oct-11	41.47
		Nov-11	36.67

Dec-11	29.46
Jan-12	34.98
Feb-12	35.41
Mar-12	40.39
Apr-12	38.44
May-12	40.36
Jun-12	39.93
Jul-12	41.03
Aug-12	42.22
Sep-12	42.46
Oct-12	39.60
Nov-12	36.59
Dec-12	31.99
Jan-13	36.31
Feb-13	36.19
Mar-13	40.07

Table S3. Descriptive statistics for energy expenditure and meteorological/daylight variables in different natural environments.

	Energy expenditure (MET-minutes)[a]	Maximum temperature during daylight hours (°C)[b]	Maximum wind speed during daylight hours (m/s)[b]	Maximum rainfall during daylight hours (mm/hour)[b]	Daylight hours[b]
Overall (n=47613)	300.00 (528.35)	13.68 (6.01)	6.15 (2.31)	0.49 (1.15)	13.82 (3.16)
Park (n=11988)	265.80 (371.27)	14.01 (6.09)	5.91 (2.19)	0.46 (1.09)	13.93 (3.14)
Woodland (n=2947)	270.00 (468.30)	12.99 (6.10)	6.19 (2.43)	0.46 (1.09)	13.46 (3.17)
Inland waters (n=2561)	360.00 (719.67)	14.00 (5.97)	6.12 (2.27)	0.47 (1.08)	14.05 (3.15)
Coast (n=4271)	420.00 (709.68)	14.47 (5.89)	6.39 (2.37)	0.47 (1.16)	14.25 (3.10)

[a] Medians and standard deviations are presented due to high positive skew (hence the log-transformation of MET-minutes in models presented below).
[b] Means and standard deviations are presented.
N.B Daylight hours includes civil twilight time.

Table S4. Frequencies of respondents within the predictors included in regression models.

	Frequencies in models where n=47613	Frequencies in models where n=21767	Frequencies in "parks" model (n=11988)	Frequencies in "woodlands" model (n=2947)	Frequencies in "inland waters" model (n=2561)	Frequencies in "coast" model (n=4271)
Max. temperature during daylight (°C)	47613	21767	11988	2947	2561	4271
Max. wind speed during daylight (m/s)	47613	21767	11988	2947	2561	4271
Daylight hours	47613	21767	11988	2947	2561	4271
Rainfall (No rainfall=ref)	17437	8093	4364	1092	950	1687
Light rain (>0mm to 0.5mm)	19302	8842	4940	1190	1049	1663
Moderate/heavy rain (>0.5mm)	10874	4832	2684	665	562	921
Type of natural environment (Parks=ref)	-	11988	-	-	-	-
Woodland	-	2947	-	-	-	-
Inland waters	-	2561	-	-	-	-
Coast	-	4271	-	-	-	-
Temperature x Park	-	11988	-	-	-	-
Temperature x Woodland	-	2947	-	-	-	-
Temperature x Inland waters	-	2561	-	-	-	-
Temperature x Coast	-	4271	-	-	-	-
Wind speed x Park	-	11988	-	-	-	-
Wind speed x Woodland	-	2947	-	-	-	-
Wind speed x Inland waters	-	2561	-	-	-	-
Wind speed x Coast	-	4271	-	-	-	-
Daylight x Park	-	11988	-	-	-	-
Daylight x Woodland	-	2947	-	-	-	-
Daylight x Inland waters	-	2561	-	-	-	-
Daylight x Coast	-	4271	-	-	-	-
No rain x Park	-	4364	-	-	-	-
No rain x Woodland	-	1092	-	-	-	-
No rain x Inland waters	-	950	-	-	-	-
No rain x Coast	-	1687	-	-	-	-
Light rain x Park	-	4940	-	-	-	-
Light rain x Woodland	-	1190	-	-	-	-
Light rain x Inland waters	-	1049	-	-	-	-
Light rain x Coast	-	1663	-	-	-	-
Moderate/heavy rain x Park	-	2684	-	-	-	-
Moderate/heavy rain x Woodland	-	665	-	-	-	-
Moderate/heavy rain x Inland waters	-	562	-	-	-	-
Moderate/heavy rain x Coast	-	921	-	-	-	-

