Conducting robust ecological analyses with climate data

Andrew J. Suggitt[1,2], Philip J. Platts[1], Izabela M. Barata[4], Jonathan J. Bennie[3], Malcolm D. Burgess[5,6], Nadia Bystriakova[7], Simon Duffield[8], Steven R. Ewing[9], Phillipa K. Gillingham[10], Anna Harper[11], Andrew J. Hartley[12], Deborah L. Hemming[12], Ilya M. D. Maclean[2], Katherine Maltby[5], Harry H. Marshall[3], Mike D. Morecroft[3,7], James Pearce-Higgins[13], Paul Pearce-Kelly[14], Albert B. Phillimore[15], Jeff T. Price[16], Ayesha Pyke[9], James E. Stewart[5], Rachel Warren[17] and Jane K. Hill[1]

[1]Dept of Biology, Univ. of York, York, YO10 5DD, UK.
[2]Environment and Sustainability Institute, Univ. of Exeter, Penryn, UK.
[3]College of Life and Environmental Sciences, Univ. of Exeter, Penryn, UK.
[4]Durrell Inst. of Conservation and Ecology, School of Anthropology and Conservation, Univ. of Kent, Canterbury, UK.
[5]College of Life and Environmental Sciences, Univ. of Exeter, Exeter, UK.
[6]RSPB Centre for Conservation Science, The Lodge, Sandy, UK.
[7]Life Sciences, Natural History Museum, London, UK.
[8]Natural England, Nobel House, London, UK.
[9]RSPB Centre for Conservation Science - Scotland, Edinburgh, UK.
[10]School of Applied Sciences, Bournemouth Univ., Fern Barrow, Poole, UK.
[11]College of Engineering, Mathematics, and Physical Sciences, Univ. of Exeter, Exeter, UK.
[12]Met Office Hadley Centre, Exeter, UK.
[13]British Trust for Ornithology, Thetford, UK.
[14]Zoological Society of London, London, UK.
[15]Inst. of Evolutionary Biology, School of Biological Sciences, Univ. of Edinburgh, Edinburgh, UK.
[16]School of Environmental Sciences, Univ. of East Anglia, Norwich, UK.
[17]Tyndall Centre for Climate Change Research, School of Environmental Sciences, Univ. of East Anglia, Norwich, UK.

Corresponding author: Andrew J. Suggitt, Dept of Biology, Univ. of York, York, YO10 5DD, UK. E-mail: andrew.suggitt@york.ac.uk

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Abstract:

Although the number of studies discerning the impact of climate change on ecological systems continues to increase, there has been relatively little sharing of the lessons learnt when accumulating this evidence. At a recent workshop entitled 'Using climate data in ecological research' held at the UK Met Office, ecologists and climate scientists came together to discuss the robust analysis of climate data in ecology. The discussions identified three common pitfalls encountered by ecologists: 1) selection of inappropriate spatial resolutions for analysis; 2) improper use of publically available data or code; and 3) insufficient representation of the uncertainties behind the adopted approach. Here, we discuss how these pitfalls can be avoided, before suggesting ways that both ecology and climate science can move forward. Our main recommendation is that ecologists and climate scientists collaborate more closely, on grant proposals and scientific publications, and informally through online media and workshops. More sharing of data and code (e.g. via online repositories), lessons and guidance would help to reconcile differing approaches to the robust handling of data. We call on ecologists to think critically about which aspects of the climate are relevant to their study system, and to acknowledge and actively explore uncertainty in all types of climate data. And we call on climate scientists to make simple estimates of uncertainty available to the wider research community. Through steps such as these, we will improve our ability to robustly attribute observed ecological changes to climate or other factors, while providing the sort of influential, comprehensive analyses that efforts to mitigate and adapt to climate change so urgently require.

Introduction

The fingerprint of anthropogenic climate change is increasingly evident in many of the world's ecosystems (Scheffers et al. 2016). Ecologists are therefore increasingly seeking to represent and analyse these effects for a more complete understanding of their study systems, and to inform conservation or wider interests. Even for those experienced with analysing climatic impacts, the array of options and scale of the data involved can make the process challenging. Furthermore, the assumptions or uncertainties that underlie publically available data and computer code can be poorly described, causing ecologists to use them uncritically. A recent meeting entitled: 'Using climate data in ecological research' held at the UK Met Office (Exeter, UK) sought to address some of these issues, and discuss examples of good practice (and bad). Participants noted that much of the advice on making climate analyses more robust has not been published formally in the literature, or online (but see Foden and Young 2016 for specific guidance aimed at conservation practitioners).

The aim of this *Forum* article is to highlight some important considerations for any ecologist concerned with the use of climate data in their analyses. We adopt the usual chronology of ecological research, proceeding from the design stage, to preparatory work, before discussing some key considerations for undertaking the analyses.

