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Coarse climate change projections in a fine-scaled world

RUNNING HEAD:

Coarse Resolution Climate Data

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Abstract

Accurately predicting biological impacts of climate change is necessary to guide policy. However, the resolution of climate data could be affecting the accuracy of climate change impact assessments. Here we review the spatial and temporal resolution of climate data used in impact assessments and demonstrate that these resolutions are often too coarse relative to biological scales. We then develop a framework that partitions climate into three important components: trend, variance, and autocorrelation. We apply this framework to map different global climate regimes and identify where coarse climate data is most and least likely to reduce the accuracy of impact assessments. We show that impact assessments for many large mammals and birds use climate data with a spatial resolution similar to the biologically relevant area of a population. Conversely, impact assessments for many small mammals, herpetofauna, and plants use climate data with a spatial resolution that is orders of magnitude larger than the area of a population. Most impact assessments also use climate data with a very coarse temporal resolution. Climate data with a coarse spatial resolution likely reduces the accuracy of impact assessments the most in climates with high spatial trend and variance (e.g., much of western North and South America) and the least in climates with low spatial trend and variance (e.g., the Great Plains of the USA). Climate data with a coarse temporal resolution likely reduces the accuracy of impact assessments the most in the northern half of the northern hemisphere where temporal climatic variance is high. Climate data with an appropriate resolution is unavailable for most species. Our framework provides one way to evaluate where using coarse climate data will affect the accuracy of impact assessments.

Global change is changing the abundance and distribution of species, which is altering biological communities, ecosystems, and their associated services to humans (Parmesan & Yohe, 2003; Cardinale et al., 2012; Kortsch et al., 2015). These changes are expected to accelerate due to climate change (Maclean & Wilson, 2011; Urban, 2015). Accurately predicting biological responses to climate change is therefore necessary to help assess the potential impacts of climate change and guide policy designed to mitigate those impacts.

A growing number of studies indicate that the accuracy of climate change impact assessments is affected by the temporal and spatial resolution of climate data used to model climate change (Randin et al., 2009; Early & Sax, 2011; Gillingham et al., 2012; Lenoir et al., 2013; Bennie et al., 2013; Nabel et al., 2013). For example, an average of 52% of high-elevation plant species were predicted to become extirpated from two regions of Switzerland when assessments of extirpation used climate data with a coarse spatial resolution (19 by 13 km grid cells; Randin et al., 2009). However, up to 100% of these species were predicted to persist when predictions were made using climate data with a fine spatial resolution (25 by 25 m grid cells; Randin et al., 2009). The temporal resolution of climate data can also be important. For example, predictions made using coarse temporal climate data (i.e., two time periods 100 years apart) suggest that most western U.S. amphibians will persist under climate change by shifting their range to track suitable climates (Early & Sax, 2011). However, decadal climate fluctuations could prevent many amphibians from accessing future suitable climates, which would significantly increase their risk of extinction under climate change (Early & Sax, 2011).

The appropriate spatial and temporal resolution of climate data for climate change impact assessments requires further research, but likely depends on a few key factors. First, the appropriate spatial and temporal resolution of any study depends on the organism and process under investigation (Addicott et al., 1987; Wiens, 1989; Levin, 1992; Bennie et al., 2014). Organisms have adapted to regional climates by evolving unique life history strategies, dispersal abilities, physiological tolerances, and behaviors that affect how they experience climate (Cohen, 1966; Levin et al., 1984; Tewksbury et al., 2008; Kearney et al., 2009). Moreover, climatic variation at different resolutions (e.g., daily and seasonal) can interact to have complex effects on these traits (Chan et al., 2016). Traits that are adapted to climate can make some species sensitive to fine resolution weather events and micro-climates while allowing other species to moderate the effect of high climatic variability (Deutsch et al., 2008; Buckley et al., 2012). Consequently, the appropriate resolution of climate data will depend on key species traits such as dispersal kernels and generation times.

Second, the appropriate resolution of climate data likely depends on the climate within the focal region. Using coarse resolution climate data in climates with low variation could have minimal effect on climate change impact assessments because the average climate used in coarse resolution data will be representative of climates at finer resolutions (Woodcock & Strahler, 1987). Stochastic population dynamics are well represented by deterministic models when variation is low for the same reason (Chesson, 1981). However, in regions with high climate variation, important climate components could be masked by using coarse resolution climate data (Randin et al., 2009; Early & Sax, 2011).

Whether climate change impact assessments are using climate data with biologically relevant spatial and temporal resolutions is a matter of debate. A recent review compared the spatial resolution of species distribution models (i.e., the most common models used to evaluate the ecological impacts of climate change) to the body length of focal organisms (Potter et al., 2013). The spatial resolution of species distribution models was approximately 10,000 times larger than the body length of focal animals and 1000 times larger than the body length of focal plants (Potter et al., 2013). Potter et al. (2013) used this data to suggest a large spatial mismatch between the resolution of species distribution models and the scale at which species experience the environment.

Bennie et al. (2014) responded to this review, however, and suggested that the body length of focal organisms may not be the appropriate spatial resolution to consider when modeling species distributions. Bennie et al. (2014) suggest that the aim of species distribution models is to predict the presence or absence of populations and therefore the area that encompasses a population could be an appropriate spatial resolution to use in climate change impact assessments. They further suggest that the resolution required to map population presence and absence is similar to the resolution of climate data, although they do not provide data to support this claim.

In this paper, we first show that many climate change impact assessments are using coarse resolution climate data even when compared to the area that encompasses a population. We also evaluate the temporal resolution of climate data used in climate change impact assessments. In the second part of the paper we suggest that climate can be partitioned into three components in both space and time - trend, variance, and autocorrelation – and we discuss the biological relevance of each component. We then demonstrate that using coarse climate data can misrepresent these three important climate components, which likely affects the results of climate change impact assessments. Last, we use these three climate components to map eight global climate regimes and identify where coarse climate data is most and least likely to misrepresent regional climates. This analysis provides some guidance on where the use of coarse resolution climate data could have the biggest effect on climate change impact assessments.

The Resolution of Climate Data Used in Climate Change Impact Assessments

METHODS

We recorded the spatial and temporal resolution of future climate projections used in a recently compiled list of 131 climate change impact assessments evaluating extinction-risk for multiple species under climate change (Urban, 2015). We standardized the spatial resolution of climate data across studies by calculating the grid-cell area (km^2) so that grid cells with unequal lengths and widths could be compared accurately to those with equal lengths and widths. For resolutions presented in degrees, we converted the latitudinal dimension to km using a factor of 111.325 km per degree and the longitudinal dimension using $\cos\left(\frac{\pi}{180}y\right)111.325$, where y is the approximate latitude of the center of the study area (Loarie et al., 2009).

