# Winter is Coming:

# The long-run intensification effects of climate change on conflict, 1400-1900 CE*

# (Incomplete)

Murat Iyigun Nathan Nunn Nancy Qian

April 15, 2016

**Abstract**

This paper investigates the long-run effects of climate change, atmospheric cooling in our context, on conflict. We construct a geo-referenced and digitized database of historical conflicts in Europe, North Africa, and the Near East from 1400-1900, which we merge with historical temperature data. The results provide novel evidence for *intensification* – i.e., conflict increases monotonically with the duration of climate change. The results are driven by regions that were agricultural, politically fractionalized and which had colder climates to begin with.

**Keywords:** Environment, Development, Political Economy.

**JEL Classification:** D74; Q34; P16.

*We thank Isaiah Andrews, Tim Armstrong, Susan Athey, Steve Berry, Marshall Burke, Melissa Dell, Solomon Hsiang, Benjamin Jones, Dan Keniston, Ted Miguel, Nicholas Ryan, Joseph Shapiro and Chris Udry for their insights; the participants at the Zurich Applied Economics Seminar, University of Lausanne Applied Seminar, University of Geneva Seminar, LSE/UCL Development Seminar, Stanford Development Seminar, University of California at Berkeley Development Seminar, Duke University Development Seminar, and the Yale Political Economy and Development Conference for useful comments; Erin Fletcher, Nicola Fontana, Anna Hovde, Eva Ng, Joshua Schabla, Brittney Stafford-Sullivan and Jaya Wen for excellent research assistance. Please send comments and suggestions to murat.iyigun@colorado.edu, nnunn@fas.harvard.edu, nancy.qian@yale.edu.

# 1 Introduction

Climate change is one of the most pressing problems faced by developing countries today as it continues in the 21st century. Recent studies provide a large body of important evidence on the adverse effects of weather shocks on economic and political outcomes in the short to medium runs (Burke and Emerick, 2015; Dell et al., 2012; Hornbeck, 2012; Hsiang and Jina, 2014; Miguel et al., 2004). There is much less rigorous empirical evidence on the long run effects (on any outcome).[1] This gap in the literature is important since climate change is a long-run phenomenon and because long-run and short-run effects can be very different.

The long-run effects can be less or more adverse than the short-run effects. On the one hand, there may be what the literature commonly refers to as "adaptation". Populations may relocate, or may adopt new technologies, production processes, crops, or even social or institutional structures that better suit the new environment. On the other hand, there may be "intensification", a term coined by (Dell et al., 2014) to refer to the positive interaction effect of climate change over different lagged periods. For example, one year of drought may have little adverse effect by itself, but a year of drought that follows three successive years of drought may have larger adverse effects as savings are eroded. Longer periods of continued climate change – for example, decades or centuries – can even affect the deeper determinants of peace and prosperity such as state capacity.

The goal of this paper is to empirically estimate the long-run effects of climate change. For this, we would need to examine the effects of climate change many years into the future, or alternatively, to study the effects of climate change which occurred many years into the past. Thus, the main empirical challenge is the limited availability of long panel data, which are necessary for estimating the long-run effects.

The principal contribution of this study is to overcome this difficulty and estimate the long-run effect of climate change on conflict, an outcome that has featured prominently in the literature in economic and political development, by constructing a dataset that extends over fifty years from 1400 to 1900 CE. Specifically, we merge two datasets. The first is one that we construct. It includes

[1] See Dell et al. (2014) for an overview of the climate change literature.

all conflicts with more than 32 combat mortalities as reported by two well-known sources in the historical conflict literature, Brecke (1999, forthcoming) and Clodfelter (2008). These sources provide information on wars and battles, as well as characteristics such as location and year. Over a period of six years, we manually digitized the information and geo-referenced each conflict to construct a dataset that records the date and location of over 4,000 conflicts in Europe, North Africa and the Near East between 1400 and 1900 CE. To the best of our knowledge, this is the most comprehensive digitized and geocoded data of historical conflicts. We follow the existing conflict literature and examine the incidence of conflict as our main outcome measure.[2] We merge the conflict data with historical climate data constructed by geologists and climatologists (Mann et al., 2009). These data, which are based on climate proxies such as ice-cores and tree rings provide reliable decadal temperature means and have been used in several recent studies in geology, economics and political science.

The main sample that we use is at the decade and grid-cell level, where each grid-cell is 400km by 400km. The long panel provides two important benefits. The first is that the longer time horizon will allow us to directly estimate long-run effects. The second is that having more data over time will allow us to estimate interactions of past climate change, which allows us to detect intensification or adaptation effects.

The context of our study experienced several long periods of cooling, which like climate change in the 20th and 21st centuries, was accompanied by high variability in precipitation. This phenomenon is sometimes called the "Little Ice Age" by climatologists and historians, who document that during periods of cooling, glaciers expanded, and seas froze as far south as present day Turkey. This, together with record levels of precipitation preceded or followed by drought drastically reduced agricultural productivity, which led to famine and extensive conflict of various forms (e.g., rebellions, foreign invasions). There was temporal and spatial variation in the intensity of cooling. For example, Russia experienced very little cooling.[3]

We note that the historical climate change that we examine differs from modern climate change

[2] We show that the results are robust to alternative measures.

[3] See Section 2 for a discussion of the historical context.

in that the adverse effects of historical climate change is driven by cooling, while those of modern climate change is driven by warming. This reflects the fact that the adverse effects of temperature are non-linear across temperature levels. For example, Figure 3 is taken from Burke et al. (2015) and shows that the relationship between conflict (in the modern era) and temperature levels is U-shaped.[4] For the purpose of our study, the important question is whether the change that occurred increased or reduced productivity. Since our study takes place in a cold climate context, cooling reduced productivity.

Our study is conceptually similar to studies of global warming in the modern context because historical cooling and modern warming both capture the idea that environmental change disrupts economic activity, which can lead to conflict.[5] Specifically, cooling reduces agricultural productivity for two reasons. First, it shifts temperature levels away from optimal levels for production. Second, shifts away from the optimal level is correlated with increased environmental volatility. This underlies the climate change literature's use of temperature as a sufficient statistic for capturing environmental changes of the time (Nordhaus, 1993). With a subsample of our data for which annual rainfall data are available, we will document cooling is associated with increased volatility in precipitation.

The empirical analysis proceeds in several steps. Section 3 motivates our preferred specification: a distributed lag model, where the dependent variables are changes in average regional temperature over fifty-year periods, and where we interact the lags. Our main interest is in the interaction term. If it is negative, then adaptation dominates intensification. If it is positive, then intensification dominates adaptation. To the best of our knowledge, we are the first to estimate a distributed lag model, which allows the effects of climate change to differ depending on when it occurred, or to estimate the interaction of climate change over different periods. Since our panel is long, we are able to control for time (decade) as well as grid-cell fixed effects. The former accounts for common changes in conflict (e.g., changes in military technology, the rise of the nation state)

[4] In the context of modern climate change, several studies have documented effects of negative temperature shocks. For example, Braga et al. (2001) and Curriero et al. (2002) study daily temperature data for cities in the United States. Both studies find that very cold days are associated with higher mortality rates.

[5] See Section 7 for a discussion of the implications of our results for modern global warming.

over time. The latter control for time-invariant differences across regions (e.g., geography).[6]

Our analysis produces several results. First, an examination of the long-run effects of cooling shows that it is the contemporaneous impact of cooling that is important – looking across fifty-year intervals, cooling during the previous fifty years (100 years ago to fifty years ago) has little effect on changes in conflict incidence during the current fifty-year interval (fifty years ago to now). In contrast, cooling during the current fifty-year interval has a positive impact on the change in conflict incidence during the current fifty-year interval. Conflict incidence will increase by 0.03 standard deviations more in a region that experienced cooling by one-standard deviation over the current fifty-year interval.

Second, we provide strong evidence of intensification. The interaction of cooling over the current and previous fifty-year intervals is positive and large in magnitude. Together with the first result, this means that while cooling during the previous fifty-year interval has little direct effect on changes in conflict, it has large adverse indirect effects because it intensifies the effect of cooling during the current fifty-year intervals. For example, our estimates indicate that the increase in conflict incidence is 0.09 standard deviations higher in a region that experienced cooling over the past 100 years, where each fifty-year interval cooled by one standard deviation, relative to a region that did not experience any change in temperature. The magnitudes are quantitatively important, but also plausibly moderate in magnitude since there were many other factors which determined the patterns of conflict in our context. The fact that the effect of cooling which lasts 100 years is larger than the effect of cooling which lasts fifty years implies that intensification dominates adaptation. In other words, the adverse effects of climate change on conflict increases with the duration of climate change.

The baseline specification is parsimonious because the introduction of additional controls alters the interpretation of the estimates. Nevertheless, to address concerns of omitted variables, we show that our results are similar or even larger in magnitude when we control for additional factors, such as latitude, longitude, elevation, hilliness, distance to the coast, agricultural suitability, urbanization

[6]Since mean change (over time) is around zero, demeaning by controlling for regional fixed effects does not alter the interpretation of the estimates. See Section 3 for a more detailed discussion.

in 1401-1450 and temperature in 1401-1450. We always interact these controls with the full vector of time fixed effects to allow their influences to be flexible. We also show that the results are robust to alternative levels of clustering, the omission of earlier years when the historical climate data is lower quality, and the omission of any given large war. The latter is important for ruling out the concern that our estimates are spuriously driven by large wars that coincided with cooling. We also demonstrate that the results are not likely to be biased upwards by classical measurement error in the climate variables.[7]

To shed light on the mechanisms driving the results, we investigate heterogeneous effects. We find that the main results are driven by regions that are suitable for the production of agricultural staples and inland regions away from the coast. Both of these findings are consistent with our interpretation that climate change affected conflict mainly by reducing agricultural productivity. Thus, it had relatively less effect in regions that were less productive and coastal areas, where economies relied relatively more on trade. We also find suggestive evidence that the negative effects of cooling are larger in regions that were cooler in 1401-1450. This is consistent with our interpretation that cooling had adverse effects because it occurred in regions that were already marginal for agricultural production due to their generally colder climate. In addition, the results show that the effects of cooling are similar for conflicts that are part of civil and inter-state wars, but are driven by conflicts that are part of medium-scale wars and regions that were politically fractionalized during 1401-1450.

In addition to the main estimates that examine the effect of cooling which lasts up to 100 years, we also examine the very long-run effects of cooling on conflict by estimating the effect of cooling for five lagged fifty-year intervals and all of their interactions. The goal of this somewhat heroic estimate is to investigate whether there is any evidence that the effect of cooling on conflict is non-monotonic with respect to duration – i.e., as cooling persists for very long periods of time, can the forces of adaptation dominate such that the effects on conflict decline with the duration of cooling. We find that the change in conflict incidence during the current fifty-year period is monotonically

[7] See the Robustness section for these and other sensitivity checks.

increasing with the duration of cooling (although the predicted effects are statistically similar). The estimates imply that relative to regions that experience no change in temperature, conflict incidence during the current fifty-year period will increase by 0.047, 0.196, 0.223, 0.4 and 0.44 standard deviations in regions that experience cooling which lasts fifty, 100, 150, 200 and 250 years (where each fifty-year interval cools by one standard deviation).

That we find strong evidence for adaptation and intensification effects suggests that restrictive econometric models that do not allow for the effect of climate change to vary with time or allow for interaction effects will be misspecified. Thus, the final exercise compares our preferred flexible specification with more restrictive specifications, such as a distributed lag model which does not allow for interactions and the long-difference model that is popular in estimates of medium-run effects. Both are special cases of the fully flexible model. We show that the latter two models severely underestimate the effects of continued climate change because they do not allow for intensification over time.

Our estimates should be cautiously interpreted as being specific to our context. We discuss the similarities and differences between our historical context and that of developing countries experiencing climate change today in Section 7.

This study adds to two literatures. First, it adds to the climate change literature. It is the first to provide direct estimates of long-run (i.e., beyond fifty or sixty years) and very long-run effects (i.e., beyond 100 years) on any outcome. Past studies, could only infer long-run effects indirectly from cross-sectional comparisons (Mendelsohn et al., 1994) or by plugging in short-run estimates into "business-as-usual" models to project long-run effects (Deschenes and Greenstone, 2011). In attempting to estimate causal effects beyond the short-run, we are most closely related to studies of the medium-run effect of climate change in the United States (Burke and Emerick, 2015; Dell et al., 2012), which we discuss in more detail later in the paper, and of the medium-run effects of natural disasters (Hornbeck, 2012; Hsiang and Jina, 2014). Our study differs conceptually from the latter two studies in that they examine the effects of a climate shock on outcomes many years in the

future, where as we are interested in the effects of prolonged/continued climate shock.[8] Our results are also consistent with the findings of a working paper by Ludlow and Hsiang (2016), which find no evidence of adaptation to climate change in the historical Irish context.

This study is also the first to provide evidence of intensification effects and more generally, that the effect of climate change is non-linear with respect to the duration of change. In examining non-linearities, we are most closely related to Deschenes and Greenstone (2011) and Schlenker and Roberts (2009) , which provide evidence on the non-linear relationship between temperature levels and short-run outcomes in the United States. To the best of our knowledge, we are the first to point out that the flexible functional form is more appropriate for capturing long run effects. This specification is discussed, though not estimated, in the review article by Dell et al. (2012).[9]

In our study of climate change during the Little Ice Age, we are most closely related to a recent working paper by Waldinger (2014), which examines the relationship between mean temperatures over fifty and 100 year periods and urbanization during 1fifty0-1750. Our finding that cooling increases conflict is consistent with her finding that colder temperatures are associated with lower urbanization. The results are also consistent with the findings from Anderson et al. (2016), who show that periods of cooling are associated with greater religious violence and persecution against Jewish populations in Europe between 1100-1800, as well as with Oster's (2004) finding of a relationship between cooling and witch killings in Renaissance Europe.

Second, we add to the empirical literature on the determinants of conflict. Our investigation of the long-run effects of climate complements studies of the short-run effects of weather shocks and agricultural price shocks on conflict (e.g., Miguel et al., 2004; Dube and Vargas, 2013).[10] As we

[8]For example, Hornbeck (2012) finds that the Dust Bowl reduced property values for several decades in the United States. Similarly, Hsiang and Jina (2014) find that the occurrence of tropical cyclones reduces growth for at least two decades into the future.

[9]We note that several recent studies in political science have examined the effects of climate change on conflict in the historical context. For example, (Lee et al., 2013) recently linked historical conflict data provided by Brecke (1999, forthcoming) and climate data from (Mann et al., 2009) to argue that climate change increases conflict. These studies differ from ours in relying exclusively on time series variation, which means that they cannot distinguish the effects of climate change from other changes over time. Moreover, these studies do not examine adaption or intensification.