Sex (Females=ref)	24755	11300	6357	1540	1171	2232
Males	22858	10467	5631	1407	1390	2039
Age (16-34=ref)	13534	7180	4900	644	570	1066
35-64	24298	10748	5406	1787	1396	2159
65 and over	9781	3839	1682	516	595	1046
Social grade (AB=ref)	11535	4761	2255	822	658	1026
C1	13810	6456	3584	910	740	1222
C2	9675	4399	2360	591	532	916
DE	12593	6151	3789	624	631	1107
Ethnicity (All other ethnicities=ref)	6312	3911	3251	167	209	284
White-British	41301	17856	8737	2780	2352	3987
Long term illness or disability (No=ref)	40141	18535	10308	2542	2132	3553
Yes	7472	3232	1680	405	429	718
Marital status (Not married=ref)	18143	8807	5348	928	930	1601
Married	29470	12960	6640	2019	1631	2670
Work status (Not working=ref)	7493	3742	2446	394	320	582
Full-time	18184	8460	4470	1315	1080	1595
Part-time	6925	3168	1789	453	355	571
In education	2754	1580	1162	104	92	222
Retired	12257	4817	2121	681	714	1301
Children in household (None=ref)	32404	14392	7291	2027	1963	3111
At least one	15209	7375	4697	920	598	1160
Days of physical activity	47613	21767	11988	2947	2561	4271
Visit day (Weekday=ref)	30266	13702	7707	1817	1602	2576
Weekend	17347	8065	4281	1130	959	1695
Visit type (Local visit=ref)	17484	8815	6314	954	745	802
Further afield visit	30129	12952	5674	1993	1816	3469

Table S5. Minimally-adjusted, adjusted, and adjusted (with interaction) full results for generalised additive models predicting energy expenditure (MET-minutes) from meteorological conditions and daylight hours.

Untransformed	Minimally-adjusted model n=47613 R^2=.01			Adjusted for covariates n=47613 R^2=.09 (*F*=380.76, *p*<.001)[a]			Additionally adjusted for meteorology x environment interactions n=21767 R^2=0.10 (*F*=25.31, *p*<.001)[b]		
	edf	res df	*F*-test	edf	res df	*F*-test	edf	res df	*F*-test
Max. temperature during daylight (°C)[c]	4.50	5.58	***10.06	1.02	1.03	***46.76	1.00	1.00	***37.89
Max. wind speed during daylight (m/s)[c]	1.01	1.03	*4.33	1.01	1.01	***11.66	1.00	1.00	**8.54
Daylight hours[c]	6.17	7.33	***12.41	5.63	6.78	***12.02	1.00	1.00	***13.04
	b	LCI	UCI	*b*	LCI	UCI	*b*	LCI	UCI
(Intercept)	457.14	448.90	465.38	265.60	241.10	290.09	240.57	205.53	275.61
Rainfall (No rainfall=ref)	/	/	/	/	/	/	/	/	/
Light rain (>0mm to 0.5mm)	-5.65	-16.88	5.57	-0.08	-10.74	10.58	-1.10	-21.94	19.73
Moderate/heavy rain (>0.5mm)	-12.46	-26.42	1.50	5.96	-19.06	7.14	-1.39	-27.15	24.36
Type of natural environment (Parks=ref)	/	/	/	/	/	/	/	/	/
Woodland	-	-	-	-	-	-	17.14	-17.87	52.15
Inland waters	-	-	-	-	-	-	***143.83	107.36	180.30
Coast	-	-	-	-	-	-	***124.79	95.41	154.17
	edf	res df	*F*-test	edf	res df	*F*-test	edf	res df	*F*-test
Interaction terms	/	/	/	/	/	/	/	/	/
Temperature x Park[c]	-	-	-	-	-	-	1.00	1.00	***15.21
Temperature x Woodland[c]	-	-	-	-	-	-	1.00	1.00	***19.25
Temperature x Inland waters[c]	-	-	-	-	-	-	1.00	1.00	**7.87
Temperature x Coast[c]	-	-	-	-	-	-	0.00	0.00	0.10
Wind speed x Park[c]	-	-	-	-	-	-	1.00	1.00	2.45
Wind speed x Woodland[c]	-	-	-	-	-	-	1.00	1.00	2.33
Wind speed x Inland waters[c]	-	-	-	-	-	-	0.00	0.00	0.02
Wind speed x Coast[c]	-	-	-	-	-	-	1.00	1.00	2.64
Daylight hours x Park[c]	-	-	-	-	-	-	1.00	1.00	**7.35
Daylight hours x Woodland[c]	-	-	-	-	-	-	1.00	1.00	0.39
Daylight hours x Inland waters[c]	-	-	-	-	-	-	0.00	0.00	0.00
Daylight hours x Coast[c]	-	-	-	-	-	-	1.00	1.00	3.71
	b	LCI	UCI	*b*	LCI	UCI	*b*	LCI	UCI
Light rain x Woodland	-	-	-	-	-	-	3.78	-43.42	50.97
Light rain x Inland waters	-	-	-	-	-	-	31.58	-17.73	80.89
Light rain x Coast	-	-	-	-	-	-	40.01	-0.45	80.47

