Designing ecological climate change impact assessments to reflect key climatic drivers

Helen R. Sofaer, Joseph J. Barsugli, Catherine S. Jarnevich, John T. Abatzoglou, Marian K. Talbert, Brian W. Miller and Jeffrey T. Morissette

Abstract

Identifying the climatic drivers of an ecological system is a key step in assessing its vulnerability to climate change. The climatic dimensions to which a species or system is most sensitive – such as means or extremes – can guide methodological decisions for projections of ecological impacts and vulnerabilities. However, scientific workflows for combining climate projections with ecological models have received little explicit attention. We review Global Climate Model (GCM) performance along different dimensions of change and compare frameworks for integrating GCM output into ecological models. In systems sensitive to climatological means, it is straightforward to base ecological impact assessments on mean projected changes from several GCMs. Ecological systems sensitive to climatic extremes may benefit from what we term the ‘model space’ approach: a comparison of ecological projections based on simulated climate from historical and future time periods. This approach leverages the experimental framework used in climate modeling, in which historical climate simulations serve as controls for future projections. Moreover, it can capture projected changes in the intensity and frequency of climatic extremes, rather than assuming that future means will determine future extremes. Given the recent emphasis on the ecological impacts of climatic extremes, the strategies we describe will be applicable across species and systems. We also highlight practical considerations for the selection of climate models and data products, emphasizing that the spatial resolution of the climate change signal is generally coarser than the grid cell size of downscaled climate model output. Our review illustrates how an understanding of how climate model outputs are derived and downscaled can improve the selection and application of climatic data used in ecological modeling.

Keywords: climate bias-correction, climate change impacts, climate extremes, climate variability, delta method, ecological projections

Received 19 September 2016; revised version received 17 January 2017 and accepted 18 January 2017

Introduction

Climate change poses an ongoing and increasing threat to ecological systems (McCarty, 2001; Walther et al., 2002; Parmesan & Yohe, 2003; Hoegh-Guldberg & Bruno, 2010; Groffman et al., 2014; IPCC, 2014). Climate change impact and vulnerability assessments are therefore a critical tool for understanding, mitigating, and managing effects on biodiversity and ecosystem function (Cramer et al., 2001; McMahon et al., 2011; Pacifici et al., 2015). Previous work has emphasized the importance of identifying key climatic drivers of the system of interest (Mote et al., 2011; Snover et al., 2013; Vano et al., 2015), as well as the advantages of considering climate change effects that go beyond measures of mean change (Katz & Brown, 1992; Zimmermann et al., 2009; Reside et al., 2010; Bateman et al., 2012; Helmuth et al., 2014). Yet, selecting and using appropriate climatic data for impact assessments remains nontrivial, as the methods that are most appropriate depend on the system and question of interest (e.g., Barsugli et al., 2013). In particular, ecological research on the impacts of climatic variability and extremes has not focused on analytical frameworks for integrating climate projections into ecological response models and ecological vulnerability assessments.

Many ecological impact assessments and adaptation planning efforts have focused on understanding the implications of projected changes in mean temperature...
and precipitation (Helmuth et al., 2014). However, changes in climatic variability and in the frequency and intensity of extreme climatic events have substantial impacts on ecological systems (Easterling et al., 2000; Parmesan et al., 2000; Vázquez et al., 2017), as well as on human health and well-being (Millennium Ecosystem, 2005; Nelson et al., 2013; IPCC, 2014; Thornton et al., 2014). Projected changes in variability and extremes are not always well represented by projected changes in climatic means (e.g., Mears et al., 1984; Schär et al., 2004), implying that additional information can be extracted from climate models to inform ecological impact assessments.

Projected changes in plausible climatic conditions for the remainder of the current century are primarily derived from Global Climate Models (or General Circulation Models; GCMs, here including Earth System Models). Whether a given set of climate projections is suitable for ecological modeling depends on climate model performance and spatial resolution. For example, the coarse native resolution of GCM output is not appropriate for many ecological applications, which instead commonly use statistically downscaled GCM projections. Nevertheless, ecologists may not always appreciate that the spatial resolution of downscaled climate projections does not necessarily reflect the spatial resolution of the climate change signal (Fig. 1). In addition, ecological researchers should consider whether downscaled climate projections incorporate methods that capture dimensions of climate change beyond the mean (Fig. 2). The most recent suite of GCMs, which comprise the Coupled Model Intercomparison Project Phase 5 (CMIP5, Taylor et al., 2012), have archived outputs widely available at fine temporal resolutions (e.g., daily), providing information on short-duration climate extremes. However, this information is often overlooked in summarized climate data. Integrating additional measures of climate change could improve the realism of ecological impact and risk assessments, and there are compelling reasons to consider how best to utilize a fuller range of summary statistics from GCM output.

Knowledge of the key climatic drivers of an ecological system of interest can guide workflows for climate change impact assessments. There are several good general reviews of climate projections for ecologists (e.g., Beaumont et al., 2008; Snover et al., 2013; Harris et al., 2014). Other work also summarizes the strengths and weaknesses of different downsampling methods in the context of impacts assessment (e.g., Gutmann et al., 2014; Hewitson et al., 2014; Pourmokhtarian et al., 2016). Here, we delve deeper into the attributes of GCM projections along different climatic dimensions (e.g., means, variability, and extremes) and the implications for their utility in ecological assessments. Specifically, we (i) describe the degree to which characteristics of contemporary climate are well represented in GCMs and implications for selecting among climate projections; and (ii) compare frameworks for how climate projections are integrated into impact assessments.

