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A reassessment of the impact of temperature change on European conflict during the second millennium CE using a bespoke Bayesian time-series model

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Abstract

Recently, there has been a lot of discussion about the impact of climate change on human conflict. Here, we report a study in which we revisited the findings of a paper that has been cited many times in the discussion. The paper in question focused on the association between temperature and conflict in Europe between 1000 and 1980 CE and suggested that colder temperatures led to more conflict. However, there are reasons to be skeptical of this finding. Most importantly, the analytical technique used by the paper's authors was not suitable for the conflict dataset because the dataset is count-based and contains autocorrelation. With this in mind, we developed a Bayesian time-series model that is capable of dealing with these features, and then we reanalysed the dataset in conjunction with several temperature reconstructions. The results we obtained were unambiguous. None of the models that included temperature as a covariate outperformed a null hypothesis in which conflict levels at any given time were determined only by previous levels. Thus, we found no evidence that colder temperatures led to more conflict in Europe during the second millennium CE. When this finding is placed alongside the results of other studies that have examined temperature and conflict over the long term, it is clear that the impact of temperature on conflict is context dependent. Identifying the factor(s) that mediate the relationship between temperature and conflict should now be a priority.

Keywords Climate change · Conflict · Temperature · European history · Bayesian time-series analysis

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1 Introduction

In recent years, a number of important organisations, including the European Union and the US Department of Defense, have warned that climate change will exacerbate conflict around the world (High Representative of the European Union for Foreign Affairs and Security Policy 2013; US Department of Defense 2010). However, the scientific literature is far from clear about the impact of climate change on conflict levels. Studies dealing with the relationship between temperature and conflict have returned inconsistent findings, with some suggesting that warmer conditions lead to more conflict and others indicating that cooler conditions increase conflict (e.g. Burke et al. 2009; Zhang et al. 2006; Tol and Wagner 2010). Results regarding the impact of changes in precipitation on conflict have also been inconsistent (e.g. Von Uexkull et al. 2016; Theisen et al. 2012). Frustratingly, attempts to clarify the situation by reviewing the literature (Koubi 2019), carrying out meta-analyses (Hsiang et al. 2013), and eliciting the views of experts (Mach et al. 2019) have not been particularly successful. Needless to say, given the obvious downsides of misunderstanding the impact of climate change on conflict, there is a need for additional research to reduce the uncertainty.

Here, we report a study that revisited the findings of a paper that has been influential regarding the impact of temperature change on conflict levels—Tol and Wagner's (2010) 'Climate change and violent conflict in Europe over the last millennium'. These authors quantitatively compared the frequency of conflict in Europe in the second millennium CE to several temperature and rainfall reconstructions. The conflict record they analysed contained annual counts for conflicts between 1000 and 1980 CE, details of which were extracted from three historical databases: (1) the Peter Brecke Catalogue; (2) the Uppsala Conflict Data Program; and (3) the COSIMO dataset. The temperature and rainfall reconstructions were drawn from a number of palaeoclimatological studies. Tol and Wagner (2010) searched the conflict and climate records for correlations and then tested for a significant impact of climate change on conflict with regression models involving different temperature and rainfall covariates. In some of the models, they attempted to account for the effect of previous conflict levels by including lagged versions of the conflict record as a covariate. They also analysed numerous sub-periods to see if the effects were consistent through time. The analyses returned a range of different results, but it was one finding in particular that has made the study influential—that colder temperatures led to more conflict.

While Tol and Wagner's (2010) study has been widely cited (>200 times at the time of writing, according Google Scholar), there are reasons to question the reliability of its results, including the most influential one. Most notably, the regression models employed by Tol and Wagner (2010) assumed that the conflicts were normally distributed. Although this assumption is reasonable for many datasets, it is not appropriate for Tol and Wagner's (2010) conflict time series. The conflict time series is count-based and therefore is better described by a counting probability function such as the Poisson distribution than by a normal distribution. The misspecification in Tol and Wagner's (2010) model is evident in a plot they presented showing their model's estimated levels of conflict for the study period (see Fig. 5, Tol and Wagner 2010). The plot reveals that the model estimated *negative* levels of conflict for some portions of the period. Needless to say, this is an impossible prediction, which indicates that the probability distribution they used did not fit the conflict data.

A second major shortcoming of Tol and Wagner's (2010) chosen methodology concerns autocorrelation. Their conflict record contains significant temporal autocorrelation (see SI). To account for this, Tol and Wagner (2010) included a lagged version of the conflict dataset as a covariate in their main regression model. While widely used, this method of accounting for autocorrelation is known to produce biased regression coefficients (Wilkins 2018; Keele and Kelly 2006). The bias occurs partly because of feedback among covariates, the error term, and the dependent variable; and partly because residual autocorrelation beyond the lag(s) is not properly modelled. That the inclusion of a lagged version of the conflict dataset was problematic is supported by the fact that Tol and Wagner (2010) obtained inconsistent findings when they explored different model settings—an observation that led them to conclude that the association between colder temperatures and increased conflict was not particularly robust.

