Fine-scale climate change: modelling spatial variation in biologically meaningful rates of warming

Running title: *Fine-scale spatial variation in warming*

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Abstract

The existence of fine-grain climate heterogeneity has prompted suggestions that species may be able to survive future climate change in pockets of suitable microclimate, termed 'microrefugia'. However, evidence for microrefugia is hindered by lack of understanding of how rates of warming vary across a landscape. Here we present a model that is applied to provide fine-grained, multi-decadal estimates of temperature change based on the underlying physical processes that influence microclimate. Weather station and remotely-derived environmental data were used to construct physical variables that capture the effects of terrain, sea-surface temperatures, altitude and surface albedo on local temperatures, which were then calibrated statistically to derive gridded estimates of temperature. We apply the model to the Lizard Peninsula, United Kingdom to provide accurate (mean error = 1.21ºC; RMS error = 1.63ºC) hourly estimates of temperature at a resolution of 100 m for the period 1977 to 2014. We show that rates of warming vary across a landscape primarily due to long-term trends in weather conditions. Total warming varied from 0.87 to 1.16ºC, with the slowest rates of warming evident on north-east-facing slopes. This variation contributed to substantial spatial heterogeneity in trends in bioclimatic variables: for example, the change in the length of the frost-free season varied from +11 to -54 days and the increase annual growing degree-days from 51 to 267 ºC days. Spatial variation in warming was caused primarily by a decrease in daytime cloud cover with a resulting increase in received solar radiation, and secondarily by a decrease in the strength of westerly winds, which has amplified the effects on temperature of solar radiation on west-facing slopes. We emphasise the importance of multi-decadal trends in weather conditions in determining spatial variation in rates of warming, suggesting that locations experiencing least warming may not remain consistent under future climate change.

Introduction

Biodiversity conservation and environmental management increasingly depend on our ability to understand and predict the responses of species and ecological communities to climatic change. To date, however, most predictions for the effects of climatic change on biodiversity have been derived using grid cell resolutions that are three to four orders of magnitude coarser than the size of the focal species being studied (Potter *et al.*, 2013). Wind patterns and landscape features such as local terrain, vegetation and soil properties interact with regional climate to create complex mosaics of temperature and water availability (Dobrowski, 2011, Hannah *et al.*, 2014, Maclean *et al.*, 2012, Suggitt *et al.*, 2011). This fine-grained variation in climate strongly influences species' distributions (Lassueur *et al.*, 2006, Randin *et al.*, 2009, Scherrer & Körner, 2011, Sebastiá, 2004) and their predicted responses to future climatic change (Franklin *et al.*, 2013, Gillingham *et al.*, 2012).

The existence of fine-grain heterogeneity has prompted suggestions that species may be able to survive future climatic change by exploiting pockets of suitable microclimate, often termed 'microrefugia' (Hannah *et al.*, 2014, Rull, 2009). The term 'microrefugia' is borrowed from paleoecology and is usually used to describe locations with unusual microclimate in which isolated populations survive unsuitable regional climate (Rull, 2009). After the Last Glacial Maximum, many species recolonized parts of their historic range at rates much faster than predicted from dispersal models (Clark *et al.*, 1998). While long-distance dispersal may be important in explaining this phenomenon (Phillips *et al.*, 2008), an alternative explanation is that species recolonized from localities with suitable microclimate much closer to their former range (Stewart & Lister, 2001). Nonetheless, the possible existence of microrefugia is still widely debated (Hylander *et al.*, 2015, Tzedakis *et al.*, 2013) and empirical evidence for the existence of microrefugia, particularly in the context of recent and ongoing climatic change, is still remarkably scarce (Suggitt *et al.*, 2014).

It is sometimes argued that the existence of fine-grained heterogeneity in itself will buffer species against the effects of climatic change (e.g. Willis & Bagwhat 2009). However, many species are already restricted to specific microclimates, and if warming microclimates at the trailing edge of species' ranges are vacated at the same rate as sites become newly occupied at the leading edge, then the effects of microclimate variation will "average out" (Bennie *et al.*, 2014). A further consideration of whether or not microclimates buffer the effects on species of regional climate warming is whether or not all parts of the landscape are undergoing climatic change at the same rate. To date, however, the extent to which rates of change in local climate are decoupled from regional climate has received little attention from biologists, in spite of its importance as a mechanism for explaining how species are able to persist in microrefugia (though see Pepin *et al.* 2011 and Pike *et al.* 2013 for examples in the climate literature). A possible reason for this is that it is difficult to quantify fine-grained variation in rates of climatic change, because this requires climate to be modelled or measured both: a) over a sufficiently long time period to encompass an appreciable level of global warming, and b) at a sufficiently fine resolution to quantify local variation in rates of change.