We also estimated the area of a population for 223 populations of 180 species. Some species were represented more than once if data from distinct studies or regions were available. We grouped species into five taxonomic groups: birds (n = 45), small mammals (n = 13), large mammals (n = 14), herpetofauna (n = 58), and plants (n = 93). This data allowed us to evaluate if grid-cell area was similar to the area that encompasses a population for each of the five taxonomic groups.

We estimated the area of a population for each species using Wright's dispersal neighborhood (Wright, 1946); one of the most common ways to estimate the area of a population (Crawford, 1982; Richardson et al., 2014). Wright's dispersal neighborhood is the area that encompasses 86.5% of dispersal events and is therefore an area where individuals are likely to interact both ecologically and genetically. We estimated the dispersal-neighborhood area as $\pi(2\sigma)^2$, where 2σ is 1.6 times the mean or 1.7 times the median dispersal distance of a species

(Urban, 2011). We obtained information on the mean or median dispersal distance of species using existing reviews on species dispersal distances (Sutherland et al., 2000; Semlitsch & Bodie, 2003; Vittoz & Engler, 2007).

RESULTS

The average spatial resolution (i.e., grid-cell area) of climate data used in 110 studies using spatial climate data was 3,576 km^2 (SD = 16,213 km^2, range = 0.0004 – 133506 km^2, Fig. 1a), which is equivalent to a square grid-cell with 60 km sides. The spatial resolution of climate data decreased over time; however, the resolution varied substantially in any given year, including recent years (Fig. 1b).

The spatial resolution of climate data used in climate change impact assessments was similar regardless of the focal taxa (Fig. 1c). The spatial resolution of climate data was similar to the area of a population for many birds and large mammals (Fig. 1c). However, the spatial resolution of climate data was orders of magnitude larger than the area of a population for many small mammals, herpetofauna, and plants (Fig. 1c). Hence, many climate change impact assessments for small mammals, herpetofauna, and plants used climate data with grid cells that could encompass multiple populations of the focal species, which could affect predictions of biological responses to climate change (Randin et al., 2009; Gillingham et al., 2012; Lenoir et al., 2013).

The majority of studies (89%) that used temporal climate data compared the mean of weather variables in a historical period to the mean of the same weather variables in one to three future periods (Fig. 2). This method ignores climate dynamics between the historical and future periods (Fig. 2). Two percent of studies used a linear change in climate between a historical and future period, which also ignores much of the climate dynamics between the historical and future time period (Fig. 2). Only 9% of studies used an annual or decadal resolution that captures some of the climate dynamics that will occur between the historical and future time period (Fig. 2).

These results suggest that many climate change impact assessments are using climate data that is not mapped at a biologically relevant spatial or temporal resolution. Next we demonstrate that climate data can be partitioned into three biologically relevant components and demonstrate how using coarse resolution climate data can misrepresent these components in climate change impact assessments.

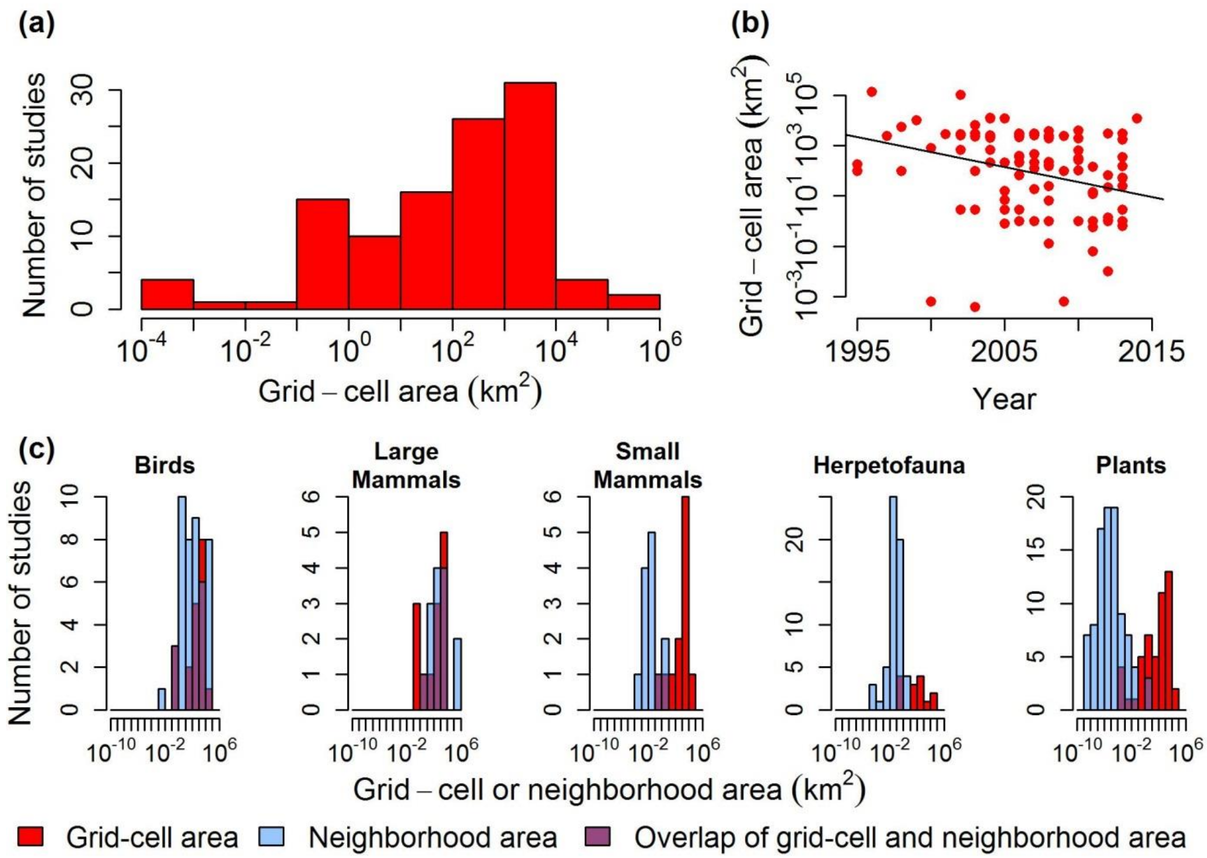

Figure 1. (a) The spatial resolution of future climate projections used in 110 climate change impact assessments for all taxa and (b) the change in the spatial resolution used in climate change impact assessments over time. The trend in b is -0.119 km^2 per year (p = 0.002). (c) The spatial resolution of future climate projections used in climate change impact assessments and the area of a population (i.e., the area of Wright's dispersal neighborhood) for species from five taxonomic groups.

