A causal inference framework for climate change attribution in ecology

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Abstract

As climate change increasingly affects biodiversity and ecosystem services, a key challenge in ecology is accurate attribution of these impacts. Though experimental studies have greatly advanced our understanding of climate change impacts on ecological systems, experimental results are difficult to generalize to real-world scenarios. To better capture realized impacts, ecologists can use observational data. Disentangling cause and effect using observational data, however, requires careful research design. Here we describe advances in causal inference that can improve climate change attribution in observational settings. Our framework includes five steps: 1) describe the theoretical foundation, 2) choose appropriate observational data sets, 3) design a causal inference analysis, 4) estimate a counterfactual scenario, and 5) evaluate assumptions and results using robustness checks. We then demonstrate this framework using a case study focused on detecting climate change impacts on whitebark pine growth in California's Sierra Nevada. We conclude with a discussion of challenges and frontiers in ecological climate change attribution. Our aim is to provide an accessible foundation for applying observational causal inference to climate change attribution in ecology.

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Data and code availability

Data and code for the case study analysis can be found in two places. 1) GitHub: https://github.com/Landscapes-of-Change-Lab/CausalClimateAttribution.git and 2) the Open Science Framework at DOI: 10.17605/OSF.IO/NM36A

Author contributions

Author contributions are defined using the Contributor Roles Taxonomy (CRediT; https://casrai.org/credit/). Conceptualization: J.D., L.D., R.H., J.B., K.S.; data curation: J.D., formal analysis: J.D.; project leadership: J.D., visualization: J.D.; writing—original draft: J.D., L.D., R.H., J.B., K.S., writing—review and editing: J.D., L.D., R.H., J.B., K.S.

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Abstract

As climate change increasingly affects biodiversity and ecosystem services, a key challenge in ecology is accurate attribution of these impacts. Though experimental studies have greatly advanced our understanding of climate change impacts on ecological systems, experimental results are difficult to generalize to real-world scenarios. To better capture realized impacts, ecologists can use observational data. Disentangling cause and effect using observational data, however, requires careful research design. Here we describe advances in causal inference that can improve climate change attribution in observational settings. Our framework includes five steps: 1) describe the theoretical foundation, 2) choose appropriate observational data sets, 3) design a causal inference analysis, 4) estimate a counterfactual scenario, and 5) evaluate assumptions and results using robustness checks. We then demonstrate this framework using a case study focused on detecting climate change impacts on whitebark pine growth in California's Sierra Nevada. We conclude with a discussion of challenges and frontiers in ecological climate change attribution. Our aim is to provide an accessible foundation for applying observational causal inference to climate change attribution in ecology.

Introduction

The increasing impacts of climate change on ecological systems underscores the urgent need for accurate attribution in ecology (Lloyd & Shepherd 2020; Parmesan *et al.* 2011). Disentangling climate change impacts from other drivers of ecosystem change (e.g., land use, endemic disturbance regimes) is critical to understand how climate change is modifying ecosystems and to identify effective management strategies. If climate change impacts are misidentified, interventions can fail because management success greatly depends on addressing the dominant drivers of change (Aplet & McKinley 2017; Dudney *et al.* 2018; Hobbs *et al.* 2009). Though climate change and associated extremes threaten biodiversity and ecosystem services worldwide (Anderegg *et al.* 2020; Millar & Stephenson 2015), quantification and **attribution (see glossary, Box 1)** remain very challenging. Prior syntheses, for example, suggest that anthropogenic climate change attribution (hereafter **climate change attribution**) is often too difficult to pursue given the complexity of impacts and the many study design and data limitations faced by ecologists (Parmesan *et al.* 2013). Thus, major methodological advances are needed to accurately attribute shifts in ecological systems to climate change.

Accurately attributing shifts in ecological systems to climate change requires isolating the causal effect(s) of relevant climate variables from other drivers. To identify causal effects of climate change, ecologists use a variety of techniques, including lab-, field-, and computer-based experiments. For example, tank experiments have quantified the effects of warming on coral species (Dove *et al.* 2013; McLachlan *et al.* 2020), and the Jasper Ridge Global Change Experiment has found variable responses of above- and below-ground grassland communities to warming (Gutknecht *et al.* 2012; Liang & Balser 2012; Zhu *et al.* 2016). Complementary empirical studies and process-based models have provided further evidence of causal links between warming and ecological processes, including changes in butterfly emergence (Kearney *et al.* 2010), tree mortality (Adams *et al.* 2013; Choat *et al.* 2018), and species' range shifts (Fitt*et al.* 2019). Comparative analyses of experimental and observational studies, however, suggest that experimental results often underestimate climate change impacts and rarely capture realized climate change effects (Catford *et al.* 2022; Cottingham *et al.* 2005; Lenoir 2020; Smith *et al.* 2024). Given these limitations, developing more sophisticated analytical approaches to identify real-world causal effects is a critical frontier in ecology (Parmesan*et al.* 2013).

Though observational studies can provide insight into realized climate impacts in natural (i.e., unmanipulated) systems, estimating causal relationships between climate and observed changes is very challenging (Gonzalez *et al.* 2023). Obstacles to observational causal attribution include ecological complexity, data limitations that can undermine statistical power, and most critically, the challenge of isolating climate from other drivers of change (including**confounding variables**). Standard statistical approaches in ecology, such as information-theoretic approaches that optimize for a models' explanatory performance (Arif & MacNeil 2022a; O'Connor*et al.* 2015; Parmesan *et al.* 2011, 2013), are limited in their ability to disentangle climate effects from other correlated drivers. Thus, in ecology, we need to move beyond predictive models to accurately isolate climate change from other drivers in observational settings.

Here we outline a causal inference framework that can robustly quantify realized climate change effects in ecological systems using observational data. To illustrate this approach, we use longitudinal tree-ring data to estimate climate change effects on whitebark pine (*Pinus albicaulis Engelm.*). Subsequently, we discuss important strategies and limitations associated with this framework and highlight new research directions at the frontier of climate change attribution. Our goal is to provide an accessible foundation for applying causal inference to climate change attribution studies in ecology, thereby extending our ability to quantify impacts and manage the accelerating threat to natural systems.

Observational causal inference is well-suited for climate change attribution

Climate change attribution in ecology seeks to draw causal conclusions about the effects of climate change on biological systems (Rosenzweig*et al.* 2008). Increasingly, ecologists are pursuing causal questions using observational data by applying causal inference methods (Butsic *et al.* 2017; Dee *et al.* 2023; Dudney *et al.* 2021; Larsen *et al.* 2019; Suskiewicz *et al.* 2024a). Causal inference seeks to isolate and quantify the effect of some change (e.g., temperature) on an outcome of interest (e.g., net primary productivity) using a combination of theory and robust statistical tools. By isolating causal effects using observational data, these techniques provide an important complement to climate change attribution approaches in ecology (e.g., experiments and mathematical models) that can sometimes oversimplify complex systems.

Causal inference approaches can provide accurate estimates of climate effects using observational data by focusing on reducing bias to isolate the causal relationship of interest (Arif & MacNeil 2022a; Larsen*et al.* 2019). For example, temperature and plant productivity may both be affected by increases in $CO_{2.}$ If CO_2 is omitted from the model, it can confound the causal relationship between temperature and productivity. This example of **omitted variable bias** is one of many forms of statistical bias that leads to misidentification of the true causal relationships of interest (Byrnes & Dee 2024). A key challenge for observational causal inference is to rule out biases through: 1) *a priori* knowledge about the influences on the response variable of interest, and 2) careful research design and statistical control of potential sources of bias. When implemented correctly, causal inference is well-suited to climate change attribution because it can isolate the impact of climate change drivers from the complex array of potentially **confounding variables** (Hsiang & Kopp 2018).