While next-generation fine-grained climate models are emerging, our understanding of local variation in rates of change remains limited. Kearney et al. (2014) present a mechanistic model of gridded hourly estimates based on local modifiers of the solar radiation budget for the period 1961 to 1990, but the grid cell resolution of this model is a relatively coarse 15 km and local variation in rates of change is not explored. Dobrowski (2011) identifies terrain features that are likely to be effectively decoupled from regional climatic patterns, but stops short of explicitly modelling the effects of these features over an extended time period. Gunton *et al.,* (2015) model local ground temperatures across Europe, but do not provide long-term estimates of change. Likewise Bennie et al. (2008), using similar principles, modelled near-surface temperatures at resolutions of one metre, but again do not assess local variation in long-term change. Heterogeneity in long-term warming was assessed in a study by Ashcroft *et al*., (2009) in which rates of warming between 1972 and 2007 were modelled within a 10 km x 10 km region approximately 80 km south of Sydney, Australia. However, long-term estimates of temperature change in this study and determinants of local variation in change are estimated using a phenomenological approach based on statistical relationships established over a relatively short period. Models based on phenomenological descriptions can be unreliable when used to predict beyond the realm of existing data (e.g. Rice, 2004). While models based on the physical processes can be difficult to parameterise and necessitate assumptions to be made about model structure, they are often more likely to provide reliable predictions under novel conditions (Evans, 2012).

Here we present a model that incorporates the important mechanistic processes that govern variation in climate to provide fine-grained (100 m) hourly estimates of temperature over decades at regional scales. The model is applied to assess spatial variation in rates of warming and changes in biologically meaningful derivatives of temperature between 1977 and 2014 across a 20 x 30 km region located on the southwest coast of Britain (The Lizard Peninsula in Cornwall). While all parts of the landscape warmed during this period, rates of warming differed by a factor of 1.3, with significantly slower rates of mean warming evident on north-east-facing slopes and valley bottoms. This spatial variation in temperature change has led to even greater spatial variation in the rate at which bioclimatic variables have altered, with the overall change in the length of the frost free growing season, for example, varying from a decrease of 11 days to an increase of 54 days. We provide insight into the mechanisms governing rates of warming, demonstrating how landscape features interact with changing weather patterns to decouple local changes in climate from regional averages.

Materials and methods

Overview of approach

The study was conducted on the Lizard Peninsula (50º 2'N, 5º 10'W), a Special Area for Conservation (92/43/EEC) located on the most southerly point of Britain (Fig. 1). The climate has a strong maritime influence with mild winters and low annual temperature range. The site is surrounded on three sides by the sea, has an elevation range of 0 to 185 metres above sea level and comprises a mosaic of grassland, woodland and heath on a variety of slopes and aspects. We model hourly local temperature anomalies from a standard meteorological station as a function of landscape features that interact with physical determinants of local temperatures. Estimates are for one metre above the ground at a grid cell resolution of 100 m for the period 1st January 1977 to 31st December 2014.

To drive the model, hourly weather data for the period 1st January 1977 to 31st December 2014 were obtained for Culdrose weather station (Fig. 1). A small number (<0.01%) of observations were missing and were imputed by fitting a cubic spline using the Forsyth *et al.* (1977) method implemented by the spline function in R (R Development Core Team, 2013). Five groups of factors were considered to influence local temperatures, details of which are provided below: (i) coastal influences, as a function of sea surface temperatures, wind speed and direction and sea-exposure; (ii) the local radiation balance, as a function of weather conditions, surface albedo, slope and aspect; (iii) altitudinal effects, as function of elevation and humidity; (iv) latent heat exchange, as function of evapotranspiration and condensation; and (v) cold air drainage into valley bottoms, as a function of flow accumulation potential and weather conditions that lead to katabatic flow.

To calibrate the model, 35 iButton temperature dataloggers were deployed in open, unwooded areas across the Lizard Peninsula between 1st March 2010 and 14th December 2011, and set to record temperatures at hourly intervals. Loggers were placed to capture spatial gradients in the main determinants of climate and provided 89,250 measurements of temperature for model calibration. Each logger recorded temperature with a specified accuracy of ± 0.5 ° C, and 0.0625 ° C resolution. Loggers were attached to a wooden pole one metre above the ground and orientated to face north and shielded from direct sunlight using a white plastic screen. To provide an independent validation of the model results, an additional 30 loggers were deployed between March and November 2014 at nearby, but not identical locations to those deployed in 2010-11 (mean distance between pairs of locations: 381 m; Fig. 1).

To improve readability, we omit mathematical details of our methods from the main text. Further details and functions for implementing individual components of the model, written using R statistical software (R Development Core Team, 2013), are provided in supporting information (Appendix S1 and S2). However, an overview of the underlying rationale and a synopsis of our approach are provided below.

Coastal influences

We obtained a one degree gridded dataset of monthly sea ice and sea surface temperatures from the Met Office Hadley Centre (Rayner *et al.*, 2003) and extracted data for the four grid cells corresponding to the region 49-51ºN and 4-6ºW. We resampled these datasets at 100m grid cell resolution using bilinear interpolation and projecting them onto the Ordnance Survey equal area grid (OSGB36). We then calculated the mean sea surface temperature for the marine portion of our entire study area. We obtained hourly values by simple linear interpolation, assuming that the mean value for each month corresponded to the mid-point of that month. Due to the high specific heat capacity of water, sea surface temperatures undergo only minor high frequency fluctuations (Stacey & Davis, 1977), so simple interpolation was deemed a reasonable approximation.

