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

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## ARTICLE INFO

## 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 = 47,613), 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.

## 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., 2017b). 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., 2017a; 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 $\geq 1$ visit in the previous week ($\approx 42\%$ 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 62,238 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 $0.5$ mm/hour), and "moderate/heavy rain" ($> 0.5$ mm/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 = 11,182); (iii) visits without complete meteorological data (n = 588); and (iv) visits with duration < 1 min (n = 14). This left 47,613 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 = 21,767). 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 $\approx 23$ °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 h, followed by an increase and further plateau after 15 h (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 ($F$ (1,821,726) = 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
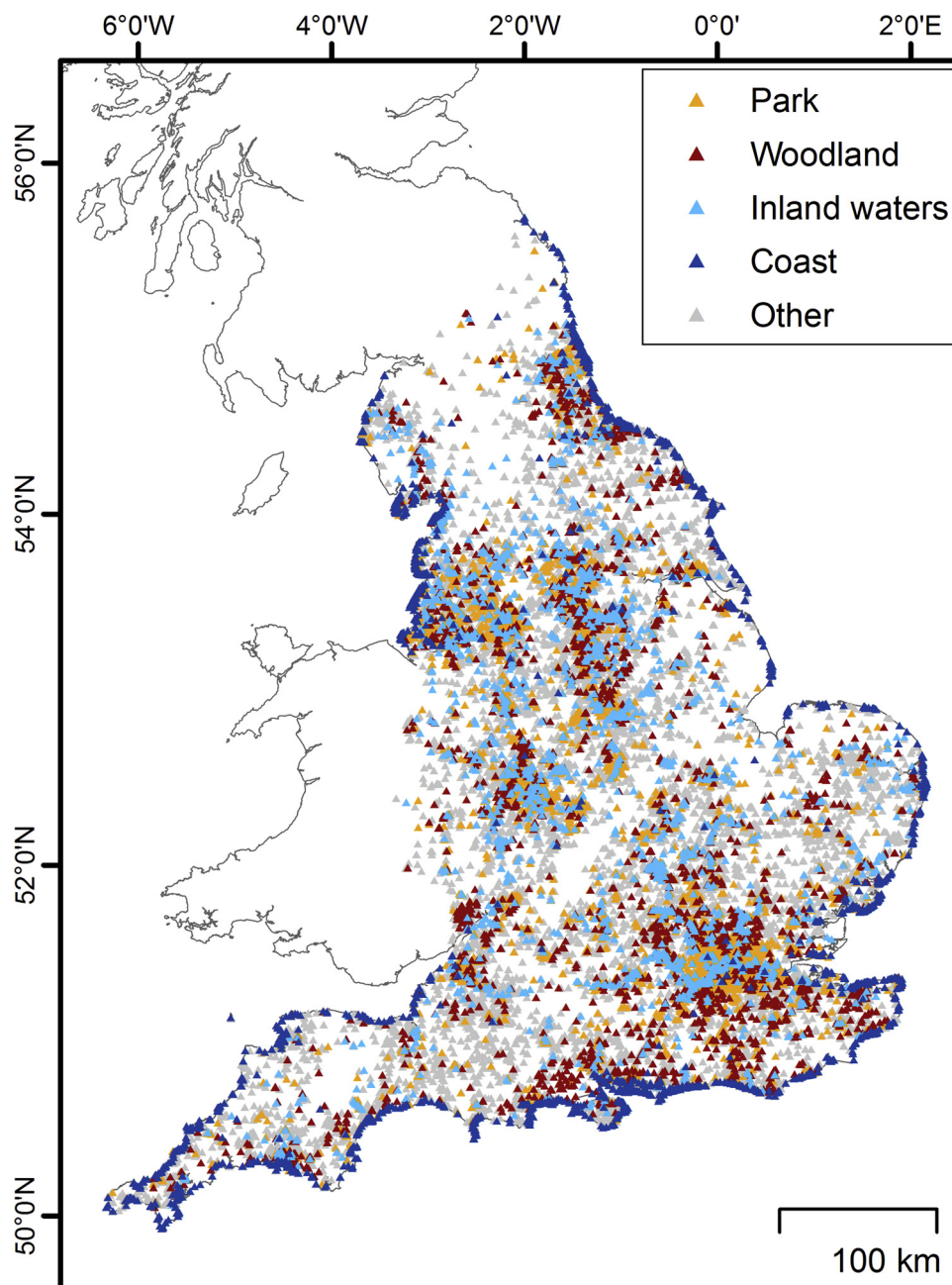
**Fig. 1.** Map of the locations of the 47,613 leisure visits to natural environments in England (2009–2013) included in analyses and their environments.

and smoothed terms, in all environments, were penalised to 1° 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 S7).