Moderate/heavy rain x Woodland	-	-	-	-	-	-	-28.98	-87.38	29.42
Moderate/heavy rain x Inland waters	-	-	-	-	-	-	29.24	-32.23	90.71
Moderate/heavy rain x Coast	-	-	-	-	-	-	15.42	-34.59	65.42
Sex (Females=ref)	/	/	/	/	/	/	/	/	/
Males	-	-	-	***92.62	83.01	10.25	***85.17	71.18	99.16
Age (16-34=ref)	/	/	/	/	/	/	/	/	/
35-64	-	-	-	***-31.05	-43.04	-19.05	***-40.00	-56.98	-23.03
65 and over	-	-	-	***-52.29	-73.29	-31.26	***-72.96	-104.79	-41.14
Social grade (AB=ref)	/	/	/	/	/	/	/	/	/
C1	-	-	-	**-17.61	-30.19	-5.02	-3.94	-22.74	14.87
C2	-	-	-	*-14.39	-28.10	-0.68	0.90	-19.62	21.41
DE	-	-	-	*-14.96	-28.61	-1.31	13.81	-6.40	34.01
Ethnicity (All other ethnicities=ref)	/	/	/	/	/	/	/	/	/
White-British	-	-	-	3.74	-10.04	17.52	-15.08	-33.48	3.32
Long term illness or disability (No=ref)	/	/	/	/	/	/	/	/	/
Yes	-	-	-	***-26.45	-39.62	-13.29	-1.41	-21.14	18.33
Marital status (Not married=ref)	/	/	/	/	/	/	/	/	/
Married	-	-	-	***-21.06	-31.43	-10.69	**-19.98	-35.06	-4.90
Work status (Not working=ref)	/	/	/	/	/	/	/	/	/
Full-time	-	-	-	11.75	-3.24	26.73	18.31	-3.03	39.64
Part-time	-	-	-	4.85	-12.34	22.03	15.83	-8.74	40.40
In education	-	-	-	31.47	7.60	55.34	30.67	-1.29	62.64
Retired	-	-	-	12.72	-7.95	33.39	7.39	-23.62	38.39
Children in household (None=ref)	/	/	/	/	/	/	/	/	/
At least one	-	-	-	*13.59	2.58	24.61	***30.73	14.89	46.56
Days of physical activity	-	-	-	*-2.13	-3.85	-0.41	-0.94	-3.48	1.61
Visit day (Weekday=ref)	/	/	/	/	/	/	/	/	/
Weekend	-	-	-	***28.16	18.71	37.61	***34.55	20.80	48.29
Visit type (Local visit=ref)	/	/	/	/	/	/	/	/	/
Further afield visit	-	-	-	***280.64	271.13	290.15	***229.30	215.17	243.44
Log-transformed	Unadjusted model n=47613 R^2=.02			Adjusted for covariates n=47613 R^2=.16 (F=743.11, p<.001)[a]			Additionally adjusted for meteorology x environment interactions n=21767		