What is 'climate', and is it relevant to the ecological question?

Here, we take 'climate' to be a measure (e.g. the mean, or variability) of the weather conditions over some period of time. This measure can be derived from data spanning a few months to a few millennia. Although a period of thirty years is commonly adopted by climate scientists (Arguez and Vose 2011), ecologists tend to use the term 'climate' to refer to data spanning shorter time periods than this. Because usage and understanding of the terms 'weather' and 'climate' varies across the literature, we simply refer to ‘climate’ throughout this paper, rather than adopting our own distinction. Whichever term is adopted, we argue that the precision and clarity with which it is defined is of the most importance, and that the reasoning for using a particular time period should be provided.

Before considering how to include climatic effects in ecological studies, it is also worth considering if climate is actually relevant to the particular focal question at all. Listing the situations in which climate could be relevant is beyond the scope of this paper, but here we echo the views of Lawton (1999), who argued that the profound influence of climate on the distribution of species and biomes means that it should at least be considered at the design stage of most ecological studies. At a basic level this can simply be via the inclusion of one or more climate variables as a control, or the selection of field sites to control for one or more climate variables, such as gradients in temperature or precipitation. Ecologists wishing to quantify the specific role of climate within a system may however wish to adopt one of the more complex approaches we discuss below.

Which aspects of the climate are relevant?

The identification of appropriate climate data by ecologists first requires an understanding of which aspect of the climate the study organism or system responds to (if any). This is not always a straightforward process, as organisms may respond to interactions between several variables, or different variables at different life-stages. Where this information cannot be gleaned from the literature or previous work, a more exploratory approach can be adopted, and in highly complex systems this is likely to be a requirement (van de Pol et al. 2016). Because the choice of which variables to include in experiments often has a substantial effect on the eventual results (Porfirio et al. 2014), care should certainly be taken to test the sensitivity of any analytical framework to a range of predictor combinations. Operating at (or switching between) different spatial or temporal resolutions may also lead to different conclusions (Gillingham et al. 2012, Pearce-Higgins and Green 2014), as shown in the illustrative Fig. 1a where the estimated frequency of temperature threshold exceedance is sensitive to the temporal resolution of the underlying data. Responses to weather or climate can also be lagged (Fig. 1b), such that an ecological response is discerned some period of time after the climatic trigger itself (in this case, overwintering temperature). The interaction of climatic events at different temporal resolutions can also be responsible for particular ecological effects; in Fig. 1c, fire risk is approximated by the total annual precipitation – a useful correlate of longer term moisture content of the vegetation – and the temperature of the hottest month, which correlates with the probability of ignition. Note that many other factors, such as wind strength, humidity and the passage of weather fronts, are associated with fire risk, and the relative importance of these drivers is dependent on the spatial and temporal scale of analysis. Therefore in this example and more generally, there is a need to select and work at appropriate resolutions.

Also of potential importance is the duration or 'persistence' of climatic events, which can result in both positive (Fig. 1d) and negative (Fig. 1e) effects on a study species. The period of growth in plants, or other thermal conforming species (including most insects, Davies et al. 2006), can often be described by the period of time at which the temperature (often the mean temperature) is above a physiologically-relevant threshold (Fig. 1d). But persistent periods of low rainfall create the necessary conditions for a meteorological drought (Fig. 1e). The particular sequence in which multiple events occur can expose populations (or individuals) to conditions that single events acting in isolation would not achieve. In the last example (Fig. 1f), an unusually warm spring (weeks 4-6) has the counterintuitive effect of increasing the exposure of nearby ground-dwellers to the subsequent cooler conditions (i.e. the late frosts of weeks 10 and 11). All the illustrated examples could potentially be drawn from the same climate dataset, highlighting that findings will depend as much on how the data are made relevant to the research question as they do on the choice of climate data product that is analysed (this choice is discussed below).

Although the impact of changes to the frequency or severity of extreme events can be as important as the impact of an overall mean trend (e.g. McDermott Long et al. 2017), extremes tend to be the subject of far less research effort in ecology (Jentsch et al. 2007). Most of the studies that have analysed extremes have focussed on the short-term impact of single events (e.g. Morecroft et al. 2002), leaving the effects of multiple events and long-term impacts understudied (Bailey and van de Pol 2016, but see Palmer et al. 2017). This is concerning given the number of species known to be sensitive to such effects (e.g. Cuoto et al. 2014), and likely reflects the inability of relatively short duration ecological data series to encompass extremes, which by definition are rare. It is therefore likely that many of the ecological effects of extremes are yet to be described.