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 h 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 h 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 h 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).
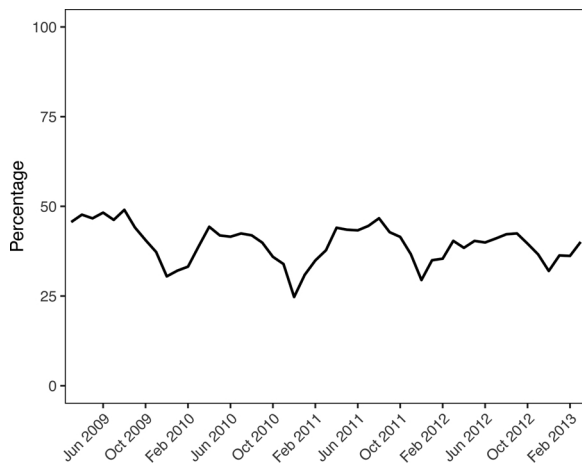
**Fig. 2.** Percentage of respondents reporting at least one recreational visit to a natural environment in the previous week as a function of month of interview.

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 S8) 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).
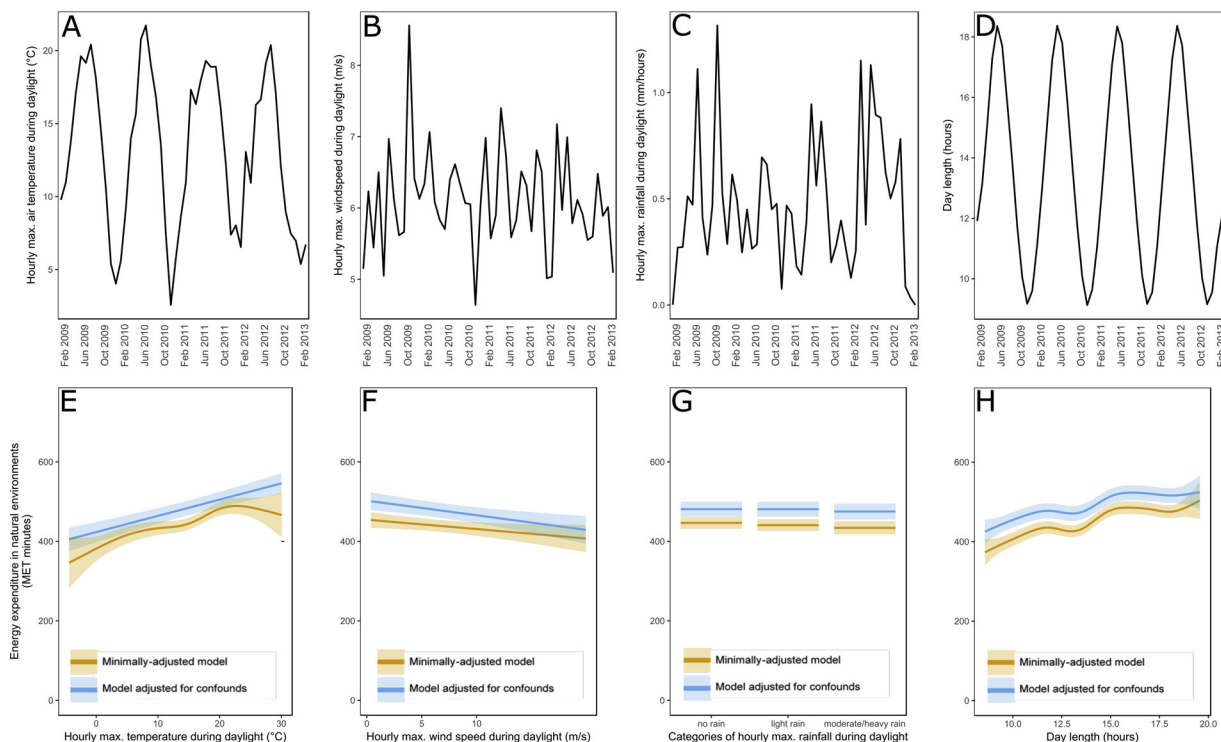


**Fig. 3.** Monthly averaged (a) daily maximum temperature during daylight hours, (b) wind speed during daylight hours, (c) rainfall during daylight hours, and (d) daylight hours, for the leisure visits to natural environments in England (2009–2013) included in analyses. See supplementary materials for 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. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

**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 = 47,613).

| | 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 (> 0 mm to 0.5 mm) | −5.65 | −16.88 | 5.57 | −0.08 | −10.74 | 10.58 |
| Moderate/heavy rain (> 0.5 mm) | −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 (> 0 mm to 0.5 mm) | −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 (> 0.5 mm) | −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° 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.