							R^2=.15 (F=22.82, p<.001)[b]		
	edf	res df	*F*-test	edf	res df	*F*-test	edf	res df	*F*-test
Max. temperature during daylight (°C)[c]	4.83	5.95	***13.36	1.00	1.01	***67.91	1.00	1.00	***43.38
Max. wind speed during daylight (m/s)[c]	1.01	1.02	***16.96	1.01	1.01	***29.61	1.00	1.00	**7.43
Daylight hours[c]	6.19	7.35	***17.88	5.94	7.11	***15.76	1.88	2.34	**4.58
	b	LCI	UCI	*b*	LCI	UCI	*b*	LCI	UCI
(Intercept)	5.72	5.71	5.74	5.38	5.34	5.41	5.37	5.32	5.43
Rainfall (No rainfall=ref)	/	/	/	/	/	/	/	/	/
Light rain (>0mm to 0.5mm)	-0.02	-0.03	0.00	-0.00	-0.02	0.01	-0.00	-0.04	0.03
Moderate/heavy rain (>0.5mm)	-0.03	-0.05	*-0.01	-0.01	-0.03	0.01	-0.01	-0.05	0.03
Type of natural environment (Parks=ref)	/	/	/	/	/	/	/	/	/
Woodland	-	-	-	-	-	-	0.01	-0.05	0.06
Inland waters	-	-	-	-	-	-	***0.19	0.13	0.25
Coast	-	-	-	-	-	-	***0.22	0.17	0.26
	edf	res df	*F*-test	edf	res df	*F*-test	edf	res df	*F*-test
Interaction terms	/	/	/	/	/	/	/	/	/
Temperature x Park[c]	-	-	-	-	-	-	1.00	1.00	***12.80
Temperature x Woodland[c]	-	-	-	-	-	-	1.00	1.00	***21.06
Temperature x Inland waters[c]	-	-	-	-	-	-	1.00	2.34	**7.54
Temperature x Coast[c]	-	-	-	-	-	-	0.00	1.00	0.03
Wind speed x Park[c]	-	-	-	-	-	-	1.00	1.00	0.71
Wind speed x Woodland[c]	-	-	-	-	-	-	1.00	1.00	0.71
Wind speed x Inland waters[c]	-	-	-	-	-	-	0.00	0.00	0.14
Wind speed x Coast[c]	-	-	-	-	-	-	1.00	1.00	1.78
Daylight hours x Park[c]	-	-	-	-	-	-	1.00	1.00	0.71
Daylight hours x Woodland[c]	-	-	-	-	-	-	1.00	1.00	0.00
Daylight hours x Inland waters[c]	-	-	-	-	-	-	0.00	0.00	0.00
Daylight hours x Coast[c]	-	-	-	-	-	-	1.00	1.00	0.68
	b	LCI	UCI	*b*	LCI	UCI	*b*	LCI	UCI
Light rain x Woodland	-	-	-	-	-	-	0.02	-0.05	0.09
Light rain x Inland waters	-	-	-	-	-	-	0.03	-0.05	0.10
Light rain x Coast	-	-	-	-	-	-	0.01	-0.05	0.08
Moderate/heavy rain x Woodland	-	-	-	-	-	-	-0.02	-0.11	0.07
Moderate/heavy rain x Inland waters	-	-	-	-	-	-	0.05	-0.05	0.14
Moderate/heavy rain x Coast	-	-	-	-	-	-	0.01	-0.07	0.08
Sex (Females=ref)	/	/	/	/	/	/	/	/	/
Males	-	-	-	***0.17	0.16	0.19	***0.15	0.13	0.17

Age (16-34=ref)	/	/	/	/	/	/	/	/	/
35-64	-	-	-	***-0.08	-0.10	-0.06	***-0.09	-0.12	-0.06
65 and over	-	-	-	***0.14	-0.17	-0.11	***0.16	-0.21	-0.12
Social grade (AB=ref)	/	/	/	/	/	/	/	/	/
C1	-	-	-	**-0.03	-0.05	-0.01	-0.00	-0.03	0.03
C2	-	-	-	***-0.04	-0.07	-0.02	0.01	-0.02	0.04
DE	-	-	-	***-0.04	-0.07	-0.02	0.02	-0.01	0.05
Ethnicity (All other ethnicities=ref)	/	/	/	/	/	/	/	/	/
White-British	-	-	-	***-0.07	-0.09	-0.05	***-0.09	-0.11	-0.06
Long term illness or disability (No=ref)	/	/	/	/	/	/	/	/	/
Yes	-	-	-	***-0.10	-0.12	-0.08	***-0.06	-0.09	-0.03
Marital status (Not married=ref)	/	/	/	/	/	/	/	/	/
Married	-	-	-	***-0.04	-0.06	-0.02	***-0.04	-0.07	-0.02
Work status (Not working=ref)	/	/	/	/	/	/	/	/	/
Full-time	-	-	-	-0.00	-0.02	0.02	0.00	-0.03	0.04
Part-time	-	-	-	0.00	-0.03	0.03	0.02	-0.02	0.06
In education	-	-	-	*0.04	0.00	0.08	0.04	-0.01	0.09
Retired	-	-	-	**0.05	0.02	0.08	*0.05	0.01	0.10
Children in household (None=ref)	/	/	/	/	/	/	/	/	/
At least one	-	-	-	***0.06	0.05	0.08	***0.10	0.07	0.12
Days of physical activity	-	-	-	*-0.00	-0.01	-0.00	-0.00	-0.01	0.00
Visit day (Weekday=ref)	/	/	/	/	/	/	/	/	/
Weekend	-	-	-	***0.09	0.07	0.10	***0.10	0.08	0.12
Visit type (Local visit=ref)	/	/	/	/	/	/	/	/	/
Further afield visit	-	-	-	***0.63	0.62	0.65	***0.51	0.48	0.53

[a] Test of model fit compared to unadjusted model.
[b] Test of model fit compared to adjusted model (NB to facilitate this comparison, the adjusted model sample size was reduced to only include the same respondents as were present in the adjusted model with interactions).
[c] Smoothed regression terms fitted with thin-plate regression splines (NB instead of an environment reference category for interaction terms, a smooth is run for each environment with smoothness penalties duplicated for each).
***$p<.001$
**$p<.01$
*$p<.05$

Table S6. Maximally-adjusted linear regression models predicting energy expenditure (MET-minutes) from meteorological conditions and daylight hours stratified by the type of environment the respondent visited.