In our study, we created a time-series model specifically for autocorrelated count-based time-series, and then reassessed the impact of temperature variation on Tol and Wagner's (2010) conflict record. Our model is a Bayesian state-space time-series representation of count-based processes that includes an autoregression term and covariates. State-space time-series models distinguish between observations and a latent process that produced them. Parsing out the autocorrelation process results in conditional independence of the dependent variable and avoids bias-generating feedback. It also allows the full autocorrelation structure of the time-series to be accounted for, as opposed to a small number of lags. In our model, the number of conflicts in a given year is considered to be an empirically observed measurement that was produced by an unobservable, abstract conflict process. This latent process can be affected by both external forces and past conflict levels. The external forces are represented in the model by covariates, while the impact of past conflict levels is captured by an autoregression term.

Using the new model, we compared Tol and Wagner's (2010) conflict record to several temperature reconstructions. Once the parameters were estimated, the temperature-covariate models were competed against a benchmark model—one in which the effect of the temperature covariates was set at zero and therefore future levels of conflict were only impacted by previous levels. The benchmark model served as a null hypothesis under which temperature was assumed to have no impact on conflict. For a given temperature covariate to be considered a correlate of the conflict record, the regression model that included it had to have a significantly higher Bayes Factor than the null model. If temperature had an impact on conflict levels, we reasoned, at least one of the models should outperform the null model.

Tol and Wagner (2010) recognised that it is possible that sociopolitical changes affected the relationship between temperature and conflict, and therefore included a dummy variable to account for the potential impact of what they considered to be the most important societal change during the time period covered by their data, the Reformation. We dealt with this issue in a different way. Rather than incorporating a dummy variable, we included a change-point variable, the temporal location of which was estimated from the data. We opted for the change-point variable approach because it allowed for the possibility that sociopolitical changes other than the Reformation affected the temperature-conflict relationship.

2 Materials and methods

2.1 The data

Our analysis involved Tol and Wagner's (2010) conflict time series and four published temperature reconstructions. The conflict dataset was kindly provided by Richard Tol. Originally, the data were drawn from three complimentary authoritative historical databases. The databases are still being maintained and updated, and they are obtainable (as of the time of writing) from https://www.prio.org/Data/Armed-Conflict/?id=348, http://brecke.inta.gatech.edu/research/conflict/, and https://hiik.de/hiik/verein/. Tol and Wagner (2010) counted conflicts from these databases that occurred in every year from 1000 CE to 1980 CE to produce an annual index of violent conflict spanning most of the second millennium CE.

The temperature data we employed were obtained from an online data repository maintained by the National Oceanic and Atmospheric Administration (NOAA) https://www.ncdc.noaa.gov/data-access/paleoclimatology-data/datasets. One of the datasets we employed was developed by Mann and Jones (2003). We included this dataset because Tol and Wagner (2010) used it in their regression analyses and we wanted to be able to compare our results directly to theirs. However, the dataset is less than ideal for investigating the question at hand. One problem is that it is a hemispheric reconstruction rather than a Europe-specific one. A second problem is that it is a composite of other reconstructions that are themselves based on dozens of individual proxy records (Mann and Jones 2003), so it is at least twice removed from the raw data. A third problem is that it was smoothed with a 10-year filter to remove variation on timescales shorter than a decade, which limits its relevance to the annual conflict record. Given these shortcomings, we searched the NOAA database for additional temperature reconstructions to include in the study. Specifically, we looked for Europe-specific reconstructions based directly on proxy data that retain annual-level variation.

We identified three such reconstructions. One was developed by Glaser and Riemann (2009) from Central European historical documents. It provides a rare glimpse of climate and weather as they were experienced by individuals living during the period under analysis. Unfortunately, this reconstruction begins in 1005 CE, which meant that we had to set the start date of our analyses to 1005 CE rather than 1000 CE—this was a minor change with no significant effect on our results. The documents include annals and diaries from different regions in Europe between the eighth and nineteenth centuries CE. As one might expect, the density of historical information varies over time, with more recent periods better represented in the corpus. The spatial coverage (source locations of the material) varies as well, but is fairly comprehensive, spanning most of the continent—though concentrated in the central regions. Glaser and Riemann (2009) converted textual descriptions of temperature-related conditions and weather phenomena (e.g. descriptions of droughts, crop yields, and so on) into scaled ordinal indices. These indices were then calibrated using instrumental data from 1761–1970 CE. The correlation between the two datasets was as high as 0.88 (Pearson R) and they were closely matched at various temporal scales.