### 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 = 16,812), 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 h 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
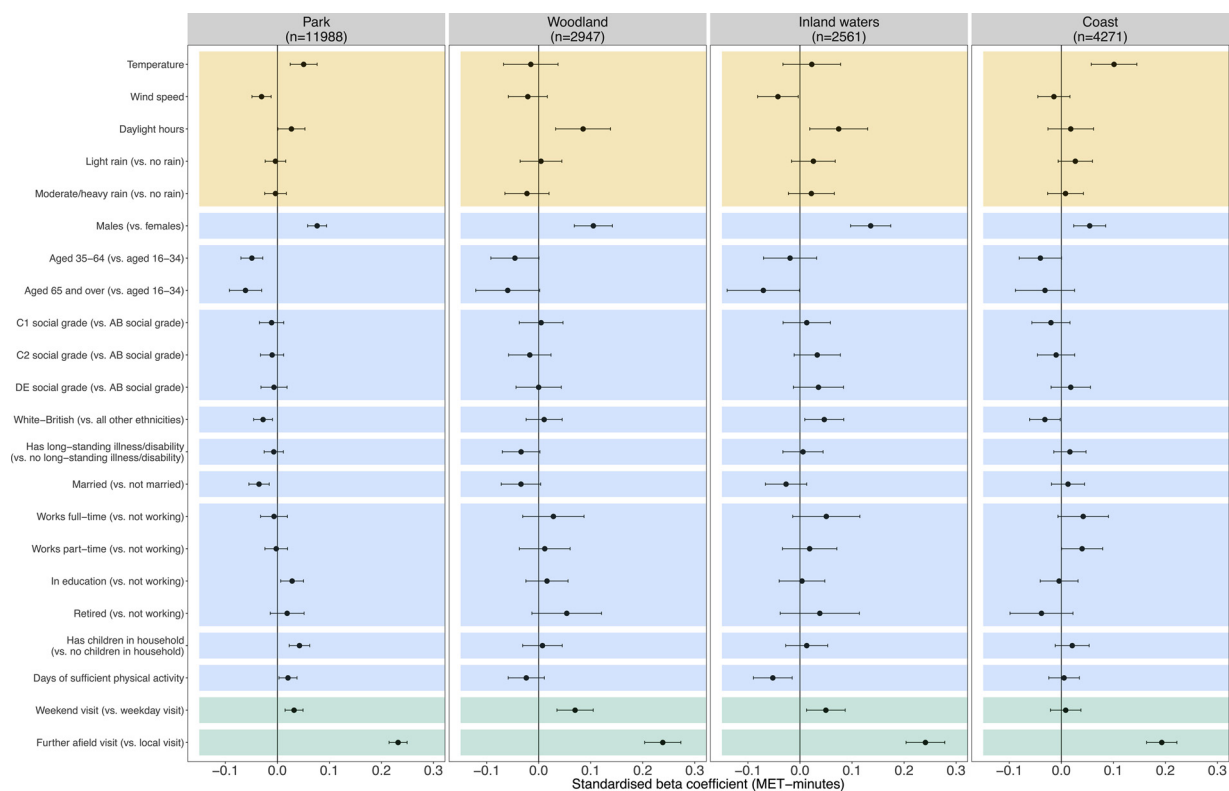
**Fig. 4.** Standardised coefficients and 95% confidence intervals showing the relative strength of all variables in adjusted least-squares linear regression models stratified by type of environment visited for selected leisure visits to natural environments in England (2009–2013). Standardised coefficients 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).

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 for instance caused by migration (Perch-Nielsen et al., 2008) or temperature-related mortality (Gasparrini et al., 2017), 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 ($M = 224$ min) 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. For example in the minimally-adjusted model, meteorological conditions and daylight hours only explained 1% of the variance in energy expenditure. Therefore, while statistically significant, these only appear to play a small role in determining how much energy an individual might expend at a particular natural environment, with other factors such as sex, or whether the visit was further afield, playing a larger role. Future prospective work could investigate how changes in weather or daylight hours might affect energy expenditure within the same individuals over multiple visits, and thus better illuminate the impact of these on energy expenditure where this cross-sectional work could not. In spite of this, we note that 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

### 5.1. 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.

### 5.2. 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 Fig. 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 20 km 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.