Importantly, causal inference techniques are distinct from many statistical approaches that ecologists have traditionally applied to observational data (Gonzalez *et al.* 2023). For example, ecologists often prioritize prediction and generalizability, as evidenced by the common practice of selecting models based on their parsimony or predictive skill (Hernán *et al.* 2019). However, predictive skill does not necessarily imply causation (Arif & MacNeil 2022a; Ferraro *et al.* 2019). To answer the important questions at the heart of climate change attribution (e.g., what is the causal effect of climate change?), ecologists can benefit from statistical approaches that use observational data to estimate causal effects.

A causal inference framework for climate change attribution

Our framework for climate change attribution using observational causal inference (Fig. 1) is focused on attributing historical climate change to observed changes in outcome variables of interest. Below, we explain the five critical steps of the framework: 1) describe the theoretical foundation, 2) choose appropriate observational data, 3) design a causal inference analysis, 4) estimate a counterfactual scenario, and 5) evaluate assumptions and results using robustness checks. We then apply these steps to a case study in the following section.

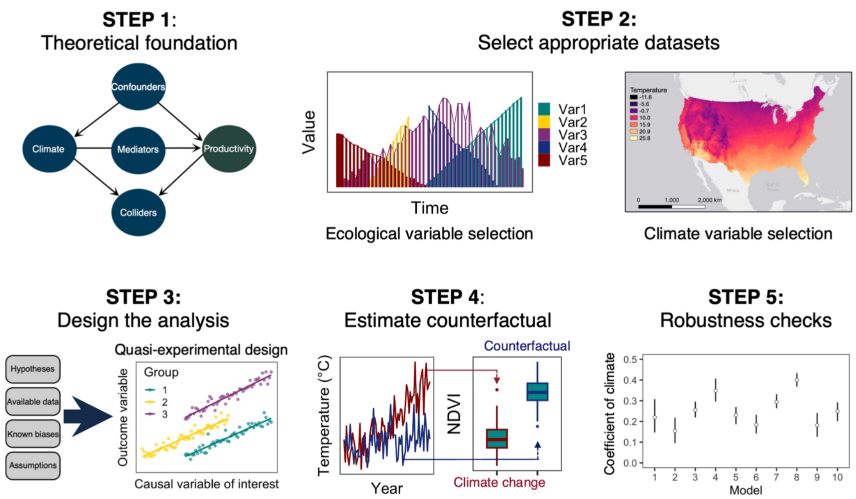

Fig. 1. A causal inference framework for climate change attribution in ecology. Step 1: Describe the theoretical foundation, including the causal relationships of interest and confounding variables. Step 2: Choose appropriate observational datasets of the treatment, response, and confounding variables. Step 3: Design a causal inference analysis based on the question and the available data. Step 4: Estimate a counterfactual using the causal relationships estimated in Step 3 and compare this to the "actual" climate change scenario. Step 5: Evaluate results and robustness checks to build certainty and validity.

Step 1. Describe the theoretical foundation

The first step of a causal analysis is to clearly define the research question and associated hypotheses based on prior knowledge. To develop a defensible causal analysis, the hypothesis should be strongly grounded in logic, theory, and prior knowledge. Once the question and hypothesis have been defined, a common approach that can help researchers identify and evaluate causal relationships is using Directed Acyclic Graphs (DAGs) (Cunningham 2021; Huntington-Klein 2022). DAGs are a graphical representation of causal, directional effects (Fig. 1, Step 1). They identify not only the primary causal path(s) of interest (e.g., temperature effects on forest productivity) but also the potential confounding variables and other sources of bias (e.g., colliders) (Huntington-Klein 2022). A robust DAG includes all arrows from confounding variables (that need to be controlled for) to establish a defensible foundation for the causal research design (see case study). Huntington-Klein (Huntington-Klein 2022) and Arif & MacNeil (Arif & MacNeil 2022b) offer accessible introductions to DAGs with descriptions of the underlying terminology and assumptions that must be evaluated in the formation of a DAG.

When developing causal models, evaluating tradeoffs between simplicity and complexity is important. Researchers might gravitate towards simple models because they are often easier to fit and interpret, reduce concerns of overfitting, and can lead to greater statistical power (e.g., by trimming explanatory variables) (Aho *et al.* 2014). Favoring simplicity, however, is not always beneficial for causal inference (Coelho *et al.* 2019). An imprecise but unbiased estimate (i.e., the expected value of the estimate is equal to the true value of the relationship being estimated (Dee *et al.* 2023; Simler-Williamson & Germino 2022)) is preferred to a precise yet potentially biased estimate from a simple model. Though simplicity is not the focus, an initially complex system of causal relationships can ultimately result in a simple statistical model (see Step 3 below). A causal relationship of interest that is embedded in a complex system, for instance, can be estimated with just a few variables if there are no confounding variables. Ultimately, the goal is to carefully identify the causal effect and control for known and potentially unknown confounding variables, regardless of complexity.

Step 2. Choose appropriate observational datasets

After articulating the relationship(s) of interest (Step 1), the next step is to identify appropriate data to test the hypothesized causal relationships (Fig. 1, Step 2). There are at least three types of variables to consider: 1) the dependent, outcome variable(s) of interest (e.g., biomass, mortality, fecundity), 2) the explanatory variable(s) (e.g., precipitation, temperature, soil moisture) (Box 2), and 3) variable(s) that may confound the relationship of interest (e.g., population density or land-use change). For each variable, researchers can weigh trade-offs across multiple desired attributes, including a dataset's theoretical consistency, accuracy, spatio-temporal extent, and spatio-temporal resolution.

Researchers ideally address several key aspects of their datasets to minimize bias and ensure reliable causal estimates. First, they can evaluate how well available data aligns with the causal model of interest. Existing datasets, for instance, may describe an imperfect proxy (e.g., remotely sensed vegetation indices) to approximate the true variable of interest (e.g., carbon stored in aboveground biomass); as a result, bias may be introduced and should be discussed as a limitation in the analysis. Second, assessing data measurement accuracy is crucial, as measurement error can result in bias and reduce the accuracy or precision of coefficient estimates (Bound *et al.* 2001; Regan*et al.* 2002). Third, datasets must provide adequate spatial and temporal coverage for the processes under study, with special attention to matching the scales of weather and outcome variables (Auffhammer*et al.* 2013). For instance, gridded climate data at scales $> 4\text{km}^2$ may be unsuitable for studying organisms influenced by microclimates (De Frenne *et al.* 2021; Ford *et al.* 2013). Finally, researchers can test for spatial and temporal autocorrelation in climate data, which can affect standard error estimates and subsequent statistical inference (Dell *et al.* 2014a). To ensure a transparent causal interpretation, discussions of limitations, potential sources of bias, and model specification decisions are critical to include in every analysis.

Step 3: Design a causal inference analysis

Causal inference approaches emphasize the importance of research design, causal assumptions, and reproducibility, rather than the specific estimation procedure. With a causal question in mind, researchers can parse a complex DAG to identify the variables that will be included in the regression analysis. For example, by removing redundant or irrelevant variables, eliminating variables that are affecting the outcome via the casual relationship of interest (i.e., mediator variables), or identifying a minimal set of covariates blocking confounders, researchers can simplify a causal model (Huntington-Klein 2022; Shrier & Platt 2008). These approaches carefully solve the DAG to retain relevant information and control for confounding, thereby reducing sources of bias.