Another of the reconstructions we used was produced by Büntgen et al. (2011). It is based on high-resolution tree-ring data. These data consist of tree-ring widths measured from 1089 stone pine and 457 European larch trees located at high elevation in multiple central European countries. The samples include cores from living trees, historical lumber, and fossil wood. Ring width in these species is known to correspond to summer temperatures and, thus, can be used to create a chronologically accurate record of temperatures spanning millennia. According to Büntgen et al. (2011), the tree-ring series correlates strongly—in the range of 0.72–0.92—with instrumental records from 1864–2003. Significantly for present purposes, Büntgen et al. (2011) also demonstrated that it corresponds closely with temperatures recorded throughout central Europe *and* the Mediterranean, suggesting that it can be used as a general indicator for European-wide annual temperature variations covering the entire 1000-year conflict record.

The last reconstruction we utilised is based on multiple lines of evidence (Luterbacher et al. 2016). This reconstruction is the product of a large network of palaeoclimate scientists, the PAGES 2k Consortium (http://www.pastglobalchanges.org/science/wg/2k-network/intro). The consortium's members' aim was to create a high-resolution regional temperature reconstruction spanning the last 2000 years. They employed a combination of new Bayesian Hierarchical Modelling methods and a long-established method called Composite-Plus-Scaling (CPS) to derive a gridded (spatial) time-series with a resolution of 2° by 2° covering Europe and the Mediterranean. They also produced an average model for Europe specifically, which is the reconstruction we used in our study. This reconstruction spans the last 2000 years and is based on a combination of tree ring widths, maximum late wood density, and documentary data from across Europe. These data include the tree ring width records collected by Büntgen et al. (2011) and at least some of the documentary data used in Glaser and Riemann's (2009) reconstruction (other documentary sources appear to have been included as well). In line with the methods used for previous reconstructions, the proxy was calibrated against instrumental data—in this case the instrumental period used was from 1850–2003 CE. The composite reconstruction preserves inter-annual variation and shows strong agreement with twentieth century instrumental temperature data. According to Luterbacher et al. (2016), the Pearson correlation between the reconstructions and instrumental records was 0.81 and 0.83 for the Bayesian model and CPS model, respectively (Fig. 1).