Over longer time frames, some measure of the 'stability' of the climate is also important, and there are a number of metrics that seek to quantify this (Garcia et al. 2014). Examples include the climate velocity (Loarie et al. 2009), which is the velocity of species movement required to track analogous climates as the conditions change, and the timing of climatic 'departure' from current conditions, i.e., the point at which climate at a location moves beyond the historical observed range of variability (Mora et al. 2013). The principal driver for the development of this type of metric has been the multitude of studies demonstrating an exacerbating effect of climate change on extinction risk (Urban 2015), although they also offer a means of assessing species' vulnerability to climate change where good ecological data are lacking (Foden and Young 2016). A further motivation for assessing stability is to establish the existence of modern day 'refugia' (Ashcroft 2010) or 'microrefugia' (Rull 2009) from climate change; these were areas of atypical climate that buffered species from the adverse climate conditions of the past (Baker 1980). Efforts to describe the locations and beneficial effects of these refugia have been enhanced by recent progress in climate downscaling (see next section).

There will also be situations where deriving ecologically relevant climate predictors is simply not possible given the limitations of the climate data. More and continued communication and collaboration between climate scientists and ecologists would help climate scientists to identify such limitations and to orient their climatological outputs towards the user community (e.g. Dobor et al. 2015), whilst also ensuring that ecologists use and analyse climate data robustly. Ideally engagement should take place: 1) in person – during symposia, interactive workshops, and targeted sessions at conferences such as INTECOL; 2) on paper – with grant proposals and scientific publications; and 3) online – via popular media platforms and blogs.

Obtaining climate data

‘Climate data’ consist of one, or a blend, of the following products: point-based meteorological observations, gridded observations (including reanalysis products), satellite-derived estimates of climate, and simulations of climate derived from Global Climate Models or Earth System Models, i.e. model data. We briefly deal with these in turn, pointing out their strengths, weaknesses and other factors that require consideration.

Point-based meteorological observations

Many ecologists will be interested in the conditions that organisms experience at the local level (centimetres to hectares). This can be at odds with the design of meteorological station networks, which are purposefully sited away from particularly unusual habitats or atypical landscape characteristics in order to be more indicative of wider atmospheric conditions (WMO 1996). The extent to which a station can be considered a useful record of the climate conditions over an area of ecological interest is a function of the distance to the station, the climatic variable of interest, and any differences in landscape characteristics that decouple the study site from the atmospheric conditions captured by the station (such as elevation, topographic slope and aspect, and distance to coast). Adjusting meteorological outputs to account for these site-level effects forms the basis for generating higher resolution climate data (see below).

Where station data do not capture what ecologists require, other approaches to measurement have been adopted, ranging from siting a bespoke observing station within a fieldsite (e.g. Bennie et al. 2008), installing miniaturised dataloggers (e.g. Suggitt et al. 2011), thermography (e.g. Scherrer and Körner 2010), or even trapping the study organism and directly attaching or implanting monitoring equipment (‘bio-logging’, e.g. Ropert-Coudert and Wilson 2005). The life history and distance over which a species can move will define which of these techniques is required (if any), with smaller, thermal non-conforming species more likely to occur in atypical conditions, thereby requiring specialist monitoring. Species will often also occupy differing three-dimensional spaces within a single day; measurements taken at the soil surface or vegetation canopy are an attempt to represent the properties of these spaces more closely. On the other hand, because migratory species cross countries and even continents, these broader-ranging species are also likely to require more tailored representations of their climate (Small-Lorenz et al. 2013).

At a minimum this would involve the collection of data to establish their location at critical points in their life cycle. As technology improves and all types of ecological data become more detailed, interdisciplinary collaborations will lead to the development of new, higher resolution climate metrics that can make best use of them (Potter et al. 2013).

There have been huge increases in the capabilities of meteorological sensors, data storage capacities, and channels for dissemination to the wider public (from Twitter updates by meteorological organisations, to publically accessible archives such as NOAA-NCEI; https://www.ncei.noaa.gov/). To assist the research community in traversing these rich but sometimes disparate sources of data (NOAA's NCEI, GHCN, WMO, UK Met Office, and many others), we advocate their collation in a global catalogue, providing a one-stop shop for those wishing to assess their availability.

Similarly, the reduction in size and cost of data loggers and automatic weather stations means that individual research groups, independent researchers, and amateur enthusiasts are now collecting large volumes of data that could be voluntarily contributed to this single online repository (e.g. MICROCLIM, www.microclim.org.uk), together with any historical data digitised from paper archives. Similar endeavours in other fields have been hugely successful, most prominently the GenBank genetic sequence database (Benson et al. 2011). A 'ClimBank', based on similar principles, would foster new collaborations and scientific advances through the preservation, collation and meta-analysis of existing climate data.