Once the appropriate variables have been identified, a number of different causal inference approaches can be used (often referred to as "quasi-experimental research designs") that help control for confounding variables in different ways (Butsic *et al.* 2017; Byrnes & Dee 2024; Cunningham 2021; Larsen *et al.* 2019)· For example, instrumental variables (IV) (Imbens 2014) and regression discontinuity (Cattaneo & Titiunik 2022; Imbens & Lemieux 2008) help control for both observed and unobserved confounding variables when their assumptions are met (Fig. 1, Step 3). Fixed effect panel models (Box 3) have emerged as a common method to estimate climate change effects on economically relevant outcomes (Carleton 2017; Hsiang 2016; Mérel & Gammans 2021a), which we use in our case study below. Within each research design, a variety of regression techniques are available for estimation (e.g., OLS, Bayesian, and structural equation models). Ultimately, the design and choice of statistical models should be selected based on the contemporary understanding of the system, hypotheses (Step 1), available data (Step 2), and known sources of bias.

All causal inference designs make assumptions that need to be considered and interrogated. These causal assumptions are in addition to statistical assumptions commonly evaluated in ecological analyses (e.g., linearity, heteroskedasticity, clustering of residuals, or non-Gaussian error distributions) (Zuur *et al.* 2009). Examples of important causal assumptions include, no confounding from observed and unobserved variables, the absence of spillovers across units with different treatment exposures (part of the **Stable Unit Treatment Value Assumption (SUTVA)**), and appropriate statistical model specifications that control for bias (see the frontiers section for further discussion). Thus, to develop a defensible causal analysis, it is critical to evaluate the assumptions made in the research design and transparently describe how the research design controls for theoretically relevant sources of bias.

Step 4. Estimate a counterfactual scenario

Statements about climate change impacts implicitly compare two states of the world—a world with the observed climate change effects and a counterfactual world without climate change effects (Fig. 1, Step 4). Researchers can model and compare these two states (i.e., following Steps 1-3; estimate models often use variation in weather to approximate the effect of climate (Box 2)). This "counterfactual approach" aims to disentangle how much anthropogenic forcing (i.e., climate change) has contributed to the observed changes—i.e., separate and quantify the effects from anthropogenically-driven climatic influences, yielding stronger evidence of climate change impacts (Swain *et al.* 2020). Examples of counterfactual analyses include Lobell et al.'s (2011) analysis of climate change's impacts on crop yields, or Dudney et al.'s (2021) analysis of tree disease range shifts. The researchers first estimated the magnitude of the effect of climate on the outcome of interest. Then they used historical, observed weather data to predict the outcome under observed climate change (the "actual" scenario) and compared it to the counterfactual scenario, which was predicted using weather distributions reflecting the absence of climate change. By comparing the actual and counterfactual scenarios, the authors provided robust estimates of "how much" climate change shifted outcomes.

Though estimating counterfactual scenarios is an essential step for climate attribution, it presents significant methodological challenges. Past studies have used a variety approaches, including historical climate data taken from the period predating climate change (Dudney*et al.* 2021), detrended data (e.g., data that removes the increasing temperature trend)(Lobell *et al.* 2011), or publicly available counterfactual climate datasets (Mengel *et al.* 2021) (Fig. 2). Each method has limitations. Trend removal, for example, can be sensitive to the chosen spline function and selected time period, whereas model-based approaches can inherit uncertainties from climate models. The choice of counterfactual can significantly influence attribution results (Hannart *et al.* 2016), underscoring the need for careful justification and consideration of multiple approaches to ensure robust conclusions. In several cases, researchers have also used counterfactual analyses to *predict future* climate change impacts by estimating a variety of counterfactual scenarios using the results of climate models (Hsiang 2016). Though counterfactual analysis is imperfect, this step is critical to quantify the realized impact of climate change—otherwise the analysis simply presents a causal relationship with climate, which may or may not accurately capture the effect of climate change during the time period of interest.

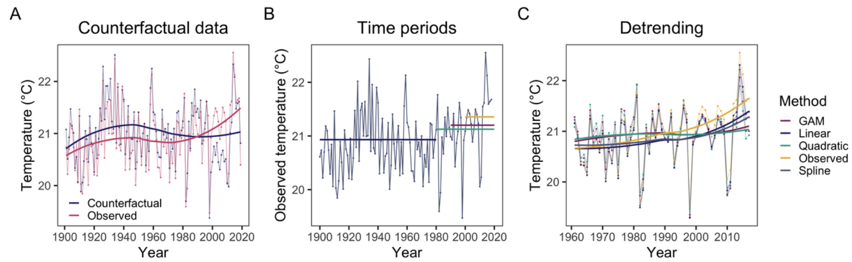

Fig. 2. Various approaches that can be used to estimate counterfactual climate scenarios . **A)** The comparison between the observed temperature trend from randomly selected plots across CA using PRISM (Daly et al. 2008) data and an estimated counterfactual temperature estimate (i.e., the absence of anthropogenic emissions) using a published counterfactual climate dataset (Mengel et al. 2021).**B)** The counterfactual scenario (blue line; length of the counterfactual time period may vary depending on the system and available data) for analyses that average change in outcome variables across multiple years (time periods; colored lines) rather than estimating a continuous counterfactual estimate. **C)** The continuous counterfactual temperature is estimated by detrending the PRISM dataset using four different approaches (Generalized Additive Model ("GAM"), a linear model ("Linear), a quadratic term ("Quadratic"), the PRISM values ("Observed"), and a cubic spline ("Spline).

Step 5. Evaluate results and robustness checks

Finally, researchers should conduct additional analyses to build confidence that their results reveal true causal relationships (**internal validity**) and the extent to which these results can be generalized to other systems and conditions (**external validity**). An important concern that could undermine both internal and external validity is a researcher's degrees of freedom: researchers can make decisions about data selection, processing, and statistical analyses that may consciously or subconsciously accentuate desired statistical results(Head *et al.* 2015). One way to address this concern is to pre-register each of these decisions through a pre-analysis plan (Nosek *et al.* 2018). If researchers have not pre-registered their analysis, they can explicitly demonstrate the robustness of their results to a wide variety of alternate specifications. For example, a researcher may want to present a specification chart (Fig. 1, Step 5) that clearly illustrates the effect that these decisions have on the final result (Simonsohn *et al.* 2020). The chart can comprise different weather variables and windows, alternate model structure (e.g., nonlinear terms), and possible variations among statistical packages or estimation methods to probe the robustness of the researcher's design. If the results are consistent across many different model specifications, this increases the overall confidence that the analysis has captured a true effect (Dee *et al.* 2023).

In contrast, external validity can be probed by reflecting on whether the causal climate relationships hold true across different populations, settings, time periods (Spake *et al.* 2023), and variations in climate change treatment (Wolkovich *et al.* 2012). Researchers can also add counterfactual no-climate change scenarios and conduct a cross-validation or subgroup analysis (e.g., subsetting the data randomly or with natural groupings in the data, including specific regions or plots; also referred to as heterogeneity analysis (Burke*et al.* 2015)). However, often observational data do not capture the full range of climate effects across space and time—particularly under future conditions not yet observed—leading to greater internal than external validity.

Estimating climate change impacts on whitebark pine growth

We provide an accessible, simplified application of our climate change attribution framework to isolate climate change's impacts on whitebark pine growth in California's Sierra Nevada region. Since the 1970s, this system has experienced a statistically significant increasing temperature trend (Fig. 3C,E; Supplementary Section

1) (Lehner *et al.* 2020). As managers seek to protect this threatened species, understanding how more recent temperature changes have affected annual growth is critical to support conservation strategies.