To capture the influence of sea temperatures on local temperatures, which is itself affected by wind direction (Haugen & Brown, 1980), we calculated the proportion of 100 m x 100 m pixels that were land as opposed to sea upwind of each focal pixel in each of 36 different compass directions (0º, 10º…350º) using a 100 m resolution gridded dataset of land and sea. We then weighted these proportions by the inverse of the distance to the coast, to ensure that coastal grid cells were attributed a higher coastal exposure influence (function *inv.ls* in Appendix S1). Coastal effects on local temperatures are also influenced strongly by wind speed (Haugen & Brown, 1980). However, surface friction tends to reduce airflow, and wind speeds at one metre height differ from those measured at the height of the Culdrose anemometer (33 m above the ground). To adjust for height, and derive estimates for one metre above the ground, a logarithmic wind speed profile was assumed (Allen *et al.*, 1998; function *wind.hgt* in Appendix S1). The sheltering effect of local topography was accounted for by computing the shelter coefficient described by Ryan (1977; function *windcoef* in Appendix S1).

Solar radiation

Local temperature anomalies due to variation in solar radiation approximate a linear function of the net radiation flux at a location, with the slope of this relationship determined by local wind speed (Bennie *et al.*, 2008). Net radiation is determined by the balance of short- and long-wave radiation and surface albedo. We estimated surface albedo from 25 cm resolution visual and 50 cm colour-infrared aerial photographs obtained from Bluesky (Bluesky International Ltd, Coalville, UK). We weighted the reflectance value in each band by the expected proportion of total solar energy contributed by each band by assuming that the relationship between energy and wave-length approximates the 5250ºC blackbody spectrum described by Planck's law (function *albedo* in Appendix S1). This ignores temporally variable, but relatively minor discrepancies caused by atmospheric absorption of specific wavelengths. The mean value in each 100 m grid cell was calculated.

Satellite-derived estimates of direct and diffuse shortwave radiation are available at hourly intervals at a horizontal grid cell resolution of 0.03º from the Satellite Application Facility on Climate Monitoring (Posselt *et al.*, 2011). However, as they do not span the duration of our study, we developed a model for predicting solar radiation from meteorological station estimates of cloud cover (recorded in oktas). First we obtained satellite-derived estimates of radiation for the grid cell corresponding to the location of Culdrose weather station for every hour in 2005 (the year with fewest missing weather station observations). Then, because solar irradiance is affected by solar azimuth and zenith, we computed the proportion of potential direct irradiance intercepted by a flat surface located at Culdrose (hereafter referred to as the solar coefficient) for every hour using the methods outlined in Hofierka & Ŝúri (2002; function *solarindex* in Appendix S1). Second, because solar energy is attenuated more by clouds when the sun is low above the horizon, we calculated the airmass coefficient for every hour in 2005. The airmass coefficient is the direct optical path length of a solar beam through the Earth's atmosphere, expressed as a ratio relative to the path length vertically upwards. To account for the earth's curvature, we used the method by Kaston and Young (1989) in which the air mass coefficient can be derived from the solar zenith (function *airmasscoef* in Appendix S1). Next, to estimate the effects of cloud cover on full beam solar irradiance, we divided each satellite-derived estimate of direct and diffuse solar irradiance by the solar coefficient. As direct irradiance is affected both by cloud cover and the airmass coefficient, we fitted a linear model with the full beam estimates of direct irradiance as a dependent variable, and airmass coefficient, cloud cover and an interaction between cloud cover and the airmass coefficient as predictor variables. To reduce heteroscedasticity, we performed square-root transforms on cloud cover and full-beam irradiance and a logarithmic transform on the airmass coefficient. As diffuse irradiance is highest with intermediate levels of cloud cover, we fitted a linear model with diffuse radiation as the dependent variable and just cloud cover and the square of cloud cover as predictor variables. Again to reduce heteroscedascity, we square-root transformed scaled solar irradiance. Coefficient estimates of these models were used to derive hourly estimates of full beam solar irradiance and diffuse radiation for the entire duration of our study.

Slope, aspect and topographic shading influence strongly the amount of radiation intercepted by a surface and act as one of the dominant influences on local temperatures (Bennie *et al.* 2008). To account for the effects of local terrain on direct radiation, we calculated the solar coefficient for an inclined surface using the method detailed in Bennie *et al.* (2008; function *solarindex* in Appendix S1) and multiplied our coarse-grained cloud-cover derived estimates of full beam radiation by this coefficient. Topographic shading is also accounted for when implementing this method by assuming that a surface receives no direct radiation when the sun is below the local horizon. Slope, aspect and horizon angles were derived from a 5 m resolution digital terrain model obtained from Bluesky (Bluesky International Ltd, Coalville, UK) coarsened to 100 m resolution by computing mean values within each grid cell. Local topographic effects on diffuse radiation were calculated by scaling our cloud-cover derived estimates of diffuse radiation by the proportion of sky in view, using methods described in Hofierka & Ŝúri (2002; function *skyview* in Appendix S1).