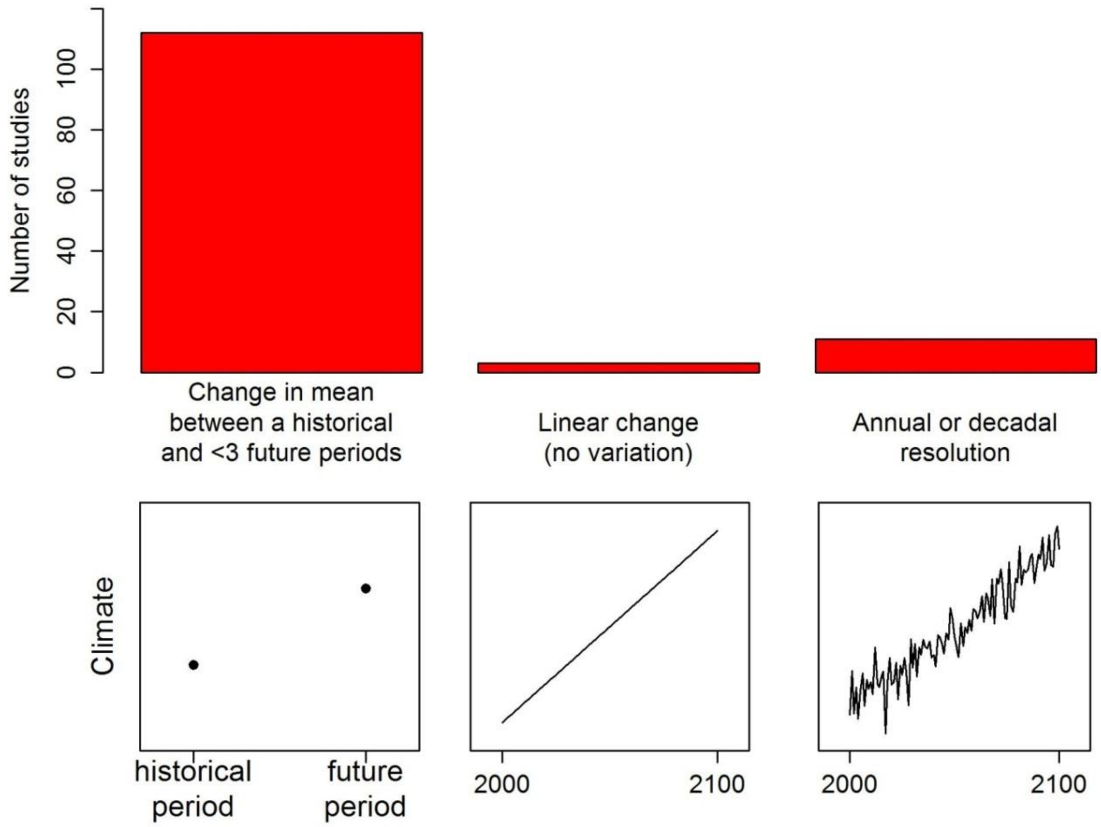

Figure 2. The number of climate change impact assessments using three different temporal resolutions. The figures below each bar provide examples of the three temporal resolutions.

Partitioning Climate into Three Biologically Relevant Components

Climate can be partitioned into three components over both space and time: (1) trend, (2) variance, and (3) autocorrelation (Fig. 3). Climatic trend is a consistent increase or decrease in the mean of a weather variable (e.g., average annual temperature) over large temporal or spatial scales relative to biological scales (Box 1). For example, climate change is a temporal climatic trend and latitudinal and elevational gradients in climate are spatial climatic trends (Fig. 3). Climatic variance is the average deviation of climate from the trend within a time period or region (Fig 3). Climatic variance measures the degree of fine-scale variability (relative to biological scales) in a weather variable over time or space. Climates with high variance have a wide range of weather conditions measured at a fine scale over time or space (Fig. 3). Autocorrelation is a measure of the similarity of neighboring observations of a weather variable in time or space. Climatic autocorrelation measures the length of periods with similar weather over time and the size of climatically similar patches in space (Fig. 3). Long periods of similar weather and large patches of similar climate occur more often in highly autocorrelated climates or regions (Fig. 3). Climatic autocorrelation also measures the predictability of weather over time and climates in space. For example, in climates with low temporal autocorrelation, the weather in one time period will not accurately predict the weather in future time periods (Fig. 3b). Similarly, for climates with low spatial autocorrelation, the climate in one location will not accurately predict the climate in neighboring locations (Fig. 3a).

Climate change impact assessments have primarily focused on climatic trend. For example, the average rate of climate change has been associated with the magnitude of species range shifts under recent climate change (Chen et al., 2011) and can affect the ability of species to adapt in situ (Lynch & Lande, 1993; Burger & Lynch, 1995; Burger & Krall, 2004). Spatial trends have facilitated range shifts under climate change by allowing species to continuously track suitable climates as the climate changes (Chen et al., 2011). A combination of temporal and spatial trend has also been used to estimate the rate that species will need to move to track suitable climates (Loarie et al., 2009).

Climatic variance and autocorrelation have received much less attention in climate change impact assessments. However, environmental variance and autocorrelation (including climatic variance and autocorrelation) have long been known to affect population dynamics (Lande, 1993; Ripa & Lundberg, 1996; Benton et al., 2002; Holt et al., 2003; Drake & Lodge, 2004; Schwager et al., 2006; Schreiber, 2010) and the ability of species to move across the landscape (With, 2002), coexist (Chesson & Warner, 1981; Caswell & Cohen, 1995; Chesson, 2000; Büchi & Vuilleumier, 2014), and adapt to local conditions (Lynch & Lande, 1993; Burger & Lynch, 1995; Gomulkiewicz & Holt, 1995; Lande & Shannon, 1996; Holt, 2004; Burger & Krall, 2004; De Mazancourt et al., 2008; Schiffers et al., 2014). For example, both theory and experiments suggest that time to extinction of closed populations decreases as the temporal environmental variance and autocorrelation increase (Ripa & Lundberg, 1996; Benton et al., 2002; Drake & Lodge, 2004). Temporal environmental variance and autocorrelation can also increase the size of open populations (Holt et al., 2003; Matthews & Gonzalez, 2007), which can affect the probability that a sink population will adapt to become a source (Holt, 2004). The well-known effects of temporal and spatial environmental variance and autocorrelation on ecological and evolutionary dynamics suggest that climatic variance and autocorrelation will affect species responses to climate change.