Untransformed	Park n=11988 R^2=.08			Woodland n=2947 R^2=.08			Inland waters n=2561 R^2=.10			Coast n=4271 R^2=.06		
	b	LCI	UCI	*b*	LCI	UCI	*b*	LCI	UCI	*b*	LCI	UCI
(Intercept)	-598.60	-1024.39	-172.81	86.54	-42.25	215.34	-135.74	-346.82	75.34	117.38	-51.71	286.46
Max. temperature during daylight (°C)	***3.08	1.50	4.66	-1.16	-5.18	2.85	2.73	-3.96	9.42	***12.22	6.94	17.50
Max. wind speed during daylight (m/s)	**-5.14	-8.26	-2.02	-4.03	-11.26	3.20	*-13.43	-25.83	-1.04	-4.26	-13.52	5.00
Daylight hours	*3.20	0.12	6.27	**12.61	4.81	20.40	**16.99	4.27	29.72	4.15	-5.86	14.16
Rainfall (No rainfall=ref)	/	/	/	/	/	/	/	/	/	/	/	/
Light rain (>0mm to 0.5mm)	-2.76	-17.72	12.20	4.24	-34.06	42.52	37.66	-23.76	99.08	39.22	-8.84	87.28
Moderate/heavy rain (>0.5mm)	-3.17	-21.67	15.33	-25.24	-72.70	22.23	37.99	-38.81	114.78	13.96	-45.40	73.33
Sex (Females=ref)	/	/	/	/	/	/	/	/	/	/	/	/
Males	***56.86	43.26	70.45	***98.51	64.11	132.91	***196.20	140.37	252.04	***77.48	33.78	121.18
Age (16-34=ref)	/	/	/	/	/	/	/	/	/	/	/	/
35-64	***-36.55	-52.20	-20.89	-43.75	-88.02	0.52	-27.59	-101.30	46.12	-57.05	-114.73	0.62
65 and over	***-65.48	-98.68	-32.28	-73.34	-149.08	2.41	*-120.01	-238.61	-1.4	-51.68	-145.59	42.23
Social grade (AB=ref)	/	/	/	/	/	/	/	/	/	/	/	/
C1	-9.00	-30.00	10.00	4.81	-37.77	47.28	20.59	-51.78	92.96	-31.26	-88.81	26.29
C2	-9.37	-30.11	11.36	-19.95	-67.57	27.68	58.79	-19.94	137.52	-17.31	-79.09	44.47
DE	-5.15	-25.18	14.87	-0.06	-49.86	49.75	59.23	-21.19	139.64	29.37	-31.95	90.69
Ethnicity (All other ethnicities=ref)	/	/	/	/	/	/	/	/	/	/	/	/
White-British	**-22.95	-38.00	-7.90	21.30	-48.98	91.58	*122.59	24.14	221.04	*-89.83	-173.65	-6.01
Long term illness or disability (No=ref)	/	/	/	/	/	/	/	/	/	/	/	/
Yes	-7.36	-27.04	12.33	-45.95	-95.10	3.21	11.10	-63.48	85.69	31.45	-27.32	90.22
Marital status (Not married=ref)	/	/	/	/	/	/	/	/	/	/	/	/
Married	***-26.29	-40.90	-11.68	-34.28	-72.53	3.96	-40.07	-99.56	19.42	18.89	-27.67	65.45
Work status (Not working=ref)	/	/	/	/	/	/	/	/	/	/	/	/
Full-time	-4.91	-24.65	14.84	26.64	-28.89	82.17	73.67	-20.34	167.68	61.68	-9.54	132.90
Part-time	-2.29	-24.97	20.39	15.14	-48.18	78.46	38.68	-70.19	147.54	*83.39	1.05	165.72
In education	*35.60	8.08	63.13	40.50	-62.37	143.37	14.97	-154.95	184.90	-13.55	-129.82	102.72
Retired	18.29	-13.38	49.95	59.94	-14.40	134.28	61.16	-60.98	183.21	-58.70	-152.06	34.66
Children in household (None=ref)	/	/	/	/	/	/	/	/	/	/	/	/
At least one	***32.32	17.36	47.28	7.33	-31.13	45.79	21.96	-46.62	90.53	33.50	-18.51	85.51
Days of physical activity	*2.92	0.44	5.41	-4.18	-10.28	1.91	**-14.29	-24.47	-4.12	1.41	-6.45	9.28