[10]To establish causal identification, most studies of other determinants of conflict in the recent literature have also focused on the effect of transitory shocks on contemporaneous conflict. Another example of the effect of transitory weather shocks on conflict is Bai and Kung (2011). Using a long panel which include 2,000 years, they find that rainfall shocks in the previous decade increases nomadic attacks, but shocks during one decade earlier has no effect.

discussed earlier, existing studies have not directly examined long-run effects. In this sense, we are related to studies on the relationship between non-transitory agricultural shocks and conflict in the historical context. For example, in a companion paper, Iyigun et al. (2015) use the same conflict data as this paper to show that the adoption of potatoes in Europe, which presumably increased agricultural productivity, reduced conflict in the 18th and 19th centuries. Similarly, Jia (2014) finds that the introduction of sweet potatoes acts as an insurance mechanism and reduces peasant rebellions in China during rainfall shocks. More generally the construction of a comprehensive digitized and geo-referenced dataset of battles in Europe, the Near East and North Africa during 1400-1900, which we plan to make public, will help to facilitate future research on the determinants of conflict in the long-run.

This paper is organized as follows. Section 2 discusses the historical background. Section 3 motivates the empirical specification. Section 4 describes the data. Sections 5 and **??** report the empirical results. Section 7 discusses the implications of our results for modern climate change while section 8 offers preliminary conclusions.

# 2 Background

## 2.1 Climate Change and Agricultural Production

In addition to the climate proxy data that we use in our study, historians have used a variety of other sources to compile a rich narrative linking climate change to conflict for the period of our study. Such sources include written texts (farmers almanacs, histories, chronicles, letters, diaries, government records, newspapers, ships logs), epigraphic or archaeological information, and instrumental data from select locations in Europe starting in 1650 Parker (2013, loc. 425).

Prior to the period we study, climate in the northern hemisphere was characterized by stable long

Kung and Ma (2014) examine annual data and document a relationship between rainfall-shortages/crop failures and peasant rebellions during the Qing dynasty in China. For some other examples, see Nunn and Qian (2014), Crost et al. (2014) and Dube and Naidu (2013) for recent studies of aid on conflict. See Hsiang et al. (2013) and Burke et al. (2015) for a thorough literature review of studies of the relationship between weather and conflict.

summers. From approximately 1310 to the mid 1800s, the climate became more unpredictable, cooler and subject to extremes Fagan (2000, loc. 582). The period of our study 1400-1900 is characterized by the "Little Ice Age", which climaxed in the 17th Century.[11] For example, nine out of fourteen summers between 1666-1679 in Northern Europe were very cold Parker (2013, loc. 660). Rivers and seas uncharacteristically froze. During the winter of 1620-21, the Bosphorus froze over such that people could walk between Europe and Asia Parker (2013, loc. 754). Cycles of excessive cold and unusual rainfall often lasted for a decade or longer Fagan (2000, loc. 599).

Historical accounts indicate that, like modern global warming, periods of climate change were characterized by high variability in precipitation. The volatility reduced agricultural production Parker (2013, Ch. 3). Cold spells during germination, droughts during the early growing season and major storms just before harvest were particularly disastrous for crops. Climate also affected crops indirectly. Excessive rain encouraged rodents, while droughts encouraged locusts Parker (2013, loc. 1122). Climate change caused some marginal lands to become permanently unproductive. Severe cooling lowered the altitude and latitude of productive land. In addition, the expansion of glaciers caused many high altitude land to be uninhabitable. The later retreat of glaciers removed the fertile top soil. Similarly, successive years of flooding and excessive rain washed away the nutrients in the soil that took decades to replenish.

The historical context, like many modern developing economies, lacked sophisticated instruments for savings and insurance. This made it difficult for the population to cope with consecutive crop failures that resulted from climate change. For example, seventeenth century Finland saw eleven entire crop failures Parker (2013, loc. 1135). Contemporaries noted the devastation of these long periods of climate change: "What area does not suffer, if not from war, then from earthquakes, plague and famine? This seems to be one of the epochs in which every nation is turned upside down" Parker (2013, loc. 407).

The drastic reduction in agricultural productivity often caused surges in the price for food. For

[11] We note that climatologists debate whether the Little Ice Age was a large deviation from very long-run historical trends. This does not affect our study. The discussion in this section uses terminology which follows existing historical narratives from this period.

example, severe weather caused successive crop failures in Scandinavia during the early 17th Century, "causing bread prices to climb far beyond the reach of families already weakened by two decades of [bad harvests and] war" Parker (2013, loc. 6256). In France, successive years of bad weather during the same period drove bread prices to the highest levels in the century. Similar relationships between crop failure and high food prices are seen in other contexts, such as Britain and Switzerland during the 1730s Fagan (2000, loc. 1554). Waldinger (2014) provides some quantitative evidence on the relationship between cold temperatures and higher food prices during this period.

The increase in the price of food reduced per-capita food availability. In Europe, cereals provided approximately three-quarters of total calorie intake Parker (2013, loc. 1145). This is important to note since it suggests that the traditional vehicle for savings/insurance – slaughtering livestock during poor harvests – would not have tided farmers for extended periods. Lower nutrition from periods of cooling can be observed in stunting of French soldiers born during these periods and in Dutch skeletal remains Parker (2013, loc. 1299).

Not surprisingly, the reduction in food availability reduced population size through increased mortality, reduced fertility and migration. For example, during the mid-seventeenth century cooling, the population in Ireland fell by at least one-fifth, the rural population in Germany may have declined by thirty to forty percent, and Census data from Poland, Russia and the Ottoman empire suggest that the population fell by one-third Parker (2013, loc. 1296). During 1600-1650, the temperature cooled by up to two degrees Celsius in Scotland, leading to a severe reduction in agricultural production; 100,000 men, which comprise one-fifth of the male population are believed to have left Scotland during this period to live abroad Parker (2013, loc. 3065). At the end of the 17th century, after a series of bad harvests, Finland lost as much as a third of its population from famine and disease Fagan (2000, loc. 1498).

Climate change was not uniform across regions or over time. This is driven by the geographical variation in the areas that we examine. "Climate change varied not only from year to year but from place to place. The coldest decades in northern [western] Europe did not necessarily coincide with

those in say Russia....” Fagan (2000, loc. 612). In fact, the Russian empire absorbed a significant number of emigres from devastated regions such as France and Germany.

Coastal and high altitude areas were often more affected due to the freezing of coastlines and the movement of glaciers. For example, during the coldest period of the seventeenth century, sea temperatures along the Norwegian coast fell below two degrees Celsius for twenty to thirty years. The Faroe cod fisheries stopped producing during this period as the sea surface temperature became five degrees colder than today. Production was scarce as far south as the Shetland Islands. Fagan (2000, loc. 834, 1308). During the late 17th century, the ice laid only thirty kilometers from shore along parts of the Dutch coast, such that many harbors were closed and shipping halted in the North Sea Fagan (2000, loc. 1291). Alpine glaciers expanded during 1546 and 1590, and again during 1600 and 1616 Fagan (2000, loc. 1396). “Between 1628 and 1630, Chamonix lost a third of its land through avalanches, snow, glaciers and flooding....” Fagan (2000, loc. 1397). Similarly, flood plains were affected by flooding and areas in drier climates are more susceptible to droughts.

The Eastern Mediterranean experienced particularly severe climate change during the Little Ice Age. “Most areas suffered drought and plague in the 1640s, the 1650s and again in the 1670s, while the winter of 1684 was the wettest on record for five centuries, and the winters of the late 1680s were at least 3 Celsius cooler than today” Parker (2013, loc. 5727). For several decades, the areas near the Aegean and Black seas also experienced general cooling and the worst droughts of the millennium Parker (2013, loc. 5582).

## 2.2 Climate and Conflict

Several historians and political scientists have noted that upticks in historical conflict were associated with climate change (e.g., Lamb, 1995). For example, during the seventeenth century, Europe only experienced three years of complete peace, while the Ottoman empire only experienced ten years Parker (2013, loc. 436). Recently, political scientists document that conflict was positively associated with cooling over time (Lee et al., 2013).

Historians provide a large body of evidence that the reduction in agricultural productivity led

to conflict. Such conflict took many forms. There are examples of peasant rebellions in times of famine Parker (2013, Ch. 3). Historians have also linked foreign invasions to climate change, in particular, to cooling. This could be due to a reduction in the cost of invasion because natural barriers such as rivers or seas freeze over, allowing for more easy troop movement, or because reduced agricultural production increased demand for other sources of revenues and incentivized governments to invade relatively fertile neighbors. At the same time, belligerent neighbors sometimes viewed the weakening of state capacity caused by climate change as a good opportunity for invasion. For example, in 1686-7, the Ottoman Empire experienced its second severe cold spell of the century (i.e., it was the second time that the Golden Horn froze over), and for several years, it had experienced months of winters with no precipitation and summers with record high level of precipitation. The impoverished government did not pay its army, which mutinied and forced Mehmet IV to abdicate, the fifth forced removal within sixty years. During this time, the Hapsburgs and Venetians attacked. In 1699, after the Golden Horn froze again, the Ottomans signed a peace treaty where it ceded most of modern Hungary and Greece Parker (2013, loc. 5706). Conflicts of different forms often occurred simultaneously during periods of climate change. For example, in the early 1600s in Russia, "20 years of famines, rebellions, and civil wars and invasions by both Sweden and Poland had reduced the Russian population by one-quarter" Parker (2013, loc. 4257).

The impoverished agricultural sector made it easy for governments to recruit soldiers. After the Great Winter of 1708-9, a French general said "we could only find so many recruits because of the misery of the provinces ... The misfortune of the masses was the salvation of the kingdom" Parker (2013, loc. 3091). Thus another reason climate change could increase conflict would be by reducing the cost of arming.

## 2.3 Adaptation and Intensification

The discussion so far provides many examples of how the effects of climate change on conflict intensified as climate change continued. Specifically, the historical accounts suggest that continued climate change can weaken state capacity, which in turn reduces internal political stability and

make states vulnerable to external invasion as well as internal strife. A striking example of reduced state capacity is the Ottoman Empire. Parts of the Ottoman Empire experienced severe cooling and suffered repeated agricultural productivity shocks during the late 16th and the first half of the 17th centuries. "In several regions of Anatolia, the number of rural taxpayers fell by three-quarters between 1576 and 1642, and almost half of all villages disappeared" Parker (2013, loc. 5191).

At the same time, historical accounts also give examples to suggest that afflicted populations were able to adapt with time. There are numerous accounts of migration and the relocation of economic activity. Production of certain types of crops permanently ceased in some regions. For example, exceptionally harsh winters during the 1430s significantly reduced wine production in Britain. In 1469, wine production stopped altogether. During the coldest period of the seventeenth century, sea temperatures along the Norwegian coast fell below two degrees Celsius for twenty to thirty years. The Faroe cod fisheries stopped producing during this period. Production was scarce as far south as the Shetland Islands and did not fully recover until 1830 Fagan (2000, loc. 993).

Historians also argue that farmers sometimes adapted to their new environments by experimenting with new agricultural technologies, which improved productivity. For example, Flemish and Dutch farmers used windmills to drain the land of excess precipitation and began to experiment with lay farming and crop rotation. Dutch engineers developed better methods for reclaiming land and protecting against floods during the 1600s Fagan (2000, loc. 1215-6). To cope with colder winters, northern European farmers introduced turnips and potatoes as field crops in the mid- and late-1600s and early-1700s Fagan (2000, loc. 1235).[12]

Another example occurred in Norway, where the traditional industry of fishing suffered severely from the cold temperatures of the 17th century. By the beginning of the 18th century, many coastal villages had been abandoned and instead, the population engaged in logging, the export of timber and ship building. Norway developed a large merchant fleet based on the timber trade, which transformed the economy of its southern regions Fagan (2000, loc. 1307-8).

[12]The effects of new crops is ambiguous ex ante since sometimes, the lack of knowledge caused cultivation to interact poorly with environmental change. For example, the production decline in Ireland in the 18th century was partly caused by the potatoes' vulnerability to precipitation (long droughts followed by excessive rains) Fagan (2000, Ch. 11).

# 3 Conceptual Framework

This paper is interested in understanding the effects of continued, i.e., prolonged, climate change. This section motivates and interprets the empirical specification and is guided by the recent review article by Dell et al. (2014).

As discussed in Dell et al. (2014), studies of climate typically have in mind an underlying economic model which assumes that the relationship between temperature and the outcome of interest is locally linear and that there is an optimal temperature for the outcome of interest. This means that deviations from the optimal level in any direction will reduce productivity. As we discussed in the introduction, our context focuses on colder environments becoming colder, where as studies of the adverse effects of modern climate change typically focus on warm environments becoming warmer. Moreover, temperature deviations from the optimal level also captures increased volatility in the general environment. Thus, the measure of temperature captures several different channels through which climate can affect agricultural production.

In order to establish causality, recent studies of climate change (on any outcome) focus on the short-run effects of temperature/rainfall levels on outcomes such as conflict, agricultural productivity and income (e.g., Dell et al., 2012; Deschenes and Greenstone, 2011; Miguel et al., 2004). Using panel data, such studies estimate

$$y_{i,t} = -\alpha T_{i,t} + \rho_i + \varsigma_t + \varepsilon_{i,t}, \tag{1}$$

where outcome levels in region $i$ and time period $t$ is a function of the level of the climate variable, typically temperature or rainfall, $T_{i,t}$, region fixed effects, $\rho_i$, and time fixed effects, $\varsigma_t$. For the purpose of simplifying the discussion, we will just refer to $T$ as temperature. Region fixed effects control for time-invariant differences across regions that would affect conflict levels, such as geography. Time fixed effects control for common trends in conflict, such as changes in military technology. Variation in temperature, $T_{i,t}$, is assumed to be exogenously driven. In our setting, the cross section unit $i$ is a grid-cell, and the time period is a decade, which we denote $d$. The outcome

of interest, $y_{i,d}$, is the incidence of civil war i grid cell $i$ during the decade $d$.

To estimate effects of continued climate change beyond the short-run year-to-year variation, existing studies adopt two different strategies. The first is to plug the short-run estimates into a "business-as-usual" model. By construction, "business-as-usual" models hold factors important for long-run effects, such as the factors of productivity, constant. A well-known recent example of this is Deschenes and Greenstone (2011), which finds that short-run temperature fluctuations increase mortality and energy consumption. They interpret the latter as a proxy for air temperature control used to mitigate the negative effects of environmental temperature fluctuations – i.e., adaptation. They then plug their estimates into a "business-as-usual" climate model to project long-run effects.