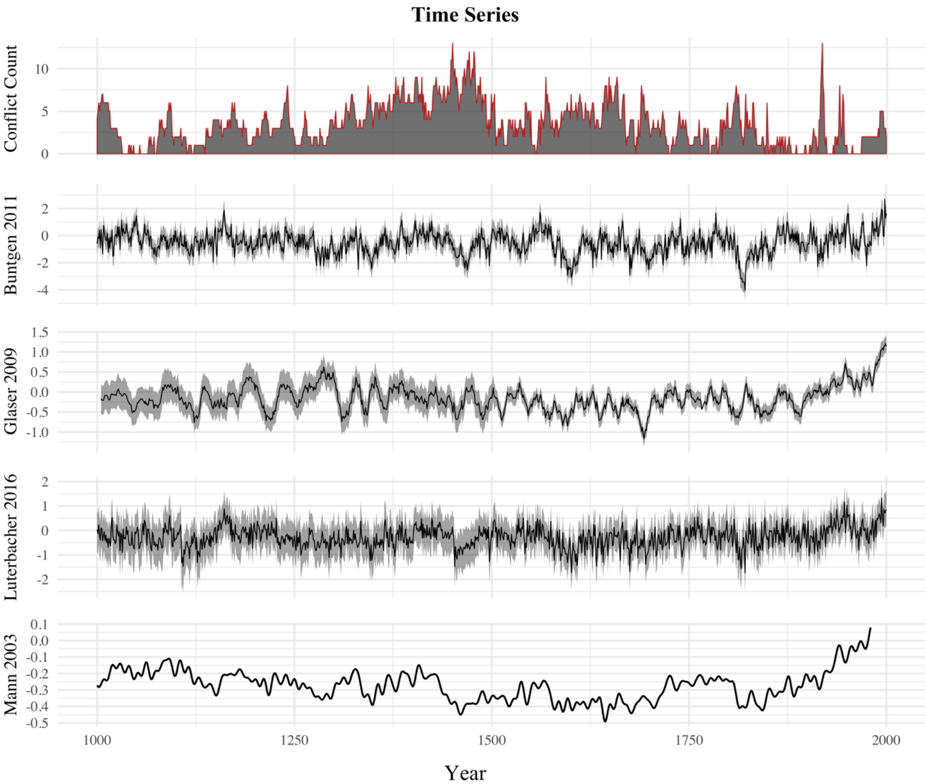

Fig. 1 Time-series data

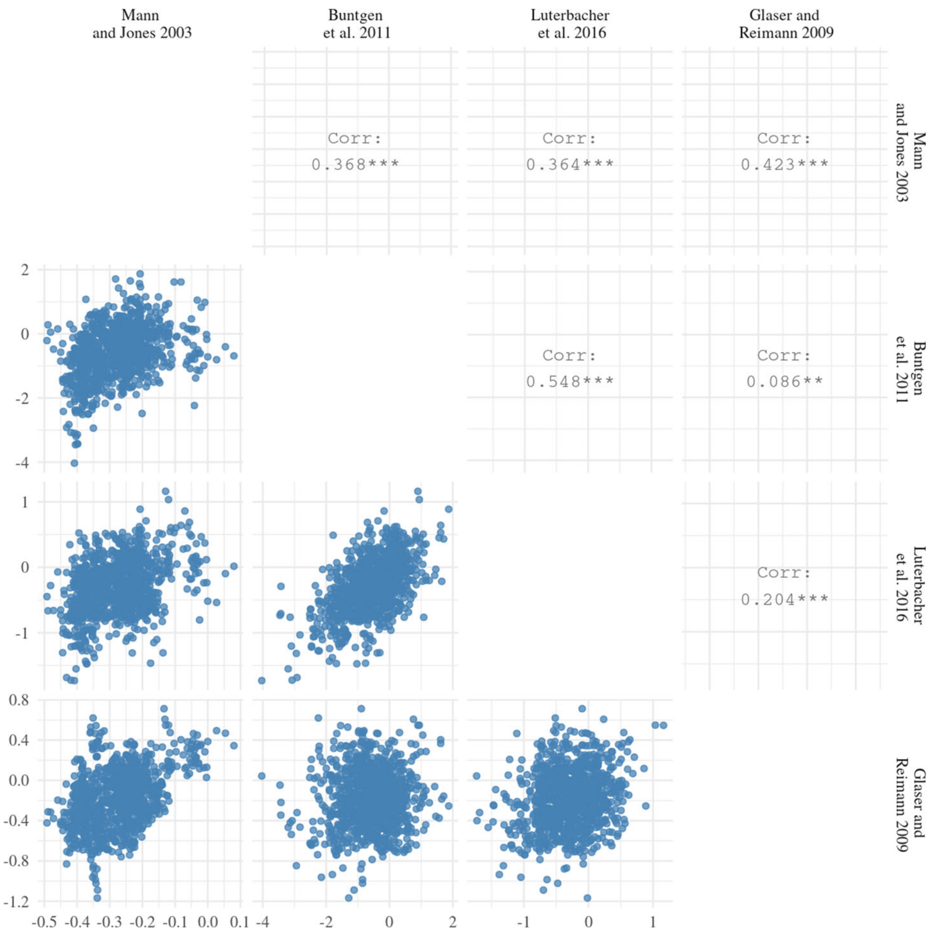

Fig. 2 Pair-wise correlations among the annually-resolved temperature reconstructions used in our analyses

We performed a preliminary quantitative comparison of the temperature proxies by computing simple correlation coefficients. The correlations were less than perfect, presumably because of the differences in data and methods used to produce the proxies (see Fig. 2). However, as Fig. 2 shows, all of the records correlate positively, even at an annual resolution. When smoothed, the correlations improved significantly, which suggests that long-term temperature variation is represented consistently in all three records (see SI). Given the regional coverage of the data on which these proxies are based, and their broad agreement at annual and coarser time-scales, it seems reasonable to conclude that the three reconstructions offer a robust account of temperature variation in Europe over the relevant time period.

2.2 The model

As mentioned earlier, the model we employed is a Bayesian state-space time-series model. We developed it specifically for analysing autocorrelated count-based data and tailored it to account for a potential change in the climate-conflict dynamics of second millennium Europe (e.g. the Reformation, as suggested by Tol and Wagner' 2010, or the Industrial Revolution).

The number of conflicts per year in the European record can be thought of as a series of Poisson-distributed random variables, denoted $Y = [y_{t_1}, y_{t_2} \dots, y_{t_T}]$ where $t \in [1, T]$ is the period—year, in the present case—of T periods. The conflict-count variables are therefore modelled as follows:

$$y_t \sim P(\lambda_t) \tag{1}$$

In this equation, y_t is the number of conflicts at time t, and λ_t is the mean of the Poisson process. The mean of the conflict-count process is, in turn, determined by the latent (i.e. unobservable) conflict process, which includes external inputs in the form of covariates. This latent process is represented by the following equation:

$$\lambda_t = e^{X_t \beta_1 + \beta_2 \Delta_t + \delta_t} \tag{2}$$

Equation 2 is a standard linear regression modified to incorporate a structural change in the relationship (regression coefficients) between the independent and dependent variables. In this regression, X_t is a matrix of (mean-centered) covariates including an intercept (column of 1's), β_1 is a vector of regression coefficients that represents that baseline impact of a the covariates on conflict, and β_2 is a deviation from that baseline that only has an effect when Δ is non-zero. The regression is related to the Poisson mean by a log-link function, which is why the terms are exponents of e. The last term, δ_t, is also an exponent of e and it represents the underlying, endogenous autocorrelated conflict process. By including this term, we accounted for the substantial observable autocorrelation in the conflict record (Fig. S1). The term represents an autocorrelated, normally distributed process,