Relatively few studies have specifically addressed how climatic variance and autocorrelation affect species responses to climate change. The few that do address these components demonstrate strong effects on outcomes (Randin et al., 2009; Early & Sax, 2011; Gillingham et al., 2012; Schiffers et al., 2013; Nabel et al., 2013). For example, both spatial and temporal variance in the environment can maintain standing genetic variation that could allow species to persist under many decades of climate change (Kelly et al., 2003; Yeaman & Jarvis, 2006) or slow the rate of evolutionary adaptation of species with dormant life stages (Rubio et al., 2015). Also, the magnitude of climate change to which a species can adapt decreases as the temporal variance and autocorrelation of the environment increases (Lynch & Lande, 1993; Lande, 1993; Burger & Lynch, 1995; Burger & Krall, 2004). Spatial and temporal climatic variance can also prevent species from tracking suitable climates (Early & Sax, 2011; Canning-Clode et al., 2011; Nabel et al., 2013; Bennie et al., 2013).

More research is needed to determine how spatial and temporal climatic variance and autocorrelation will affect species responses to climate change, but climatic variance and autocorrelation are likely important. Therefore, it is critical to ensure that these components of climate are accurately represented in models used to assess the impacts of climate change.

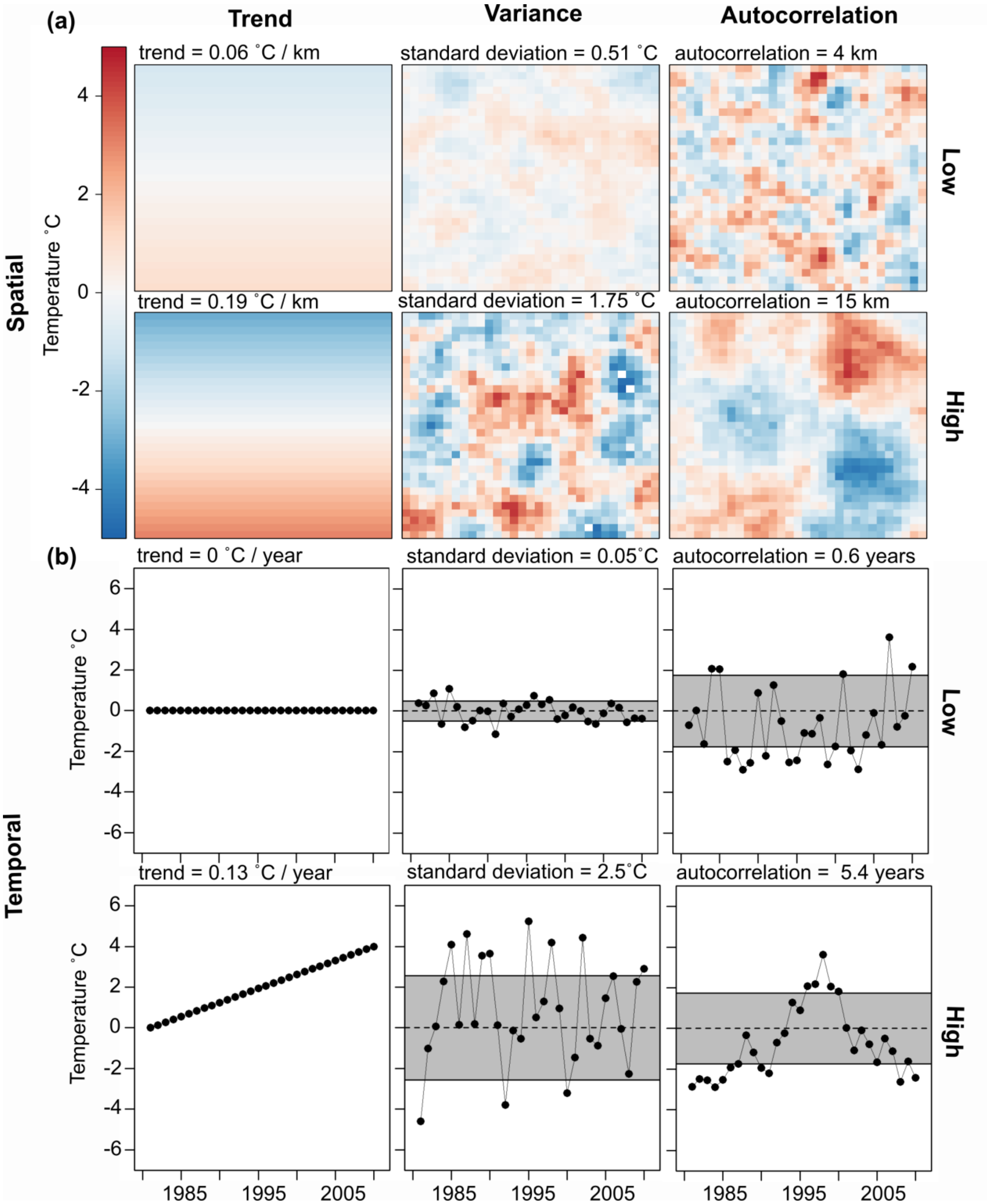

Figure 3. Examples of (a) spatial and (b) temporal trend, variance, and autocorrelation. Examples with high and low values of each component are shown for contrast. Spatial trend is represented as a systematic change in the color from the top to the bottom of the plots. Spatial variance is

represented by the range of colors in each plot and spatial autocorrelation is represented by the size of similarly colored patches. The black points in the temporal plots represent estimates of mean annual temperature, the dashed line represents the temporal trend, and the gray shaded area represents temporal variance ($\pm$ 1 SD). Temporal autocorrelation is represented by consecutive years with similar temperature measurements (e.g., on the same side of the trend line).

Where Will Coarse Climate Data Affect the Accuracy of Impact Assessments

In order to accurately represent climatic trend, variance, and autocorrelation in climate change impact assessments, it is necessary to use an appropriate temporal and spatial neighborhood (i.e., time period and area of interest) and climate data with the appropriate spatial and temporal resolution (Boxes 1 and 2).