Net long-wave radiation was calculated from temperature and relative humidity data using the method described in Allen *et al.* (1998; functions *netlong* in Appendix S1). Using this approach, the effects of cloudiness are accounted for by estimating the ratio of net shortwave to clear sky shortwave radiation, which in our model was estimated directly from cloud cover. Longwave radiation was assumed to be uniform across the landscape and hence the meteorological station temperature was used.

Altitudinal effects

We assumed a simple dry adiabatic lapse rate such that temperature declines with altitude at a standard dry adiabatic lapse rate of 9.8ºC per 1000 m, but accounted for shallower temperature-altitude gradients under saturated conditions by explicitly calculating latent heat exchange (see below), resulting in typical adiabatic lapse rates of 4 to 6ºC per 1000 m. Differences in altitude between the standard meteorological station and each location were calculated from digital elevation data.

Latent heat exchange

Condensation releases latent heat energy warming local air temperatures by as much as 2ºC (Geiger, 1965). Conversely, evapotranspiration uses latent heat energy, cooling local temperatures. Localised variation in these can result in small, but important variations in temperature. As calculation of condensation and evapotranspiration relies on knowledge of local temperatures, but in this instance is also used to derive local temperatures, we used the local temperature anomaly (i.e. the difference between modelled local temperature and that at the meteorological station) in the previous time step, to derive estimates of local differences in latent heat exchange from our reference meteorological station. We assume condensation occurs when drops in temperature result in relative humidity exceeding 100%. First, from Allen *et al.* (1998) we calculate the local relative humidity as a function of the relative humidity measured at the met station, saturated vapour pressure and absolute humidity, which is assumed to remain constant, thus allowing local relative humidity to exceed 100% (function *rh.change* in Appendix S1). Where local relative humidity is less than 100%, condensation is assumed not to occur, but where relative humidity would exceed 100% as a result of temperature decreases, the surplus water is assumed to condense (function *water.conden* in Appendix S1). Following Allen *et al.* (1998) potential evapotranspiration was calculated as a function of net radiation, local temperatures (estimated from anomalies in the previous time step), relative humidity, atmospheric pressure and wind speed using the Penman-Monteith equation (function *CRE* in Appendix S1).

Cold-air drainage

Under clear sky conditions with low wind speed, katabatic flow occurs, such that cold air drains into valley bottoms (Dobrowski, 2011). Two components of cold air drainage were considered. First we modelled the potential for different parts of the land surface to receive cold air by calculating accumulated flow to each cell, as determined by accumulating the weight for all cells that flow into each downslope cell, using the hydrological tools in ArcGIS 10.2 (ESRI, Redlands). We then identified the synoptic weather conditions under which cold air drainage is likely. Following McGregor & Bamzelis (1995), we first collated and/or calculated the following meteorological variables from the meteorological station data, aggregating data into 24-hour averages: (i) cloud cover (oktas), (ii) mean temperature (ºC), (iii) diurnal temperature range (ºC), (iv) surface atmospheric pressure (hPA), (v) relative humidity (%), (vi) wet bulb temperature (ºC), (vii) the dew point temperature (ºC), (viii) visibility (km), (ix) net radiation (MJ m^{-2} hr^{-1}), (x) the westerly wind component (m s^{-1}) and (xi) the southerly wind component (m s^{-1}). Visibility data were log-transformed to reduce heteroscedasticity and all variables were z-score standardised. Meteorological variables were also de-seasoned by applying a 15 day running mean filter. Second, as the resulting variables were highly correlated with one another, we performed principal components analysis (PCA). To determine how many components to retain, we produced a scree plot, retaining four components which together explained 85% of the variance in the original data. Finally we performed Bayesian model-based clustering on these data using the R package mclust (Fritsch & Ickstadt, 2009), to group our data into distinct synoptic weather types. Using this approach, prior cluster partitions are identified using hierarchical agglomeration, and then Bayesian expectation-maximization is performed to automatically identify the final cluster number and membership thereof. Seven was considered the most likely number of distinct synoptic weather types using this method (see results). The synoptic weather type characterised by clear sky, high pressure, a high diurnal temperature range, good visibility and low relative humidity was considered to be the conditions under which temperature inversions occur (see e.g. Barr & Orgill, 1989). Temperature inversions were set to occur at night only as daytime cold air drainage into valleys is highly unusual in maritime climates (Gustavsson *et al.*, 1998).