A second approach uses long-difference measures of temperature (e.g., the difference in mean temperature for the past three decades and the mean temperature in the previous three decades) to estimate the long-run effect of climate change on outcomes. Existing works have used this approach to estimate medium-run effects of climate change over fifty or sixty years. For example, Dell et al. (2012) find that temperature increases during 1950 to 2003 reduce income and growth across countries. They find modest effects of adaptation. In a working paper, Burke and Emerick (2015) finds that temperature change over 1950 and 2005 reduced U.S. agricultural productivity.

The long-differences can be estimated as follows:

$$\Delta^k y_{i,d-j} = y_{i,d-j} - y_{i,d-j-k} = -\alpha(T_{i,d-j} - T_{i,d-j-k}) + \varepsilon_{i,d} = \alpha \Delta^k C_{i,d-j} + \varepsilon_{i,d}, \qquad (2)$$

where $\Delta^k C_{i,d-j} = -(T_{i,d-j} - T_{i,d-j-k})$ is the cooling in the $k$ decades after decade $d-j$ (i.e. from decade $d-j$ to $d-j-k$). Note that we define $\Delta^k C_{i,d-j}$ as the negative of a change in temperature so that it is positive in sign if there is cooling to make the interpretation of our results easier since the relevant climate change in our context is cooling.

This specification focuses on the effect of a change in climate, but is directly motivated from the levels equation, equation (1). Taking first differences controls for time-invariant differences in

conflict. It addresses, for example, the possibility that the evolution of conflict differs according to past levels of conflict. Another motivation for examining the first differences of the outcome variable is that there may be spurious trends in outcomes such as income or agricultural production.

The long-difference specification, equation (2), makes several strong implicit assumptions. To clearly see this, consider our preferred specification of a distributed lag model, where we interact two non-overlapping periods of cooling.

$$\begin{aligned}\Delta^5 y_{i,d-5} = \alpha_1 \Delta^5 C_{i,d-5} + \alpha_2 \Delta^5 C_{i,d-10} \\ + \beta(\Delta^5 C_{i,d-5} \times \Delta^5 C_{i,d-10}) + \delta_d + \varepsilon_{i,d}.\end{aligned} \tag{3}$$

Following existing medium-run studies, we focus on changes over about five decades, $k = 5$, so that $\Delta^5 y$ denotes a change in $y$ over five decades.[13] Thus, the equation implies that a change in conflict over a fifty year period (from decade $d-5$ to the current decade) in region $i$, $\Delta^5 y_{i,d-5}$, is a function of: cooling over the same five decades in region $i$, $\Delta^5 C_{i,d-5}$; cooling over the previous five decades in region $i$, $\Delta^5 C_{i,d-10}$; the interaction of cooling in the two periods, and a vector of time (decade) fixed effects; $\delta_d$.

It is easy to see, that aside from the time fixed effects, the long-difference model in equation (2) is essentially a special case of our preferred specification, where $\alpha_2 = 0$ and $\beta = 0$. The long-difference model therefore assumes that *i*) the effect of climate change occurred in earlier periods has no effect on conflict during the current period, and *ii*) there are no interaction effects over time.

This makes clear the two important conceptual difference between our preferred flexible specification and the long-difference model. First, the flexible model allows the effect of cooling in earlier periods to also matter, $\alpha_2$ doesn't have to equal zero. Second, we all for the effect of cooling to vary according to duration. This is how we will infer the presence of adaptation and intensification. We cannot separately identify adaptation from intensification. $\beta < 0$ implies that adaptation dominates intensification, and as such provides evidence for the presence of adaptation. $\beta > 0$

[13] We will discuss the interval length in more detail in our Data section.

implies that intensification dominates adaptation, and as such, provides evidence for the presence of intensification.

The cumulative effect of cooling for two consecutive fifty-year periods is $\alpha_1 + \alpha_2 + \beta$. If $\alpha_1 + \alpha_2 + \beta > \alpha_1$, then the effect of cooling on conflict is increasing with the duration of cooling.

Besides these main conceptual differences, there are several practical features of our baseline specification to keep in mind.

First, note that we have included time fixed effects because our panel is very long and we need to control potentially spurious trends in conflict and climate that are common to all grid-cells. In other words, climate change (in the historical context) is exogenous, so the main identification concern is spurious correlates.[14] We acknowledge that in controlling for time fixed effects, we tradeoff the identification difficulty of omitted variables for the other identification difficulty of over-controlling – i.e., the inclusion of time period fixed effects alters the interpretation of our estimates of interest to be the effect of climate change that deviates from changes that are common to all locations in our sample. Thus, our estimates miss the effects of common climate shocks.

The same tradeoff applies to region fixed effects, which we have not yet discussed. Not controlling for region fixed effects raises the concerns that cooling occurred in regions that experienced other changes which could increase conflict. Controlling for region fixed effects demeans the left- and right-hand-side variables by their regional-mean (i.e., the mean change in temperature over time in each region), which would alter the interpretation of the coefficients to be the effect of change that deviates from the mean rate of change. This turns out to not be a problem in our context because temperature (and conflict) both increase and decrease over our very long time horizon, such that the mean rate of change is around zero. Thus, demeaning by the regional average does not alter the coefficients.

Our main baseline specification will therefore control for both time, $\delta_d$, and region (grid-cell), $\rho_i$, fixed effects.

[14]Climate change in the 20th century has been argued to be an outcome of human actions. To the best of our knowledge, the major human-induced environmental changes in our context such as deforestation did not affect the atmospheric temperature.

$$\Delta^5 y_{i,d-5} = \alpha_1 \Delta^5 C_{i,d-5} + \alpha_2 \Delta^5 C_{i,d-10} \tag{4}$$

$$+ \beta(\Delta^5 C_{i,d-5} \times \Delta^5 C_{i,d-10}) + \delta_d + \rho_i + \varepsilon_{i,d} \tag{5}$$

There are many other potential omitted variables that can confound the interpretation of the estimates. For example, the historical evidence discussed earlier suggests that cooling was more pronounced in coastal areas, which may have experienced changes in other factors that could have influenced conflict. We do not attempt to control for these omitted variables in the baseline because each additional control introduces the tradeoff that we just discussed. On the one hand, it will reduce the concern of omitted variables. On the other hand, it alters the interpretation of the estimates. After we present the baseline results, we will show that the baseline estimates are if anything, conservative relative to when we include additional controls. Thus, the main results are unlikely to overstate the true effects of cooling because of omitted variables.

The second feature to note is that our data are at the decade level (for reasons that we will later discuss) and the explanatory variables are overlapping fifty-year intervals. We will discuss the length of the interval in the next section on Data. Here, we point out that there is significant serial correlation in climate variables, and the overlap of intervals will increase the serial correlation. To address serial correlation, we cluster all of our standard errors at the region level.

# 4 Data

## 4.1 Conflict

We use two sources of data to construct a digitized and geo-referenced historical conflict database. The main data is Michael Clodfelter's 2008 *Warfare and Armed Conflicts*, a statistical encyclopedia of global conflicts between 1494 and 2007. To be comprehensive and provide a some cross-validation, we also coded conflicts from Brecke's *Conflict Catalogue*, a compilation of the annual

record of all violent conflicts with a Richardson's magnitude 1.5 (equal to 32 battle deaths) that occurred between 1400 CE and the present.[15] The coverage for Europe, the Middle East, North Africa and the Near East is complete. This determines the geographic scope of our data.

The final sample is the union of the two datasets.[16] Both sources report the locations of the battles included in the dataset. Combining the two datasets allow us to maximize coverage and accuracy.

Over the course of six years, we manually geo-referenced and digitized the dates of each conflict. The main difficulty in coding the data is that several hundreds of conflicts had location names that matched multiple places during the time-period of the conflict. In these cases, we researched the conflict in question to pinpoint the correct location. In the sample that we use for this paper, there are 2,787 battles.[17]

The main estimates use a balanced grid-level panel, where each observation is a $400km \times 400km$ grid-cell and a decade interval. The temporal and spatial resolution of our observations is determined by the climate data, which we describe further below. The panel ranges from 1401 to 1900. Since we observe the data at ten-year intervals, temperature in 1410, will, for example, refer to mean temperature during the 1401-1410 window, and conflict in 1410 will refer to the incidence of conflict from the 1401-1410 interval. Our panel is very long, especially when compared to typical studies in the climate change or conflict literatures. This is an important advantage because

[15]The Brecke data are reported at the war level. However, for each war, it lists all of the battles. We code this additional information into a battle-level dataset. A limitation of this data is that it only lists up to four battles per war, which is problematic for studying long-lasting or large wars. For each war recorded in the catalog, the primary information covers (*i*) the number and identities of the parties involved in the conflict; (*ii*) the common name for the confrontation, if it exists; and (*iii*) the date(s) of the conflict. On the basis of these data, there also exists derivative information on the duration of conflicts and the number of fatalities, but the latter are only available for less than a third of the sample. For more information on Brecke's dataset and for an application of his data see Iyigun (2008).

[16]Our results are similar if we use the Clodfelter data only. An alternative large historical conflict dataset is the Jacques data. A recent paper by Gennaioli and Voth (2015) uses war-level information from these data. To check the robustness of our data, we also geo-referenced and digitized the battle-level data. The two datasets are quite similar (see Appendix A.1). Thus, it is not surprising that the baseline estimates is qualitatively similar between the two data . We prefer the Clodfelter data because it is better documented (e.g., sample restrictions are clearly articulated). The results from using only Clodfelter or Jacques are available upon request.

[17]An alternative large historical conflict dataset is the Jacques data. A recent paper by Gennaioli and Voth (2015) uses war-level information from these data. To check the robustness of our data, we also geo-referenced and digitized the battle-level data. The two datasets are quite similar (see Appendix A.1). Thus, it is not surprising that the baseline estimates is qualitatively similar between the two data (available upon request). We prefer the Clodfelter data because it is better documented (e.g., sample restrictions are clearly articulated).

it means that we can control for time period and grid-cell fixed effects even when we examine the influence of climate change measured over long time intervals. Our sample only includes conflicts fought on land.[18]

Figure 1 plots the conflicts in our data onto a map according to when the conflict occurred. It shows that over time, conflicts moved from being mostly in the northwestern parts of our sample to the southeastern parts. Thus, later, it will be important to show that our results are robust to controlling for latitude interacted with time effects.

For reasons that we will discuss later when we discuss the climate data, a unity of observation is a decade and a 400km grid-cell. These grids are very large. For example, modern day France is less than four grids. This is important since it means that the grid is likely to capture the conflict caused by environmental fluctuations. For example, disruptions to agricultural productivity can lead to migration, which will lead to conflict not just in the original location, but also the destination of the migrants. Very small grid-cells are unlikely to capture these conflicts, where as the 400km grid-cell is likely to capture them.

Following existing empirical studies on conflict, such as Miguel et al. (2004), our main outcome variable is the incidence of conflict. This makes our estimates easier to compare to existing ones on the short-run effects of weather and conflict. It also mitigates concerns of measurement error since the measure of the number of battles is more vulnerable to measurement error than that of the incidence of conflict.

While our underlying data is at the conflict level, it is interesting to note that conflicts belong to larger wars. The 2,787 battles in our sample belong to 912 wars. We are able to code several characteristics at the war level. For example, we can compute the size of the war in terms of the number of conflicts. On average, there are two conflicts per war. But there is significant variance, from one to 74 conflicts (the peninsular Napoleonic War, 1807-1814). Around 20% of battles belong to single-conflict wars.

We also know whether a war was an inter-state (involved actors from multiple states) or intra

[18]There are very few sea battles (less than 300 for the entire sample).

state (involved actors from within a state). Later, we will use this information to divide the conflict data, although we note that historical concepts of states often differ from modern concepts of states.

## 4.2 Climate

Historical temperature data are provided by climatologists, who use climate proxies to infer historical temperature Mann et al. (2009). More than a thousand tree-ring, ice core, coral, sediment, and other assorted proxy records spanning the ocean and land regions of both hemispheres are applied to a climate field model to reconstruct the historical data. The data have global coverage and report average temperature for five degree latitude by five degree longitude grids, and are available for each year from fifty0 to 1959.[19] The data are most accurate for the Northern Hemisphere where our study takes place because of the large number of climate proxies from that region.

The data accurately proxy for decadal temperature averages, but not for less disaggregated time periods. Similarly, they are accurate as averages over space, but not for specific geographic points. See Mann et al. (2009) for a detailed discussion of the data. Our analysis will therefore be at the decade and $400km^2$ grid-cell level.

The historical temperature data are reported as deviations from the 1961-1990 mean temperature in units of degrees Celsius. Figure 2a plots the average temperature for each decade. On average, the decadal means are below zero, which means that the period we study is on average cooler than the modern period. Consistent with historical accounts, the data show three major periods of cooling. The first begins during the middle of the 15th century and lasts until the end of that century. The second begins approximately at the beginning of the 17th century and lasts for one century. The third is of shorter duration and occurs towards the beginning of the 19th century and lasts for three decades.

Figure 2b plots the decadal temperature means and standard deviations. It shows that there is significant spatial variation in temperature for any given decade.

[19] One degree is approximately 111km. At the northern latitudes that we examine, one degree longitude is on average 80km.

To better illustrate the long-run trends, Figure 2c plots the fifty-year moving averages of the temperature means. The pattern corresponds to historical accounts to show severe cooling during the late 15th century, the mid 17th century and the early 19th century. The figure shows that the long-run trend is flat and mean temperature "cycles" between cooling and warming. And as we discussed earlier, mean temperature change (over time) across regions is around zero, which means that over the fifty0-year sample period, the cumulative amount of cooling roughly equals the cumulative amount of warming.[20] However, the duration of cooling episodes can still vary across regions and over time. This variation is important, since it drives our empirical estimate.

To observe the variation in the duration of cooling, Table 1 lists the number of decades that are cooling (relative to the previous decade) within a given period. For example, in the first row, we show the number of decades that experienced cooling within five decades. The minimum and maximum possible number of decades to experience cooling within five decades are zero and five. Indeed, we find that there are some cells that go through five decades with no cooling, and others that experience cooling in five consecutive decades. The second row show that within ten decades, there are cells which experience no cooling, but no cells experience cooling in all ten decades. Instead, the maximum number of decades of cooling within ten decades is nine. We see that there are regions that experience no cooling for as long as 150 years. In contrast, in some regions, there is persistent cooling over a long duration. In our sample, some regions cool for 5, 9, 11, 16 and 18 decades during fifty, 100, 150, 200 and 250 years, respectively. The disparity between the minimum and maximum number of decades of cooling is also reflected in the large standard deviation. On average, observations experience 2.5, 5, 7, 9, and 9.6 decades of cooling during 50, 100, 150, 200 and 250 years, respectively.