Gridded meteorological observations

The expense and effort of collecting direct meteorological observations, coupled with the desire to give them more ecological meaning, has led to the generation of fine-grained, spatially-gridded datasets for studies of climate change impacts (Fig. 2). Here, the resolution of gridded data can be tailored to the spatial scale of ecological response, although the ultimate accuracy of these data is constrained by the observational data that underlie them (see section on data resolution below), and the techniques used in gridding these data.

Approaches to generating gridded data vary in complexity, from simple interpolations based on latitude, longitude and elevation, to local adjustments for topography (lapse rate, solar radiation regime, cold air pooling), coastal effects, wind, latent heat exchange and snow. Generating fine-grained precipitation data often requires more underlying data than temperature, with storm tracks and wind direction to take into account, depending on the temporal resolution required. Specialised gridding routines (e.g. PRISM or equivalent) can be used to generate such grids over local areas if enough data are available, and some gaps are also filled with reanalysis products, which combine observed weather data with numerical weather prediction model output. Note that uncertainties underlie all these approaches – including that arising from the source(s) of the observation(s), the choice of local climate ('microclimate') effect(s) to include, and also the means of including them. It is important to consider the degree to which the assumptions behind simplifying relationships are valid, such as temperature lapse rate adjustments, which may assume dry or stable atmospheric conditions.

There are strong ecological motivations for generating climate data at finer spatial resolutions, because the evidence for the ecological relevance of local climate effects is strong. This is particularly true for topographic effects, which account for a large part of the variance in temperature and moisture in montane regions (Dobrowski 2011), and are therefore a particularly important control on the distributions of flora (Scherrer and Körner 2011) and fauna (Ashton et al. 2009) in these regions. Many upland or high-altitude plants also rely on the ameliorative effect of snow lie on frost risk, thus reductions in the extent or thickness of snow lie could leave these species at higher risk of extinction in the spring (Bannister et al. 2005). Other species have specific microclimatic requirements at or near their range margins, and so the inclusion of fine-scale climate information can improve our understanding of their range dynamics (Lawson et al. 2014, Huntley et al. 2017), and distributional shifts under climatic change (Bennie et al. 2013). Microclimate surfaces are also feeding into studies seeking to identify 'refugia' from climate change, both in palaeoecological and contemporary contexts (Suggitt et al. 2014).

Satellite-derived (blended) estimates of climate

Gaps in the spatial coverage of meteorological data can limit their usefulness in areas with fewer observations, such as rural areas or in the tropics. To overcome this, point-based surface observations have been combined with satellite observations to create blended climate data products that make the best of both formats (e.g. MODIS/Terra land surface temperature; Tropical Rainfall Monitoring Mission, or TRMM).

Much of the effort in developing satellite-blended products has focussed on improving the utility of rainfall data for drought monitoring, and its subsequent impact on vulnerable human communities (e.g. Funk et al. 2015), although their applicability to other types of ecological research is clear (Pettorelli et al. 2014). Their use is therefore increasing, particularly in regions where the topography is complex or existing monitoring is sparse (e.g. rain gauge networks in Africa, Maidment et al. 2014), both of which can make interpolation less robust. For example, Deblauwe *et al*. (2016) found that blended data improved the performance and transferability of species distribution models in the tropics when compared with data derived solely from surface observations. A key constraint on the quality of these datasets in high latitudes and/or elevations is cloud cover, with time-sensitive analyses (such as phenology) particularly affected, and estimates derived for these hard to reach areas are also more difficult to ground-truth. Usage of these products will nevertheless continue to rise as the spatial and temporal resolution, coverage and accessibility of satellite observations improves.

Model-derived estimates of climate

Global Climate Models (GCMs) represent the patterns of weather and climate arising from the atmospheric and ocean circulations. Earth System Models (ESMs) are a more recent development, and are GCMs that include more sophisticated representations of the atmospheric, terrestrial, and ocean biogeochemical cycles. Because this type of model includes a number of additional biogeochemical processes (such as interactions between land use, vegetation and the atmosphere) and interactive atmospheric chemistry, outputs from ESMs are highly relevant to research questions in ecology. The outputs from almost all the GCMs and ESMs in the latest Climate Model Intercomparison Project (CMIP5) have been made freely available online for non-commercial use, via the Earth System Grid Federation (pcmdi.llnl.gov). Although the new CMIP experiments – CMIP6 – began in 2016, it will be a few years before the model data behind the next IPCC report are made available for analysis (Eyring et al. 2015).