$$\delta_t \sim N(\rho\delta_{t-1}, \sigma) \tag{3}$$

where the mean is represented by $\rho\delta_{t-1}$ and the standard deviation is represented by σ. The mean, $\rho\delta_{t-1}$ has two parts. The first, ρ, is an autocorrelation term; the second, δ_{t-1}, is the level of the endogenous conflict process at the previous time (i.e. $t-1$). The autocorrelation term applies a weight to the influence of past conflict counts on present and future conflict. A positive value for ρ implies that endogenous conflict is increasing over time because the influence of past conflict is accumulating whereas a negative value implies it is declining because the influence is diminishing. The standard deviation of the distribution, σ, determines the volatility of the endogenous autocorrelated conflict process. Higher σ indicates higher magnitude fluctuations in the endogenous conflict process while lower σ indicates lower magnitude fluctuations.

Because the model is Bayesian, several parameters have prior distributions. The priors include normal distributions for the regression coefficients (β) of Eq. 2, the autocorrelation coefficient (ρ) of Eq. 3, and the first estimate of the endogenous conflict process (δ_0) in Eq. 3. The last of these is the estimated level of conflict in the period immediately prior to the beginning of the conflict record. The priors we used were informed by reasonable assumptions about their likely impact on conflict given the scale of the climate covariates and the observed levels of conflict in the record—i.e. we used *weakly-informative priors*, which is considered best practice in applied contexts (Gabry et al. 2019). For instance, we chose variances for the priors applied to regression coefficients, β, that would limit predicted numbers of conflicts per year to less than five on average with a low probability for higher values (see Supplementary Information). While using more agnostic priors would not likely change the posterior estimates for the model's parameters, implausibly vague priors are known to undermine model comparisons involving Bayes Factors (Wagenmakers et al. 2010). The three priors were parameterised as follows:

$$\beta_1 \sim N(0, 2) \tag{4}$$

$$\beta_2 \sim N(0, 2) \tag{5}$$

$$\rho \sim N(0, 10) \tag{6}$$

$$\delta_0 \sim N(0, 10) \tag{7}$$

We also used a prior for the standard deviation, σ, in Eq. 3. Instead of a normal distribution, however, we used an exponential one so that the value would be positive, which is a requirement for standard deviations. This prior was parameterised as follows:

$$\sigma \sim Exp(0.7) \tag{8}$$

Lastly, we used a uniform prior for the change-point variable, Δ, from Eq. 2. This variable represented the year in which a structural change in the regression might have occurred. We decided to allow the prior for the change-point to include the entire series so that the model would be able to account for a change at the time of the Reformation, as hypothesised by Tol and Wagner (2010), a change during the Industrial Revolution, or a change at any other time. The change-point parameter was defined as follows:

$$\Delta \sim U(1, T) \tag{9}$$

where $U(a, b)$ represents a uniform distribution parameterised by a start (a) and end (b) index of the time series under analysis. For our analysis, the end index, b is T, the length of the series. This prior could, therefore, take on any integer in $[1, T]$, which refers to an index of the conflict time-series that could be converted into a year CE.

All of the prior distributions were ultimately transformed by the data and likelihood for the model via Bayes Theorem into posterior estimates of the relevant parameters (Gelman et al. 2014).

2.3 Hypothesis testing

To test the hypothesis that temperature affected conflict in Europe during the second millennium CE, we used Bayes Factors (Gelman et al. 2014). Bayes Factors (BFs) indicate the weight of evidence for a given model compared to another model, with higher BFs indicating better fitting models. BFs are commonly used in Bayesian hypothesis testing and can be employed for comparing a given model to a null hypothesis according to which a parameter of interest is fixed at a given value. For present purposes, the null hypothesis we used states that there was no impact of temperature on conflict levels, which would mean that the regression coefficients, β_1 and β_2, should be indistinguishable from zero. More formally, it implies

$$\beta_1 = \beta_2 = 0. \tag{10}$$

We reasoned that if temperature had an impact on European conflict during the second millennium at least one of the models should have a higher BF than this null—i.e. one or both of the regression coefficients should be non-zero. We estimated the BFs with the well-known Savage-Dickey Ratio (Wagenmakers et al. 2010), which we computed for the two-dimensional case in Eq. 10 with the kernel density estimation tools in the R package KernSmooth (Wand 2015).