The ability to scale climate data to the appropriate resolution for use in climate change impact assessments will be limited by the availability of fine-scale climate projections. Climate data generated by current atmospheric-ocean-general-circulation models can often be obtained with a fine temporal resolution (e.g., daily, hourly), but the spatial resolution is often on the order of 200 by 200 km (Intergovernmental Panel on Climate Change, 2014). This coarse spatial resolution is larger than the area that encompasses a population for most species (Fig. 1). Although, advances in spatial down-scaling are allowing researchers to use climate data with much finer spatial resolutions in climate change impact assessments (Hannah et al., 2014), it is still difficult to obtain climate data with an appropriate resolution for many species and many types of models. Hence, we need to understand where using coarse resolution climate data is likely to have the biggest effect on predictions of biological responses to climate change.

The degree to which climatic trend, variance, and autocorrelation are misrepresented by using coarse resolution climate data depends on the magnitude of each climate component in the focal neighborhood (Woodcock & Strahler, 1987; Chou, 1991). For example, spatial climatic variance is likely to be highly underestimated by using coarse resolution climate data in areas with high spatial climatic variance. This is because neighboring fine-resolution landscape cells with very different climate values are aggregated to their mean in the coarse resolution climate data, which can reduce the variance among coarse-resolution landscape cells (Woodcock & Strahler, 1987). However, spatial climatic variance may not be underestimated by using coarse resolution climate data in areas with low spatial climatic variance because the fine-resolution landscape cells have similar climate values to the mean in the coarse-resolution cells (Woodcock & Strahler, 1987).

The magnitude of each climate component varies across the global land surface. Hence, we can estimate where using coarse resolution climate data will have the biggest effect on climate change impact assessments by first mapping global climate regimes defined by the magnitude of each climate component and then evaluating the degree to which using coarse resolution climate data will misrepresent each climate component in each climate regime. This analysis is one way to identify where using coarse resolution climate data is most likely to affect predictive accuracy of climate change impact assessments.

METHODS

We mapped different combinations of high and low values of trend, variance, and autocorrelation in mean annual temperature across the global land surface (Fig. 4). We estimated each of the three climate components using generalized least squares (Supporting Information).

We estimated spatial trend, variance, and autocorrelation by first dividing the global land surface into 31 by 31 km spatial neighborhoods (Box 2). We chose this neighborhood size as a compromise between the size of the neighborhood and the computation time required to estimate each climate component in the neighborhood. We estimated the spatial trend, variance, and autocorrelation within each neighborhood using estimates of historical annual average temperature mapped at a 1 km by 1 km cell resolution (Hijmans et al., 2005). This resolution is similar to the area that encompasses a population for many herpetofauna, plants, and small mammals (Fig. 1) and is the finest spatial resolution of climate data currently available at a global scale. We estimated temporal trend, variance, and autocorrelation using a time series of annual average temperature between 1900 and 2010 in each 0.5˚ by 0.5˚ grid cell covering the global lands surface (Harris et al., 2014).

In both the spatial and temporal case, we reclassified estimates of trend, variance, and autocorrelation into categorical high and low values using the median value as the cutoff between high and low. We then mapped different combinations of the high and low values for each climate component to produce maps of eight different global climate regimes for both space and time (Fig. 4). For example, a climate with high spatial trend, low spatial variance, and high spatial autocorrelation was one of the eight climate regimes (Fig. 4).

We chose 1000 random locations in each climate regime and estimated the trend, variance, and autocorrelation at each location using two resolutions. In the spatial context, we used a 1 by 1 km resolution and a 5 by 5 km resolution (Box 2). In the temporal context, we used we used a 1-year resolution and a 5-year resolution (Box 2). We could not use coarser resolutions because decreasing the resolution also decreases the sample size and estimates of trend, variance, and autocorrelation are inefficient with a small sample size.

We evaluated the root-mean-squared-difference between estimates of each climate component made using the original resolution and those made using the coarser resolutions. Climate regimes with the highest root-mean-squared-difference for each component are the climate regimes where using coarse resolution climate data has the largest effect on estimates of each climate component. We also evaluated the proportion of the 1000 locations that overestimated the magnitude of each climate component, which provides an assessment of the bias in each climate component caused by using coarse resolution climate data in each climate regime.

SPATIAL RESULTS

Using coarse resolution climate data had the largest effect on estimates of spatial trend and variance in climate regimes with high spatial trend and variance (Fig. 5). Spatial trend and variance were underestimated when using coarse resolution climate data in most climate regimes. In contrast, coarse climate data overestimated spatial autocorrelation in all climate regimes (Fig. 5). This overestimation was particularly high in two climate regimes: (1) low trend, high variance, and low autocorrelation; and (2) high trend, low variance, and low autocorrelation.

TEMPORAL RESULTS

The effect of using coarse resolution climate data was largest in climate regimes with low temporal trend and high temporal variance (Fig. 5). Using coarse resolution climate data had the largest effect on temporal variance in climate regimes with high temporal variance and low temporal autocorrelation and the smallest effect in climate regimes with low temporal variance. Temporal variance was underestimated in all climate regimes when using coarse resolution climate data. Temporal autocorrelation was overestimated by a similar amount in all climate regimes when using coarse resolution climate data.

WHERE AND HOW COULD IMPACT ASSESSMENTS BE AFFECTED

The above results suggest that using climate data with a coarse spatial resolution could have the largest effect on the results of climate change impact assessments in climate regimes with high spatial trend and high spatial variance (Fig. 5). These climate regimes are common in mountainous areas around the globe such as western North and South America (Fig .4). Climate change impact assessments in these climate regimes could overestimate the rate at which species will need to move to track suitable climates by underestimating the spatial trend (Loarie et al., 2009). They could also overestimate local extinction risk by underestimating the spatial climatic variance, which could underestimate the number of potential climate refugia (Randin et al., 2009; Gillingham et al., 2012; Lenoir et al., 2013). Indeed, estimates of population persistence of high-elevation plants were most affected by using coarse resolution climate data in areas with high spatial variance in temperature (Randin et al., 2009).

Using climate data with a coarse spatial resolution could have the smallest effect in climate regimes with low spatial trend and low spatial variance. These climate regimes are common in flat regions around the globe such as the Great Plains of North America and the Pampas region of South America (Fig. 4).

Using climate data with a coarse temporal resolution could have the largest effect on climate change impact assessments in climate regimes with high temporal variance. Climates with high temporal variance occur in the northern half of the northern hemisphere (Fig. 4). Climate change impact assessments in these areas could overestimate the rate of evolution (Lynch & Lande, 1993; Burger & Lynch, 1995) or the ability of species to shift their ranges under climate change (Early & Sax, 2011; Canning-Clode et al., 2011) by underestimating the temporal variance in climate.