The fact that the duration of cooling varies across regions together with the fact that the mean change over time is around zero implies that all regions experience temperature declines that roughly equal temperature increases – i.e., temperature "cycles" or that the long-run trend for the fifty0-year period is flat, but the length of the cycles differ across regions.

[20] Specifically, $\overline{\Delta^5 C_{i,d-5}} = -.0084$ $(std.dev.\ 0.033)$. In our sample, mean conflict incidence change is also zero: $\overline{\Delta y_{i,d-5}} = -.0004$ $(std.dev.\ 0.014)$.

To visualize the spatial variation in cooling, we calculate the amount of cooling for every fifty year interval, and then for each interval, rank cells according to how much they cooled. Figure 4 maps the rank of cooling. The darkest blue represents the most cooling and the warmest orange represents the least cooling (i.e., warming). For brevity, we only present maps for the three periods with the most average cooling.

Several features emerge from the maps. First, there is significant spatial variation in each period. Second, cooling is not concentrated along latitude or longitude, or in a given region. For example, Figure 4a shows that during the 15th century, there was cooling all along the Atlantic coast, around the Mediterranean, where the most severe cooling was experienced in present day Turkey. Figure 4b shows that during the 17th century, the most severe cooling was felt in northern central and easter Europe in present-day Ukraine and western Russia. Figure 4c shows that during the 19th century, cooling abated in the central parts of northern Europe in relative terms, and increased in the Mediterranean.

The Mann et al. (2009) data are available as far back as fifty0 A.D. However, the data become less accurate at the regional level as one goes further back in time because of the limited number of climate proxies for earlier periods. To the best of our knowledge, existing studies have only used these earlier data to examine global trends, and have not used the regional variation in these data. We follow the existing literature on the Little Ice Age to begin our investigation with climate data in 1400 (e.g., Mann et al., 2009; Waldinger, 2014). For our sample, the main concern is that there were fewer climate proxies and thus lower quality data prior to 1600.[21] After we present the baseline results, we will show that our main findings are robust to the exclusion of data from this earlier period.

Another concern with the historical climate data is classical measurement error, which can bias the estimates. For the uninteracted terms, the bias will be towards zero. For the interaction term, the bias is ambiguous. We will address this concern after we present the main results.

Note that another source of historical temperature data is the Luterbacher et al. (2004) data.

[21] See Mann et al. (2009) for a detailed discussion.

This is reported at the annual level and much smaller geographical units and has been used by studies such as Waldinger (2014). The main difference between this alternative data and our data is that the former supplements geological climate proxies with a large quantity of documentary evidence. We choose to not use these data because documentary evidence raises the concern of reverse causal channels – e.g., people may perceive the weather differently during a conflict, or the availability/quality of temperature measures may be worse during conflict. The Mann dataset only uses a few pieces of documentary evidence. Later in the paper, we will show that our results are similar if we omit this piece of data.

#### 4.2.1 Units of observation, interval lengths, grid size

As we discussed earlier, our unit of observation is at the most disaggregated level of meaningful variation of the temperature data: decade and $400km^2$ grid. Note that as we expand the size of the grid cell, we lose variation in climate change. This can be see from the spatial variation in cooling shown in the maps in Figure 4. Similarly, we have defined the dependent and independent variables of our empirical analysis to be change over fifty year intervals because longer intervals will reduce the variation in climate change (this can be seen from the time variation in average temperature in Figure2a), while shorter intervals are subject to difficulties from serial correlation.

#### 4.2.2 Temperature as a sufficient statistic for climate change

Our main measure of climate change is temperature. It is the only variable that is measured systematically in our context and we interpret it as a sufficient statistic for climatic events which reduce agricultural productivity. This is consistent with the historical evidence: "...an overall decline in mean temperatures is normally associated with a greater frequency of severe weather events – such as flash floods, freak storms, prolonged droughts and abnormal (as well as abnormally long) cold spells. All of these climatic anomalies can critically affect the crops that feed people" Parker (2013, loc. 1102). It is also consistent with modern research on climate change. "In thinking about the impact of climate change, one must recognize that the variable focused on in most analyses – global

averaged surface temperature – has little salience for impacts. Rather, variables that accompany or are the result of temperature changes – precipitation, water levels, extremes of droughts or freezes, and thresholds like the freezing point... will drive the socioeconomic impacts. Mean temperature is chosen because it is a useful index of climate change that is highly correlated with or determines the more important variables" (Nordhaus, 1993).

Table 2 documents this with historical rainfall data, which are available for a subsample of our analysis. These data are reported by Pauling et al. (2006). Column (1) shows that controlling for time-invariant differences across regions and common time trends (i.e., cell and time fixed effects), cooling over two decades is positively, but not statistically significantly, associated with average rainfall. Columns (2) and (3) show that cooling is associated with a decline in rainfall, where rainfall is measured as the cumulative amount of rain and the fraction of years that experience declines in rainfall over a decade. Column (4) shows that cooling is associated with an increase in the variance of rainfall across years (within a decade). These statistics are consistent with our interpretation.

# 5 The Long-Run Effect of Cooling on Conflict

## 5.1 The "Short-Run" effect of Temperature on Conflict

Before our main analysis on the effects of cooling, we first estimate the effect of temperature during the current decade on conflict. This is equation 1. Given the large body of evidence that weather should affect conflict in the short run, and the historical accounts about how colder climates during our context caused conflict, this serves as a "sanity" check. Table 3 reports the estimates. Column (1), which controls only for time period and cell fixed effects shows that the coefficient for temperature is negative and significant, which means that higher temperatures reduce conflict incidence. This is consistent with the historical accounts discussed in Section 2.

## 5.2 Baseline Results

Our study focuses on examining the non-linearity in the relationship between the duration of climate change and conflict. We follow recent studies of the medium-run effects such as Dell et al. (2012) and Burke and Emerick (2015) and assume that the effect of a change in climate over several decades is linear in the magnitude of the change in temperature. However, given the evidence that the relationships between temperature and outcomes such as agricultural production and mortality are non-linear (e.g., Deschenes and Greenstone, 2011; Schlenker and Roberts, 2009), we investigate whether the linearity assumption in the relationship between medium-run change and conflict is reasonable by allowing for higher-order terms. The results in Table 3 columns (2)-(4) show that the higher-order terms have little effect.

To examine whether the relationship between cooling and conflict is monotonic in cooling, we estimate a piecewise linear specification where we regress conflict on three dummy variables for the quartile of change in temperature over the past fifty years (i.e., higher quartiles reflect more cooling). The lowest quartile (which is warming) is the reference group. We control for the baseline controls. Column (5) shows that the coefficients increase in magnitude with the extent of cooling. The coefficient for the most cooling (fourth quartile) is slightly larger than that for the third quartile group, but they are statistically indistinguishable. Thus. there is no evidence for non-monotonicity. For simplicity, we continue to use a linear measure of cooling for the main analysis.

Column (6) estimates the effect of two lags and their interaction controlling only for time fixed effects. In column (7), we include region fixed effects. The two specifications produce nearly identical estimates. As we discussed earlier, this is most likely because mean temperature change and mean conflict incidence change are both roughly zero in our sample. Column (7) estimates our baseline equation, equation (5). It shows that a 1-degree decline in temperature over the past fifty years (which is not preceded by earlier cooling) increases conflict incidence over the same period by 4.14 percentage-points. This is consistent with the short-run evidence that lower temperature increase conflict incidence. In contrast, a 1-degree decline in temperature 100 to fifty years ago (which is not followed by more cooling) has no affect on the change in conflict in the past fifty

years. The coefficient, 0.00442, is statistically insignificant and very small in magnitude. This shows that earlier climate change has no effect on conflict and is consistent with the long-difference model.

The interaction effect is large, positive and statistically significant. It shows that for two regions that experienced cooling in the past fifty years, the region that also experienced cooling in the previous fifty years will experience an increase in conflict in the most recent past fifty years by an additional 9.63 percentage-points. This is evidence for the presence of intensification effects. Specifically, intensification dominates the second type of adaptation effects that we discussed in Section 3. The fact that the interaction effect is significant and non-zero goes against the assumptions of the long-difference model. We will compare the different models more explicitly later when examining the very long-run effects.

At the bottom of the table, we present the sum of the two uninteracted coefficients and the interaction coefficient, as well as the standard error for the joint estimate. It shows that for regions that cooled by one-degree per fifty-years for two consecutive periods (i.e., cooled by two degrees over 100 years), conflict incidence will increase by 13.3 percentage-points relative to a region that did not experience any temperature change in the past 100 years.

To assess the magnitude of the estimate, consider a one-standard deviation decline in temperature, which is 0.224 degrees. Our estimates imply that for a region that experiences two consecutive periods of such decline, conflict incidence will rise by 2.89 percentage-points more than a region that experiences no change in temperature. In our sample, one-standard deviation of a change in conflict incidence is 0.32 percentage-points. Thus, this implies that two consecutive periods of a one-standard deviation decline in temperature results in a 0.09 standard deviation rise in conflict incidence ($0.045/0.322 = 0.14$).

The magnitude is sizable. It is also plausibly moderate since we believe that many other factors determined the overall variation in conflict in Europe during this period.

In column (8), we introduce a control for the level of temperature during the current decade. This addresses the concern that cooling co-moves with temperature levels. Specifically, the effects of

temperature may be non-linear such that temperature below a certain threshold will cause conflict. If the only way to reach this threshold is to experience cooling for, say, 100 years, then the effects of cooling will be confounded by the effects of the level of temperature. Our study is agnostic about the effect of the level, but we would like to be able to distinguish the effect of a change in environmental conditions from the effect of across a threshold, since they are conceptually different. As we discussed earlier, the effect of a change in temperature captures the effect of how conflict responds to environmental change without assuming an optimal level, while the effect of crossing a temperature threshold assumes that there is an optimal level of temperature. Column (8) shows that our results are statistically similar to the inclusion of the current temperature level. At the same time, the negative relationship between current temperature and conflict is robust to controlling for the change in temperature.

## 5.3 Robustness

### 5.3.1 Correlates of Conflict and Cooling

Given the belief that climate change is a largely exogenous variable, our main worry is that cooling occurred in places that had other features which caused them to experience more conflict over time. To address this concern, we control for variables that are potentially correlated with cooling and conflict as motivated by the existing literature. We document these correlations in Table 4, which present the bivariate correlations between cooling over fifty years and the stated variable.

The correlations show that cooling is unrelated to the incidence of conflict in the base year. We define the base period to be 1401-1450 to minimize noise. We can divide conflicts according to the the type of war to which they belonged. Both conflicts from inter-state and intra-state (civil conflicts) during the base period are unrelated to cooling. Alternatively, we can examine the number of conflicts during the base period. It is also uncorrelated with cooling.

Cooling is positively correlated with temperature in the base year, which means that places that experienced more cooling on average were places that were warmer in the base period. At the same time, we find that places that experienced more cooling were those that were less suitable

for the production of both Old World staple crops that existed prior to the Columbian Exchange (wheat, dry rice, wet rice, barley and rye) as well as potatoes, which were introduced as a field crop on continental Europe in the 17th and 18th centuries (Nunn and Qian, 2010, 2011). Note that because of the high correlation across suitability for the five staple crops, we use the first principal component of the five suitability measures provided by the FAO.[22]

Using the Bairoch data for cities, we compute the number of cities per grid-cell in each period. We find that the number of cities in the base period, 1401-1450, is uncorrelated with cooling.

Finally, we examine geographic characteristics which are believed to be correlated with cooling: latitude, longitude, distance to the nearest coastline, slope and elevation. The correlates show that northern and western regions in our sample experienced more cooling. Given the geographic shift in conflict from north to south that we observed earlier in Section 4, this raises the concern that not controlling for latitude can cause our baseline estimates to be confounded.

The correlates show that regions nearer the coast and regions that are flatter experienced more cooling. This pattern of cooling will confound our estimates if coastal areas or regions with flatter terrain experienced other changes during cooling periods that could influence conflict. Over the long time horizon that we study, we are most concerned about the many changes in military technologies which may have changed the costs and benefits of fighting over certain types of terrain.

In Table 5 columns (2)–(7), we control for each potential correlate interacted with time (decade) fixed effects. The interaction allow the influences of the potential confounders to vary fully flexibly over time. In column (5), we control for the suitability for the cultivation of Old World staples interacted with time period fixed effects and the suitability for potato cultivation interacted with a post-1700 dummy variable. The latter control is motivated by the fact that potatoes were not cultivated as an important field crop until the end of the 1600s. We include both the significant and insignificant correlates to be cautious. The magnitudes of the coefficients are almost identical to the baseline shown in column (1). Thus, it is highly unlikely that our main results are driven by spurious correlations.

[22]See the Data Appendix for a description of the FAO data. The first principal component is the only component to have an eigenvalue of more than one. Iyigun et al. (2015) uses a similar measure.

In column (8), we cluster the standard errors at the 800km×800km grid-cell level to address the possibility that our main results overstate the precision of the estimates because of spatially correlated standard errors. This larger level of clustering, which is approximately the size of modern France, has little effect on the standard error.

### 5.3.2 Alternative Time Periods

Another concern arises from the relative inaccuracy of the weather data from the earlier time periods. Mann et al. (2009) discusses how the data are most accurate after 1600, when there were a large number of weather proxies. Thus, we check that our results are robust to excluding data from these earlier periods. Table 6 presents the full sample baseline estimates, and estimates from using data from 1400-1700, 1fifty0-1800 and 1600-1900. The positive coefficient for cooling in the most recent period is significant and similar in magnitude for all three periods, except the first when the climate proxy data are known to be less reliable. The coefficient for cooling during the earlier period is small in magnitude and statistically insignificant in all sub-samples. The interaction coefficient is positive, similar in magnitude and statistically significant in all three sub-samples. The joint estimates at the bottom of the table show that the cumulative effects for cooling that lasts 100 years is significant for all periods. Thus, our main results are robust to using only data from the later periods when the data are most accurate.

### 5.3.3 Measurement Error in Temperature

The historical temperature data are constructed using climate proxies, which are interpolated over time and space. This raises the concern of measurement error, which is probably classical given the way the temperature data are modeled.[23] To the best of our knowledge, existing studies that have used these data have not addressed the concern of measurement error and have simply treated the temperature measures as observational data. This is what we do in our main analysis. In this section, we consider the possibility of classical measurement error. For the uninteracted variables,

[23] See Mann et al. (2009) for a detailed construction.

this measurement error implies attenuation bias. For the interaction term, the sign of the bias is ambiguous. Our concern is therefore that the large positive interaction effect is a result of measurement error rather than intensification effects. We know of no obvious econometric methods for dealing with this issue. Thus, to address the concern that the estimated interaction effect is biased upwards, we restrict our sample to observations where there is presumably less measurement error and compare these estimates to the full sample estimates.