### 5.3. Results

Daily maximum temperatures in England show modest increases under both scenarios to 2040. Differences between the two scenarios become more pronounced in 2090 (Fig. A1) with increases under high emissions scenarios approximating 2 °C–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 (Fig. 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 5–6 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).
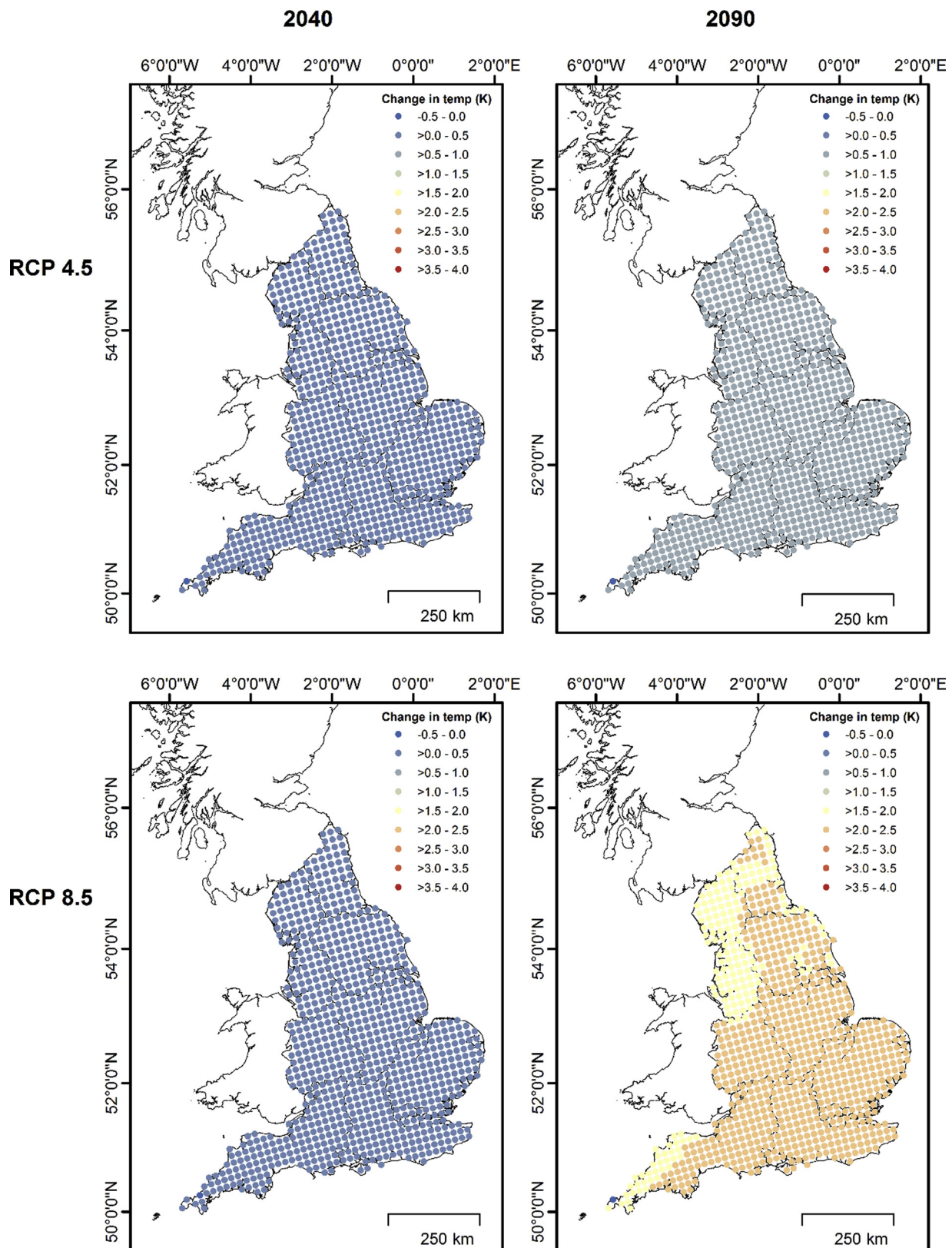
**Fig. A1.** Change (from modelled 2012 data) in mean daily maximum temperature in the four regional climate models.