Dimensions of climate change and their representation within climate models

The key climatic drivers of ecological patterns and processes differ across scales and among systems, and identifying the climate variables likely to be important drivers is central to climate change impact assessments. Climate variables are used as predictors in statistical ecological models or as drivers of mechanistic ecological models in studies focused on historical, contemporary, and future time periods. Metrics of climate change at a given location include projected changes in monthly or long-term means of daily temperature (minimum, maximum, or mean) and precipitation, altered patterns of seasonality, and a changing variance or frequency of climatic extremes (García et al., 2014). Most climate change impact assessments have focused on projected changes in temperature and precipitation, and we maintain that focus here. However, the GCMs that comprise the CMIP5 ensemble also output additional variables useful for projecting changes in surface water balance and associated drought indices (e.g., sensible and latent heat fluxes, wind speed, relative humidity, and solar and longwave radiation). These variables can be used to provide physically based estimates of evapotranspiration, which are relevant for many ecological systems but have frequently been derived based on temperature information, despite substantial limitations in this approach under significant warming (e.g., Milly & Dunne, 2011).

Ecological impact assessments are often based on statistically downscaled projections because the coarse spatial scale of GCM output (typically >100 km) precludes their direct application to many ecological systems. For example, mountain ranges are smoother and have lower peak elevations at the GCM spatial resolution, implying that climate refugia for alpine species cannot be captured at this grid cell size. GCMs also have coarse resolution of coastlines and of lakes and may not accurately model even very large lakes with physical realism (Giorgi & Mears, 1991; Brilley et al., 2015). A variety of statistical downscaling methods are used to bring GCM signals to finer spatial resolutions, including spatial disaggregation, regression-based methods, analog approaches, and weather generators (reviewed in Wilby & Wigley, 1997; Fowler et al., 2007; Schoof, 2013). For the purposes of this study, we lump simple empirical downscaling methods and stochastic methods with classic predictor-predictand statistical
downscaling methods under the term ‘statistical downscaling’. Most of these methods can produce gridded output at a finer spatial scale than the GCM, and it is these gridded, downscaled data sets that are typically available from downscaled climate data web portals. An exception is found in weather generators (i.e., ‘stochastic downscaling’), which simulate sequences of (usually daily) weather that have similar statistical properties as the observed weather at a specific location or set of locations. For projections of future weather, the statistical parameters that describe these weather sequences can be shifted to capture changes projected by GCMs (reviewed in Wilks, 2010, 2012). Downscaling methods often incorporate bias-correction procedures, which remove systematic error from historical simulations and projections compared to observations. Bias-correction methods are quite varied (see Maraun, 2016 for a recent overview) and differ in how the original climate change signal is affected (Pierce et al., 2015). One common method for bias-correction is quantile

![Comparison of projected annual average temperature change (°C; upper panels) and percent change in annual precipitation (%; lower panels) in the GFDL-ESM2M climate model between the periods of 1971–2000 and 2070–2099 for (a & c) GCM output interpolated to a 1° x 1° degree grid, and (b & d) bias-corrected and spatially downscaled model output (to 1/8° degree resolution via the Bias-Correction Spatial Disaggregation method; BCSD). Beyond the interpolation introduced by downscaling, the spatial pattern and magnitude of the climate change signal differs little for change in temperature, whereas there are some differences for change in precipitation in this example. Both the choice of downscaling method and the variable of interest affect the spatial detail and magnitude of the climate change signal. Data from Reclamation (2013).](image)
mapping, which applies projected changes for each quantile of the GCM to the corresponding quantile of observed data; this method allows for differences in the rate of change between climatic means and extremes (Fig. 2a).

Previous work has highlighted trade-offs associated with the choice of downscaling method, as methods that more closely mimic historical patterns may be less able to incorporate future changes (Gutmann et al., 2014). The statistical downscaling method can affect ecological predictions, but less so than other methodological choices (Pourmokhtarian et al., 2016). Here, we do not focus on downscaling techniques, but rather recognize that the climate change signal (e.g., magnitude of change) entrained into downscaled data typically remains at a large spatial scale (Fig. 1), and may not be improved over the signal at the native GCM resolution (Maurer & Pierce, 2014). While some statistical downscaling methods may create small-scale detail in the change signal, these details are based on statistical relationships in the present climate rather than on the physical processes at these finer scales and can be highly dependent on the choice of statistical model. In contrast to statistical downscaling methods, which generally assume stationarity in the relationship between large-scale and small-scale climate, Regional Climate Models (i.e., dynamical downscaling; RCMs) can alter the climate change signal in ways that provide added value by representing physical processes of change at these scales (Di Luca et al., 2015; Rummukainen, 2016; Rupp et al., 2016). The high computational demands of RCMs have limited the number of GCM simulations downscaled in this manner, and RCM outputs typically require bias-correction and perhaps additional downscaling, but are particularly valuable for projecting changes in extreme precipitation (Preim et al., 2017). The strategies we discuss for incorporating climate model outputs into ecological models apply to RCMs as well as to GCMs.

Many ecologists recognize that GCMs, like any models, contain uncertainties and biases and that there are established methods for decision-making under uncertainty (Littell et al., 2011; Runge et al., 2016). However, ecologists are not generally trained to assess the magnitude of biases in climate models nor the implications of these biases and uncertainties for ecological projections. Indeed, many ecological modelers work with bias-corrected climate data and have little exposure to ‘raw’ GCM output in which biases are more apparent. In order to select which GCMs to use (whether raw data or downscaled and bias-corrected), the ecological community often relies on model assessments produced by climate scientists (such as Sheffield et al., 2013), particularly those assessments that have evaluated the historical performance of GCMs for a specific region (e.g., Rupp et al., 2013). The ability of climate models based on physical principles to simulate patterns, quantities, and trends that approximate historical observations is the basis for confidence in their ability to provide credible projections of future change. One challenge is that model performance may be considered adequate for climatological research, for example, because broad-scale observed spatial patterns are reproduced by model simulations, but climate attributes important to ecological processes may not be assessed, and even bias-corrected model output may still contain biases that could propagate through subsequent ecological analyses. Here, we draw on the climate science literature to distill generalizations regarding the performance of GCMs for the types of climate variables of greatest interest to ecologists, and discuss implications for climate change.