Table 7 presents the results. Column (2) uses grids that have at least one climate proxy in any time period (not every observation contains a climate proxy). Column (3) further restricts the sample to observations that have at least one climate proxy. Column (4) further restricts the sample to grids that contain a climate proxy for every period. The interaction effects in columns (2)-(4) range from 0.094 to 0.2 and are similar or larger than the full sample estimate of 0.087 in column (1). Since there is presumably less error in measurement in columns (2)-(4), these results suggest that the interaction effect is unlikely to be biased upwards by measurement error. We note that the precision declines with the sample size.

In column (5), we exclude the few observations with documentary evidence as climate proxies. This addresses the concern of reverse causal channels – e.g., people may perceive the weather differently during a conflict, or the availability or quality of temperature measures may be worse during conflict.[24] The results are nearly identical to the full sample.

#### 5.3.4 Spurious Correlation with Large Wars

Given that the largest wars have 74 battles, one may be concerned that our results are driven by spurious correlations between large wars and cooling. For example, if a region experienced cooling when a large war occurred for spurious reasons, then our results will be confounded. To address this, we alternatively omit the 25 largest wars from the sample. As we discussed earlier, the largest war contains 74 battles. The 25th largest war contains 18 battles. Our results are unchanged. See Appendix Table A.2.

[24]Note that this is why we do not use the Lutebacher historical climate data.

## 5.4 Heterogeneous Effects

**Geography** Our interpretation of the main results is that climate change – i.e., cooling – increased conflict because it reduced agricultural productivity. To explore this idea further, we examine whether the effects vary according to agricultural productivity. Table 8 Columns (1) and (2) divide the data according to whether a cell is suitable for the production of Old World staple crops: wheat, dry rice, wet rice, rye and barley. We measure suitability as the first principal component of suitability for these five crops. Then, we divide the sample according to whether a grid is above or below the sample median. The estimates show that our main results are driven by regions that are more suitable for agricultural production. The coefficients in column (2) are larger in magnitude and more precise than those in column (1). Columns (3) and (4) restrict our attention to suitability for the cultivation of staples that survive better in cold climates – rye and barley – and potatoes, which was introduced after the Columbian Exchange. The results are similar to the earlier results for agricultural suitability for all staples. These results imply that cooling increased conflict more in regions that were more suitable for agricultural production. This is consistent with the notion that a reduction in agricultural productivity should not have a large impact on conflict in regions that weren't necessarily productive.

Next, we divide the sample according to whether they are near or far from the coast. Ex ante, the direction of the difference is ambiguous. On the one hand, coastal areas rely less on agriculture, which means that climate change can have a smaller effect on conflict. On the other hand, the historical accounts in Section 2 discuss how the freezing of coastline often made countries more vulnerable to invasion. Similarly, the freezing of trade routes could reduce the inflow of food and revenues from exports. We calculate the distance from the center of each grid to the nearest coastline and divide the sample into cells that are above or below the median. Table 8 columns (5) and (6) show that the effects are qualitatively similar between coastal and inland regions, but the magnitude is larger for inland regions, which is consistent with the notion that coastal areas are less sensitive to shocks on agricultural productivity.

Similarly, we examine the effect for urban and non-urban regions. We divide the sample ac-

cording of whether a cell contained any cities in 1401-1450. Most cells did not contain any cities. Thus, the sample size in column (7) is much larger than that in column (8). The signs of the estimates are similar for both samples. The magnitudes are much larger for cells with cities. This could be due to a mechanical relationship between population and conflict. For example, consider the extreme scenario – conflict cannot arise in an unpopulated area. This is also consistent with the notion that urban areas were more vulnerable to agricultural productivity shocks, since they relied on production from other areas. However, the estimates for the urban cells are statistically insignificant, which is not surprising given the small sample size. The estimates for the sample without cities are statistically significant.

Finally, we divide the sample according to the mean temperature during 1401-1450. This is motivated by studies, such as Burke and Emerick (2015),Dell et al. (2012), and Waldinger (2014), who investigate the scope of adaptation by examining whether the relationship between temperature levels and outcomes differ according to base-period temperature. The logic in these earlier works is that, if technological adoption can mitigate the effects of climate change, then the adoption cost should be lower for places with baseline temperatures that are closer to the temperatures that occurred with climate change. The results in columns (9) and (10) are qualitatively similar to regions that were above and below the median. The interaction effect is larger in magnitude for regions that were colder in the base period.

**Type of Wars** The results so far follow studies such as Miguel et al. (2004) and Dube and Vargas (2013) and examine conflict incidence as the dependent variable. We can alternatively examine number of conflicts and number of conflict onsets. Table 9 column (1) restates the baseline result for changes in the conflict incidence. Column (2) examines the changes in the logarithm of the number of conflicts in each cell. We take the logarithm so that we can interpret the change as a percentage difference. In column (3), we examine the change in the logarithm of the number of conflict onsets. Onsets are defined as new battles. In both columns, we add 0.1 to the number of battles and the number of new battles in each cell and decade so that we do not lose observations

with no conflict or no new conflict. The estimates are qualitatively similar to the results for conflict incidence.

In columns (4) and (5), we divide the data according to whether a conflict belonged to an intra-state or inter-state war. We find that the estimates are qualitatively similar for both types of conflicts. The coefficient for cooling in the most recent period is statistically significant for both periods. The interaction coefficient is always positive and large in magnitude, but less precisely estimated for inter-state conflicts. The effect of earlier cooling is small in magnitude and statistically insignificant for both types of conflict. The cumulative effect shown on the bottom of the table is positive and significant for both types of conflicts. The magnitude is larger for interstate conflicts, but the difference in magnitude between the two types of conflict is not statistically significant. This is consistent with historical accounts which show that cooling increased inter-state as well as civil conflicts. Note that the number of observations is similar in both samples, because we construct the number of each conflict type for each grid cell and time period. In other words, we do not exclude observations with zero intra- or inter-state conflicts.

In columns (6) - (8), we divide the data according to whether a conflict belonged to a small, medium or large war. The size of the war is determined by categorizing conflicts into three equal-frequency groups.[25] We find that the results are driven by medium sized wars. This lends credibility to the results since it is hard for small wars (which mostly contain one battle) to capture intensification, and very large wars are likely to be affected by many factors other than climate change.

**Political Fractionalization** Next, we examine whether regions that were politically more fractionalized were more sensitive to climate change. In columns (9) and (10), we divide the data according to whether a cell contained a border in 1401-1450. On average, almost half of the observations contain a border. We digitized data on borders for every fifty years.[26] The estimates are qualitatively similar in the two types of cells. However, the magnitude is larger in cells with borders. In columns (11) and (12), we divide the data according to whether a cell contained a bor-

[25]The raw conflict data report fatalities. But these data are not systematic.

[26]These are reported by Reed, Frank E. *Centennia: Historical Atlas*. Clockwork Software Incorporated, 2014. http://www.historicalatlas.com.

der in the prior fifty-year period. We find that the results are much larger in regions with a higher number of polities. These results support the notion that regions with higher fractionalization are more sensitive to climate change. More generally, they are consistent with the idea that political fractionalization is an important determinant of heterogeneity.

# 6 The Very Long-Run Effects of Cooling on Conflict

In this section, we take advantage of the length of our panel data to estimate very long-run effects – i.e., up to five lagged periods (250 years). Expanding our baseline equation, we get the following equation.

$$\begin{aligned}\Delta^5 y_{i,d-5} = &\sum_{k\in K_5} \alpha_k(\triangle^5 C_{i,d-k}) + \sum_{k\in K_{10}} \beta_{5,k}(\triangle^5 C_{i,d-5} \times \triangle^5 C_{i,d-k}) \\ &+ \sum_{k\in K_{15}} \beta_{10,k}(\triangle^5 C_{i,d-10} \times \triangle^5 C_{i,d-k}) + \sum_{k\in K_{20}} \beta_{15,k}(\triangle^5 C_{i,d-15} \times \triangle^5 C_{i,d-k}) \\ &+ \beta_{20,25}(\triangle^5 C_{i,d-20} \times \triangle^5 C_{i,d-25}) + X_{i,d}\Gamma + \rho_i + \delta_d + \varepsilon_{i,d},\end{aligned} \tag{6}$$

where $K_5$, $K_{10}$, $K_{15}$, and $K_{20}$ denote the following sets of numbers: $K_5 = \{5, 10, 15, 20, 25\}$, $K_{10} = \{10, 15, 20, 25\}$, $K_{15} = \{15, 20, 25\}$, and $K_{20} = \{20, 25\}$. $k$ denotes a number within a set. Change in conflict is therefore a function of changes in temperature over the past five fifty-year intervals and all of the interactions.

This estimate will suffer from a lack of precision since including additional lags reduces the size of the sample. However, it will provide an interesting illustration of the very long-run effects and shed light on whether the effect of environmental disruptions on conflict diminishes with the duration of the disruptions. We will also compare the flexible functional form that we use to more restrictive ones that are more typical in the literature for estimating medium-run effects to show that the latter are misspecified because they cannot account for intensification effects.

## 6.1 Flexible Estimates

For brevity, we focus our discussion on the estimate with cooling over five lagged periods and all of their interactions that is shown in equation (6).[27] The cumulative effects of cooling and the 90% confidence intervals are plotted in Figure 5. The figure shows the incidence of conflict increases monotonically with respect to the duration of cooling. For example, the incidence of conflict will be approximately 6.78 percentage-points higher in a region that experiences cooling for fifty years (where each fifty-year period cools by one degree) relative to one that experiences no change in temperature. For regions that experience 100, 150, 200 and 250 years of continued cooling (where each fifty-year period cools by one degree), the incidence of conflict will be 28, 31.9, 57.3 and 63.4 percentage-points higher than a region that never experienced any change in temperature during these earlier periods. To put the magnitudes into perspective, recall that a one-standard deviation decline in temperature in the sample is 0.224 degrees. Thus, if temperature cooled by one-standard deviation each fifty-year period, then the incidence of conflict will be 1.5, 6.3, 7.1, 12.8 and 14.2 percentage-points higher in regions that experience cooling for fifty, 100, 150, 200 and 250 years relative to regions that experienced no temperature change. Also recall that one standard deviation in conflict in the sample is 32.2 percentage-points. Thus, if temperature cooled by one-standard deviation each fifty-year period, then the incidence of conflict will be 0.05, 0.2, 0.22, 0.4 and 0.44 standard deviations higher in regions that experience cooling for fifty, 100, 150, 200 and 250 years relative to regions that experienced no temperature change.

The predicted cumulative effects, where temperature cools by one-standard deviation each fifty-year period are shown in Table 10.

**Robustness** To check that the very long-run estimates are not driven by spurious correlations, we introduce a similar set of geographic controls as earlier. We also control for current temperature. Figure 6 plots the cumulative effects with these additional controls. The estimates are very similar to the baseline, which is shown as the thick solid black line, and well within the 90% confidence

[27] The coefficients and standard errors for this estimate and for estimates with fewer lags are shown in Appendix Table A.3.

intervals of the baseline specification. The estimates are shown in Appendix Table A.4.

We also show that the very long-run estimates are not biased upwards by our choice of the dependent variable. When we use alternative measures of conflict, the logarithm of the total number of battles and the logarithm of the total number of new battles, the predicted cumulative effects are larger. These are shown in Appendix Figure **??**.[28] Similarly, our estimates are similar if we cluster the standard errors at the larger 800km grid-cell level. See Appendix Figure A.3.

Finally, we examine the best fit model by using LASSO. We restrict the model to condition on the time and grid-cell fixed effects. The LASSO-chosen model includes four lagged temperature changes and two interactions, including the most recent two lagged periods and their interactions (and the time period and grid-cell fixed effects because of the restrictions that we imposed). The patterns are similar to the main specification and shown in Appendix Figure A.4. However, we note that LASSO is not designed for choosing the correct economic model. Thus, we view the LASSO results as reassuring, but do not use the model as our main specification.

## 6.2 Uninteracted Specification

To understand the importance of allowing full flexibility in estimating the cumulative effects of cooling, we systematically impose additional restrictions on the econometric model until we estimate the standard long-difference model. First, we assume that there are no interaction effects, while continuing to allow the effects of cooling to vary over time. The estimates show that if there is only cooling over one period, only cooling in the most recent period increases conflict. This is consistent with the fully flexible estimates in showing strong evidence for the hypothesis that general equilibrium effects can offset the short-run adverse effects of climate change on conflict (see Appendix Table A.6).[29]

However, the predicted cumulative effects are very different. This can be clearly seen by com-

[28] The coefficients and standard errors are shown in Appendix Table A.5.

[29] Appendix Table A.6 column (1) shows the estimates for equation (6), where we assume that the interaction effects are zero, and include decade and region fixed effects. Columns (2)-(4) gradually add additional lag periods of cooling until we include five lag fifty-year periods of cooling on the right-hand side. The estimates are stable across columns.

paring Figure 7, which plots the cumulative effects from column (4), to Figure 5, which plots the analogous predicted cumulative effects from the fully flexible specification. The scale of the y-axes are similar for comparison purposes. In the uninteracted model, the predicted cumulative effects are constant with the duration of cooling, while in the interacted model, it increases. Mechanically, this is because only cooling in the most recent period matters and the uninteracted models assume that the interactions effects are zero. When we sum the coefficients to estimate the cumulative effects, we simply add the coefficient for cooling in the most recent period to zeros, which results in cumulative effects that are similar to the effect of cooling in the most recent period regardless of how long the cooling lasts.

Intuitively, this reflects the fact that intensification are large and adaptation effects are never sufficient for offsetting them as environmental disruptions are prolonged. However, the uninteracted model misses the intensification effect.

The difference in the cumulative effects estimated from the two models can also be seen in Table 10, which present the cumulative effects when temperature cools by one-standard deviation every fifty years. Column (2) shows that the cumulative effect is roughly constant with the duration of cooling, which contrasts sharply with the flexible cumulative effects in column (1).

## 6.3 Long Difference

Finally, we move to the long-difference model that is used by existing studies to estimate medium-run effects by additionally restricting that cooling which occurred in the past has no effect. This is the least flexible of the three specifications that we compare. We estimate equation (2) (with the addition of time and region fixed effects) five times, where each estimate uses a long-difference over a different interval length. The estimates are shown in Appendix Table A.7. The coefficients from the five regressions are plotted in Figure A.7. The scale of the y-axis is similar to Figures 7 and 5 for comparison. The figure shows that the effect of cooling on conflict is roughly constant with the duration of cooling.