Model calibration

Temperature anomalies were modelled using standard linear regression as a function of the following sets of terms:

Radiation effects: $R_{net} + u_1 + u_1 R_{net}$

Coastal influences: $u_i L + u_1 L + L T_s$

Altitudinal effects: ΔT_a

Latent heat exchange: $E + C + W$

Cold air drainage: $I_C F$

Where R_{net} is net radiation, u_1 is wind speed one metre above the ground, u_i is the inverse of wind speed given by $1/(u_1^{0.5}+1)$, L is the inverse distance-weighted measure upwind land-to-sea ratio at Culdrose minus that at the site, T_s is sea-surface temperature minus that at Culdrose, ΔT_a is the expected difference in temperature due to altitude, E is evapotranspiration at Culdrose minus that at the site, C is condensation at Culdrose minus that at the site, W is the change in lapse rate due to water condensation, F is accumulated flow and I_c is a categorical variable set at one when temperature inversions exist, and 0 when temperature inversion conditions do not exist. The terms are listed in anticipated descending order of importance.

To fit the model, we sequentially added each set of terms to linear models and assessed whether their inclusion improved model parsimony by computing the Akaike Information Criterion (AIC). To reduce the effects of temporal autocorrelation, we randomly selected 2000 of the 89,250 logger-derived local temperature data and repeated the analyses 9999 times, computing AICs and coefficient estimates for each model run. To test the effects of sample size on the retention of model terms, we repeated analyses varying the number of randomly selected data points. To assess the sensitivity of our model selection to the sequential adding of terms, we also fitted models with all possible combinations of terms, but due to computational constraints, did this for 999 model runs only.

Running and testing the model

To run the model, median model coefficient estimates were used. The model was run in hourly time steps for the period 1st January 1977 to 31st December 2014, deriving temperature estimates for each 100 m grid cell of our study area. To test the model, model predictions were compared with the observed data obtained through the deployment of temperature loggers in 2014. To assess the relative contribution of individual components of the model, we re-ran the model with only the set of coefficients with each effect included, holding other coefficients at their mean. The model was coded and deployed in R statistical software (R Development Core Team 2015) using a 2032 CPU Core Beowulf cluster.

Spatial variation in climatic change

To examine spatial variation in rates of warming, we calculated the overall degree of temperature change in each grid cell using linear regression on hourly values over (a) the entire duration of our study and (b) for 2010 to 2014, a period in which land temperature rose much faster than sea temperatures. To examine how spatial variation in temperature change manifests itself in changes to bioclimatic variables, we calculated the overall 1977-2014 change in (i) exposure to high temperatures, (ii) the number of growing degree-days, (iii) the length of the frost-free season, (iv) diurnal temperature ranges, (v) isothermality, (vi) temperature seasonality, (vii) maximum annual temperatures, (viii) minimum annual temperatures, (ix) annual variations in temperature and (x-xiii) mean temperatures in the warmest, coldest, driest and wettest quarter of each year. Exposure to high temperatures was expressed as the number of hours in which temperatures equalled or exceeded 20ºC, growing degree-days were calculated as the difference between mean daily temperatures and a base temperature of 10ºC, with temperatures capped at 30ºC and values summed for each year, and the frost free season is the number of days between the last day in spring in which air temperatures drop below zero and the first such day in autumn, with spring frost set at 1st of Jan and autumn frost at 31st Dec in instances when temperatures did not drop below zero. The diurnal temperature range was calculated as the difference between the maximum and minimum hourly temperature in any given 24-hour period, the annual temperature range as the difference between the maximum and minimum temperatures in any given year and isothermality as the mean diurnal range divided by the annual temperature range. The temperature seasonality was expressed as the standard deviation of temperatures expressed as a percentage of the mean of those temperatures, with temperatures expressed in Kelvin (Hijmans *et al.*, 2005). A quarter is here defined as any 90 day period. Temperature data from the Culdrose weather station were used to calculate the warmest and coldest periods, and 5km grid daily rainfall data available from the UK Met Office used to calculate the wettest and driest periods. In each case, values were calculated separately for each year and linear-regression on yearly values used to calculate the overall change. To gain insight into the factors affecting warming, we reran the model calculating the separate contribution of each of the five groups of factors to produce hourly temperatures. This was achieved by fitting the model using only coefficients associated with to each group of terms, holding all other terms constant at their mean value. Long-term trend in selected weather variables (wind speed and direction, cloud cover and the prevalence of each synoptic weather type) were also calculated using linear-regression.

Results

Model performance

Our cloud-cover derived model provided good approximations of direct (Mean error = 34.9 Wm^{-2}; RMS error = 71.8 Wm^{-2}), diffuse (mean error = 21.1 Wm^{-2}; RMS error = 39.5 Wm^{-2}) and total solar irradiance (Mean error = 38.6 Wm^{-2}; RMS error = 74.6 Wm^{-2}). Full results are presented in supporting information (Appendix S3).

Our cluster analysis of weather variables identified seven synoptic weather types, one of which represents conditions where no clear pattern could be discerned (Table S1 in Appendix S3). Box and whisker plots indicating the median and range in meteorological variables associated with each weather type and UK Met Office synoptic charts for dates conforming to each synoptic weather type are shown in Appendix S3.

The most parsimonious model was that which included all terms. This model explained on average 78% of the variation in local temperature anomalies (r^2 = 0.711 to 0.831), with a mean error of 1.21 ºC and RMS error of 1.63ºC. Parameter estimates, their standard deviation and partial r-squared values are shown in Table 1. Comparisons between modelled hourly predictions of temperature and recorded temperatures at two sites with divergent local climatic conditions are shown in Figure 2. Further details of model performance are shown in Appendix S3.