Fig. 2 Climate model projections include different rates of projected change for different quantiles of the distribution of each variable; extremes may be projected to change more or less than the mean, as shown in this hypothetical example. Methods to derive climate inputs for ecological impact models may (a) incorporate information on different rates of change from the climate model or (b) assume that all portions of the distribution will change at the same rate, typically that of the mean projected change.
impact assessments. We emphasize that these generalizations may not apply to all GCMs, variables, or regions, but are nevertheless likely to be useful for the ecological community, particularly when more specific assessments are not available. We encourage additional quantitative regional comparisons of GCM performance and reliability with respect to each of these types of variables.

**Climatic means**

Mean temperature and precipitation are critical determinants of ecological systems, as exemplified by Whittaker’s (1975) delineation of biome types according to variation in the mean annual values of these two variables. Climate normals are an accepted way to characterize average climatic conditions over a specific time period, typically covering at least 30 years. Mean temperature and precipitation, summarized at monthly, seasonal, and annual time intervals (e.g., many of the BICOCLIM variables; Booth et al., 2014), are the most widely used variables in ecological climate change impact assessments.

Summaries of minimum, mean, and maximum temperature and precipitation provide a first point of comparison in evaluations of GCM performance because of the relatively long and widespread observational records of these variables. Climate models typically simulate large-scale patterns of mean surface temperatures well, in that historical patterns at continental scales and in most subcontinental regions are reproduced with minimal bias in the multimodel ensemble mean (Flato et al., 2013). Individual models vary in their regional biases, with spread among models on the order of ±3 °C. GCMs do less well simulating global patterns of mean precipitation, relative to patterns of temperature, and biases in precipitation can be substantial and variable at regional and local scales. The bias in annual mean precipitation rate can be over ±1000 mm yr⁻¹ in tropical regions (Flato et al., 2013).

In evaluations of climate model performance, spatial and temporal patterns of bias can be more important than the absolute magnitude of bias. For example, equilibrium climate sensitivity (i.e., the magnitude of the global average temperature increase arising from a doubling of CO₂) is not consistently related to the magnitude of bias (Knutti et al., 2010). Therefore, a GCM may ‘run hot’, but produce projected changes similar in magnitude to GCMs with smaller biases. Models with systematic biases that are relatively consistent throughout the year are better candidates for bias correction than models with a strongly distorted seasonal cycle or spatial pattern; such distortions in spatial and temporal patterns are more common for precipitation than for temperature (Flato et al., 2013). However, there are cases where biases in climatic means are worrisome, for example, when biased temperatures affect patterns of freezing, melting, and snowfall, which in turn can affect the magnitude of land-atmosphere feedbacks in mountainous (Leung et al., 2004) and polar (Hall & Qu, 2006) regions. Regional assessments of raw GCM performance are helpful because biases can be notable, particularly along coastlines of oceans and large lakes and in areas of complex topography, where the coarse spatial resolution of GCMs fails to resolve these features. Patterns of bias can also reflect distortions of the physical processes that determine climate such as those that lead to systematic biases in the El Niño Southern Oscillation (Flato et al., 2013), the monsoons (Sheffield et al., 2013), or in mid-latitude storm tracks and circulation (McAfee et al., 2011; Simpson et al., 2016).

Projected changes in climatic means should be evaluated in the context of historical and projected climatic variability, as this perspective is key for both detecting human-induced climate change and for assessing its ecological impacts (e.g., Boyd et al., 2016). For example, high latitudes are projected to experience the largest rates of warming but also have large interannual variability in mean temperature, so that the time to emergence of a climate change signal can be greater than at low latitudes (Hawkins & Sutton, 2012). From an ecological perspective, this means that despite lower absolute rates of climatic changes, tropical organisms are likely to experience conditions outside the historical range of variability sooner than organisms at high latitudes (Mora et al., 2013); physiological research has also emphasized the high sensitivity of tropical ectotherms to relatively small increases in temperature (Ghalambor et al., 2006; Deutsch et al., 2008; Dillon et al., 2010).

Natural climatic variability (the variability that would exist in the absence of anthropogenic forcing) can complicate inference about the effects of anthropogenic change, particularly at regional scales (Deser et al., 2012, 2014; Hawkins & Sutton, 2012). There is generally larger climatic variability at smaller spatial scales, leading to relatively larger signal-to-noise ratios at global and continental scales. However, the effects of natural variability can be significant even at continental scales, and for trends out to mid-century (Deser et al., 2012), and will impact even 30-year climate normals. For projections to midcentury and beyond, the signal of change in mean temperature is often large relative to natural variability, which is not the case for projected changes in mean precipitation in many or most regions of the globe (IPCC, 2013).

A large fraction of natural variability on decadal timescales is due to the chaotic interactions within the climate system. Climate scientists often estimate this
Cleland et al. among the earliest and most widespread impacts of climatic variability (e.g., Sofaer et al., 2016). This allows different realizations of the model’s weather and climate oscillations such as the El Niño Southern Oscillation and the Pacific Decadal Oscillation to develop. Considering many such realizations reveals the model’s change signal, and delineates the shifting envelope of variability due to anthropogenic forcing. Ecological impact assessments would benefit from careful attention to the role of natural variability, ideally by considering a large ensemble of realizations from many different GCMs. To date, the reality of model choice within the CMIP5 data set, the availability of downscaled data, and the complexity of the ecological modeling and analysis have usually prohibited this exhaustive approach. Ecological assessments are often carried out using single realizations from multiple GCMs, which simultaneously sample both the (modeled) natural variability and the uncertainty in projected climate due to different GCM formulations (e.g., Sofaer et al., 2016).