The public availability of model data means that the ecological implications of various sources of uncertainty can be explored, such as the choice of climate model, different assumptions of climate sensitivity, and various commitments to greenhouse gas mitigation (Beaumont et al. 2008). The potential for the ecological systems themselves to act as sources of uncertainty in the global climate system is huge (e.g. via carbon cycle or land use feedbacks, Qian et al. 2016), and thus greater uptake of model data by the ecological research community is also in the interests of climate scientists. In using such data it is important to understand their limitations, to report on the source of the data and, especially, the baseline time period used in any analysis. For example, there is no facility within the experimental design for CMIP5 to account for the protection status of land, nor any potential changes in urban areas, which limits their applicability for investigating changes in land use. Climate scientists will be more aware of these types of potential pitfall, and ecologists could therefore reduce the risk of drawing erroneous conclusions by collaborating more widely.

Model data are commonly made available at the cell size typical of most GCMs/ESMs, which ranges from 0.75° to 2.8° horizontal resolution. Although this is coarse compared to the resolution of most ecological studies, the model data can be downscaled to finer cell sizes using statistical (e.g. Mitchell and Osborn 2005) or dynamical techniques (e.g. Jones et al. 2004). Many ecologists employ the ‘delta’ or ‘change factor’ method of imposing interpolated future anomalies onto finer-grained observational datasets, to generate future gridded climates that better reflect local heterogeneity (e.g. Pearson et al. 2014, Platts et al. 2015). The implicit assumption here is that the present day spatial patterning of local climate will persist under future climate change, which is valid in some landscape contexts but not in all (Maclean et al. 2017).

Considering appropriate spatial resolutions for analysis

The estimated impact of climate change on a study species can change if different spatial resolutions of climate data are employed (e.g. Trivedi et al. 2008, Gillingham et al. 2012). The question of which resolution is 'appropriate' will depend upon species' life cycle stage, movement ability (flight, mobile, static) and the component of the climate being analysed. It is also possible that species will respond to climate at a variety of scales, sometimes more than one at particular points in time, and in this case preliminary work will help to identify the critical life stage to focus on.

As highlighted above, many ecologists will be interested in how well coarse-scale models represent the climate that their study species experience(s). A recent meta-analysis of SDM use estimated that grid cell sizes are typically 1,000 (for plants) to 10,000 (for animals) times larger than the size of the organism they focus on (Potter et al. 2013), highlighting the challenge of representing the biotic interactions (e.g. Pateman et al. 2012) or demographic effects (Kearney 2013) that can be important modifiers of responses to climate (Ockendon et al. 2014). These concerns have contributed toward the recent drive towards finer-scale data for use in ecology (Fig. 2). It should however be noted that there are many cases in which coarse-scale climate data are appropriate for modelling coarsely mapped response variables, such as the extinction or persistence of populations (Bennie et al. 2014), and thus the ultimate decision on which spatial resolution is appropriate will depend upon the research question.

Although the use of finer-scale, gridded climate data has improved our ecological understanding considerably, the spatial accuracy of these grids (indeed all climate grids) are a function of both: a) the density of meteorological and satellite observations that contribute to them, and b) the complexity of local climatic processes that operate in the region of interest (Nadeau et al. 2016). Thus the absolute value of differences between nearby cells may fall within the bounds of uncertainty in the data they are derived from, and where resulting effect sizes are found to be within this range of uncertainty, this should be acknowledged. This perhaps highlights a need for improved communication of uncertainties in gridded climate datasets by their creators in order to ensure that user communities are fully aware of how factors such as weather station density affect the climate data generated for a given study area.

Thinking critically about published data and code

An increasing emphasis on open access to data and computer code means that a huge variety of material is freely available for use by ecologists, via open source platforms such as R (R Core Team 2016). But although these approaches and data may have been the most appropriate tools to test the researchers' original ideas, they are not always appropriate in other analytical contexts. A recent disagreement over the calculation of growth thresholds using the CMIP5 model data at daily resolution (PLoS Biology 2015) served to highlight how the views of some scientists over the appropriate use of data are not always shared by the wider community. Stated levels of precision should not be mistaken for accuracy, and where the accuracy of the data is unclear, this should be checked with the authors or custodians of the dataset. Critically, assumptions in the data or methods used (baselines and downscaling techniques) may not even be readily available. Ecologists should therefore share their analytical code when publishing data papers, so that this is available to those interested in greater methodological detail. More collaboration between ecologists and climate scientists would ensure that any methodological concerns can be headed off at an early stage of project development (Table 1).

A critical eye should also be applied to the code of others. In broad terms, 'code' represents a step-by-step record of a computational method that another scientist has developed. Because no ecologist follows another's field protocol without question, some level of critical thought should therefore also be applied when using a computational method supplied by another. This does not necessarily involve examining code line-by-line, but rather that adjustable parameters should be set and checked appropriately, and the uncertainties and assumptions behind the approach determined. The literature on how to do this is growing substantially, especially for the more popular software packages (e.g. MaxEnt, Philips and Dudík 2008, Philips et al. 2017), and the Zoön Project for species distribution models (Lucas et al. 2016) offers a possible template for how to make code more open, shareable and accessible for all.