Changes in weather variables

Linear regression of hourly temperatures recorded at Culdrose weather station revealed an increase of 0.94 ºC between 1977 and 2014 (95% CI = 0.89 to 0.99, n = 333096; Fig. 3a). Over the same period, linear regression of monthly sea-surface temperatures showed an overall increase of 0.89 ºC (95% CI = 0.21 to 1.57, n = 649; Fig. 3b). Among other weather variables, there were two notable trends. First, linear regression on hourly estimates reveals that although cloud cover has changed little (<0.2%) over the duration of the study (95% CI = -0.49% to 0.15%, n = 333096), daytime cloud cover decreased by 4.0% (95% CI = -5.1% to -2.9%, n = 166602; Fig. 3c), whereas night-time cloud cover increased by 1.2% (95% CI = 0.7% to 1.7%, n = 166602; Fig. 3d). Changes in cloud cover appear to have manifested themselves in moderate increases in received solar radiation: direct radiation was estimated to have increased by 11.9 Wm^{-2} over the period of the study (95% CI = 5.2 to 18.7, n =333096; Fig. 3e). However, diffuse radiation has changed little (95% CI = -2.8 to 7.0 Wm^{-2}, n =333096; Fig. 3f).

Second, there appears to have been a shift in wind vectors. Linear regression of hourly values reveals a decrease in zonal (west to east) wind velocity of 0.66 ms^{-1} over the duration of the study (n =333096, 95% CI = -0.71 to -0.60; Fig. 3g) and a decrease in meridional wind velocity (the northerly wind component) of 0.44 ms^{-1} (n =333096, 95% CI = -0.49 to -0.39; Fig. 3h). Somewhat paradoxically, however, the synoptic weather type associated with easterly winds, weather type 1, also indicative of weakly anticyclonic conditions, high pressure and high relative humidity, decreased by 2.2% from 10.1% to 8.0% (n=38, 95% CI = -4.3 to -1.3%) and was the only type for which a trend was evident (Fig S6). The most likely explanation of this is that while the mean zonal component of the wind vector in any given year remained relatively constant over time during periods in which synoptic weather type 1 prevailed (95% CI = -0.93 to 1.01 ms^{-1}, n=38), the zonal component in any given year during periods in which synoptic weather types other than type 1 prevailed, decreased substantially (-1.75 ms^{-1} over the duration of the study; 95% CI = -1.41 to -2.09 ms^{-1}, n=38).

Spatial variation in climatic change

Linear regression of hourly temperatures in each grid cell demonstrated that grid cells have warmed, but rates of warming between 1977 and 2014 varied from 0.87ºC to 1.16ºC, with two dominant patterns evident (Fig. 4a). First, grid cells receiving high solar radiation have, on average warmed by more than those receiving low radiation. Second, east-facing slopes, particularly those exposed to the sea have warmed the least. The period 2010 to 2014, in which temperatures recorded at Culdrose rose by 2.30 ºC in comparison to sea-surface temperatures rising by 1.34 ºC (Fig. 3a,b), reveals broadly similar patterns, although an east-west gradient is more evident, with the highest temperature increases occurring towards the west of our study area (Fig. 4b).

Temperature increases were higher in the cold-season (22nd Dec-21st Mar) than in the warm- (18th Jun-15th Sep) and dry-season (14th Mar to 12th Jun), but were least marked in the wet-season (5th Oct-2nd Jan), implying that it is late-winter temperatures that have risen the most (Appendix S4g-j). Spatial patterns of change in bioclimatic variables (e.g. Appendix S4a-f) highlight that even moderate variations in temperature increase can lead to marked variation in biologically meaningful climate variables. The overall change in the number of hours of exposure to high temperatures (>20ºC) varied from a decrease of 15 hours to an increase of 256 hours, with the greatest increases occurring in areas with the greatest temperature increase, such as on southwest-facing slopes (Fig. 5a). The total increase in growing degree-days varied by more than a factor of 5, ranging from 51 ºC days on north-east facing slopes at higher altitudes, to 267 ºC days on steep southwest-facing slopes (Fig. 5b). Changes in the length of the frost-free season also varied substantially, with marginal decreases of up to 11 days along sheltered river valleys subject to cold-air drainage, but substantial increases of up to 54 days along eastern coastal regions of our study area (Fig. 5c). Here, the strong east-west gradient is driven primarily by the overall likelihood of frost, which is markedly lower in western coastal areas.

Closer inspection of the individual components of our model that most contribute to the spatial variation in warming suggests that the effects of solar radiation are most important (Fig. S9 in Appendix S3). This appears to have manifested itself in two ways. First, reductions in daytime cloud cover (Fig. 3c) have resulted in a general increase in direct radiation received at each cell, which in turn means that grid cells receiving high radiation have warmed by more than those receiving less radiation (Fig S9a). Second, reductions in the westerly wind vector (Fig. 3g), and the concomitant increase in easterly winds, appears to have had the dual effects of decreasing the effects of radiation on these slopes (Fig S9c) and increasing coastal effects towards the east of our study area, particularly during periods of slow rises in sea temperature (Fig 3b).