Seasonality
Organisms’ life cycles are highly responsive to patterns of seasonality, and shifts in phenology have been among the earliest and most widespread impacts of climate change (Parmesan, 2006; Schwartz et al., 2006; Cleland et al., 2007). However, taxa differ in the drivers of their phenological responses, including in the contributions of photoperiod versus climatic factors (Carey, 2009; Körner & Basler, 2010; Tooke & Battey, 2010), and in the climatic factors to which they are most sensitive (e.g., Borchert, 1998; Peñuelas et al., 2004; Inouye, 2008; Hurlbert & Liang, 2012). Differences among species responses can affect biotic interactions and community dynamics (e.g., Visser & Both, 2005; Ovaskainen et al., 2013; Hua et al., 2016). For many species, both mean changes and shifts in seasonal timing are likely to contribute to biological responses, and the overall sensitivity of ecological systems will depend on interactions among species’ responses as well as the magnitude of climatic change relative to historical variability.

Seasonal variation in temperature is highly predictable and is captured relatively accurately in GCMs’ historical simulations. In contrast, the seasonality of precipitation is often not well captured by climate models. For example, GCMs differ in their simulation of the intensity and spatial extent of the monsoon season in the Southwestern United States and Mexico (Sheffield et al., 2013). Failure in simulating the seasonal pattern of precipitation calls into question projected changes in precipitation, given that they are unlikely to be based on the correct physical mechanisms. Therefore, major mismatches in the pattern of precipitation seasonality may be a basis for excluding GCMs from regional climate change impact assessments. Because these mismatches are not apparent in bias-corrected data, regional assessments of model performance (e.g., Rupp et al., 2013) are critical, but are lacking for most regions.

Climatic variability and extremes
With an eye to the potential impacts of climate change, ecological research has increasingly focused on climatic variability (Wang & Dillon, 2014; Vázquez et al., 2017; Boyd et al., 2016) and extreme events (Jentsch et al., 2007; Smith, 2011; Knapp et al., 2015; Bailey & van de Pol, 2016). Studies have demonstrated the implications of climatic variance and extremes for behavior (Rubenstein, 1992; Papaj et al., 2007; Frick et al., 2012), demography (Sæther, 1997; Langin et al., 2009; Jönsson et al., 2013), distributions (Reside et al., 2010; Bateman et al., 2012), community composition (Albright et al., 2010; Hoover et al., 2014), mass mortality events (McKechnie & Wolf, 2009; Anderegg et al., 2013), fire dynamics (Westerling et al., 2006; Littell et al., 2009; Abatzoglou & Kolden, 2013), carbon cycling (Frank et al., 2015), and invasive species (Vilà et al., 2007; Diez et al., 2012; Shennard et al., 2012), among others. The temporal scale at which extreme events are defined varies from daily to multidecadal timescales, with the timescale of interest dependent on the impact of interest (e.g., heat-induced mortality versus annual gross primary productivity). Extreme climatic events do not always lead to extreme (i.e., rarely observed) ecological responses, and an overarching goal is to identify thresholds and nonlinearities in ecological systems, and evaluate whether or when those thresholds are likely to be exceeded (Smith, 2011; Kayler et al., 2015; Bailey & van de Pol, 2016).

The threats posed by climatological extremes, defined as events falling in the tails of the climatic distribution of interest, have led to an increasing focus on understanding and projecting these events. There is strong evidence that greenhouse gas emissions have already increased the magnitude and frequency of temperature and precipitation extremes (Meehl et al., 2007; Min et al., 2011; Fischer & Knutti, 2015) and drought severity (Williams et al., 2015; Abatzoglou & Williams, 2016). An increased frequency or intensity of extreme events can arise from a directional shift in the entire distribution of a variable or from an increase in its variance. Variability within a given GCM can be underestimated or overestimated at a regional scale (e.g., Rupp et al., 2013), but assessment is limited by the relatively short observational record for most variables in most locations, which limits our understanding of changes in
historical variance. In addition, the mechanisms underpinning changes in variability are still being explored, particularly for decadal variability (e.g., Newman et al., 2016). Therefore, changes in variability between a GCM’s historical and future simulations should be interpreted with caution. Analysis of paleoclimate proxies, particularly for the past millennium, can yield a larger perspective on natural climate variability including pluvials and megadroughts (e.g., Pechony & Shindell, 2010; Pederson et al., 2011; Woodhouse et al., 2016), although further discussion of paleoclimate is beyond this scope of this review.

To date, support is strongest for increases in variance of short-term (e.g., daily) patterns of precipitation, where physical principles and models align in pointing to an increase in the intensity of precipitation and particularly in the fraction of annual precipitation occurring in strong events (Collins et al., 2013; Prein et al., 2017). Precipitation intensity is expected to increase at a faster rate than mean precipitation in most regions because warmer temperatures increase the capacity of the air to hold water, leading to larger events (reviewed in Fischer & Knutti, 2016). The right tail of the precipitation distribution (representing heavy rainfall) can become wider even in locations projected to experience overall drying (Scoccimarro et al., 2013), a result of rain falling in fewer, more intense storms.