These estimates demonstrate the difficulties with the long-difference estimates that we discussed

in Section 3. The misspecification of the model will severely understate the cumulative effects of cooling for longer intervals.

Note that the magnitude of the predicted effects of cumulative cooling are not directly comparable between the long-difference specification and the earlier specifications. This is because the long-difference coefficient reflects the effect of cooling by one degree over the entire interval, where as the earlier specifications assumed cooling by one degree for each fifty years. To compare the estimates, we therefore consider the implied cumulative effects of the long-difference estimates if each fifty years experienced cooling by one degree. For example, we would multiple the coefficient for the long-difference coefficient for the 100-year interval by two, the coefficient for the 1fifty-year interval by three, etc. These predicted cumulative effects are shown at the bottom of table A.7. Alternatively, we can assume that each fifty years cool by one-standard deviation (0.22 degrees). The predicted cumulative effects are shown in Table 10 column (3).

# 7 Policy Implications

Our empirical strategy offers several important advantages for understanding the effects of future climate change. First, the flexible estimation of multiple lags of climate change can more accurately capture the effects of long-run climate change because it allows the effect of recent changes to differ from earlier ones, and the interaction of climate change in different periods allows for intensification. Second, a comparison of the coefficients for climate change that occurred at different times and explicitly estimating the interaction effects allow us to more clearly identify adaptation and intensification. Third, the fact that we have such a long panel means that we do not need to rely on extrapolations in order to obtain estimates of long-run effects. That said, we acknowledge that there are no regions that actually experience five consecutive periods of cooling. Nevertheless, as (n.d.) point out, the historical data with "long time scales are able to examine 'low frequency' changes in climate that perhaps more closely resemble future anthropogenic climate changes".

There are also several important caveats to bear in mind. First, the historical context, which

is necessitated by the examination of change over a long time horizon, is likely to differ from the modern one is ways that affect the speed of adaptation or the extent of intensification. For example, better infrastructure and more trade can mitigate the effects of climate change (e.g., Burgess and Donaldson, 2010). Similarly, faster rates of introducing new technology such as new seed varieties could greatly reduce the medium-run impact of climate change (e.g., Kyle Emerick, 2015). And the fact that modern economies, even in poor equatorial countries, typically have a larger share of workers in non-agriculture sectors than historical economies could mean that factors can reallocate more quickly (Waldinger, 2014). Since our results show that earlier climate change only affects conflict through its interaction with recent climate change, one can speculate that mitigating the negative influences of recent climate change can substantially reduce the cumulative effects of long-run change. In other words, the effect of global warming on conflict in the future will be smaller than what is implied by our estimates.

Second, the historical context (at least in our Northern Hemisphere context) differs in that the adverse environmental disruption is caused by cooling, whereas the environmental disruption in modern climate change is caused by warming. Conceptually, cooling and warming are similar since both are environmental changes which disrupt traditional economic activities. However, there is some evidence from U.S. agriculture in the 20th century that cooling is less damaging to agricultural productivity than warming by the same magnitude (e.g., Schlenker and Roberts, 2009). If this is generally true, then the effects of global warming on conflict will be larger than what is implied by our estimates.

Notwithstanding these caveats, our results provide several important insights for policy makers who are interested in understanding and mitigating the adverse effects of future climate change. First, our results provide strong evidence for adaptation. However, as the environment continues to change, the cumulative effects will be dominated by intensification such that continued environmental changes can have significant long-run effects on conflict. In other words, adaptation could not keep up with the continued demand for new technologies caused by extended periods of environmental disruptions.

One potential bright side of our results is the finding that climate change which occurred more than fifty years ago only affects conflict through its interaction with recent climate change in the past fifty years, which gives the hope that mitigating the effects of contemporaneous climate change can potentially mitigate the cumulative effects of climate change. This is an important avenue for future research.

We note that our results do not have clear implications for growth in either the modern or historical contexts. For example, studies such as Besley and Persson (2008, 2010) argue that wars, as common public goods, can increase state capacity. In the historical context, Gennaioli and Voth (2015) find that the relationship between state capacity and conflict depends on the baseline level of fractionalization.

# 8 Conclusion

The long-run impact of climate change is one of the most important questions for policymakers and economists today. A large part of the debate revolves around how much society can adapt to climate change and how much time is required to adapt. At the same time, one worries that the effects of prolonged environmental disruption could cause institutions and state capacity to weaken, which would intensify the effects of environmental change. Thus far, there is little empirical evidence to help answer these questions.

We make progress on this issue by examining the long-run effects of climate change on conflict in the historical context. To do this, we construct a large geo-referenced dataset on conflicts covering the period between 1400 and 1900 CE for Europe, North Africa and the Near East, and combined it with recently available historical climate data.

Our long panel allows us to estimate a fully flexible model which allows the effects of cooling to vary depending on when cooling occurred, and the effects of cooling over different periods to interact. We find that climate change significantly increased conflict in the long run. The cumulative effects of climate change on conflict were increasing with the duration of change. Interestingly,

we find strong evidence for both adaptation and intensification. The adverse cumulative effects suggests that adaptation in the historical context could not keep up with the continued demand for new technologies caused by extended periods of environmental change.

We demonstrate that more restrictive estimations will miss the intensification effect and therefore understate the cumulative effects of climate change.

To understand the policy implications for our results, it is important to point out some important similarities and differences between the historical context and the context of modern climate change. As we discussed in the introduction, the fact that cooling reduced agricultural production in our context while warming reduces production in the modern context is an artifact of the fact that historical climate change manifested as cooling in regions that were already cold, while modern climate change manifests as warming in equatorial regions that are already warm. Conceptually, the important point is that both historic cooling in Europe and modern warming in equatorial regions disrupt traditional economic activity. Another important similarity is that both our context and modern equatorial countries that are suffering from climate change today are pre-industrial or early-industrial economies that rely heavily on agriculture, and have poor transportation and communication infrastructures that could facilitate the flow of the factors of production. However, the historical and modern contexts differ in that the countries today engage in much more trade, which could help dampen the effects of climate change by providing other opportunities of economic activity, as well as by speeding up the flow of new technologies to the poor developing countries that are affected by global warming.

The magnitudes of our estimates should be carefully interpreted as specific to our context. However, policymakers should take note of the insight that the effects of climate change can intensify as it continues, and that the cumulative effects can be large over time. At the same time, the finding that earlier climate change only affects conflict through its interaction with recent climate change is hopeful as it suggests that the cumulative effects of climate change may be partly averted by mitigating the adverse effects of recent climate change.

Our study has several important implications for future studies of climate change. First, for

studies of the long-run effects climate change, it demonstrates the necessity of using a flexible estimation. We note that this is probably less important for medium-run studies such as Burke and Emerick (2015) and Dell et al. (2012). Second, our findings show that an important avenue for future research is to understand the mechanisms underlying adaptation and intensification. Finally, our study demonstrates the benefits of using historical data to better understand long-run processes that are directly relevant for development today. We hope that the data which we constructed will be useful to future researchers. The recent reduction in the cost of constructing large historical datasets suggests that this is, more generally, a promising direction for future research.

# References


**Anderson, Robert Warren, Noel D. Johnson, and Mark Koyama**, "Jewish Persecutions and Weather Shocks: 1100–1800," *Economic Journal*, 2016, p. forthcoming.

**Bai, Ying and James Kai-sing Kung**, "Climate Shocks and Sino-nomadic Conflict," *The Review of Economics and Statistics*, August 2011, *93* (3), 970–981.

**Besley, Timothy and Torsten Persson**, "Wars and State Capacity," *Journal of the European Economic Association*, 2008, *6* (2-3), 522–530.

_ **and** _ , "State Capacity, Conflict, and Development," *Econometrica*, 01 2010, *78* (1), 1–34.

**Braga, Alfesio Luis Ferreira, Antonella Zanobetti, and Joel Schwartz**, "The Time Course of Weather-Related Deaths," *Epidemiology*, 2001, *12* (6), 662–667.

**Brecke, Peter**, "Violent Conflicts 1400 A.D. to the Present in Different Regions of the World," 1999. Paper presented at the 1999 meeting of the Peace Science Society.

_ , "The Conflict Dataset: 1400 A.D.Present," forthcoming. Mimeo, Georgia Institute of Technology.

**Burgess, Robin and Dave Donaldson**, "Can Openness Mitigate the Effects of Weather Shocks? Evidence from India's Famine Era," *American Economic Review*, 2010, *100* (2), 449–53.

**Burke, Marshall and Kyle Emerick**, "Adaptation to climate change: Evidence from US agriculture," Stanford University Working Paper, Stanford University 2015.

_ **, Solomon M. Hsiang, and Edward Miguel**, "Climate and Conflict," *Annual Review of Economics*, 2015, *7* (1), 577–617.

**Clodfelter, Micheal**, *Warfare and Armed Conflicts: A Statistical Encyclopedia of Casualty and Other Figures, 1494-2007, 3rd Edition*, Jefferson, N.C.: McFarlane & Company Inc., 2008.

**Crost, Benjamin, Joseph Felter, and Patrick B. Johnston**, "Aid Under Fire: Development Projects and Civil Conflict," *American Economic Review*, 2014, *104* (6), 1833–1856.

**Curriero, Frank C., Karlyn S. Heiner, Jonathan M. Samet, Scott L. Zeiger, Lisa Strug, and Jonathan A. Patz**, "Temperature and Mortality in 11 Cities of the Eastern United States," *American Journal of Epidemiology*, 2002, *155* (1), 80–87.

**deJanvry Elisabeth Sadoulet Kyle Emerick Manzoor H. Dar, Alain**, "Technological innovations, downside risk, and the modernization of agriculture," Working Paper, University of California at Berkeley 2015.

**Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken**, "Temperature Shocks and Economic Growth: Evidence from the Last Half Century," *American Economic Journal: Macroeconomics*, July 2012, *4* (3), 66–95.

_ , _ , **and** _ , "What Do We Learn from the Weather? The New Climate-Economy Literature," *Journal of Economic Literature*, 2014, *52* (3), 740–98.

**Deschenes, Olivier and Michael Greenstone**, "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US," *American Economic Journal: Applied Economics*, 2011, *3* (4), 152–85.

**Dube, Oeindrila and Juan F. Vargas**, "Commodity Price Shocks and Civil Conflict: Evidence from Colombia," *The Review of Economic Studies*, 2013.

_ **and Suresh Naidu**, "Bases, Bullets and Ballots: The Effect of U.S. Military Aid on Political Conflict in Colombia," 2013. Mimeo, Columbia University.

**Fagan, B.M.**, *The Little Ice Age: How Climate Made History, 1300-1850*, Basic Books, 2000.

**Gennaioli, Nicola and Hans-Joachim Voth**, "State Capacity and Military Conflict," Forthcoming 2015.

**Hornbeck, Richard**, "The Enduring Impact of the American Dust Bowl: Short- and Long-Run Adjustments to Environmental Catastrophe," *American Economic Review*, 2012, *102* (4), 1477–1507.

**Hsiang, Solomon M. and Amir S. Jina**, "The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence From 6,700 Cyclones," Working Paper 20352, National Bureau of Economic Research July 2014.

_ **, Marshall Burke, and Edward Miguel**, "Quantifying the Influence of Climate on Human Conflict," *Science*, 2013, *341* (151), 1212–1228.

**Iyigun, Murat**, "Luther and Suleyman," *Quarterly Journal of Economics*, November 2008, *123* (4), 1465–1494.

_ **, Nathan Nunn, and Nancy Qian**, "The Long-run Effects of Agricultural Productivity and Conflict: Evidence from Potatoes, 1400-1900," Yale University Working Papers, Yale University 2015.

**Jia, Ruixue**, "Weather Shocks, Sweet Potatoes and Peasant Revolts in Historical China," *Economic Journal*, 2014, *124*, 92–118.

**Kung, James Kai-sing and Chicheng Ma**, "Can Cultural Norms Reduce Conflicts? Confucianism and Peasant Rebellions in Qing China," *Journal of Development Economics*, 2014, *111*, 132–149.

**Lamb, H.H.**, *Climate, History and the Modern World* Climate, History and the Modern World, Routledge, 1995.

**Lee, Harry F., David D. Zhang, Peter Brecke, and Jie Fei**, "Positive correlation between the North Atlantic Oscillation and violent conflicts in Europe," *Climate Research*, 2013, *56* (1), 1–10.

**Ludlow, Francis and Solomon Hsiang**, "No adaptation to climate during one millennium of Irish history," University of Berkeley at California Working Paper April 2016.

**Luterbacher, Jurg, Daniel Dietrich, Elena Xoplaki, Martin Grosjean, and Heinz Wanner**, "European Seasonal and Annual Temperature Variability, Trends, and Extremes Since 1500," *Science*, 2004, *303* (5663), 1499–1503.

**Mann, Michael E., Zhihua Zhang, Scott Rutherford, Raymond S. Bradley, Malcolm k Hughes, Drew Shindell, Caspar Ammann, Greg Faluvegi, and Fenbiao Ni**, "Global Signatures and Dynamical Origins of the Little Ice Age and Medieval Climate Anomaly," *Science*, 2009, *326*, 1256–1260.

**Mendelsohn, Robert, William D. Nordhaus, and Daigee Shaw**, "The Impact of Global Warming on Agriculture: A Ricardian Analysis," *The American Economic Review*, 1994, *84* (4), 753–771.

**Miguel, Edward, Shanker Satyanath, and Ernest Sergenti**, "Economic Shocks and Civil Conflict: An Instrumental Variables Approach," *Journal of Political Economy*, August 2004, *112* (4), 725–753.

**Nordhaus, William D.**, "Reflections on the Economics of Climate Change," *Journal of Economic Perspectives*, 1993, *7* (4), 11–25.

**Nunn, Nathan and Nancy Qian**, "The Columbian Exchange: A History of Disease, Food and Ideas," *Journal of Economic Perspectives*, 2010, *24* (2), 163–188.

_ **and** _ , "The Potato's Contribution to Population and Urbanization: Evidence from a Historical Experiment," *Quarterly Journal of Economics*, 2011, *126* (2), 593–650.

_ **and** _ , "U.S. Food Aid and Civil Conflict," *American Economic Review*, 2014, *104* (6), 1630–1666.

**Oster, Emily**, "Witchcraft, Weather and Economic Growth in Renaissance Europe," *Journal of Economic Perspectives*, 2004, *18* (1), 215–228.

**Parker, G.**, *Global Crisis: War, Climate Change and Catastrophe in the Seventeenth Century*, Yale University Press, 2013.