## 5.4. 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-
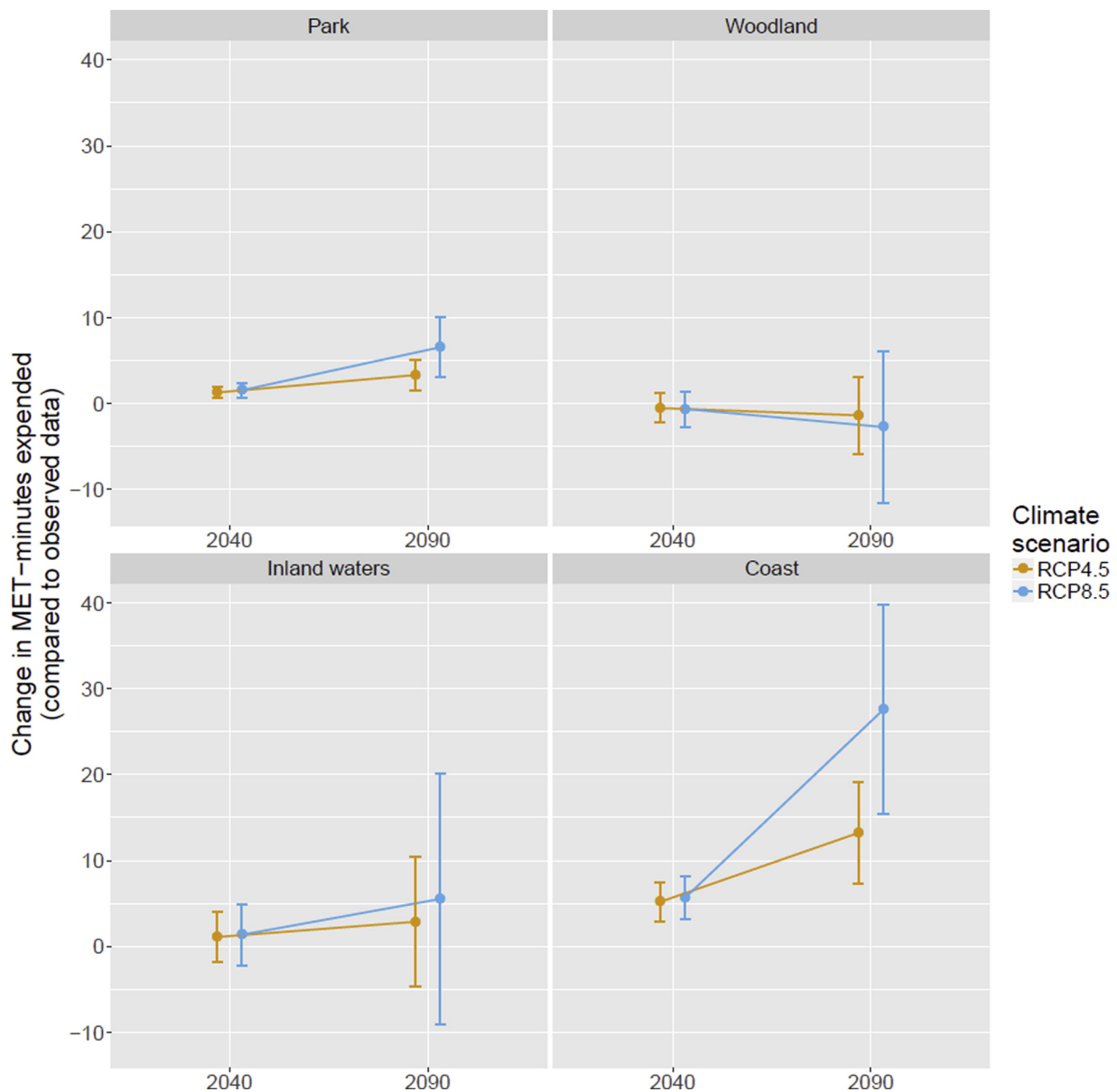
**Fig. A2.** Projected changes in MET-minutes expended parks, woodlands, indland waters, and coasts, as a function of the four regional climate models. Point estimates and confidence intervals simply reflect multiplying coefficients and confidence intervals in the original regressions presented in Table 2 and Fig. 4 by the projected temperautre increase in the 20 km grid square where the visit was located. Thus, these, especially confidence intervals, should be interpreted with caution.

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.

**Declaration of interest**

The authors have no conflicts of interest to disclose.

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## Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ufug.2019.05.005.

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