Methods for assessing change in climatic extremes depend on the return interval of the extremes of interest. Climate scientists have developed a suite of indices to quantify ‘moderate climatic extremes’, which occur with a return interval of 1 year or less, known as the ETCCDI indices (Expert Team on Climate Change Detection and Indices; Frich et al., 2002; Zhang et al., 2011). These are based on daily precipitation and minimum and maximum temperatures and include measures such as the number and intensity of hot and cold days, sequences such as the duration of hot, cold, dry, and wet periods, and measures of the intensity of large precipitation events each year. An evaluation showed that temperature-based indices were reasonably well captured by CMIP5 GCMs, and indices based on the number of days in which a percentile-based threshold was exceeded were the most robust for both temperature and precipitation (Sillmann et al., 2013a). Modeled large-scale geographic patterns of extreme precipitation events are also reasonable, although models have a tendency for underestimating precipitation intensity and show less model agreement in the tropics (O’Gorman & Schneider, 2009; Scoccimarro et al., 2013). However, the small spatial scale at which precipitation extremes occur creates uncertainty in gridded data sets used for model validation as well as scale mismatches between gridded and weather station data, making performance evaluations more difficult (Sillmann et al., 2013a; Alexander, 2016). For local studies, weather generators can provide simulations that capture extremes and correspond with the spatial scale of a weather station.

While indices specifically developed for a given ecological system are likely to maximize explanatory and predictive power, the ETCCDI indices and similar summaries may provide a first approximation of relevant climate extremes, just as the BIOCLIM variables serve as general measures of climatic means. However, despite their broad adoption in climate change research, these indices have rarely been applied to ecological questions (e.g., Zhang et al., 2013; Moran et al., 2014; Torres-Meza et al., 2014). Gridded ETCCDI indices are currently available at a coarse spatial scale for the historical period (Donat et al., 2013) and GCM simulations (Sillmann et al., 2013a,b), and software packages for their calculation are available (e.g., Bronaugh, 2015). Because extremes can be affected by bias-correction and downscaling (Cannon et al., 2015), it is worth researching whether finer-scaled historical data sets might be paired with spatially coarser projections of change in appropriate (e.g., percentile-based) indices to create accessible products for climate change impacts modeling. Such an approach would extend the ‘delta method’ to indices describing climatic extremes (see below for description of standard delta method applied to climatic means).

Climatic extremes with less frequent return intervals (e.g., 10-, 20-, or 100-year floods) may be understood using the tools of extreme value theory. In one approach, a Generalized Extreme Value distribution can be fit to the maximum value within a certain time interval, such as the maximum daily precipitation within a year. The distribution can be estimated separately for GCM output from historical and future time periods, and the return times for a given value can be compared, as can the maximum values that can be expected to occur in a certain time interval. As one might expect, estimation is sensitive to the length of the time series data; it is easier to estimate the magnitude of a 10-year flood than a 50-year flood. Large ensembles of climate model data can ameliorate the sampling problem within the model context (e.g., Fix et al., 2016), while spatial statistical modeling can help for analyses of observed data (e.g., Cooley et al., 2007; Bracken et al., 2016). Extreme value theory has been relatively underused in ecology (Katz et al., 2005), but these tools allow ecologists to tailor their analyses to each system of interest by quantifying changes in the frequency at which known or hypothesized climatic thresholds occur. Similarly, the life histories of focal organisms can be used to define a return interval of ecological relevance. Combining GCM output with extreme value
theory can therefore provide a set of system-specific projections of changes in climatic extremes, provided that parametric distributions are fitted appropriately and evaluated carefully.

Climatic sequences

The sequence of weather conditions can have important effects on ecological processes, but these are relatively rarely explored compared with the impacts of climatic means or extremes (Miao et al., 2009; Zedler, 2010; Briscoe et al., 2016). Climatic sequences refer to both the serial correlation of climate variables (e.g., persistent dry spells) and the oscillation between anomalous climate states. For example, wet conditions can lead to fuel buildup that then increases fire risk during a subsequent dry year (Balch et al., 2013) and the occurrence of a prolonged rain-free period during the fire season can promote fire growth (Abatzoglou & Golden, 2011). Sequences are therefore a potentially important factor for ecological models, including those that simulate vegetative growth, competition, and disturbance dynamics (e.g., Miller et al., 2015).

General circulation models simulate their own variability spanning from decadal and interannual to subseasonal timescales. However, GCMs can simulate unrealistic sequences of events (e.g., number of consecutive wet or dry days; Sillmann et al., 2013a), as well as inadequately reproduce the characteristic timescales, amplitude, and spatial patterns of the El Niño Southern Oscillation (Bellenger et al., 2014; Capotondi et al., 2015) and the Pacific Decadal Oscillation (Newman et al., 2016). This can influence the climatic sequences in regions that experience significant teleconnections to these phenomena, an issue that is unlikely to be eliminated by bias-correction and that is relevant for ecological systems sensitive to these oscillations. Similarly, regional precipitation variability simulated by GCMs can deviate from observations, particularly on interannual to multidecadal timescales, thereby potentially limiting the credibility of some measures of drought (e.g., Ault et al., 2012; Rupp et al., 2013). On shorter timescales, the way that precipitation is represented in GCMs can lead to rainfall occurring too often and with smaller intensity than in observations (Stephens et al., 2010; Sillmann et al., 2013a). In general, because climatic sequences are often poorly represented by GCMs, inference regarding changes in sequences is often less reliable than changes in climate means. Ecologists working in systems sensitive to climatic sequences should be aware of limitations associated with simulated sequences, as well as with any projected changes in sequences; strategies for impact assessments in these situations are discussed in the section below.

Designing impact assessments to reflect key climatic drivers

Statistical and mechanistic models incorporate climate change projections to quantify potential impacts on an ecological system or process of interest. We describe three general frameworks for generating climatic summaries for such assessments (Fig. 3). The first approach compares ecological model responses under observed climate conditions with those under future climate conditions from GCMs, herein referred to as ‘observed versus GCM projected’; this is generally not recommended. The second approach is to develop ecological projections based on climate data created with the so-called delta method (described below); this approach is commonly used and is appropriate for capturing projected changes in climatic means. The third strategy compares modeled ecological responses for each climate simulation between experiments run for future and historical climate periods. This strategy, here termed the ‘model space’ approach, allows multiple dimensions of climate change to be considered and captures projected differences in changes in means versus extremes for each climate model. In this section, we describe these approaches and discuss their advantages and disadvantages with an emphasis on how the most suitable approach depends on the climatic variables of interest.