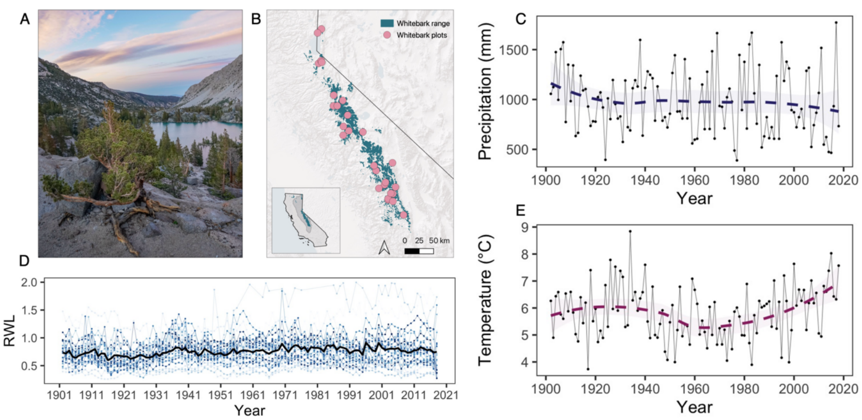

Fig. 3. **Whitebark pine study system.** **A)** Whitebark pine in the Sierra Nevada subalpine. **B)** The spatial distribution of 27 sampled plots. Green shading highlights the whitebark pine range; plots are in pink. **C)** Variation in water-year precipitation (mm; first summed across months and then averaged across all plots for each year); showing a loess smoothed trend line and the 95% C.I. in grey. **D)** Mean annual ring-width length (RWL, black line) and mean plot-level RWL (blue lines) across the times series. **E)** Average temperature across the timeseries; showing a loess smoothed trend line and the 95% C.I. in grey.

Case study step 1: Describe the theoretical foundation

We hypothesize that climate change—specifically increases in temperature—has increased tree growth based on the well-documented positive relationship between growth and temperature in energy-limited subalpine zones (Hartl-Meier *et al.* 2014; Zhai *et al.* 2012). Collating all hypothesized causal and confounding variables, we developed a DAG (Huntington-Klein 2022) that was then simplified using logic and prior knowledge (Fig. 4A). We also classified the variables into time-varying or time-invariant confounding variables. Because shifts in precipitation are difficult to link to anthropogenic emissions (Lehner *et al.* 2020; Pierce *et al.* 2018), we focused our analysis on the causal effects of temperature (Supplementary Section 1; Supplementary Table 1).

Our DAG makes two important assumptions. First, we assume that every omitted variable and arrow (relationship) has a nominal effect—i.e., there are no unobserved, confounding variables that are influencing both tree growth and temperature, often referred to as "backdoors"). Second, we assume that we have not accidentally included a**collider** variable that will bias the temperature effect if incorrectly included in the model (Huntington-Klein 2021).

Case study step 2: Choose appropriate variables

We use cross-dated ring-width length (RWL; cross-dating helps minimize measurement error) estimated from 722 tree cores from 27 sites (Fig. 3B) to capture tree growth, our outcome variable of interest (Dudney*et al.* 2023; van Mantgem *et al.* 2023). For the climate driver(s), based on the known relationships from the literature, we estimated water-year temperature (October-September) (Millar *et al.* 2012) using the PRISM dataset with a spatial resolution of 4 km (Daly *et al.* 2008). Given our DAG, we also need to include other time-invariant and time-varying variables in our analysis. Topography and rainfall are the only other available variables; thus, we will need to carefully select a research design that can control for the remaining unobserved variables (Step 3).

To evaluate the accuracy of our climate data, we also consider the possibility of measurement error. Classical measurement error, when the mean of the error is zero (i.e., the error is random), can emerge through downscaling approaches. Classical measurement error is likely present in our climate dataset, which often leads to attenuation bias (estimates biased toward zero) and thus more conservative coefficient estimates (Wooldridge 2010). Non-classical measurement error, however, where the error is not random, can lead to directional bias (Lundquist*et al.* 2010). For example, a study that uses data from one weather station may suffer from non-classical measurement error if the weather station is located in an uncharacteristically hot site. As the number of weather stations increases, however, the likelihood that this directional bias becomes random increases. Given the large spatial scale of our analysis (Fig. 3B), we assume that most of the measurement error in our climate variables is classical.

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Fig. 4. **Causal diagrams used to frame the climate change attribution analysis. A)** Directed acyclic graph (DAG) of whitebark pine growth (RWL). Thick red arrow shows the causal relationship of interest (temperature; red circle) on the outcome variable of interest (tree growth; green circle). Pink arrows show confounding, time-invariant variable effects (topography; dark grey). Blue arrows show confounding, time-varying variable effects (precipitation and CO_2; blue circles). Precipitation is also a **moderator** of temperature (thicker blue line).**B**) Explanations of how paths are broken (grey arrows and grey circles) in the DAG through model specification and statistical design. Text boxes explain the reasoning behind the solved arrow underneath (refer to main text for more details); the moderator arrow highlights that precipitation is interacted with temperature in the regression.

Case study step 3: Design a causal inference analysis

Step 3 requires a carefully-developed statistical design that can allow for causal interpretation. Given our hypothesis, DAG, and available data, a fixed-effect (FE) panel regression is ideal (Gantois 2022) (Box 3). **Fixed effects panel models** can control for **omitted variables bias** from confounding, time-invariant variables that are not included in the regression. Specifically, including a tree-level fixed effect in the regression controls for confounding observed and unobserved variables that vary by site but not over time (Gantois 2022) (e.g., slope, aspect, elevation, soil type and other unobserved, correlated drivers) (Fig. 4B). The final FE panel regression model estimates how year-to-year changes in weather for each tree affects year-to-year changes in RWL (see Supplementary Section 3 for a full model description).

The remaining—and more difficult challenge—is to control for confounding from unmeasured, time-varying variables. We can break the pathways of unobserved, time-varying variation (i.e., CO_2 concentrations) (Fig. 4B), using a combination of logic, system knowledge, and model specification solutions. Specifically, to control for annual changes in CO_2concentrations, we can include a year trend in our model, which assumes that the rate of change is the same for each tree and constant across the study period (a relatively defensible assumption (Keeling *et al.* 2005)). This year trend also partially controls for age-related**mediating** effects and we test this by comparing models that used detrended ring-width index (RWI) and cross-dated RWL (Supplementary Table 3). To control for the confounding effects of precipitation (which can shift solar radiation) (Gantois 2022), as well as the moderating effect of precipitation (i.e., the effect of temperature depends on water availability) (Dudney *et al.* 2023), we include an interaction between temperature and precipitation in our model (Fig. 5). Now that we have carefully specified our model, we estimate it using the fixest R package (Berge 2020) (Supplementary Table 2), and assume 1)**parallel trends** in the absence of climate change and 2) the climate change effects are not heterogeneous across observational units (Abadie 2005).

In addition to controlling for bias from potentially confounding variables, which is critical for causal inference, it is important to evaluate the precision of our estimates (e.g., Type 1 error—a false positive). If autocorrelation is not accounted for in a model, for example, the coefficient is not necessarily biased but the model likely overestimates the precision of the climate coefficients. Here we use Moran's I test to test for spatial autocorrelation, which is not significant. We also use clustered robust standard errors to control for heteroskedasticity, temporal autocorrelation, unobserved tree-level effects within plots, and other causes of non-independence of observations (Abadie *et al.* 2023).