**Pauling, Andreas, Jurg Luterbacher, Carlo Casty, and Heinz Wanner**, "Five Hundred Years of Gridded High-Resolution Precipitation Reconstructions over Europe and the Connection to Large-Scale Circulation," *Climate Dynamics*, 2006, *26*, 387–405.

**Schlenker, Wolfram and Michael J. Roberts**, "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change," *Proceedings of the National Academy of Sciences*, 2009, *106* (37), 15594–15598.

**Waldinger, Maria**, "The Economic Effects of Long-Term Climate Change: Evidence from the Little Ice Age, 1500-1750," Working Paper, London School of Economics 2014.

Table 1: The Persistence of Cooling

| | # of Decades that Cooled Relative to Previous Decade | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Time Interval | Obs | Mean | Std. Dev. | Min | Max |
| 50 | 15450 | 2.47 | 0.90 | 0 | 5 |
| 100 | 15450 | 4.93 | 1.44 | 0 | 9 |
| 150 | 15450 | 6.98 | 2.29 | 0 | 11 |
| 200 | 15450 | 8.98 | 3.26 | 2 | 16 |
| 250 | 15450 | 9.66 | 4.47 | 2 | 18 |

Notes: Observations are at the decade and $400^2$km cell level.

Table 2: Cooling and Precipitation

| | Dependent Variable: -1 x Temperature Drop (20 Years) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Avg Annual Rainfall | 0.203 | | | |
| | (0.141) | | | |
| -1 x Cummulative Rainfall Drops | | 0.234*** | | |
| | | (0.0836) | | |
| Fraction of Years with Rainfall Drops | | | 0.00272* | |
| | | | (0.00158) | |
| Rainfall Standard Deviation | | | | 0.991*** |
| | | | | (0.355) |
| Observations | 6437 | 6280 | 6280 | 6280 |
| R-squared | 0.454 | 0.460 | 0.460 | 0.460 |

Notes: All regressions control for time and cell fixed effects. The data is a balanced panel at the 400km$^2$ and decade level. The standard errors are clustered at the cell level.

Table 3: The Effect of Cooling on Conflict – Sensitivity to Functional Form and Regional Fixed Effects

| | Dependent Variable: | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | $Conflict_t$ | $\Delta Conflict_{t,50}$ | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) Baseline | (8) |
| $\Delta T_{t,50}$ | | 0.0457*** | 0.0449*** | 0.0603*** | | 0.0405*** | 0.0414*** | 0.0240* |
| | | (0.0143) | (0.0145) | (0.0217) | | (0.0129) | (0.0134) | (0.0129) |
| $\Delta T_{t,50}^2$ | | | -0.0187 | -0.0233 | | | | |
| | | | (0.0194) | (0.0197) | | | | |
| $\Delta T_{t,50}^3$ | | | | -0.0455 | | | | |
| | | | | (0.0302) | | | | |
| $\Delta T_{50,100}$ | | | | | | 0.00222 | 0.00442 | 0.00210 |
| | | | | | | (0.0114) | (0.0119) | (0.0120) |
| $\Delta T_{t,50} \times \Delta T_{50,100}$ | | | | | | 0.0858** | 0.0872** | 0.0873** |
| | | | | | | (0.0361) | (0.0375) | (0.0372) |
| $Temperature_t$ | -0.0251*** | | | | | | | -0.0391** |
| | (0.00795) | | | | | | | (0.0157) |
| $\Delta T_{t,50}$ Dummy Vars | | | | | | | | |
| 2nd Quartile | | | | | 0.0197** | | | |
| | | | | | (0.00999) | | | |
| 3rd Quartile | | | | | 0.0250** | | | |
| | | | | | (0.0104) | | | |
| 4th Quartile (Largest Decline) | | | | | 0.0214* | | | |
| | | | | | (0.0110) | | | |
| Controls | | | | | | | | |
| Grid-cell FE | Y | Y | Y | Y | Y | N | Y | Y |
| Time FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 15450 | 14,214 | 14,214 | 14,214 | 14,214 | 12669 | 12669 | 12669 |
| R-squared | 0.296 | 0.015 | 0.015 | 0.015 | 0.015 | 0.013 | 0.016 | 0.016 |
| **Predicted Cumulative Effects** | | | | | | | | |
| **Cool 100 Years** | | | | | | **0.129** | **0.133** | **0.113** |
| Std. Err. 100 | | | | | | 0.0388 | 0.0403 | 0.0400 |

Notes: Observations are at the decade and $400^2$km cell level. Standard errors are clustered at the cell level.

Table 4: The Correlates of Cooling

| Temperature Decline over 50 Years | |
|---|---|
| Incidence of Conflict 1401-1450 | -0.0058 |
| Civil Conflict | 0.0214 |
| Size of War (# of conflicts in War) | -0.0061 |
| # of Conflicts 1401-1450 | -0.0061 |
| Temperature 1401-1450 | 0.1262* |
| Suitability for Wheat, Dry Rice, Wet Rice Barley and Rye (1st Principal Component) | -0.0458* |
| Suitability for Potatoes | -0.0464* |
| # of Cities 1401-1450 | -0.0064 |
| Latitude | 0.0332* |
| Longitude | -0.0922* |
| Distance to the Coast | -0.0983* |
| Slope | -0.0230* |
| Elevation | -0.0237 |

Table 5: The Effect of Cooling on Conflict – Robustness to Additional Controls

| | Dependent Variable: $\Delta Conflict_{t,50}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Baseline | Conflict Incidence 1401-1450 x Time FE | Conflict # 1401-1450 x Time FE | Temp in 1401-1450 x Time FE | Suitability for Old World Staples x Time FE, Potatoes x post-1700 | # of Cities in 1401-1450 x Time FE | Geographic Controls$^{+}$ x Time FE | Cluster at $800^2$km grid cell |
| $\Delta T_{t,50}$ | 0.0414*** | 0.0417*** | 0.0402*** | 0.0612*** | 0.0331*** | 0.0414*** | 0.106*** | 0.0414** |
| | (0.0134) | (0.0134) | (0.0134) | (0.0228) | (0.013) | (0.0134) | (0.0261) | (0.0158) |
| x $\Delta T_{50,100}$ | 0.0872** | 0.0745** | 0.0827** | 0.102** | 0.0633* | 0.0872** | 0.0938* | 0.0872** |
| | (0.0375) | (0.0342) | (0.0341) | (0.0398) | (0.0380) | (0.0375) | (0.0524) | (0.0419) |
| $\Delta T_{50,100}$ | 0.00442 | 0.00480 | 0.00502 | 0.0191 | -0.0141 | 0.00442 | 0.00461 | 0.00442 |
| | (0.0119) | (0.0115) | (0.0116) | (0.0230) | (0.0136) | (0.0119) | (0.0254) | (0.0106) |
| Observations | 12669 | 12669 | 12669 | 12669 | 11029 | 12669 | 12669 | 12669 |
| R-squared | 0.016 | 0.042 | 0.042 | 0.017 | 0.031 | 0.016 | 0.038 | 0.016 |
| # Clusters | 309 | 309 | 309 | 309 | 269 | 309 | 309 | 85 |
| **Predicted Cumulative Effects** | | | | | | | | |
| **100 Years** | **0.133** | **0.121** | **0.128** | **0.183** | **0.0822** | **0.133** | **0.204** | **0.133** |
| Std. Err. 100 | 0.0403 | 0.0379 | 0.0377 | 0.0485 | 0.0434 | 0.0403 | 0.0630 | 0.0465 |

Notes: The regression controls for cell and time fixed effects. $^{+}$Geographic controls include latitude, longitude, elevation, slope and the distance to the nearest coast. Observations are at the decade and $400^2$km cell level. Standard errors are clustered at the cell level except in column (8), where they are clustered at the larger grid-cell size stated in the column heading.

Table 6: The Effect of Cooling on Conflict – Robustness to Alternative Time Periods

| | Dependent Variable: $\Delta Conflict_{t,50}$ | | | |
|---|---|---|---|---|
| | (1) Full Sample | (2) 1400-1700 | (3) 1500-1800 | (4) 1600-1900 |
| $\Delta T_{t,50}$ | 0.0414*** | 0.0224 | 0.0372** | 0.0464*** |
| | (0.0134) | (0.0158) | (0.0146) | (0.0165) |
| x $\Delta T_{50,100}$ | 0.0872** | 0.104** | 0.0795** | 0.100** |
| | (0.0375) | (0.0419) | (0.0380) | (0.0422) |
| $\Delta T_{50,100}$ | 0.00442 | -0.0168 | 0.00875 | 0.0133 |
| | (0.0119) | (0.0179) | (0.0129) | (0.0166) |
| Observations | 12669 | 6489 | 9270 | 9270 |
| R-squared | 0.016 | 0.017 | 0.014 | 0.021 |
| **Predicted Cumulative Effects** | | | | |
| **100 Years** | **0.133** | **0.110** | **0.125** | **0.160** |
| Std. Err. 100 | 0.0403 | 0.0419 | 0.0408 | 0.0518 |

Notes: The regression controls for cell and time fixed effects. Observations are at the decade and $400^2$km cell level. Standard errors are clustered at the cell level.

Table 7: The Effect of Cooling on Conflict – Robustness to measurement error in temperature

| | Dependent Variable: $\Delta$Conflict$_{t,50}$ | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | Full Sample | > 1 proxy in any time period | > 1 proxy in period *t* | >1 proxy in every period | Omit Documentary Proxies |
| $\Delta T_{t,50}$ | 0.0414*** | 0.0927* | 0.0946 | 0.152 | 0.0424*** |
| | (0.0134) | (0.0526) | (0.0591) | (0.0932) | (0.0135) |
| x $\Delta T_{50,100}$ | 0.0872** | 0.202* | 0.149 | 0.0939 | 0.0898** |
| | (0.0375) | (0.115) | (0.122) | (0.172) | (0.0353) |
| $\Delta T_{50,100}$ | 0.00442 | -0.00516 | 0.000299 | -0.0276 | 0.00831 |
| | (0.0119) | (0.0329) | (0.0375) | (0.0471) | (0.0120) |
| Observations | 12669 | 2255 | 1984 | 984 | 12538 |
| R-squared | 0.016 | 0.049 | 0.060 | 0.070 | 0.015 |
| # Clusters | 309 | 55 | 55 | 24 | 308 |
| **Predicted Cumulative Effects** | | | | | |
| **100 Years** | **0.133** | **0.290** | **0.244** | **0.218** | **0.141** |
| Std. Err. 100 | 0.0403 | 0.118 | 0.130 | 0.183 | 0.0389 |

Notes: The regression controls for cell and time fixed effects.Observations are at the decade and 400$^2$km cell level. Standard errors are clustered at the cell level.

Table 8: The Effect of Cooling on Conflict – Heterogenous effects according to geography

| | Dependent Variable: $\Delta Conflict_{t,50}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Suitability for Agric Production | | | | | | | | | |
| | Old World Staples (Wheat, Rye, Barley, Wet Rice, Dry Rice) | | All Cold Weather Staples (Rye, Barley, Potatoes) | | Distance to Coast | | # Cities in 1401-1450 | | Temp 1401-1450 | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | <= Median | > Median | <= Median | > Median | <= Median | > Median | None | >=1 | <= Median | > Median |
| $\Delta T_{t,50}$ | 0.0212 | 0.0747** | 0.0181 | 0.0755*** | 0.0355** | 0.106** | 0.0404*** | 0.208 | 0.0466 | 0.0323 |
| | (0.0141) | (0.0291) | (0.0135) | (0.0290) | (0.0154) | (0.0488) | (0.0147) | (0.202) | (0.0315) | (0.0289) |
| x $\Delta T_{50,100}$ | 0.0127 | 0.203* | 0.0140 | 0.204** | 0.0656 | 0.0898 | 0.0720** | 0.595 | 0.200** | 0.0439 |
| | (0.0210) | (0.103) | (0.0208) | (0.103) | (0.0488) | (0.0761) | (0.0347) | (0.473) | (0.0812) | (0.0498) |
| $\Delta T_{50,100}$ | -0.00290 | 0.00329 | 0.000177 | 0.000825 | -0.0108 | 0.0358 | 0.00300 | 0.0617 | 0.0113 | -0.00550 |
| | (0.00960) | (0.0215) | (0.00936) | (0.0214) | (0.0133) | (0.0364) | (0.0118) | (0.105) | (0.0293) | (0.0227) |
| Observations | 4860 | 6264 | 4824 | 6300 | 5580 | 5544 | 10152 | 972 | 5508 | 5616 |
| R-squared | 0.023 | 0.027 | 0.022 | 0.027 | 0.018 | 0.031 | 0.014 | 0.091 | 0.024 | 0.020 |
| **Predicted Cumulative Effects** | | | | | | | | | | |
| **Cool 100 Years** | **0.0310** | **0.281** | **0.0323** | **0.281** | **0.0904** | **0.232** | **0.115** | **0.864** | **0.258** | **0.0706** |
| Std. Err. 100 | 0.0240 | 0.115 | 0.0238 | 0.114 | 0.0574 | 0.0798 | 0.0391 | 0.525 | 0.0976 | 0.0535 |

Notes: All regressions control for cell and time fixed effects. Unless stated otherwise, we divide the sample according to whether a cell has above or below median values of the variables stated in the column headings. Observations are at the decade and $400^2$km cell level. Standard errors are clustered at the cell level.