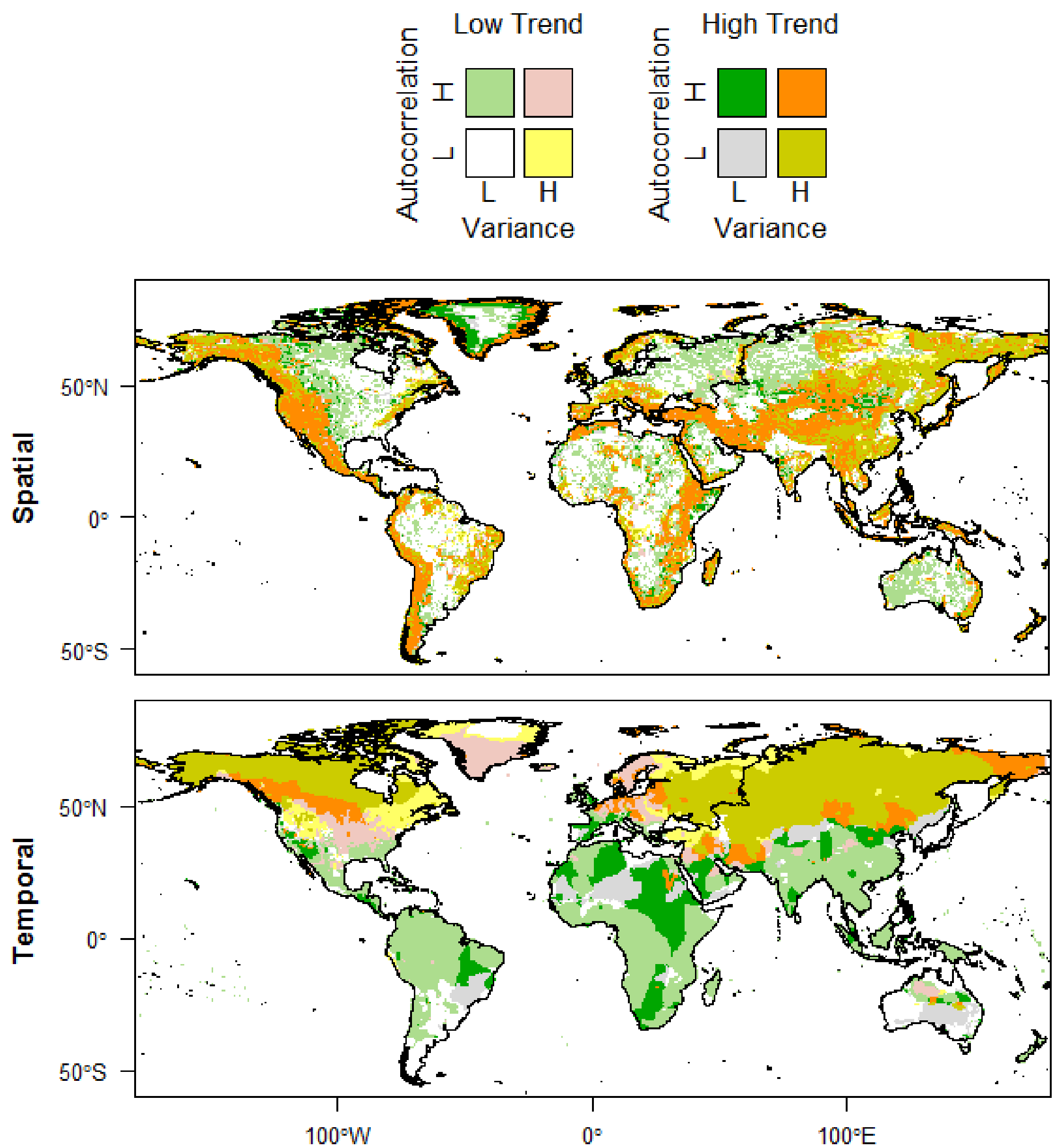

Figure 4. The location of different climate regimes based on spatial (upper subpanel) and temporal (lower subpanel) climatic variation. The climate regimes are defined using different combinations of high (H) and low (L) values of climatic trend, variance, and autocorrelation in mean annual temperature. Geographical patterns in the climate regimes are robust to our choice of climate data (Supporting Information Fig. S1).