A recent survey of species distribution modellers noted that although the "code used to conduct the science is not formally peer-reviewed… many scientists rely on the fact that the software has appeared in a peer-reviewed article, recommendations, and personal opinion" (Joppa et al. 2013). Thus the method behind an article may not be adequately assessed for quality. The increasing number of journals obliging authors to publish their code alongside their article represents a welcome move towards improving methodological clarity (Ince et al. 2012), even if conducting full assessments of these submissions for quality is unrealistic.

Accounting for uncertainty in climate data

The need to account for uncertainties in observed climate datasets was highlighted by Baker *et al.* (2016), who in a study of future climate effects found that uncertainty arising from choice of baseline climatology was often on a par with, or in fact exceeded, that arising from a GCM choice. However, although ecologists are often accustomed to dealing with the numerous sources of uncertainty in an ecological analysis (such as that arising from recording misidentifications or mislocations), they are often less aware of the uncertainty that is inherent in almost any climate data they use (IPCC 2013). Whether recognised or not, uncertainty will propagate through the many stages of processing and modelling required to derive ecologically meaningful climate data (Wilby and Dessai 2010). The level of uncertainty in observations and modelled data will depend on the characteristics of the study region, such as its topographic diversity or proximity to large water bodies, but also on both the homogeneity of the regional climate and the density of the meteorological observations taken nearby. Some datasets are provided with the uncertainty or quality control estimates enclosed (e.g. sampling and station errors in the global CRUTEM4 dataset, or MODIS quality control), and these should be utilised wherever possible.

Studies employing GCM data arguably require a greater consideration of the uncertainties involved. These uncertainties can arise from the (realistic) representation of climate variability, the alternative socioeconomic scenarios for the future, the ‘structural’ uncertainty arising from the physics behind different climate models used, and many other factors. The simplest means of exploring these uncertainties is via the use of more than one scenario (i.e. two or more RCPs) and multiple GCMs. Ideally analyses are rolled out across all the scenario-model combinations made available. Although averaged ‘ensemble’ estimates are computationally efficient, their use as inputs in analysis should be avoided wherever possible, as they can conceal large differences in projected climate (particularly for precipitation) and thus they underestimate uncertainty. The CMIP website (cmip-pcmdi.llnl.gov) provides a useful introduction to the effect of differences in the design of climate models, while also providing detailed guidance on using their outputs.

An additional consideration here is the presence of model bias, which can mean that the use of raw outputs from GCMs for certain types of impact study is not robust (e.g. accumulated time above or below a certain threshold). Scientists have overcome this problem by calibrating the projections with observed data, generating revised estimates that are more appropriate for establishing the impacts of climate change on heat stress (Hawkins et al. 2013) and river runoff (Hagemann et al. 2011). Note that biases or errors can also be inherent in any dataset of climate observations, and where these are known, these should be acknowledged, their possible effects explored, and, wherever possible, corrected for. Sensitivity analysis will reveal the degree to which conclusions are resilient to these effects.

Conclusion

The acceleration of climate change this century brings both threats and opportunities for species and ecosystems. It will be the job of ecologists to describe and make sense of these effects, and for wider society to formulate a response. We suggest a number of changes to the approaches of both ecologists and climate scientists to make successful outcomes for both disciplines more likely (Table 1). Underpinning these changes is a clear need for more interdisciplinary working and better communication among researchers. Engagement across disciplines has never been easier, with open access digital repositories, post-publication peer-review, webinars, online blogs and social media removing traditional barriers to communication. Whilst we should always be more mindful of the quality and veracity of material made available outside the peer-reviewed literature, interactions via these platforms have the potential to grow into more formal collaborations across disciplines, such as funding proposals and co-authored manuscripts. These collaborations will lead to new ways of working, new research questions to tackle, and will ultimately strengthen research findings. Scientists that adopt an interdisciplinary ethos will also find themselves well placed to address the more pressing issues of the 21st century, which due to their scope and complexity often require a broader perspective.

The challenge for ecology is to move beyond simple, indicative studies of what to expect from climate change, to a more specific, detailed approach that acknowledges issues of uncertainty and scale. In so doing, ecologists will get closer to resolving some of the fundamental questions and unknowns that remain in the discipline, while also producing the kind of informative and actionable results that are urgently required if we are to successfully mitigate and adapt to climate change.