The posterior distributions of the parameters for each model were estimated with a Markov Chain Monte Carlo (MCMC) simulation. Each MCMC simulation was run

Table 1 Table of Bayes Factors. Each row refers to a model with the given temperature proxy used a covariate

Model (temperature proxy)	Bayes factor
Mann and Jones (2003)	0.36
Luterbacher et al. (2016)	0.03
Buntgen et al. (2011)	0.03
Glaser and Riemann (2009)	0.09

for 20,000,000 iterations, with the first 1000 discarded as burn-in. We thinned the chains by retaining every 99th iteration and then used the Geweke (1992) statistic (see Supplementary Information) and visual inspection of the MCMC trace plots to evaluate convergence. The calculations were performed in R (R Core Team 2019) with the help of a newly developed Bayesian model estimation package called Nimble (NIMBLE Development Team 2018). The code used in the study can be found on GitHub (https://github.com/wccarleton/conflict-europe).

3 Results

All the analyses indicated that temperature had no significant effect on conflict levels. The most probable values for the posterior regression coefficients—representing the effect of temperature—were zero or very near zero (see Fig. 3). In line with this, the Bayes Factors (BFs) indicated that none of the models outperformed the null hypothesis (see Table 1). In fact, the BFs were less than one, which indicates that the null hypothesis has a higher probability given the data than any of the alternatives. To put it another way, the analysis yielded evidence *in favour* of the null hypothesis.

We also found no evidence of a significant structural change in the relationship between temperature and conflict levels. In some cases, the posterior density for the change-point variable contained peaks, but because the regression coefficients are likely zero or near-zero, the peaks are not informative (Fig. 3).

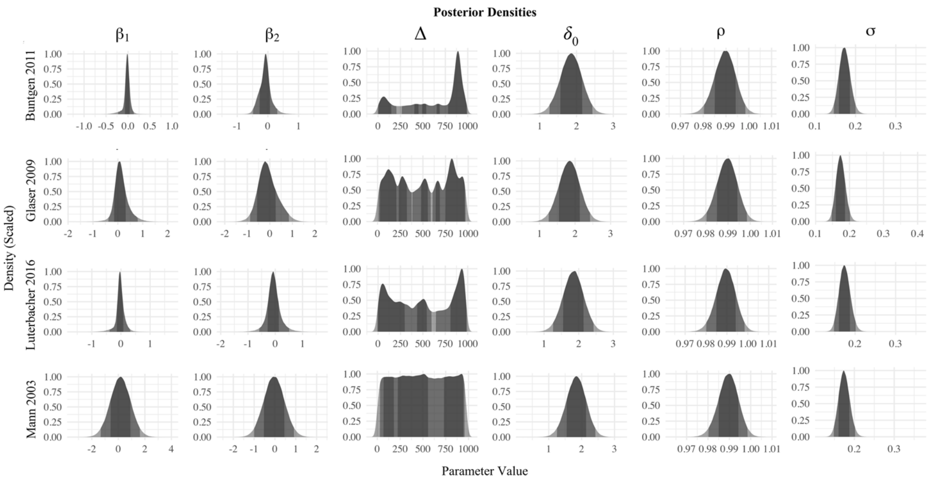

Fig. 3 Posterior densities for the main model parameters. Each row contains the posterior densities for the model parameters from a model with a given temperature proxy used a covariate

Thus, the analyses indicated that our concerns about Tol and Wagner's (2010) methodology are valid. They showed that, when Tol and Wagner's (2010) conflict time-series is analysed with a model that is specifically designed for autocorrelated count-based time-series, there is no evidence that colder temperatures—or warmer temperatures, for that matter—led to more conflict in Europe during the second millennium CE.

4 Discussion

The failure of our analyses to identify a significant association between temperature and conflict does not appear to due to problems with the data. There are, we believe, three potential shortcomings that need to be considered.

The first is insufficient variation. In theory, it is possible that we did not find a relationship because the European conflict and temperature records do not vary enough. We think this is unlikely to be the case. The time period covered by the records span some of the most fractious periods in European history, including the European Wars of Religion, the Hundred Years' War, and the War of the Roses. It also spans the Medieval Warm Period and the Little Ice Age, which are two of the most dramatic periods of temperature change in the Holocene (D'Arrigo et al. 2006; Crowley and Lowery 2000). Thus, the European conflict and temperature records include substantial variation, certainly as much as the records from other regions that have yielded a significant association between temperature and conflict.

The second potential shortcoming is proxy inaccuracy. In principle, our analyses could have returned negative results because the temperature records are insufficiently accurate. This is also unlikely to be the case, we think. To reiterate, the reconstructions we used are based on tree-ring data and/or documentary evidence. Tree-ring widths have long been known to correlate with hemispheric and continental scale temperature variation, and the biological mechanism behind the correlation is well understood, as are the main sources of uncertainty (Briffa et al. 2004). Similarly, the documentary evidence comprises environmental observations that can be clearly linked to past temperature variation. Additionally, the three proxy records not only correlate with each other (see Fig. 2), but also with instrumental records (Glaser and Riemann 2009; Buntgen et al. 2011; Luterbacher et al. 2016). Accordingly, it seems reasonable to conclude that the temperature records are sufficiently accurate for the purposes of the study.