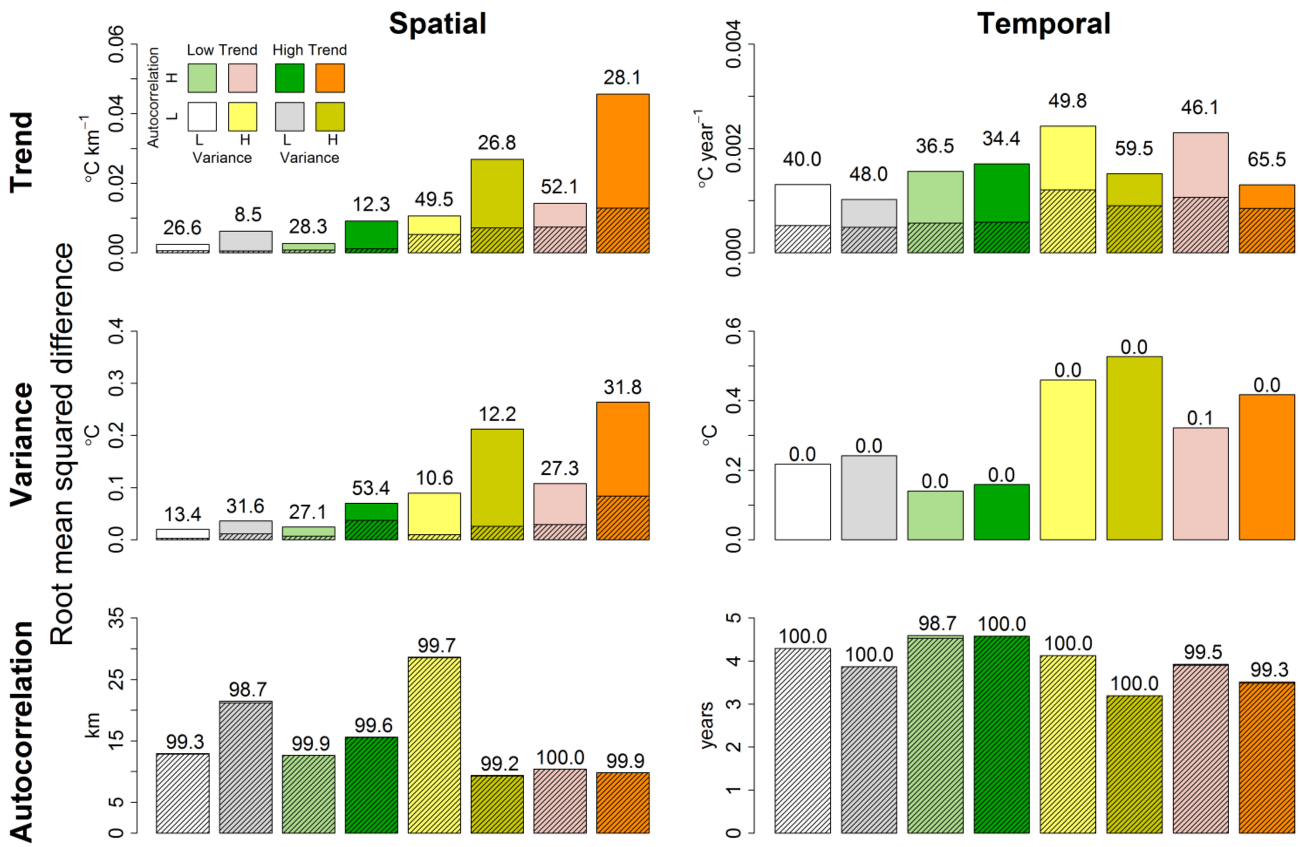

Figure 5. The effect of using coarse resolution climate data on estimates of climatic trend, variance, and autocorrelation. Colored bars represent different climate regimes based on combinations of high (H) and low (L) values of each climate component. The locations of these climate regimes are mapped in Fig. 4. Each bar represents the root-mean-squared-difference between estimates of the climate component using fine and coarse resolution climate data. The hatching and number above each bar represent the proportion of estimates that were positively biased when using coarse resolution climate data.

Conclusion

A rich literature exists on the effects of environmental trend, variance, and autocorrelation on population dynamics, adaptation, and extinction risk. However, our review suggests that these components of climate are being misrepresented in many climate change impact assessments because most studies use climate data with a coarse spatial and temporal resolution. By using coarse resolution climate data, climate change impact assessments are estimating species responses to climate change on coarse scales that do not accurately capture their exposure to important components of climate. This issue is especially problematic for the majority of organisms on earth that have short dispersal distances like we showed for many reptiles, amphibians, and plants.

Climate data is currently available with a fine temporal resolution (e.g., hourly) and we recommend that climate change impact assessments begin to incorporate climate data with temporal resolutions at least as fine as the generation time of the focal species. However, climate data with an appropriate spatial resolution is unavailable for the vast majority of species with short dispersal distances. Using coarse resolution climate data may not be as problematic in all areas of the globe. We offer some guidance on where using coarse climate data may have minimal effect on climate change impact assessments and where researchers should use caution. We focused on average annual temperature with a 1 km by 1 km or annual resolution, but our framework could also be applied to other weather variables and other resolutions. For example, daily and seasonal variation can be important to the evolution of species traits (Chan et al., 2016).

We have provided guidance on where using coarse climate data is likely to have the biggest effect on climate change impact assessments based on properties of the regional climate.

More research is needed to determine how to choose the appropriate resolution of climate data to match the traits of the focal species and the type of climate change impact assessment being employed. It is unlikely that there is a single resolution that will be appropriate for any given species. Moreover, it is unlikely that downscaling methods will allow for the accurate downscaling of climate data to scales necessary for detailed physiological models (Potter et al., 2013; Bennie et al., 2014). However, research to understand how coarse resolution climate data will affect climate change impact assessments and for what species can help identify key uncertainties and ensure that policy decisions are based on sound model results.

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Box 1: Scaling Climate Data to Focal Species

Two scaling factors will affect how climatic trend, variance, and autocorrelation are represented in both temporal and spatial climate data: the neighborhood size and the resolution (Chou, 1991). For space, the neighborhood size is the study area and the resolution is the grid-cell size (Fig. B1a). For time, the neighborhood size is the focal time period and the resolution is the time between observations (Fig. B1b).

The definition and magnitude of climatic trend, variance, and autocorrelation can differ depending on the neighborhood size and resolution of the climate data. Consequently, the neighborhood size and resolution of climate data can greatly affect how climatic trend, variance, and autocorrelation are represented in climate change impact assessments.

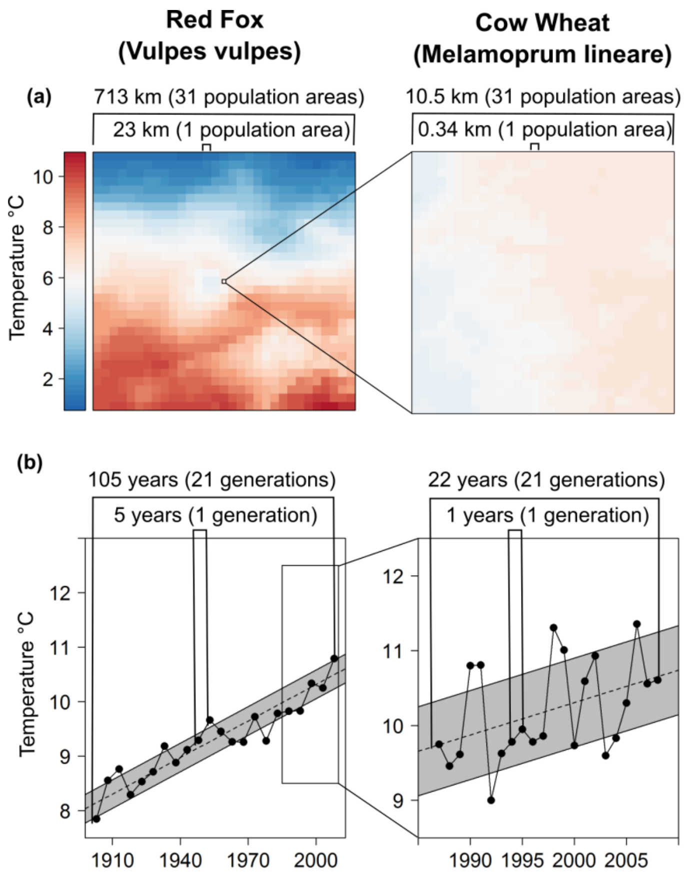
Fig. B1a provides an example of how the spatial neighborhood size and resolution can differ between two species with very different dispersal abilities: a mammal (Red Fox, *Vulpes vulpes*) and an annual plant (Cow Wheat, *Melamoprum lineare*). We scaled the spatial resolution to the area that encompasses a population for the two species. We scaled the spatial neighborhood to include 15 population areas in each cardinal direction from the center cell. This spatial neighborhood includes the landscape cells that are most likely to influence the population in the center cell over 15 generations (i.e., landscape cells that individuals from the population in the center cell could access and landscape cells that could contribute immigrants to the center cell over 15 generations via natal dispersal).