Comparisons based on observed versus GCM-projected climate

Comparing modeled ecological responses based on observed climatic data versus GCMs’ future projections (the ‘observed versus GCM projected’ method; Fig. 3a) would risk conflating biases in GCM output with the potential impacts of climate change. A mismatch such as this would generally not be intentional, because it may not be intuitive that the risk of conflating bias with potential impacts remains even if using GCM output that has been bias-corrected relative to the historical climate data set used in ecological model fitting. Bias correction matches some aspects of the probability distribution of GCM historical simulations to that of the observations over a fixed set of years at a given temporal resolution (usually monthly or daily). However, bias correction may not correct all statistical attributes of interest, meaning that biases in variability (e.g., magnitude of droughts) and sequences (e.g., consecutive wet days, frequency of El Niño events) will persist, making it problematic to directly compare results with observations. Also, differences in the years used for estimation of the ecological model (e.g., 1990–2015) and those years used as a baseline for bias correction (e.g., 1950–
1999) can lead to problems in interpretation, as a mismatch in historical distributions may be conflated with the impacts of climate change. These problems will be more acute if the ecological model was fit using one observed climate data set, but a comparison is made to GCM output that was bias-corrected to a different observed climate data set (Fig. 4). Gridded historical climate data sets are themselves estimates and can differ substantially from one another, particularly in mountainous regions (Oyler et al., 2015a,b). As a general rule, ecological models should be estimated using the observed climate data set that was used as a baseline for bias correction (or the delta method should be used), but bias correction should not be assumed to make future GCM projections directly comparable to historical climate observations.

**Comparisons based on the delta method**

Projecting ecological impacts based on climate data sets created with the delta method is a straightforward and appropriate way to capture mean projected changes within each GCM. The delta method adjusts a fine-scale historical climate data set by shifting the historical values according to the mean change projected by a GCM (Fig. 3b). Specifically, a delta (also called a change factor or anomaly) is calculated from a comparison between a GCM’s historical and future simulations, often using temporal windows of 30 years (e.g., comparing 1971–2000 with 2041–2070). The difference in the historical and future means is used to measure change in temperature, and the ratio is used to measure change in precipitation. These deltas are calculated at the coarse spatial scale of the GCM and are applied to fine-scaled historical climatic data to generate projected future conditions. Because only the projected changes are taken from the GCM, the delta method does not require additional bias correction, so that deltas can be computed from raw or bias-corrected GCM output, often on a monthly basis. For large areas, the deltas are generally derived for each cell of gridded data and therefore incorporate the spatial variation in projected changes at the GCM spatial resolution. The deltas are applied to historical observed climate data to create a set of future plausible scenarios. Quantitative impact assessments should develop projections based on the delta calculated from each GCM simulation (i.e., each run, model, and emissions pathway) and then compare,
interpret, and/or ensemble these. This reveals the variation across climate simulations, whereas developing ecological projections based on an ensemble mean of projected climate change ignores divergent projections. As noted above, including multiple simulations from each climate model can help delineate the role of internal climate variability.

The simplicity of the delta method creates advantages for model fitting and interpretation. The delta method has been used to create several readily available data sets that are widely used in ecology (e.g., WorldClim and ClimateNA; Hijmans et al., 2005; Wang et al., 2016). The delta method ensures compatibility with the observed record, which is particularly useful when the source of observed climate data has not been used as a baseline for bias-correction of a set of GCMs. The changes projected by each GCM (i.e., the difference or ratio between GCM historical and future simulations) can be applied to any historical data set to get a valid future projection. When the sequence of climatic conditions is important but sequences taken from GCMs are considered inadequate for use in subsequent modeling, an alternative method is to apply monthly deltas to the historical sequence to generate a future sequence that has the same daily and interannual variability. This method will be useful when the ecological response variable is dynamic in time and is paired with weather conditions during each time step (Reside et al., 2010; Bateman et al., 2012; Steen et al., 2014). This approach can also be useful for making the projected future sequence relatable to stakeholders who have experienced the historical sequence. For example, one can project how much worse a severe drought year might be under climate change (e.g., Williams et al., 2015), under the assumption that sequences will not change and climatic extremes will shift along with the mean (Fig. 2b).

The delta method is recommended for impact assessments where the major climatic drivers are measures of mean change or measures that are closely linked to mean change (e.g., growing degree days) and for processes that are strongly affected by the sequence of weather events that are poorly captured by GCMs. However, it is less optimal for impact assessments in systems where climatic extremes have major effects on ecological responses, as the delta method assumes that climate extremes will change at the same rate as the mean (e.g., rate of the warming of coldest daily temperature in January will equal that of mean January temperature at a given location; Fig 2b). Shifting the distribution of temperature and precipitation necessarily changes the intensity of extreme events, but these changes in intensity can differ from changes more directly based on a GCM’s projections of climatic extremes. Impact assessments based on the delta method therefore may not be able to correctly capture low risk but high impact climatic events.