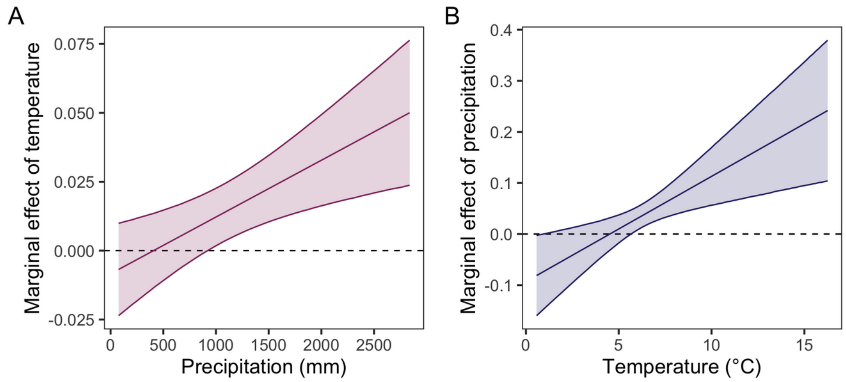

Fig. 5. **Marginal effects of temperature on tree growth. A**) Displaying the marginal effect of temperature on tree growth conditional on precipitation. **B**) Displaying the marginal effect of precipitation on tree growth conditional on temperature. Showing 95% C.I. around the mean estimated marginal effects. Coefficients extracted from a model estimated by the fixest package (Berge 2020).

Case study step 4: Estimate counterfactual

To detect the realized effect of climate change (i.e., to quantify how much anthropogenic climate change has shifted tree growth), we estimate two counterfactual scenarios. First, we estimate the counterfactual temperature scenario (i.e., annual variation in temperature in the absence of anthropogenic forcing) using a detrending approach outlined by Fallah & Rostami (Fallah & Rostami 2024) (Fig. 6A). Then, we use the estimated model from Step 3 to predict an actual and counterfactual growth scenario using the observed and counterfactual temperature variables (Fig. 6A). To incorporate model uncertainty in our predictions, we use a Monte Carlo simulation (Dudney *et al.* 2021). To estimate the average effect of climate change on tree growth (thereby answering the "how much has climate change affected growth" question), we subtract the actual scenario from the counterfactual scenario (Fig. 6B,C). We also compare different "counterfactual" time periods to test whether the impact of climate change is sensitive to the choice of time period (Fig. 6C).

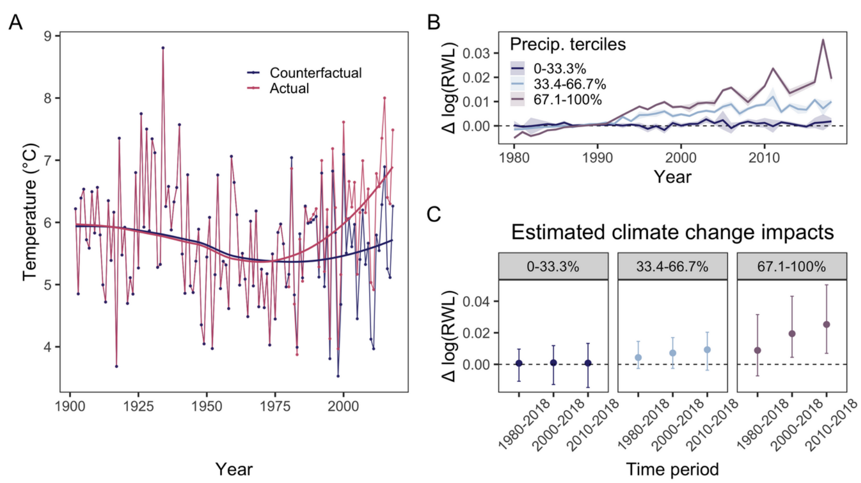

Fig. 6 **Estimated climate change impacts on tree growth. A**) The actual (i.e., the observed values; pink) and estimated counterfactual (i.e., the estimated detrended values of the "no climate change" scenario; blue) temperature values across the study period. B) A subsample (N = 10,000) of the M.C. simulation results estimating the difference between the actual and counterfactual predicted growth scenarios (log transformed ring-width length (RWL))—conditional on precipitation terciles—between 1980-2018. Showing the mean line and 95% C.I. **C**) Average change in growth (log RWL; can be interpreted as percent change) attributed to climate change across precipitation terciles for three time periods. Colored points show the mean difference and error bars represent the 95% C.I. We find that climate change began having a significant effect on growth somewhere between 1980 and 2000, but only in the wettest regions. Years with low precipitation (first tercile) did not experience significant climate change effects.

Case study step 5: Evaluate results and robustness checks

To determine robustness of our results to research design and model specification choices, we conduct multiple analytical checks and present them in specification chart (Fig. 7). We include the following comparisons to help the reader evaluate the results from different model specifications and estimators: 1) models that use different clustering of standard errors, 2) models with different climate variable specifications (e.g., lagged variables and weather windows), and 3) models using different statistical designs (e.g., linear mixed models (LMM)). The results of this specification table and Supplementary Table 3 (i.e., RWI instead of RWL), highlight that the main model of interest ("target model") is providing an accurate estimate of temperature effects (Fig. 7). In addition, we conducted a comparison of different counterfactual temperature scenarios, which suggested that our estimates of the effect of climate change are not strongly sensitive to different detrending methods (Supplementary Figure 1).

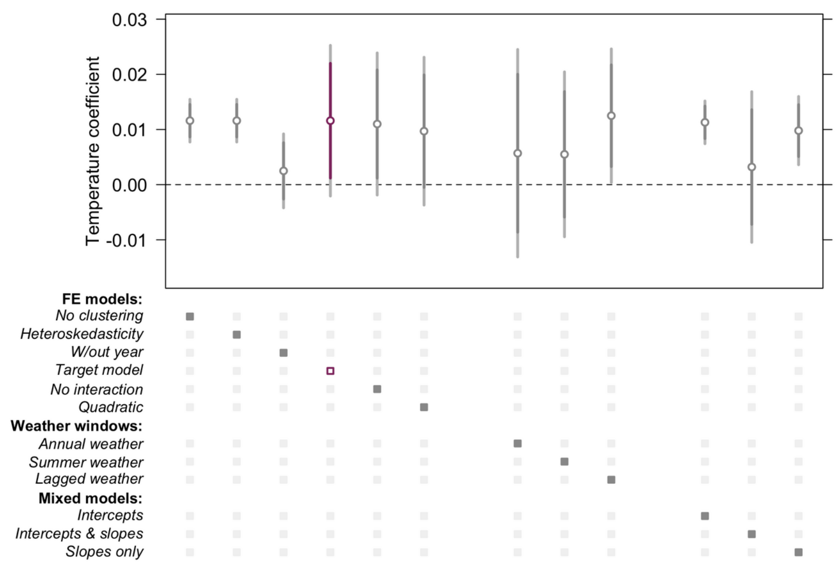

Figure: 7. Specification chart showing model comparisons of the estimated temperature coefficient. Top panel*: vertical grey lines display the 95% confidence interval (light gray is the 99% C.I.) of the direct effect of temperature (coefficient estimates are the open points); the dark pink color highlights the hypothesized model's coefficient estimate.* ***Bottom panel:*** *there are three broad robustness checks. The first "FE models" show different specifications of the fixed effects (FE) panel model with different types of clustering or no clustering, as well as the inclusion of nonlinear terms. Weather window models show panel model results with different weather windows for climate variables. Mixed models show results from different statistical modeling designs, including LMMs with different random effects specifications (see Supplementary Section 3 for full descriptions of the models used here).*

Frontiers and challenges of climate change attribution

While the framework detailed above provides a general approach for attributing specific ecological shifts to climate change, the inherent complexity of ecological systems offers multiple opportunities for further methodological development. We reflect on several important sources of ecological complexity, illustrate how they complicate our proposed framework, and identify novel tools or opportunities for future research.