The third potential shortcoming is spatial averaging. This could account for the negative result yielded by our analyses if, for example, temperature change over the last millennium in northern Europe was markedly different from that of southern Europe. To evaluate this possibility, we obtained two regional temperature reconstructions from the NOAA website and compared them to the three continental proxy records. One of the regional reconstructions was based on isotope measurements from tree-rings in southern Sweden (Edwards et al. 2017); the other was based on isotope measurements from a speleothem in northern Spain (Martín-Chivelet et al. 2011). These reconstructions are thought to represent past temperature variation in northern and southern Europe, respectively Chivelet 2011 (Edwards et al. 2017). Given this, we reasoned that, if significant regional differences in long-term trends were present, comparing the Swedish and Spanish records should reveal them. Because the reconstruction from Sweden had a 5-year resolution, we sampled the higher resolution records onto the same 5-year time-bins. Then, we ran simple pairwise correlations among the various reconstructions. We found that the records all correlate positively with each other (see Fig. 4), which indicates general agreement regarding temperature

Fig. 4 Pair-wise correlations among the temperature reconstructions used in our analyses and two regional reconstructions based on a different proxy type

variation. As such, it seems unlikely that the negative result we obtained is an artifact of spatial averaging.

Given that the three potential shortcomings with the data can be discounted, it seems reasonable to conclude that the negative result we obtained is not a false-negative but is instead an accurate reflection of the situation with regard to temperature and conflict in Europe during the second millennium CE.

Of the various studies that have examined the impact of climate change on conflict, the most directly comparable to the one reported here are Zhang et al. (2006) and a study we reported in 2017 (Carleton et al. 2017). Both of these studies examined the association between mean annual temperature and conflict levels over several hundred years in the homeland of a major civilisation, as was the case in the present study. Zhang et al.'s (2006) dataset related to China and covered the period 1000 CE to 1911 CE, while our dataset pertained to the Maya region and spanned the period 363 CE to 888 CE. Strikingly, the results we and Zhang et al. (2006) obtained not only differ from the results of the present study but also from each other. Zhang et al.'s (2006) analyses suggested that cooler temperatures led to increased conflict, whereas our Classic Maya study indicated that warmer temperatures resulted in more conflict. Thus, the three analyses of the impact of temperature on conflict levels over the long term that have been reported to date have yielded all the possible outcomes: one has suggested that cooler temperatures lead to more conflict; one has suggested that warmer temperatures result in more conflict; and one has suggested that there is no impact of temperature on conflict.

These divergent results not only indicate that temperature does not have a simple, linear effect on conflict, contrary to what a number of authors have argued (e.g. Burke et al. 2009; O'loughlin et al. 2012; Maystadt et al. 2012); they also do not support Burke et al.'s 2015 suggestion that it is extreme temperatures—hot *or* cold—that result in increased conflict. Instead, the divergent results of the three studies imply that temperature only has an impact on conflict levels in certain circumstances. We suspect that staple crops play an important role in this regard.

In our 2017 paper, we proposed that the impact of temperature on conflict among Classic Maya city-states was mediated by the productivity of the region's staple crop, maize (Carleton et al. 2017). Recent agricultural research has revealed that increasing temperature leads to increased maize yields up to about 30 °C, after which yields decline precipitously, even under optimal rainfall conditions (Lobell et al. 2011). We hypothesised that this non-linear effect accounted for the positive relationship between temperature and conflict levels among the Classic Maya (Carleton et al. 2017). Increases in temperature, we argued, led to declines in maize yields. The resulting food shortages, we suggested, undermined the legitimacy of the leaders of city-states and this, in turn, prompted them to engage in cachet-accruing activities more frequently, including leading attacks on other city-states—hence the association between warmer temperature and conflict. Zhang et al. (2006) outlined a similar hypothesis for China. They proposed that cooler temperatures resulted in decreased yields of China's main staple crop in the second millennium CE, rice, and the reduction in the amount of rice available for consumption led to population pressure. In turn, the population pressure led to a greater number of anti-tax rebellions and more conflict between states (Zhang et al. 2006). This leaves the non-relationship between temperature and conflict in second millennium CE Europe. The main staple crop of Europe, wheat, is negatively affected by both unusually high and low temperatures (Porter and Gawith 1999). So, why did the temperature changes that occurred during the second millennium CE not result in elevated conflict levels?

We suspect that the answer to this question may be provided by Wang et al.'s (2018) recent review of the effect of climate change on the yield of cereal crops. These authors reported that the available research indicates that global warming can be expected to reduce the yield of maize by 34.6 to 35.4%, of rice by 10 to 15%, and of wheat by 3.5 to 12.9% (Wang et al. 2018, p. 11). This suggests that wheat yields are less strongly impacted by temperature change than maize and rice yields. And this offers a potential explanation for the failure of the present study to find a significant association between temperature and conflict while Zhang et al.'s (2006) study and our Classic Maya study (Carleton et al. 2017) identified one: the impact of temperature variation on stable crop yields and therefore on food availability was attenuated in Europe relative to China and the Maya region. As a consequence, temperature did not become one of the significant drivers of conflict in Europe during the second millennium CE whereas it did in China over the same time period and in the Maya region in the preceding millennium. This hypothesis can, in principle, be tested by estimating crop yields and population size for the three regions over the relevant time periods.