It should be noted that advanced applications of the delta method can capture dimensions of change beyond the mean. For example, there have been modifications of the delta method to better reflect the GCM-projected change in the shape of probability distributions, while retaining the observed historical time series as the baseline (e.g., Tohver et al., 2014; Cannon et al., 2015). In addition, weather generators can be used to both simulate realistic sequences at a specific location and apply projected changes beyond the mean to those sequences (e.g., Fatichi et al., 2013). For example, parameters in a simple weather generator describe the probability of a wet day and the distribution of the amount of precipitation on days that are wet; in the most basic application under climate change, the change in these parameters can be calculated based on a GCM and applied to simulate future sequences (Wilks, 2012). Weather generators have the advantage of quickly sampling natural climate variability via many simulations (e.g., Fatichi et al., 2016) and can do so for multiple variables and at daily or subdaily temporal scales. However, an evaluation
step is necessary because it should not be assumed that an ecological model which was parameterized using weather station data produces similar predictions based on output from a weather generator – like other downscaling and bias-correction methods, a weather generator matches some, but not all, statistical aspects of the historical data. Therefore, applications using weather generators may use a combination of the delta and ‘model space’ approaches, shifting parameters according to the delta method but basing ecological inference on comparisons between weather generator simulations with original and shifted parameter space (see ‘model space’ approach below).

**Comparisons in ‘model space’**

Impact assessments in ‘model space’ are based on comparisons of the predictions of an ecological model under simulated historical and future climates. This approach is relevant for any experimental design where both the historical and future climate data come from a simulation that is not synchronous with the observed record (i.e., conditions in specific years do not match between the observed record and the simulations). This includes output from GCMs, RCMs, and weather generators, with or without additional processing via the wide range of empirical downscaling methods (Wilby & Wigley, 1997). To emphasize these methodological implications, we use the term ‘model space’ for this larger category of methods, but refer to the use of GCM output for simplicity. We highlight the utility of the ‘model space’ approach for assessing the impacts of projected changes beyond those in climatic means; therefore, we assume that any bias-correction preserves (or at least reflects) the projected changes in each quantile.

To implement the ‘model space’ approach using a correlative statistical model of the ecological response, model parameters would be estimated as usual, using observed climate data and observed ecological responses. After an evaluation step, the fitted ecological response model can then be used to generate and compare predictions under GCM historical simulations and under GCM future simulations (Fig. 3c). Impact assessments based on a mechanistic model of an ecological response can use a similar approach and compare output of the ecological model based on conditions in the historical and future simulation of each GCM and emissions scenario of interest. In summary, implementation of the ‘model space’ approach has three steps: ecological models should be parameterized based on observed climate, predictions evaluated based on historical climate model simulations, and impacts assessed based on comparisons between historical and future climate simulations (Fig. 3c).

Impact assessments conducted in ‘model space’ require additional effort and careful confirmation that data from GCM historical runs can be integrated into ecological models to produce reasonable ecological responses. In this evaluation step, ecological responses based on each GCM historical simulation should be compared to modeled ecological responses under observed climatic conditions. Climatic conditions in the historical simulation and associated modeled ecological responses are not expected to match those that were observed on a year by year basis, but should aim to be similar in terms of the response distributions (Fig. 5). The use of bias-corrected (e.g., via quantile mapping) and downscaled GCM outputs is less likely to lead to qualitative divergence in ecological predictions; to minimize divergence, studies should use GCM data that have been bias-corrected and downscaled relative to the climate observations used in model estimation (Fig. 4). However, even bias-corrected GCM simulations can differ in important aspects from observed climate, and any major changes in the corresponding ecological predictions could invalidate their use as a baseline for assessing climate change impacts. Divergence in ecological responses is more likely to occur when the ecological response depends on climatic metrics that bias correction does not fully correct, such as unrealistic sequences or lower-frequency variability; such differences could be substantial across different GCMs. When ecological responses under GCM historical simulations match the distribution of observed and predicted

![Fig. 5 Impact assessments conducted in ‘model space’ should confirm that the ecological response shows a similar distribution when predictions are based on bias-corrected historical climate model simulations. In this example, modified from Sofaer et al. (2016), such a comparison highlighted how a decrease in the variability of the response (wetland density) was attributable to both the ecological and climate models, rather than to projected climate change.](image-url)
responses under observed climate, conducting impact assessments in ‘model space’ allows for a multidimensional assessment of projected climate change.

The ‘model space’ approach offers several advantages, particularly for studies interested in climatic variability and extremes. In contrast to comparisons between observed climate and future GCM projections, conducting impact assessments in ‘model space’ isolates the effect of climate change. This is because anthropogenic emissions drive the differences between GCM historical and future simulations, whereas comparisons between observed historical data and modeled future data conflate any differences between the real and modeled worlds with the effects of climate change. Compared with the delta method, comparisons in ‘model space’ include multiple dimensions of climate change, retain the correlation structure between climate variables, and correctly capture any differences in the rate of change in climatic means versus extremes. The potential benefits of this approach for ecological studies have received little explicit attention (Sofaer et al., 2016).

A key reason for using the ‘model space’ approach is that projected changes in the intensity of extreme events will directly reflect the change between GCM historical and future simulations, which can differ in pattern and magnitude from projected changes in extremes based on a shift in the mean (i.e., the delta method). To illustrate this effect within the conterminous United States (Fig. 6), we used a statistically downscaled version of one run of one GCM, the National Center for Atmospheric Research’s (NCAR) Community Climate System Model (CCSM4) r6i1p1 under the RCP 8.5 emissions trajectory. Statistical downscaling was carried out via the Multivariate Adaptive Constructed Analogs (MACA; Abatzoglou & Brown, 2012) method v2, bias corrected to Livneh et al. (2013) gridded historical observations. Historical data and GCM simulations had a daily temporal resolution.