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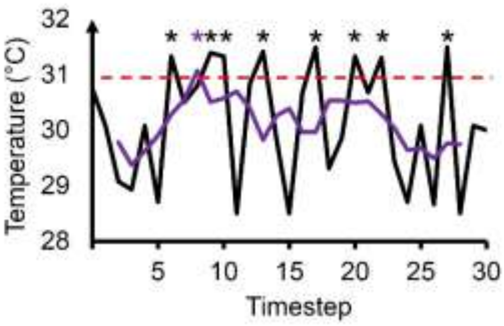
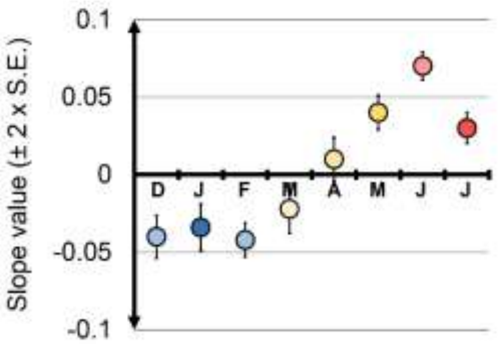
Figure legends

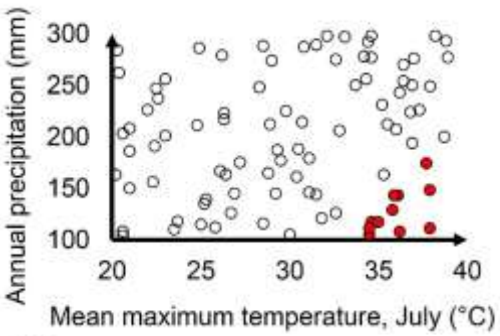
Figure 1 Making climate data relevant to ecology. In (a), the frequency of threshold exceedance is sensitive to the temporal resolution of the underlying data, with raw values (black colour) generating a different estimate to smoothed values (purple). In (b), the summer population count of an example organism is positively related to the monthly temperature means of the current summer, yet negatively related to the temperature means of the previous winter- the latter is a lagged response to conditions at that time. In (c), two climate variables calculated at different temporal resolutions contribute towards an estimate of fire risk (red circles indicating conditions of high risk). In (d), a variable describing a continual exposure to a particular set of climatic conditions has been derived - length of the frost-free growing season, *t*. In (e), both the extremity and the duration of low precipitation values have been taken into account to represent a meteorological drought (orange highlight). In (f), a sequence of events sees unusual spring warmth followed by a late frost, counterintuitively exposing ground-dwellers to cooler conditions. All examples are hypothetical and were generated using synthetic data.

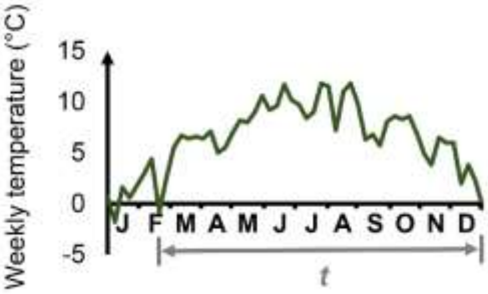
(a) (b)



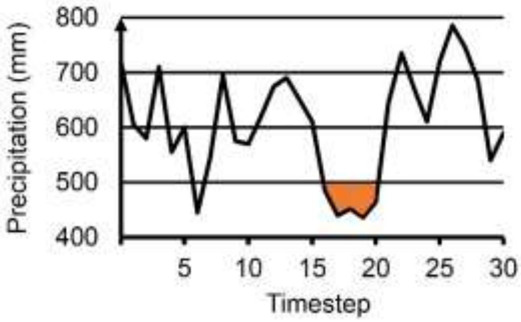


(c) (d)


Annual precipitation (mm)
300
250
200
150
100
20
25
30
35
40
Mean maximum temperature, July (°C)


Weekly temperature (°C)
15
10
5
0
-5
J F M A M J J A S O N D
t

(e) (f)


Precipitation (mm)
800
700
600
500
400
5
10
15
20
25
30
Timestep

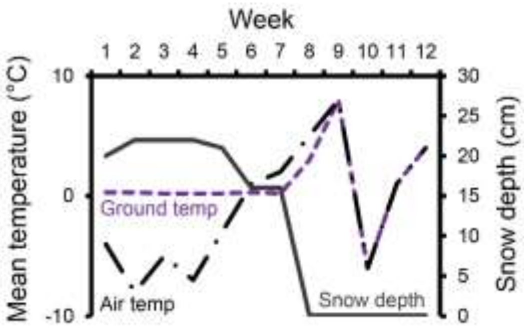

Week
1 2 3 4 5 6 7 8 9 10 11 12
Mean temperature (°C)
10
0
-10
Snow depth (cm)
30
25
20
15
10
5
0
Ground temp
Air temp
Snow depth

Figure 2 The spatial resolution and geographic extent of gridded climate datasets (cell size of 400 km^2 or less) available for use in ecology. Includes studies where the data or code (or both) are publically available. Diamond symbols indicate studies employing statistical interpolation only; square symbols indicate studies combining statistical interpolation with adjustments for landscape characteristics (e.g. solar input). The lead author and year of the associated journal article is provided; full references are available in the reference list. Where two separate datasets share the same x- and y- values they have also been assigned the same symbol (e.g. New 2002 and Kriticos 2012).