The spatial resolution and neighborhood size is 68 times greater for the Red Fox than for the Cow Wheat (Fig. B1a). This difference in the spatial scaling between the two species results in differences in how the species might experience climate and thus respond to climate change. For example, Cow Wheat will experience higher spatial trend within its spatial neighborhood (Fig. B1a), suggesting that populations of Cow Wheat may need to move shorter distances to track suitable climates under climate change in this region. The spatial trend also differs in direction between the two species: temperature increases from south to north for the Red Fox and from southwest to northeast for the Cow Wheat (Fig. B1a). Hence, the direction of range shifts under climate change may differ between the two species in this region. The Red Fox will experience more spatial variance and autocorrelation in its spatial neighborhood, which increases the likelihood that local climate refugia will exist for Red Fox in this region (Randin et al., 2009).

Fig. B1b shows an example of how the temporal neighborhood size and resolution can differ between the same two species, which have different generation times. W scaled the resolution of the time series to one generation and the neighborhood size to include 21 generations.

The neighborhood size and resolution is five times greater for the Red Fox than for Cow Wheat. This difference in temporal scaling affects how each species is likely to experience climate change over time. Cow Wheat will experience more temperature change (i.e., temporal trend) over the 21 generations (Fig. B1b). Consequently, Cow Wheat might need to adapt more or shift its range further per generation than the Red Fox to cope with climate change. Cow Wheat will also experience more temporal variance and less temporal autocorrelation than the Red Fox. These differences in variance and autocorrelation can affect the ability of the species to shift their ranges and evolve adaptations to climate change (Burger & Lynch, 1995; Burger & Krall, 2004; Early & Sax, 2011).

Models that account for other traits and other important climate variables are necessary to determine if differences in how the species experience climate will result in different responses to climate change. However, many studies suggest that differences in how species experience climate will affect their responses to climate change (Deutsch et al., 2008; Tewksbury et al., 2008; Palmer et al., 2015).



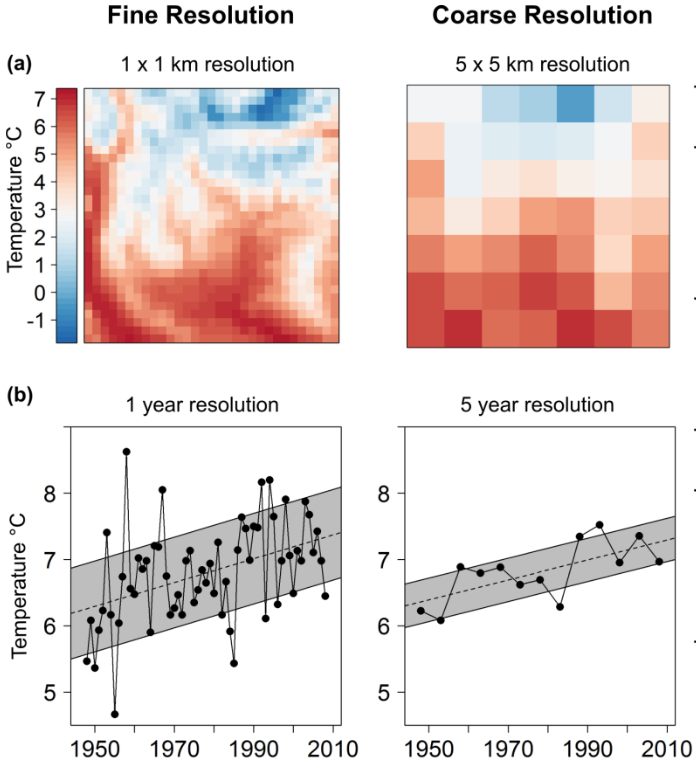
	Red Fox	Cow Wheat
Neighborhood size (km)	713 x 713	10.54 x 10.54
Resolution (km)	23 x 23	0.34 x 0.34
Trend (˚C km^{-1})	0.01	0.12
standard deviation (˚C)	0.79	0.20
Autocorrelation (km)	58.35	1.00

	Red Fox	Cow Wheat
Neighborhood size (years)	105	21
Resolution (years)	5	1
Trend (˚C year^{-1})	0.02	0.04
standard deviation (˚C)	0.26	0.59
Autocorrelation (years)	28.10	1.01

Figure B1. Examples of (a) spatial and (b) temporal climate variation for species with different traits. We scaled the spatial resolution (i.e., the grid cell area) to be the area that encompasses a population for each species. We scaled the spatial neighborhood to include 15 population areas in each cardinal direction from the center cell. We scaled the temporal resolution to one generation and the temporal neighborhood to include 21 generations.

Box 2: An Example of the Effects of Resolution on Climate Data

Fig. B2 provides one example of how using coarse resolution climate data can affect how trend, variance, and autocorrelation are represented in the climate data. Both the spatial and temporal examples are from the same location in the Cascade Mountains of Washington State USA (latitude = 47.3644, longitude = -120.9110). We scaled the fine-resolution spatial example to a 1 by 1 km resolution and a spatial neighborhood that includes 15 landscape cells in each cardinal direction from the center cell. We scaled the fine-resolution temporal example to a resolution of one year and a temporal neighborhood of 60 years. We created the coarse resolution examples by increasing the resolution of the climate data by five-fold. The “coarse” resolution in these examples is still very fine relative to the resolution of climate data used in many climate change impact assessments (Fig. 1). However, this small increase in resolution still affects how trend, variance, and autocorrelation are represented in the climate data. In both the spatial and temporal examples, increasing the resolution did not affect the trend; however it caused a decrease in the variance and an increase in the autocorrelation (Fig. B2).



	Resolution	
	Fine	**Coarse**
Neighborhood size (km)	31 x 31	31 x 31
Resolution (km)	1 x 1	5 x 5
Trend (˚C km^{-1})	0.17	0.17
standard deviation (˚C)	1.09	0.77
Autocorrelation (km)	1.74	6.25

	Resolution	
	Fine	**Coarse**
Neighborhood size (years)	60	60
Resolution (years)	1	5
Trend (˚C year^{-1})	0.02	0.02
standard deviation (˚C)	0.68	0.33
Autocorrelation (years)	0.79	3.29

Figure B2 One example of how (a) spatial and (b) temporal resolution can affect estimates of trend, variance, and autocorrelation.

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Supporting Information Captions:

Estimating climatic trend, variance, and autocorrelation: a file describing how we estimated climatic trend, variance, and autocorrelation in both time and space.