Fig. 6 Comparison of change in projected 10-year return values of July maximum temperature from 1970–1999 to 2070–2099 calculated via (a) the delta method or (b) the ‘model space’ approach, in degrees Celsius. The ‘model space’ approach captured greater projected change in climatic extremes, and a different spatial pattern of change, relative to projected change in mean July maximum temperature. Data for both panels were based on the National Center for Atmospheric Research’s (NCAR) Community Climate System Model (CCSM4) r6i1p1 under RCP 8.5, downscaled and bias-corrected using the Multivariate Adaptive Constructed Analogs method (see text for details).
We compared the projected change in the 10-year return value of maximum July temperature (i.e., the hottest July day that would be expected in a 10-year period) from 1970–1999 to 2070–2099 between the delta and ‘model space’ approaches. The delta-based approach assumes the change in 10-year return values from historically observed to future periods equals the projected change in the mean July maximum daily temperature (i.e., the mean change between GCM historical and future simulations based on all days in July; the extreme is changing at the same rate as the mean, as in Fig. 2b). For the ‘model space’ approach, we estimated return values by fitting a Gumbel distribution (a Generalized Extreme Value distribution with the shape parameter fixed at 0) to the hottest daily maximum July temperature in each cell in each year. This was carried out for simulated historical and future 30-year periods, and we quantified the projected change for each cell (R code is provided in Appendices S1 and S2).

Projected changes in the intensity of our focal extreme event – the hottest July day expected in a 10-year period – were in many locations greater in magnitude using the ‘model space’ approach compared with the delta method (Fig. 6). This reflects greater projected changes in climatic extremes than in climatic means in this example. Conversely, the delta method assumes that changes in extremes reflect those in the means (Fig. 6a). The ‘model space’ approach directly reflected the changes in extremes projected by this GCM simulation (Fig. 6b); note that the particular spatial pattern of projected changes will vary across models, and that continental and regional patterns are more reliable than local patterns. Our aim is to show that differences between projected changes in means and extremes can be striking, and of a magnitude likely to have ecological implications (here, up to 7 °C with a mean difference of 1 °C); different rates of change in means and extremes have also been seen in other impact-related contexts (e.g., Parker & Abatzoglou, 2016). We emphasize that these differences derive from the method by which the data were summarized; the data set of climate simulations was identical.

Our illustration aligns with previous studies showing how changes in the frequency and intensity of extremes are related to changes in both the climatological mean and variance (Mearns et al., 1984; Katz & Brown, 1992; Schär et al., 2004; Fischer & Schär, 2009). In general, a simple shift in the mean (i.e., the delta method) is likely to capture shifts in extremes only in some areas and for some variables (e.g., Griffiths et al., 2005; Lustenberger et al., 2014), which may be difficult to identify a priori. We therefore suggest that the ‘model space’ approach, which uses direct comparisons between historical and projected simulations from each GCM, should be considered for ecological impact assessments in systems sensitive to climatic extremes.

Conclusions

An understanding of the climatic drivers of ecological systems is one of the key insights ecologists bring to climate change risk and impact assessments. It has been widely recognized that the selection of climate variables in ecological models should be tailored to the system of interest and that dimensions of climate beyond mean conditions are important for shaping ecological systems (e.g., Zimmermann et al., 2009; Helmuth et al., 2014; Vázquez et al., 2017). Nevertheless, ecologists may have difficulty evaluating how well different types of climate variables are represented in GCM simulations, and how reliable projected changes in these variables may be. While the generalizations provided here should be supplanted by quantitative regional assessments, there is support for the assertion that attributes beyond mean projected changes can be appropriately incorporated into ecological research.

Climate change impact and risk assessments fundamentally depend on the amount of change projected for different climatic variables. A conceptual understanding of how estimates of climate change can be derived could improve the integration of climate projections in ecological models. The delta method is an efficient and appropriate way to extract the signal of mean climate change and to preserve the historical sequence of weather events. It is appropriate for situations where the selected historical climate data set has not been used as a baseline for bias-correcting GCM projections. Because the climate change signal is at the native resolution of a raw GCM, even in most statistically downscaled data sets, local-scale ecological impact and vulnerability assessments may have a study area entirely or largely within a single cell of a GCM. In these cases, applying the delta method is equivalent to a sensitivity analysis that shifts historical observations by a fixed value across the study area. The equivalence highlights the value of sensitivity studies, and indeed, the delta method can be considered a GCM-guided sensitivity analysis.

Recognition of the importance of climatic variability and extremes for ecological systems has too rarely been translated into direct incorporation of projected changes in these dimensions into ecological models. Impact assessments can be conducted in ‘model space’ by comparing predicted ecological states under simulated historical and future conditions (Fig. 3c). The ‘model space’ approach would typically be based on downscaled and bias-corrected data (e.g., via quantile
mapping) and can be used to understand whether and how climatic extremes are projected to change (Fig. 6). As opposed to the delta method, this method may better capture aspects of climate change beyond the mean (Fig. 2) and so allows additional dimensions of climate change to be quantified without assuming all such summaries will change at the same rate as the mean. Most importantly, it integrates the concept of modeled climate experiments into ecological research; each historical simulation serves as a control run to which its corresponding future simulation can be compared. Comparing modeled ecological outcomes under historical and future climate simulations is the most appropriate method to integrate multiple dimensions of climate change without conflating differences between modeled and observed worlds with the impacts of climate change.

Workflows for the integration of climate data into ecological models (Fig. 3) have received little explicit attention, despite differences in the suitability of each approach for different types of climate summaries. Regardless of the approach taken, ecological studies should describe and justify their methodological approaches. No single set of climate variables or methodological workflow is appropriate for all studies; as always, tailoring each study to the system and question of interest will yield the most credible and appropriate climate change impact and risk assessments.

Acknowledgements

This work was funded by a U.S. Geological Survey Mendenhall Postdoctoral Fellowship to HRS, the U.S. Geological Survey Invasive Species Program, and the U.S. Department of Interior North Central Climate Science Center. Our manuscript was improved by comments from J.R. Alder and three anonymous reviewers. Any use of trade, firm, or product names is for the U.S. Government.

References


METHODS FOR CLIMATE CHANGE IMPACT STUDIES


Supporting Information

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

Appendix S1. R script for Fig. 6.
Appendix S2. R function for Fig. 6.