Discussion

Model performance

Our model provides reliable estimates of local temperatures, and demonstrates the potential advantage of modelling the physical processes that drive climatic variation, albeit that assumptions must be made about the functional relationships between temperature and the features that influence this. It also provides finer-grained and more accurate estimates than previous physical-based models (Gunton *et al.*, 2015, Kearney *et al.*, 2014). Nonetheless, it is not surprising that our model provides more accurate estimates than attempts to model continent-wide local temperatures, as the geographical characteristics and weather patterns that influence local temperature anomalies are likely to vary by region. Attempts to model local ground temperatures based on local radiation budgets and weather station data situated within a few hundred metres of a study area, such that meso-climatic variation is implicitly accounted for, have resulted in models capable of estimating in excess of 90% of local variation in temperature (Bennie *et al.*, 2008), emphasising that it is the influence of regional air flows on temperature rather than the effects of local radiation that are more difficult to model reliably. At fine scales, in the order of millimetres to metres, it is local radiation that dominates the earth's energy budget, whereas at scales of metres to kilometres, the horizontal and vertical transfer of energy by moving air-masses becomes increasingly important (Geiger, 1965).

Nonetheless, over the extent of our study area, local variation in net solar radiation appears to be the dominant driver of variation in temperature, and it is thus worth highlighting that there are at least three limitations associated with our ability to capture the effects of this variation. First, because we have attempted to model long term changes in temperature, our estimates of incoming short-wave radiation are based on crude estimates of cloud cover at a single point location. Incoming radiation, as well as being affected by spatial variation in cloud clover, is also affected by cloud thickness and atmospheric conditions, notably by the concentration of aerosols and atmospheric gases (Kasten, 1996, Twomey, 1991). Spatial and temporal variation in these is unaccounted for by our model, and is likely to account for much of the unexplained variance in local temperatures. Second, our model makes no attempt to account for the effects of vegetation. Vegetation is known to have strong influence on local temperatures, and although these differences are greatest closest to the ground (Suggitt *et al.*, 2011), canopy cover and leaf area density affect solar radiation budgets (Kuuluvainen & Pukkala, 1989). Our temperature loggers were all located in areas with minimal canopy cover and our model is intended to be of temperatures in habitat types in which temperatures a metre above the ground are not strongly affected by vegetative shading. Lastly, for the purposes of efficiently modelling hourly temperatures, we use a simple linear relationship between net radiation and temperature, thus making the assumption that soil heat flux is relatively small and temperatures rapidly achieve equilibrium with environmental conditions (see also Bennie *et al.*, 2008). While it is likely that heat exchange may cause time-lags between radiation and temperature, perhaps a greater consideration is the scale-dependency of effects of topographic variation on the radiation budget. Estimates of slope and aspect for a 100 m grid cell essentially average the fine-scale variation in these measures. However, the aggregated effects on radiation of this variation may scale non-linearly with coarse-scale estimates of radiation, perhaps explaining why our model fails to capture perfectly the local temperature extremes. Future efforts to model local temperatures might benefit from exploring these non-linearities. Further improvements in modelling are also likely to be obtained by explicitly accounting for the effects of land-sea temperature gradients on coastal wind processes (e.g. Savijärvi, 2004), and by more sophisticated modelling of katabatic flows (e.g. Manins & Sawford, 1979). Our existing model provides poor representation of the effects of slope steepness on pooling and the cumulative time over which pooling occurs.

Overall, however, our study demonstrates the possibility of predicting temperatures at high spatial resolution and frequency using readily available data. We believe that the process of statistically calibrating variables that capture underlying physical processes ensures that a good combination of utility, analytical tractability and robustness, particularly to novel conditions, is achieved.

Spatial variation in climatic change

The results of this study provide evidence that there is at least some fine-scale variation in rates of warming, with rates of warming typically higher on southwest-facing slopes and in this respect, are similar to those of Ashcroft *et al.*, (2009) who also demonstrate fine scale variation in rates of warming, with higher warming on equatorward-facing slopes. While our results suggest that the variation in rates of warming is relatively moderate, being only ~20% higher on southwest-facing slopes, it is important to note that even moderate variation in temperature change manifests itself in substantial variation in the rate of change in biologically-meaningful climate variables. Overall increases in growing-degree days varied by more than a factor of five, and changes in exposure to high temperatures varied from a decrease to a marked increase. The greatest variation was, however, observed in the length of the frost free-season. Sheltered valleys subject to cold-air drainage have experienced a shortening in the frost-free season, likely due to the increase in clear-sky conditions, whereas coastal fringes in the east of our study area have experienced an increase of over a month. Our results emphasise that in frost-rare environments even minor temperature changes can lead to a large change in the likelihood of frost and spatial variation in the prevalence of frost is amplified substantially.