There are two other obvious follow-up studies. One is to investigate alternative climatic drivers of conflict frequency in Europe during the second millennium CE. While surface temperature increases are a primary feature of global climate change—in fact, they are the principle evidence for a global average increase in temperature (NOAA 2020)—it has been argued that increases in Earth's average temperature has already led to changes in environmental and ecological conditions other than surface temperature. These changes include regional precipitation patterns, drought incidence, the expansion and contraction of species' ranges, and extirpations and extinctions (IPCC 2014). All of these phenomena have the potential to affect conflict levels either directly or indirectly, and their contribution (or not) to initiating or exacerbating conflict was not evaluated in the present study. As such, investigating the impact of climatic variables other than surface temperature on conflict frequency in Europe during the second millennium CE would be a logical next step.

The other obvious follow-up study is to examine the impact of extreme temperature-change events on conflict levels. The present study looked at a period of nearly 1000 years, which included at least two major swings in temperature, the Medieval Warm Period and the Little Ice Age. In both cases, Europe experienced temperature changes that were substantial and rapid. Estimates suggest that changes of 0.5–2 °C occurred in just a few decades (Mann et al. 2009; Glaser and Riemann 2009; Buntgen et al. 2011). People likely would have noticed these changes, and they have been linked to historically important events. Some scholars have suggested, for instance, that the Medieval Warm Period permitted Norse colonisation of North America by melting enough glacial ice in the North Atlantic to allow for passage (Ogilvie et al. 2000). Many notable conflicts also occurred during the Medieval Warm Period, including the Norman conquest of England. During the Little Ice Age, Londoners frequently witnessed winters when the Thames froze to a significant depth for multi-week stretches (Lockwood et al. 2017). Notable conflicts occurred during this cold period as well, such as the War of the Roses, which began at the onset of the Little Ice Age (Mann et al. 2009). Given the severity of these climatic changes and the coincident timing of some of Europe's bloodiest wars it is plausible that the rapid large temperature changes might be related to these specific conflicts. By any reasonable definition, the Medieval Warm Period and Little Ice Age were extreme climatic changes relative to the preceding and following periods (Mann et al. 2009). So, while there may have been no relationship between temperature change and conflict at the millennial scale, there may have been short-term spikes in conflict caused by extreme changes. Investigating this possibility would also be a logical next step.

5 Conclusions

In the study reported here we revisited the findings of a paper that has been cited many times in the discussion about the impact of climate change on conflict levels (Tol and Wagner 2010). The paper in question focused on the association between temperature and conflict in Europe between 1000 and 1980 CE and suggested that colder temperatures led to more conflict. However, there are reasons to suspect that the analytical technique used by the paper's authors was not suitable for the conflict dataset because the latter is count-based and contains temporal autocorrelation. The corollary of this is that the paper's findings may not be reliable. With this in mind, we developed a time-series model that is capable of dealing with the features of the dataset, and then reanalysed it in conjunction with several temperature reconstructions.

The results we obtained were clear-cut. We found no evidence of a significant impact of temperature on conflict levels. None of the models that included temperature as a covariate outperformed the null hypothesis, in which conflict was simply temporally autocorrelated. In fact, the analyses found positive support for the null hypothesis. Thus, the analyses indicated that the concerns about Tol and Wagner's (2010) methodology are valid. They show that, when Tol and Wagner's (2010) conflict time-series is analysed with a model that is specifically designed for autocorrelated count-based time-series, there is no evidence that colder temperatures led to more conflict in Europe during the second millennium CE.

This result contrasts with the findings of the other studies that have examined temperature and conflict over several hundred years (Zhang et al. 2006; Carleton et al. 2017). Zhang et al. (2006) analysis of the association between temperature and conflict in China in the second millennium CE indicated that colder temperatures caused more conflict, while our analysis of the association between temperature and conflict in the Maya region during the Classic Period suggested that warmer temperatures led to more conflict (Carleton et al. 2017). Taken together, these divergent results indicate that temperature only has an impact on conflict levels in certain circumstances.

That temperature's impact on conflict is context dependent has implications for the issue with which we started the paper—the conversation among policy-makers regarding the impact of global warming on future conflict levels. Specifically, it implies that warnings about the impact of global warming on conflict should be framed in terms of 'may' rather than 'will'. More importantly, it also implies that policy-makers should consider directing funding towards the twin tasks of establishing the conditions in which increases in temperature can be expected to lead to more conflict and identifying the regions of the world in which those conditions hold.

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