Visit day (Weekday=ref)	/	/	/	/	/	/	/	/	/	/	/	/
Weekend	***24.85	11.47	38.23	***67.40	33.86	100.94	**73.91	18.74	129.07	12.28	-30.13	54.70
Visit type (Local visit=ref)	/	/	/	/	/	/	/	/	/	/	/	/
Further afield visit	***172.53	159.63	185.43	***238.65	203.85	273.45	***381.87	322.78	440.97	***350.77	297.80	403.74

Log-transformed	Park n=11988 R^2=.11			Woodland n=2947 R^2=.14			Inland waters n=2561 R^2=.17			Coast n=4271 R^2=.12		
	b	LCI	UCI	*b*	LCI	UCI	*b*	LCI	UCI	*b*	LCI	UCI
(Intercept)	5.24	5.15	5.34	5.16	4.95	5.37	4.94	4.68	5.20	5.09	4.89	5.29
Max. temperature during daylight (°C)	***0.01	0.00	0.01	-0.00	-0.01	0.01	0.01	-0.00	0.01	***0.02	0.01	0.03
Max. wind speed during daylight (m/s)	***-0.01	-0.02	-0.01	-0.01	-0.02	0.00	**-0.02	-0.04	-0.00	-0.01	-0.02	0.00
Daylight hours	***0.01	0.01	0.02	**0.02	0.00	0.03	*0.02	0.00	0.03	0.01	-0.00	0.02
Rainfall (No rainfall=ref)	/	/	/	/	/	/	/	/	/	/	/	/
Light rain (>0mm to 0.5mm)	-0.01	-0.04	0.02	0.02	-0.05	0.08	0.03	-0.05	0.10	0.01	-0.05	0.06
Moderate/heavy rain (>0.5mm)	-0.01	-0.05	0.02	-0.02	-0.10	0.06	0.05	-0.04	0.15	-0.01	-0.08	0.06
Sex (Females=ref)	/	/	/	/	/	/	/	/	/	/	/	/
Males	***0.13	0.10	0.16	***0.19	0.13	0.24	***0.26	0.19	0.33	***0.11	0.06	0.16
Age (16-34=ref)	/	/	/	/	/	/	/	/	/	/	/	/
35-64	***-0.10	-0.14	-0.07	-0.07	-0.14	0.01	-0.02	-0.11	0.07	**-0.09	-0.16	-0.02
65 and over	***-0.16	-0.23	-0.09	**-0.19	-0.31	-0.07	*-0.15	-0.29	-0.00	*-0.14	-0.25	-0.03
Social grade (AB=ref)	/	/	/	/	/	/	/	/	/	/	/	/
C1	-0.03	-0.07	0.01	0.03	-0.04	0.10	0.03	-0.06	0.12	0.01	-0.06	0.08
C2	-0.03	-0.07	0.02	*-0.08	-0.16	-0.00	*0.10	0.00	0.20	0.06	-0.02	0.13
DE	-0.03	-0.07	0.01	0.01	-0.07	0.09	0.09	-0.01	0.19	*0.09	0.02	0.16
Ethnicity (All other ethnicities=ref)	/	/	/	/	/	/	/	/	/	/	/	/
White-British	***-0.11	-0.14	-0.07	-0.02	-0.14	0.09	0.11	-0.01	0.23	-0.08	-0.18	0.02
Long term illness or disability (No=ref)	/	/	/	/	/	/	/	/	/	/	/	/
Yes	***-0.07	-0.11	-0.03	*-0.10	-0.18	-0.02	-0.00	-0.09	0.09	-0.03	-0.10	0.04
Marital status (Not married=ref)	/	/	/	/	/	/	/	/	/	/	/	/
Married	**-0.05	-0.08	-0.02	*-0.08	-0.14	-0.02	-0.04	-0.12	0.03	-0.00	-0.06	0.05
Work status (Not working=ref)	/	/	/	/	/	/	/	/	/	/	/	/
Full-time	-0.01	-0.05	0.03	-0.02	-0.11	0.07	0.02	-0.09	0.14	0.04	-0.04	0.13
Part-time	0.02	-0.03	0.06	-0.02	-0.12	0.09	0.00	-0.13	0.14	0.07	-0.02	0.17
In education	*0.06	0.00	0.12	-0.04	-0.20	0.13	0.02	-0.19	0.23	-0.03	-0.17	0.11
Retired	*0.07	0.00	0.13	0.11	-0.01	0.23	0.04	-0.11	0.19	-0.01	-0.13	0.10
Children in household (None=ref)	/	/	/	/	/	/	/	/	/	/	/	/