Figure 2

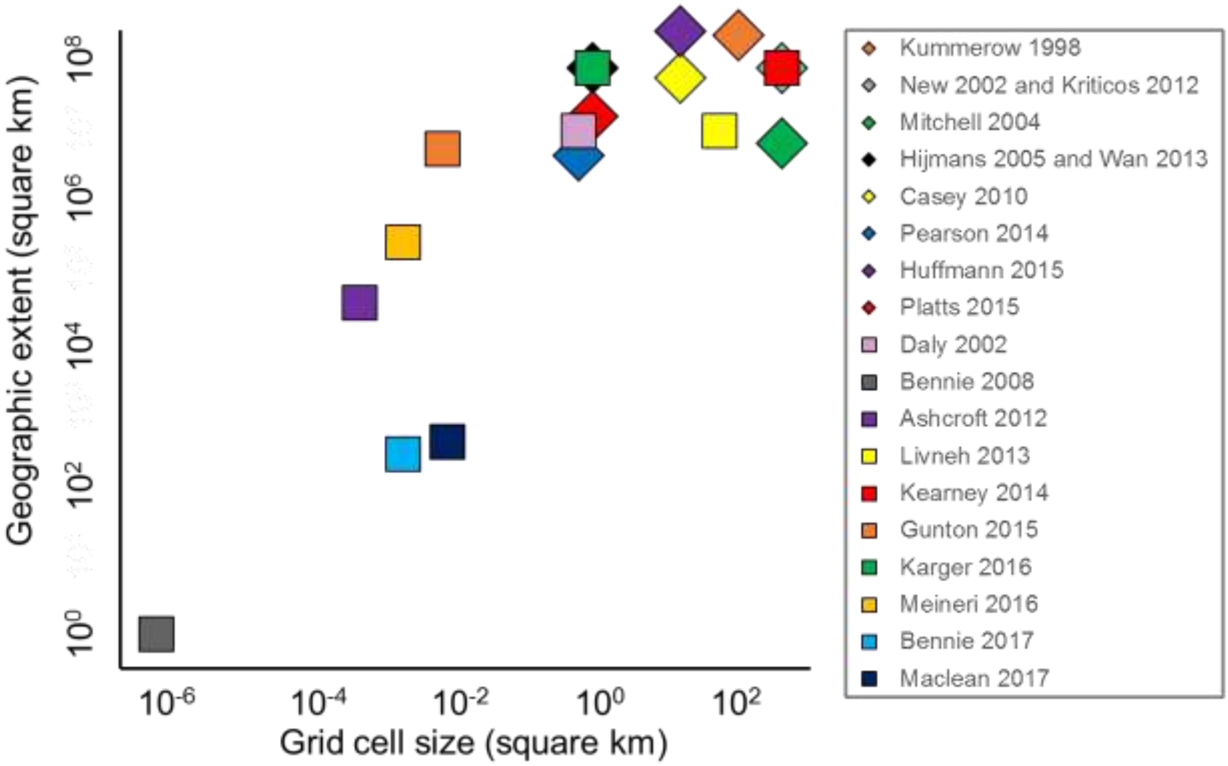


Table Legend

Table 1 Four things that ecologists and climate scientists could do more of.

Problem area	Ecologists could…	Climate scientists could…
1) Communication and collaboration.	…collaborate with climate scientists at an early stage of proposals, to ensure that projects are tailored to the strengths of the climate data, and do not fall victim to their weaknesses.	…talk to ecologists to identify and develop biologically meaningful climate variables to maximise the utility of climate datasets within the wider research community.
2) Handling uncertainty.	…acknowledge and actively explore uncertainty in all types of climate data, not simply when using projections of future climates.	…make uncertainty estimates more widely available and interpretable for others in the research community.
3) Sharing lessons and resources.	…share their own climate data and code more widely, expanding the resources available to all.	…make data products, code and guidance material easy to obtain and understand for non-specialists.

4) Selecting and using an appropriate resolution.	…develop methods to account for the scale limitations of climate models, and work with climate scientists to use appropriately-downscaled climate information.	…be clearer about the appropriate spatial resolution at which to use GCM data, and work with ecologists to develop downscaling approaches that suit ecological applications.