Acclimation and adaptation

Acclimation and adaptation are important mechanisms through which organisms and ecosystems buffer the effects of climate change. Acclimation allows individual organisms to respond to short-term weather shocks or more gradual changes over the course of their lifespan (Henn*et al.* 2018), while longer-term adaptations can enable a species to persist in the face of climate change (Gantois 2022; Nadeau *et al.* 2017). If researchers ignore these dynamic responses, they may overestimate the effects of climate change on ecosystems. For example, a model that estimates the effects of short–term fluctuations in ocean temperature on contemporaneous kelp growth may show relatively high sensitivity to temperature (Krumhansl *et al.* 2016). In the long-term, however, selective pressure can shift the local population towards more resilient genotypes, which can reduce temperature sensitivity (Vranken *et al.* 2021). These processes imply that the initial model focused on short-term responses – thereby ignoring adaptation – can overestimate the system's true sensitivity to climate change (Mérel & Gammans 2021b).

To generate accurate estimates of climate change's effects, researchers can use various methods that can either quantify or control for acclimation or adaptation to climate change. We highlight four common econometric approaches here. First, researchers can subset their data by time period or region to test whether the climate sensitivity varies through time or across space (Hsiang 2016; Kalkuhl & Wenz 2020; Schlenker & Roberts 2009). If sensitivity does not vary, researchers can cautiously conclude that acclimation or adaptation may not be playing a strong role (Burke *et al.* 2024; Hsiang 2016; Schlenker & Roberts 2009), at least within the observed data and scale. Second, researchers can include a time-period-by-climate interaction in their model to test if climate sensitivity changes over time (Dudney *et al.* 2021). Third, to test how adaptation might be mediating climate change impacts, researchers can include an interaction term of mean climate with annual weather variation, particularly for spatially extensive panels that capture distinct climates (Dell *et al.* 2014b; Gantois 2022). Fourth, including nonlinear weather variables can capture adaptation in spatially extensive datasets (Gantois 2022; Kolstad & Moore 2020; Mérel & Gammans 2021b) or researchers can focus on estimating recovery following an extreme event at different time scales to assess the degree of adaptation (Dell *et al.* 2014b).

Though these four approaches can be used to infer acclimation and adaptation in a statistical modeling context, they do not replace—but rather complement—the critical insight from direct measurements in eco-evolutionary studies. Acclimation, for example, can be quantified through observational and experimental research designs that measure organismal responses, including shifts in metabolic rates, gene expression, or phenotypic plasticity, to changes in the environment (Gunderson & Stillman 2015; Seebacher *et al.* 2015). Adaptation can be tested using common garden and evolutionary experiments (Bisschop*et al.* 2022; Merilä & Hendry 2014), while reciprocal transplant experiments can disentangle the effects of local adaptation from phenotypic plasticity (Henn *et al.* 2018). These empirical approaches provide deeper insights into the causes and mechanisms driving acclimation and adaptation, leading to a more comprehensive understanding of species' responses to climate change across different spatio-temporal scales (Nadeau *et al.* 2017).

Extreme events

Extreme climate events, such as hurricanes, floods, and heatwaves, will likely play an increasingly important role in determining climate change impacts (Diffenbaugh *et al.* 2015; Hagmann *et al.* 2021; Williams *et al.* 2023). These events often have nonlinear—and disproportionately large—effects that are difficult to measure accurately, particularly with linear models. When studying extreme events, it is critical to consider the inherent challenges of extreme event attribution that need to be addressed in order to accurately attribute their impacts to climate change.

To estimate or control for the effects of climate change-induced shifts in extreme events, researchers should ideally evaluate: 1) the functional form of climate relationships, 2) the duration of extreme event impacts relative to the length of the time series and the number of observations, and 3) the relative contribution of anthropogenic versus natural forcing. First, the functional form of climate relationships may be nonlinear (e.g., quadratic or cubic) and failing to include nonlinear terms may bias climate change estimates and misidentify the impacts of extreme events (Schlenker & Roberts 2009).*A priori* knowledge about the functional form or using non-parametric binned analyses (Gantois 2022) to flexibly identify nonlinear effects are approaches that can be used to avoid exploratory analyses of nonlinear relationships (Deschênes & Greenstone 2011; Gantois 2022). Second, capturing climate change-induced shifts in extreme events is important, but their low probability of occurrence means that they can be easily missed (Auffhammer 2018). Careful evaluation of hypothesized duration of effect (e.g., days, months, years), the spatial variability of the effect, and whether or not the study's time-period is sufficient to capture extreme event effects, is critical to measure or control for the effects of extreme events. Finally, extreme events can be driven by anthropogenic emissions, as well as external (e.g., solar cycles) and internal drivers (e.g., El Niño-La Niña cycles (Trenberth *et al.* 2015)). As a result, extreme event attribution is often associated with greater uncertainty than temperature attribution (Swain *et al.* 2020), which complicates causal identification of their effects. Until extreme event attribution is clarified or long-term data is sufficient to capture their impacts, careful and humble probing of the data is critical to determine whether the research has sufficient information to support claims about climate change impacts.

Lagged effects

Accurately measuring climate change effects in ecological systems may require estimating both immediate and lagged effects (also referred to as "legacy effects") on the outcome variable of interest. Observational research is often capturing a snapshot in time that reflects the present moment, as well as the complex history of climatic influences. Historical lagged effects can strongly influence population or system dynamics but are easily overlooked (Dudney *et al.* 2017; Suttle *et al.* 2007). Kelp abundance in New England, for example, is not only influenced by warmer spring temperatures, but also the previous summer's temperature effects on kelp mortality (Suskiewicz*et al.* 2024b). By testing for lagged effects, researchers can disentangle the immediate effects of climate change from historical influences, providing a more comprehensive understanding of ecological responses and accurate predictions of future impacts.

Accurately estimating lagged climate effects is not only an important area of study in ecology (Rastetter *et al.* 2021), but also an important influence to consider in climate change attribution studies in general to avoid bias. Ignoring lags, for example, can lead to overestimation of the direct effects (the lagged effect variation is incorrectly attributed to direct effects) (Gollob & Reichardt 1987). Various statistical designs can be used to test or control for lagged effects in regression analysis. Researchers can simply include lagged explanatory variables at the hypothesized temporal scale of influence in their model (Dudney *et al.* 2017). Distributed lag, nonlinear models (DLNMs) (Gasparrini 2011) provide a more flexible strategy that can estimate how a weather shock in one year leads to changes in an outcome of interest across multiple time periods (Moore *et al.* 2019). More novel methods include PCMCI (Peter and Clark momentary conditional independence) and CCM (Convergent Cross Mapping). PCMCI is a causal discovery algorithm that uses conditional independence tests to estimate causal effects that account for legacies in large time series data (Docquier *et al.* 2024). CCM is a method based on nonlinear state space reconstruction that can detect causal relationships in dynamical systems (Gao *et al.* 2023). Ultimately, ecological theory and hypotheses help guide researchers to explicitly test for lagged effects or to control for their effects.

Spatial spillovers

Spatial spillovers are phenomena where changes in one geographic area influence outcomes in neighboring or spatially disconnected areas. In climate change attribution studies, spatial spillovers caused by climate change are likely common due to climate teleconnections (Potter *et al.* 2003), species range shifts connecting new places (Pecl *et al.* 2017), and human migration and displacement from climate impacts (Cattaneo *et al.* 2019). For example, climate change is associated with hotter droughts, which can have spatially variable impacts on tree stress and bark beetle populations. As bark beetle populations grow exponentially in drought-stressed regions, they can attack and kill trees in nearby regions due to their high numbers, even if the trees in that location are experiencing less drought stress. Thus, the effect of climate change on tree mortality in one region has an effect on tree mortality in another region. Such spatial spillovers (also known as "interference" (Ferraro *et al.* 2019)) are an active area of research, as well as a potential source of bias in climate change attribution because they violate the **SUTVA** —i.e., causal inference analysis assumes that the treatment of one unit (e.g., at one site or tree) does not affect the outcomes of other units (e.g., other sites or trees). To account for interference, researchers are developing new methods to manage these challenges (Ogburn & VanderWeele 2014; Reich *et al.* 2021; Vanderweele & Tchetgen Tchetgen 2011), often by making additional assumptions about how spillovers might occur.