At least one	***0.13	0.10	0.16	0.03	-0.04	0.09	0.03	-0.06	0.11	*0.07	0.01	0.13
Days of physical activity	*0.01	0.00	0.01	-0.01	-0.02	0.00	***-0.02	-0.03	-0.01	-0.00	-0.01	0.01
Visit day (Weekday=ref)	/	/	/	/	/	/	/	/	/	/	/	/
Weekend	***0.09	0.06	0.11	***0.14	0.08	0.19	***0.13	0.06	0.20	**0.08	0.03	0.13
Visit type (Local visit=ref)	/	/	/	/	/	/	/	/	/	/	/	/
Further afield visit	***0.44	0.41	0.47	***0.56	0.50	0.61	***0.68	0.61	0.76	***0.61	0.55	0.68

***$p<.001$
**$p<.01$
*$p<.05$

N.B There was no evidence of multicollinearity between any meteorological/daylight variable with maximum variance inflation factor estimates not exceeding 2.33 for any one variable across all four models. There was some indication of multicollinearity between work status and age group (VIF=3.57 to 4.72 for work status depending on model). It is likely that age and work status are correlated, but we also note that inflation of the variance inflation factor is likely among variables which have 3 or more categories (Fox, J., Monette, G., 1992. Generalized Collinearity Diagnostics. Journal of the American Statistical Association 87, 178–183), so such an estimate does not concern us greatly.

Table S7. Abbreviated results from subsidiary analyses which examine the potential moderating effect of dog ownership on relationships between meteorological conditions and daylight on energy expenditure (MET-minutes) across the four key natural environment types.

Untransformed	Park n=11988 R^2=.09			Woodland n=2947 R^2=.14			Inland waters n=2561 R^2=.12			Coast n=4271 R^2=.07		
	b	LCI	UCI	*b*	LCI	UCI	*b*	LCI	UCI	*b*	LCI	UCI
(Intercept)	247.19	197.69	296.70	29.30	-123.78	182.38	-191.55	-424.30	41.20	134.36	-52.12	320.85
Max. temperature during daylight (°C)*owns dog	0.42	-3.03	3.88	5.70	-2.10	13.51	-0.30	-14.23	13.62	-3.35	-14.56	7.85
Max. wind speed during daylight (m/s) *owns dog	2.47	-4.12	9.06	-7.17	-21.26	6.92	0.41	-25.63	26.46	-8.32	-27.98	11.34
Daylight hours*owns dog	-2.41	-9.06	4.24	**-22.36	-37.48	-7.24	-16.70	-43.16	9.77	5.90	-15.29	27.10
Rainfall (No rainfall=ref)												
Light rain (>0mm to 0.5mm) *owns dog	9.56	-22.90	42.03	24.17	-50.21	98.54	-38.92	-167.53	89.68	-68.89	-172.00	34.21
Moderate/heavy rain (>0.5mm) *owns dog	3.83	-36.17	43.82	*96.86	4.44	189.27	-8.87	-168.61	150.87	-81.01	-206.29	44.27
Log-transformed	Park R^2=.16			Woodland R^2=.24			Inland waters R^2=.21			Coast R^2=.15		
	b	LCI	UCI	*b*	LCI	UCI	*b*	LCI	UCI	*b*	LCI	UCI
(Intercept)	5.24	5.14	5.35	5.19	4.95	5.43	4.93	4.64	5.21	5.23	5.01	5.45
Max. temperature during daylight (°C) *owns dog	0.00	-0.00	0.01	-0.00	-0.01	0.01	-0.01	-0.02	0.01	-0.00	-0.02	0.01
Max. wind speed during daylight (m/s) *owns dog	0.01	-0.01	0.02	-0.01	-0.03	0.01	-0.01	-0.04	0.02	-0.01	-0.04	0.01
Daylight hours*owns dog	-0.01	-0.02	0.00	-0.02	-0.04	0.01	-0.00	-0.04	0.02	*0.03	0.00	0.05
Rainfall (No rainfall=ref)												
Light rain (>0mm to 0.5mm) *owns dog	0.02	-0.04	0.09	0.00	-0.12	0.12	-0.05	-0.20	0.11	-0.05	-0.17	0.07
Moderate/heavy rain (>0.5mm) *owns dog	0.03	-0.05	0.11	0.14	-0.01	0.29	-0.01	-0.20	0.19	-0.06	-0.21	0.09

$^{***}p<.001$
$^{**}p<.01$
$^{*}p<.05$

N.B These models also control for the fixed effects of all meteorological and daylight variables, as well as dog ownership, and all other covariates listed in Table S6.