These variations in bioclimatic variables imply that organisms occupying different parts of the landscape will experience variable rates of change. We emphasise that it is not the existence of cool microclimate *per se* that leads to the potential existence of microrefugia, but it is the extent to which changes in weather conditions lead to thermal decoupling of local trends in temperature change from those occurring regionally.

Across our study area and over the duration for which our model provides estimates of temperature, there appear to be two dominant trends in weather conditions that account for the variation in temperature increase. First, daytime cloud cover has generally declined, with a particularly substantial decline over the period between the early 1990s and 2010. As a consequence net solar radiation has increased, with the overriding effect that the temperature rise is amplified in areas receiving more radiation. In consequence, cooler microclimates are also those that have experienced the least change. Second, there has been a decline in westerly airflow, and west-facing slopes have thus become less exposed to wind, which has the effect of reducing the degree of thermal coupling of the surface to the atmosphere (Bennie *et al.*, 2008, Geiger, 1965). The overriding influence of this on temperature change is that the effects of increasing radiation are amplified on west-facing slopes. A secondary effect is, however, evident during periods in which sea-surface temperatures increased more slowly than land temperatures, such as between 2010 and 2014. In these circumstances, the attenuating effect of sea temperatures on coastal land temperatures appears to be counteracted on westerly seaboards, by the reduction in coastal influences caused by reductions in westerly winds. On eastern seaboards, however, the attenuating effects of the sea are magnified, resulting in a strong east-west gradient in temperature increase.

In common with other studies (e.g. Ashcroft *et al.*, 2009, Dobrowski, 2011, Hylander *et al.*, 2015), our results emphasise the importance of changes in weather patterns in driving local variation in temperature change, but also provide additional mechanistic insight into the factors responsible. Our findings are also supported by research on the long-term trends in the prevalence of different weather types in the North Atlantic, particularly those associated with weather patterns in Spring and Summer (Philipp *et al.*, 2007). Conditions associated with blocking highs over Great Britain, characterised by high pressure and clear skies have increased sharply, particularly in Spring, likely accounting for the reduction in cloud cover and potentially also the reduction in westerly airflow. It is important to emphasise, however, that there is little evidence for uninterrupted long-term trends in the prevalence of synoptic weather conditions, and the majority undergo multi-decadal variation (Philipp *et al.*, 2007). In consequence, the localities least vulnerable to warming are prone to change, and microrefugia should be best viewed as temporary holdouts (see Hannah *et al.*, 2014 for further details of this concept). In the context of future climatic change, however, one likely effect is the slower rise in sea-surface temperatures relative to those on land (IPCC 2014). While in our study, the impacts of this are masked by trends in weather patterns, and the strong maritime influence across our entire study area, in most parts of the world coastal regions have undergone less temperature change. The effects of coastal buffering are evident in coarser-scale climatic variation across the UK (Jenkins, 2007), but are also likely to occur at finer scales. Overall, the influence of changes in weather conditions is unlikely to be unique to our study area and our findings thus provide insight into how trends in weather conditions may influence local variation in temperature change.

Ecological implications

Understanding spatial variation in rates of warming could act as a foundation for addressing the discrepancy between the scales at which organisms experience climatic changes and those at which climatic effects are typically measured and modelled (Potter *et al.*, 2013) and may serve to identify locations where species are less vulnerable to climate change or where management could be targeted to offset the effects of climate change (Greenwood *et al.*, 2016). For example, the wall brown butterfly (*Lasiommata megera*) has undergone widespread population extinctions due to warming temperatures in Northern Europe, but rates of decline are lower in areas experiencing less warming (Van Dyck *et al.*, 2015).

The results of our study also help to elucidate the physical processes that define and create microrefugia. Our study suggests that the locations of microrefugia are likely to be influenced strongly by long-term trends in weather patterns, but in common with previous work (Ashcroft *et al.*, 2009), the places experiencing the least warming under recent conditions are also those with coolest microclimates. The premise that ecological communities in such locations may be buffered against the effects of climatic change is also supported by the evidence that, within our study area, 30-year temperature-driven changes in plant communities are lower on north-east facing slopes (Maclean *et al.*, 2015).

Our study provides strong evidence that trends in synoptic weather patterns result in spatially variable rates of warming across a landscapes, leading to substantial spatial heterogeneity in biologically relevant climate variables. Most significant is the variation in the length of the frost-free season, which has slightly decreased at higher altitude inland, but has increased by over a month in south-east facing coastal regions. It is important to emphasise, however, that the long-term consistency in the locations least vulnerable to climatic changes are likely to be linked to long-term weather trends and may thus be ephemeral. Nonetheless, much of the ecology of long-term climatic change is likely to be occurring at finer scales than is currently appreciated. Methods that allow these changes to be quantified are much needed if these remaining uncertainties are to be resolved.

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Supporting information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. R code for functions referred to in the text.

Appendix S2. Accompanying documention for R functions referred to in the text.

Appendix S3. Detailed assessment of model performance.

Appendix S4. Spatial variation in trends in bioclimate variables in each 100m grid cell.