Interaction effects

Interactions are complex but important to consider in climate change attribution studies, both to avoid statistical bias and to improve our understanding of the consequences of climate change. To test the robustness of their model specifications, researchers can run additional versions of the model with and without interactions. To estimate interaction effects, there are a number of strategies in the causal inference literature. For example, extensions to DAGs, including interaction DAGs, allow researchers to determine which variables are likely to interact with each other and modify the outcome variable (Nilsson *et al.* 2021). These interactions can be incorporated into causal inference, regression-based approaches to estimate heterogeneous effects of climate, as we demonstrated in our case study above. Additionally, random forests can identify subgroups for further analysis of heterogeneous effects (Athey & Imbens 2016; Miller 2020). Epidemiologists have also developed empirical tests for causal interactions, which could be used in ecology (VanderWeele *et al.* 2012; VanderWeele & Robins 2007). By employing these methods, researchers can enhance the validity and comprehensiveness of attribution studies, leading to more accurate and nuanced understanding of complex ecological responses to climate change and their context-dependence.

Feedbacks

Identifying causal effects in Earth systems is challenging due to nonlinear processes that can feed back to affect one another across spatio-temporal time scales (Runge *et al.* 2019). There are many forms of feedbacks that are important to consider in attribution studies because they can lead to bias (Rohrer 2018). Feedbacks can confound counterfactual climate change estimates (Step 4), which often assume a static relationship with climate over time (Diffenbaugh & Burke 2019). Feedbacks can also modify direct effects through time and become magnified in tightly coupled social-ecological systems, systems that span extensive spatial scales, and systems that span multiple scales of biological organization(Lobell 2013). Prolonged drought due to climate change, for example, can stress trees, increasing their vulnerability to wildfires (Brando *et al.* 2014). Following fire, forest biomass and moisture retention is reduced, conditions that make future fires more likely (Flores *et al.* 2024). Over time, fire-drought feedbacks driven by climate change can accelerate declines in forest biomass, leading to type conversions in forest systems. How much of this transition can be attributed to climate change versus the feedbacks between drought and fire that may or may not be a direct result of climate change is difficult to disentangle using simple linear models.

Though feedbacks greatly complicate model specification and counterfactual estimation, new approaches are being developed that offer potential solutions. Recent reviews in Earth Sciences (Runge *et al.* 2019) present how causal inference frameworks and tools can aid in both detecting causal relationships in nonlinear complex systems (e.g., using causal discovery algorithms (Glymour *et al.* 2019; Spirtes*et al.* 2001) and convergent cross mapping for causal detection (Sugihara *et al.* 2012)) and testing causal hypotheses for attribution and understanding of magnitudes of effects (Hannart *et al.* 2016). These proposed workflows that combine causal discovery, followed by causal inference techniques that focus on estimation of effect sizes on different data, can be integrated into the global change ecologist's toolbox to improve the accuracy of climate change attribution. The challenge is the high bar for entry into using and interpreting output from these methods.

Conclusion

The escalating threat of climate change to biodiversity and ecosystem services necessitates a robust and accurate approach to climate change impact evaluation. To date, observational analyses that do not necessarily establish causation have limited our ability to quantify the impacts of climate change on ecology systems (Parmesan *et al.* 2013). Here we demonstrate how observational causal inference approaches, which have been used to quantify climate change impacts in social, (Auffhammer *et al.* 2013; Burke *et al.* 2015; Carleton *et al.* 2022) and more recently ecological systems, (Dudney *et al.* 2021) are well-suited for climate change attribution in ecology. If certain conditions are met, our framework helps researchers build analytical certainty and increases the accuracy of estimated climate change effects. Though our approach is not comprehensive of all causal research designs and does not guarantee causal interpretation of effects, (Imbens 2020) it does provide a useful framework for evaluating ecological research designs and statistical approaches used to identify climate change effects. Additionally, global initiatives, including the Intergovernmental Panel on Climate Change (IPCC) and the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), underscore the urgency for empirical evidence of climate change impacts (Druckenmiller 2022). By adopting our framework, ecologists can enhance the accuracy and reliability of climate change impact assessments, thereby providing policymakers and managers with the robust, empirical evidence needed to develop effective climate change mitigation and adaptation strategies.

Box 1: Glossary

Attribution: An estimate of the relative contributions of a causal driver(s) to a change in a biological variable or event. Attribution requires the detection of a change in an observed variable (i.e., statistical confidence that change in the outcome variable of interest has occurred) (Parmesan *et al.* 2013).

Climate Change Attribution: Quantifies how much of an observed ecological change can be directly linked to anthropogenic climate change. Anthropogenic climate change can include shifts in shorter-term and longer-term annual means, climate variability, extreme events, and other climate forcings (e.g., Pacific Decadal Oscillation (PDO) and El Niño Southern Oscillation (ENSO)). The cause of these climatic changes is assumed to be anthropogenic emissions; the direct link is typically not quantified. Here we use the term climate change attribution to encompass similar concepts and terms, including anthropogenic climate change attribution, double attribution' or 'end-to-end' attribution (Parmesan *et al.* 2013).

Confounding variable: A confounder is a variable that affects both the dependent and independent variable. Because the confounding variable impacts both the dependent and independent variables, its presence can distort or mask the effects of the explanatory variable of interest, leading to inaccurate estimates of the causal relationship (e.g., climate) if it is not controlled for.

Counterfactual prediction: When data with the full set of potential outcomes is not available, a counterfactual scenario can be used to estimate the potential outcomes given different treatment variables. For climate change attribution, the counterfactual is the predicted impact of climate forcing that does not include warming trends attributed to greenhouse gas emissions. This can be somewhat comparable to a predicted "control treatment" that is compared to the actual (observed) climate change impacts (Hsiang 2016; Mendelsohn *et al.* 1994). Note: counterfactual scenarios are not observed and therefore cannot be verified.

Fixed effects model: A regression model that includes individual parameters (i.e., fixed effects) that allow intercepts to vary for each unit (e.g., plot-level fixed effects) or time period (e.g., year fixed effects). Unit-level fixed effects enable the researcher to control for time invariant differences across units, while time fixed effects can control for variations across years that are common to all units.

Internal vs external validity: Internal validity refers to whether or not a study accurately identifies a causal relationship within the context of the study—i.e., whether changes in the dependent variable are caused by changes in the independent variable or whether this relationship is confounded. In contrast, external validity refers to whether the results of a study can be generalized to other settings, populations, times, and conditions beyond the scope of the study (i.e., whether or not a study can be extrapolated).

Omitted variables bias: Occurs when a **confounding variable** is excluded from a statistical model, leading the model to compensate for the missing information by misattributing its effects to the included variables, resulting in biased estimated effects of the included explanatory variables.

Mediator variables: Explain the relationship between an explanatory and an outcome variable, essentially helping to explain why an explanatory variable affects the outcome variable of interest. They typically do not need to be included in regression unless their effects are of interest.

Moderator variables: Variables that affect the strength or direction of the relationship between the explanatory variable and the outcome variable. Moderator variables are typically estimating using interactions in statistical models.

Parallel trends: The assumption that the difference between the treatment and control group is constant over time if there is no treatment—in the absence of the treatment, both treatment and control groups have identical trends through time.