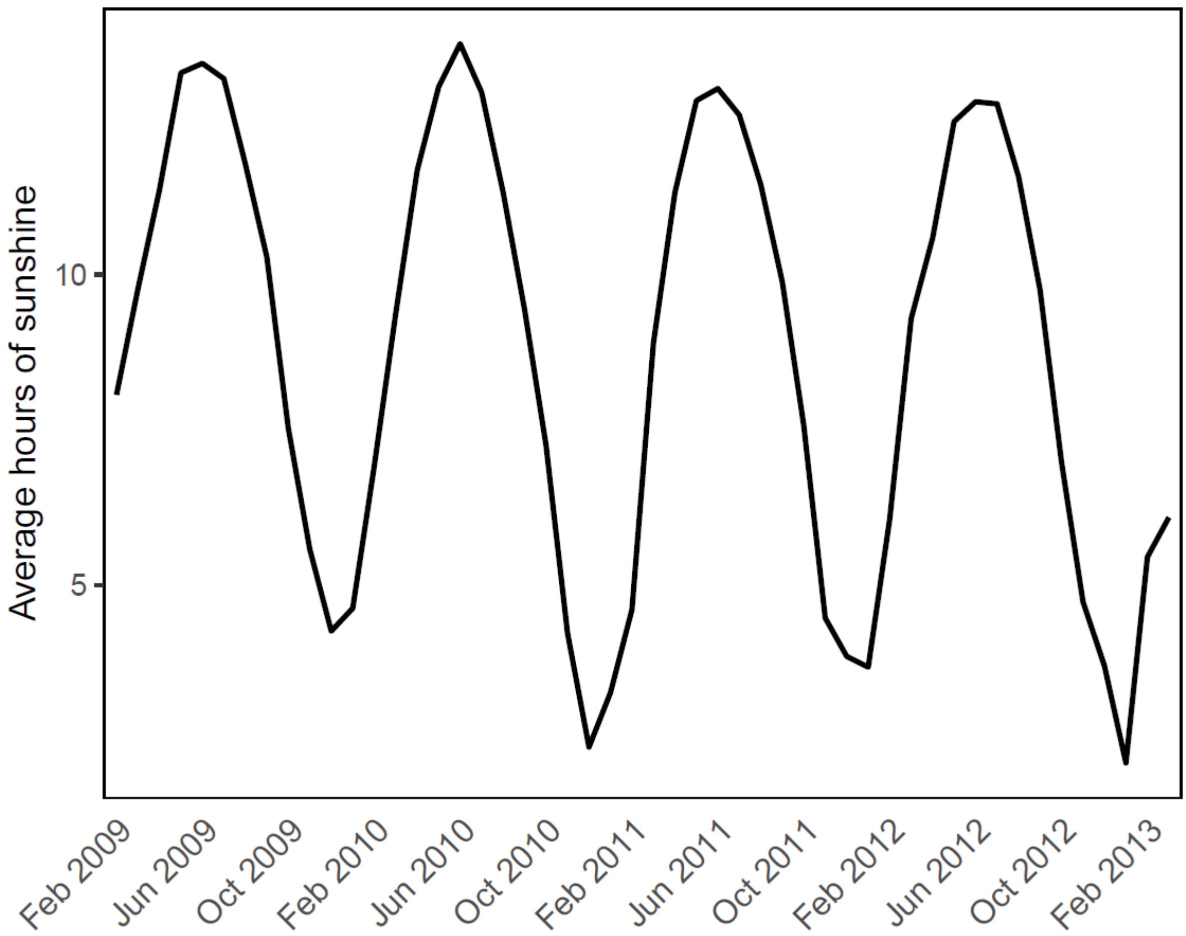


*Figure S1. Hours of sunshine on recreational visits to natural environments across the sampling period. Hours of sunshine data were derived from the Met Office's numerical weather prediction models (*https://www.metoffice.gov.uk/research/modelling-systems/unified-model/weather-forecasting).