Stable Unit Treatment Assumption : Causal inference analysis assumes that the treatment of one unit does not affect the outcomes of other units (an example of interference or spillover effects).

Box 2. Attributing effects of climate versus weather

The difference between weather and climate is nuanced and widely debated, but these definitions have important implications for climate change attribution. Here we define climate as the long-term mean and standard deviation (i.e., the distribution) of relevant climate variables at a specific location (Hsiang 2016). Each climate variable has its own distribution with a true mean and standard deviation (that is often imperfectly captured across time using weather instruments) (Hsiang 2016). Thus, climate encompasses all realized outcomes of each relevant variable over a longer time period than weather.

In contrast, weather is the distribution of climate variables of interest across a shorter duration of time at a specific location. For example, weather variables can capture the sample mean and standard deviation of daily rainfall over a year, whereas the climate variable captures the true mean and standard deviation of annual rainfall for a specific location. Specifically, weather could capture the minimum temperature during a day or a year, while the climate would capture the minimum temperature of the true theoretical temperature distribution for that day or year (Hsiang 2016).

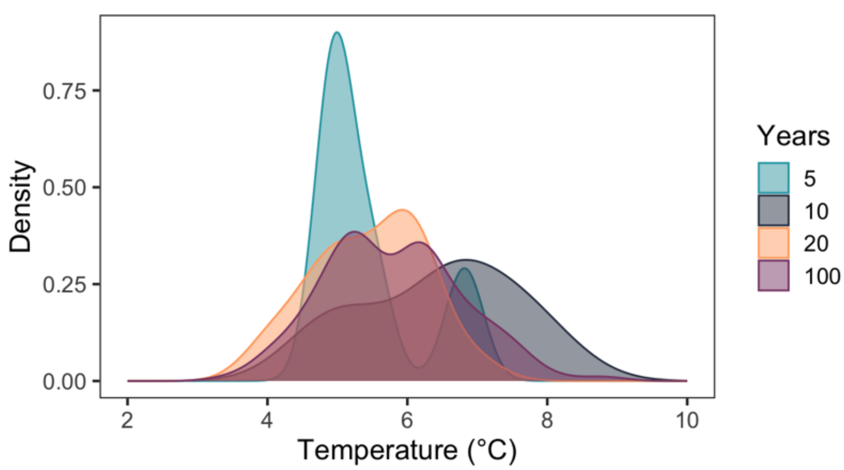

Fig. 7. Differences between weather and climate over a 100-year period. As time is extended, weather (e.g., 20 years; orange distribution) begins to approximate the climate distribution. Depending on the system, it

is important to evaluate how the selection of the weather window may bias the estimated effect of climate change. Showing density of temperature values using PRISM data from the Sierra Nevada whitebark pine plots (see case study).

As time is extended, it can be unclear if and when the weather variables begin to represent the climate variables. Climate is defined over various timescales (e.g., 30 years, 50 years, and 100 years (Burleson 2014; Keane *et al.* 2013)). Whether the climate variables capture weather or climate likely depends on characteristics of each system and the phenomenon of interest (Hsiang 2016). For example, in regions where the standard deviation of weather variables is low, a shorter amount of time is needed to capture the climate—the true mean and standard deviation of that variable. In other regions that have highly variable weather events that occur across longer times scales (e.g., Pacific Decadal Oscillation (PDO) and Atlantic Multi-decadal Oscillation (AMO)), much longer time periods are likely needed to capture the climate. Ultimately, if the weather time series is not long enough to approximate the climate, then greater caution is required in the interpretation of the coefficients, as they are likely biased (Fig. 7).

Box 3. Panel models for climate change attribution

Panel regression designs offer powerful and accessible approaches that can be used to estimate causal climate relationships in ecology. Panel regression, including one- and two-way fixed effect designs, can enable causal inference if a number of conditions are met (Dee *et al.* 2023; Larsen *et al.* 2019), and are increasingly applied to studies in conservation biology and ecology (Dee *et al.* 2023; Dudney *et al.* 2021; Ratcliffe *et al.* 2024; Siegel *et al.* 2022). Robust panel regression is conducted with spatially and temporally extensive datasets and is a powerful tool for studying climate change impacts because it can help disentangle the complexity of potential drivers.

An important advantage of a well-designed panel regression is that it can control for variables that are relatively constant through time and correlated with other explanatory variables, which could otherwise result in biased climate estimates. In panel regression, all influential observed and unobserved variables are classified as time-varying (i.e., the values change through time) and time-invariant (values remain constant throughout the study period). Topography and soil type are often considered time-invariant over a particular study period (with many exceptions, including volcano eruptions, landslides, subsidence, or major earthquakes). Two-way fixed effects (TWFE) panel models can also control for general trends that affect all locations in a given year, like a bark beetle outbreak or nitrogen deposition. The efficacy of temporal controls, however, depends on the spatial scale of the study and spatial variability of the driver's effect. These time-invariant and uniformly distributed annual effects are controlled for by including fixed effects.

Fixed effects are often group-level and year-level controls—i.e., a slope is estimated for each year and group (e.g., plot, site, or region). Because there is no partial pooling of group-level intercepts or slopes (often estimated in hierarchical, mixed effects models), panel models more precisely control for time-invariant variable effects. Additionally, linear mixed models, often used in ecology, assume that random effects are not correlated with explanatory variables; thus correlated variables—like topography—are often included in models, which can cause variance inflation depending on the strength of the correlation (Byrnes & Dee 2024). Ultimately, by comparing how different locations respond to weather over time, panel models can often provide stronger evidence for causal relationships between climate change and ecological outcomes.

Though panel models are widely used to estimate causal effects of climate change (Burke *et al.* 2015; Hsiang 2016; Nordhaus 1992), these approaches are also critiqued. For example, depending on the model structure and explanatory variables, these models typically capture shorter-term weather effects (i.e., year-to-year variation in temperature) that may be distinct from longer-term climate change effects (Wooldridge 2010). The effect of a 1.2ºC change on forest productivity in one year (as estimated in panel regression) may be different from the long-term average effect of a 1°C change in temperature (Dell *et al.* 2014b). Depending on the system, there may be a trade-off between controlling for confounding variables and estimating long-run, climate change effects (Dell *et al.* 2014b; Deschênes & Greenstone 2011). Additionally, it is challenging for panel designs to satisfy all assumptions, including: 1) the average outcome of the treatment has **parallel**

trends in the absence of treatment, 2) the treatment timing (e.g., climate change) is uniform across all observational units (Callaway & Sant'Anna 2021; Sun & Abraham 2021), and 3) the effect (e.g., of climate change) is homogenous across all observations. These assumptions are easily violated when the timing or rate of climate change differs across observational units. Emerging solutions and extensions, including robust difference-in-difference analyses, however, are being developed and new estimator packages are available in R (Roth *et al.* 2023).

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Data availability

Data for the case study analysis can be found in two places. 1) GitHub: https://github.com/Landscapes-of-Change-Lab/CausalClimateAttribution.git and 2) the Open Science Framework at DOI: 10.17605/OSF.IO/NM36A

Code availability

All of the analyses were performed using R. The code is available through GitHub https://github.com/Landscapes-of-Change-Lab/CausalClimateAttribution.git, which is also mirrored on the Open Science Framework at DOI: 10.17605/OSF.IO/NM36A

Author contributions

Author contributions are defined using the Contributor Roles Taxonomy (CRediT; https://casrai.org/credit/). Conceptualization: J.D., L.D., R.H., J.B., K.S.; data curation: J.D., formal analysis: J.D.; project leadership: J.D., visualization: J.D.; writing—original draft: J.D., L.D., R.H., J.B., K.S., writing—review and editing: J.D., L.D., R.H., J.B., K.S.

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