Table 9: The Effect of Cooling on Conflict – Heterogenous effects according to characteristics of the war, and political fractionalization

| | Dependent Variable: $\Delta Conflict_{t,50}$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Alternative Conflict Measures | | | Conflict Incidence | | | | | | | | |
| | | | | War Type | | War Size (# of Battles) | | | Border in Cell in 1450 | | Border in Cell in 50 years ago | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| | Incidence | Ln Conf # | Ln Onset # | Civil | Inter-state | Small | Medium | Large | None | Border | <= Median | > Median |
| $\Delta T_{t,50}$ | 0.0414*** | 0.108*** | 0.125*** | 0.0140* | 0.0222** | 0.00488 | 0.0208** | 0.00927 | 0.0113 | 0.101*** | 0.0125 | 0.114*** |
| | (0.0134) | (0.0372) | (0.0424) | (0.00781) | (0.0105) | (0.00849) | (0.00972) | (0.00717) | (0.00785) | (0.0357) | (0.00912) | (0.0404) |
| x $\Delta T_{50,100}$ | 0.0872** | 0.247** | 0.282** | 0.0357* | 0.0547 | -0.00609 | 0.0922*** | 0.00856 | 0.0321 | 0.0930 | 0.0281 | 0.107 |
| | (0.0375) | (0.106) | (0.120) | (0.0213) | (0.0360) | (0.0202) | (0.0317) | (0.0189) | (0.0201) | (0.0965) | (0.0243) | (0.120) |
| $\Delta T_{50,100}$ | 0.00442 | 0.0211 | 0.0361 | -0.00608 | 0.0120 | -0.0122 | -0.0132 | 0.0343*** | 0.000673 | 0.0126 | -0.00478 | 0.0255 |
| | (0.0119) | (0.0320) | (0.0365) | (0.00886) | (0.0127) | (0.00938) | (0.00830) | (0.00824) | (0.00779) | (0.0314) | (0.00979) | (0.0324) |
| Observations | 12669 | 12669 | 12669 | 12669 | 12669 | 12669 | 12669 | 12669 | 6519 | 6150 | 7094 | 5575 |
| R-squared | 0.016 | 0.018 | 0.019 | 0.018 | 0.016 | 0.010 | 0.017 | 0.034 | 0.012 | 0.025 | 0.041 | 0.033 |
| **Predicted Cumulative Effects** | | | | | | | | | | | | |
| **Cool 100 Years** | **0.133** | **0.375** | **0.443** | **0.0436** | **0.0889** | **-0.0134** | **0.0998** | **0.0522** | **0.0441** | **0.206** | **0.0358** | **0.247** |
| Std. Err. 100 | 0.0403 | 0.114 | 0.131 | 0.0235 | 0.0414 | 0.0222 | 0.0348 | 0.0222 | 0.0248 | 0.102 | 0.0279 | 0.125 |

Notes: All regressions control for cell and time fixed effects. Observations are at the decade and $400^2$km cell level. Standard errors are clustered at the cell level.

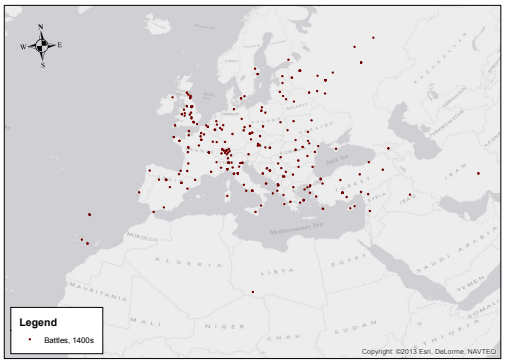
Table 10: The Very Long-run Predicted Effect of Cooling on Conflict – Comparison of alternative specifications

| | Specification | | |
|---|---|---|---|
| | Fully Interacted | Uninteracted | Long Dif |
| Years of Consecutive Cooling | (1) | (2) | (3) |
| 50 | 0.015 | 0.016 | 0.010 |
| 100 | 0.063 | 0.025 | 0.016 |
| 150 | 0.071 | 0.030 | 0.011 |
| 200 | 0.128 | 0.026 | 0.001 |
| 250 | 0.142 | 0.036 | 0.025 |

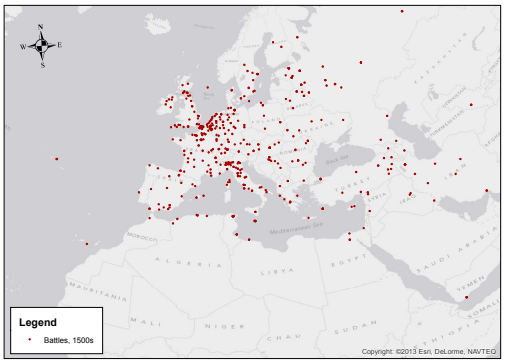
Notes: The predicted effects of cooling on the incidence of conflict, where we assume there to be 0.224 degree of cooling per 50-years, are presented in the table.

Figure 1: Conflict Data

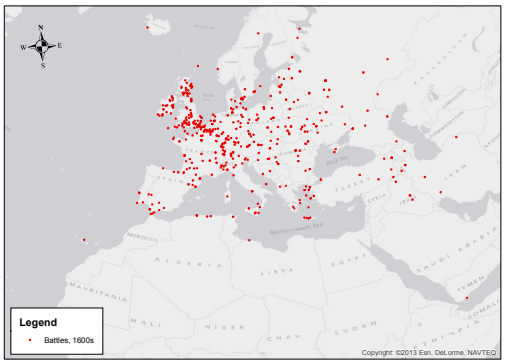
(a) 1401-1fifty0



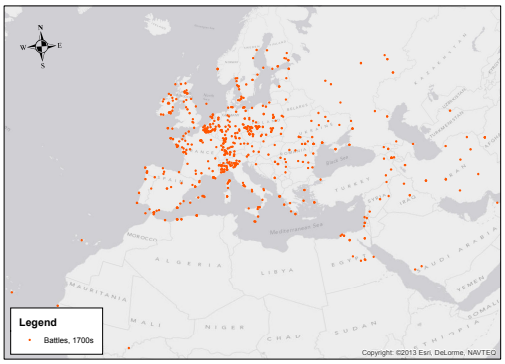

(b) 1fifty1-1600




(c) 1601-1700




(d) 1701-1800




(e) 1801-1900

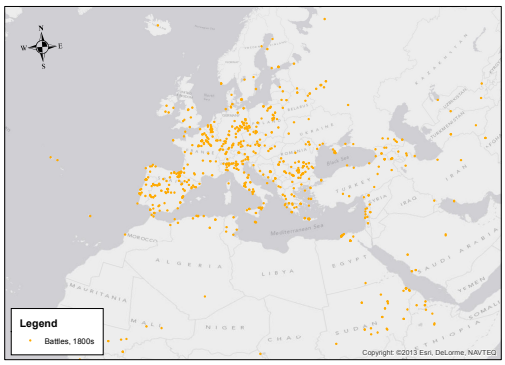
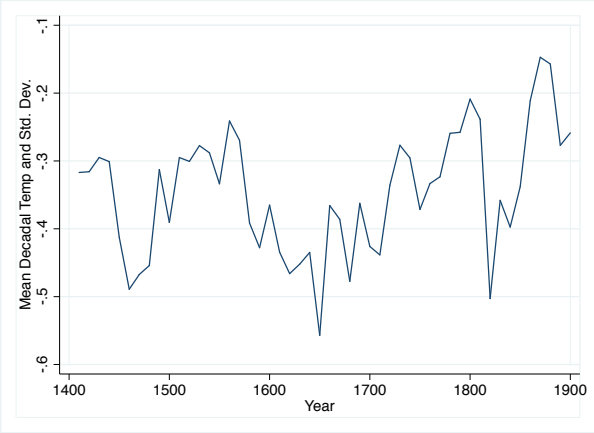
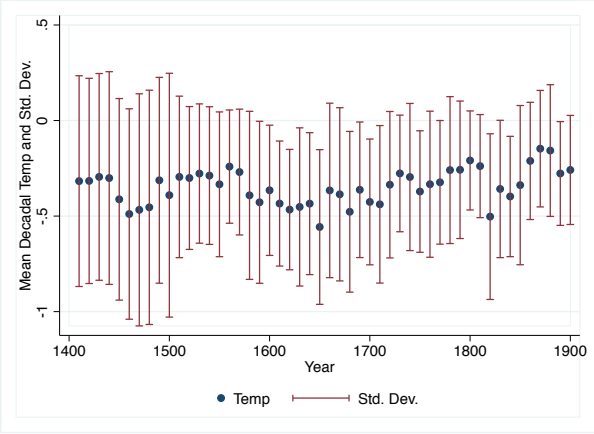


Figure 2: Temperature over Time

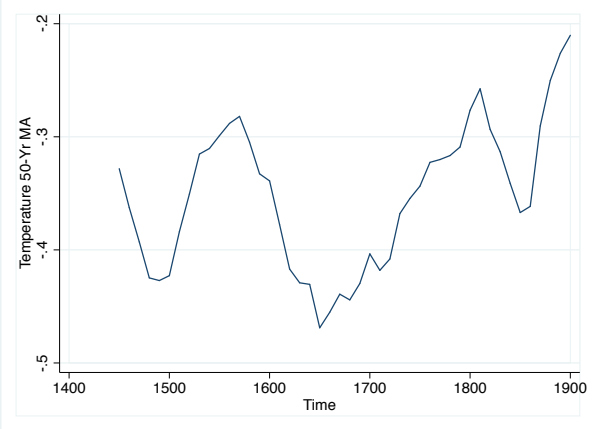
(a) Decadal Means – Main Measure




(b) Decadal Means and Standard Deviations

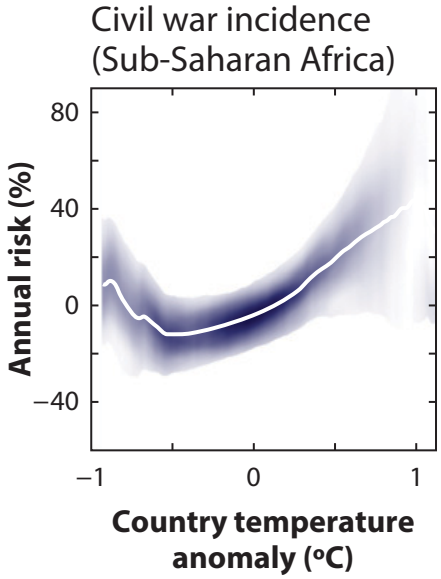



(c) fifty-Year Moving Average




Notes: The historical temperature data are constructed by Mann et al. (2009). They are reported as deviations from the 1961-1990 mean temperature in units of Celsius degrees.

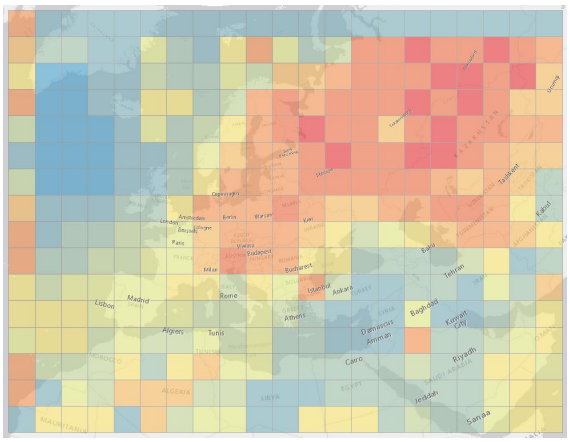
Figure 3: Nonlinear relationship between temperature and conflict



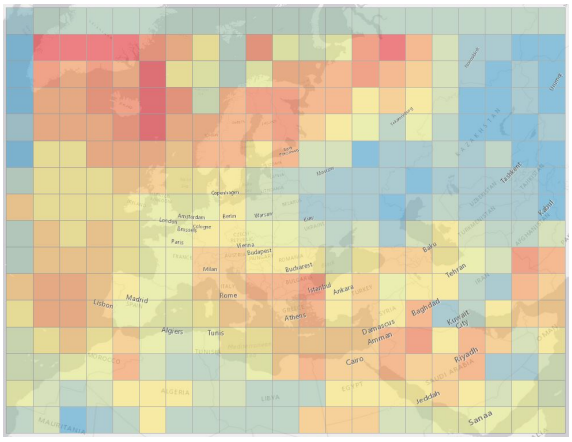

This figure is taken from Burke et al. (2015).

Figure 4: Relative cooling – $400km^2$ Grids

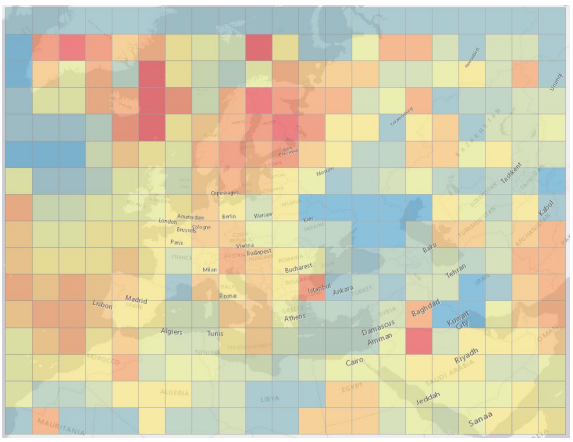
(a) 1450-1fifty0



(b) 1600-1650

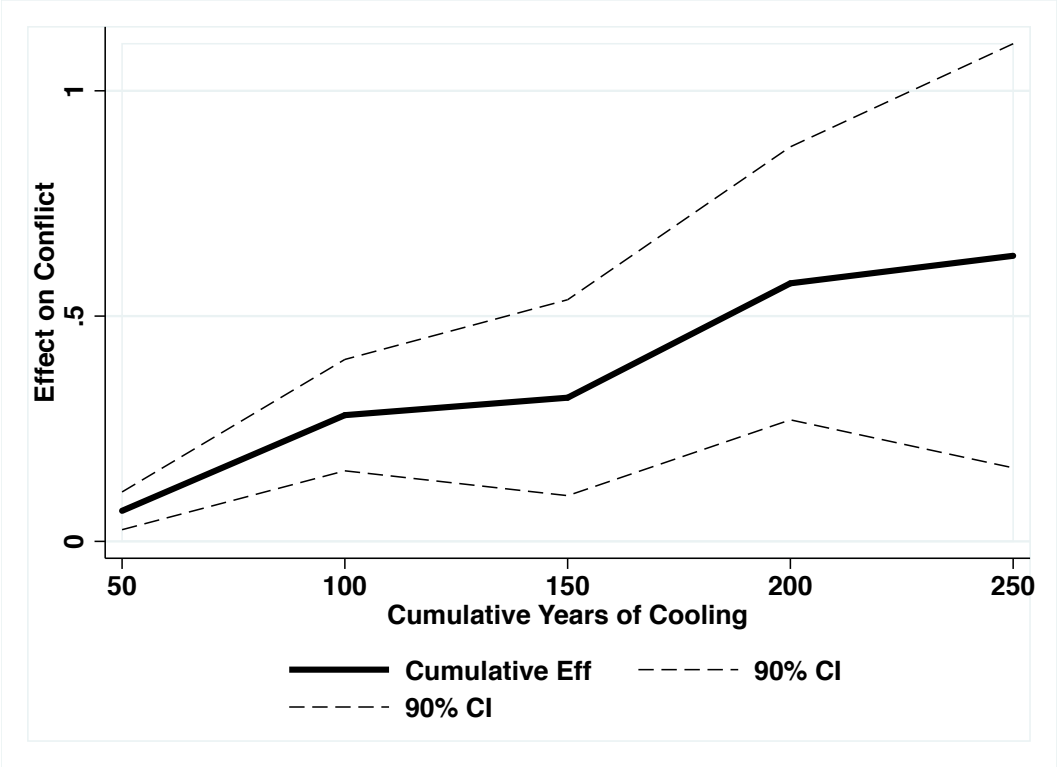


(c) 1800-1850



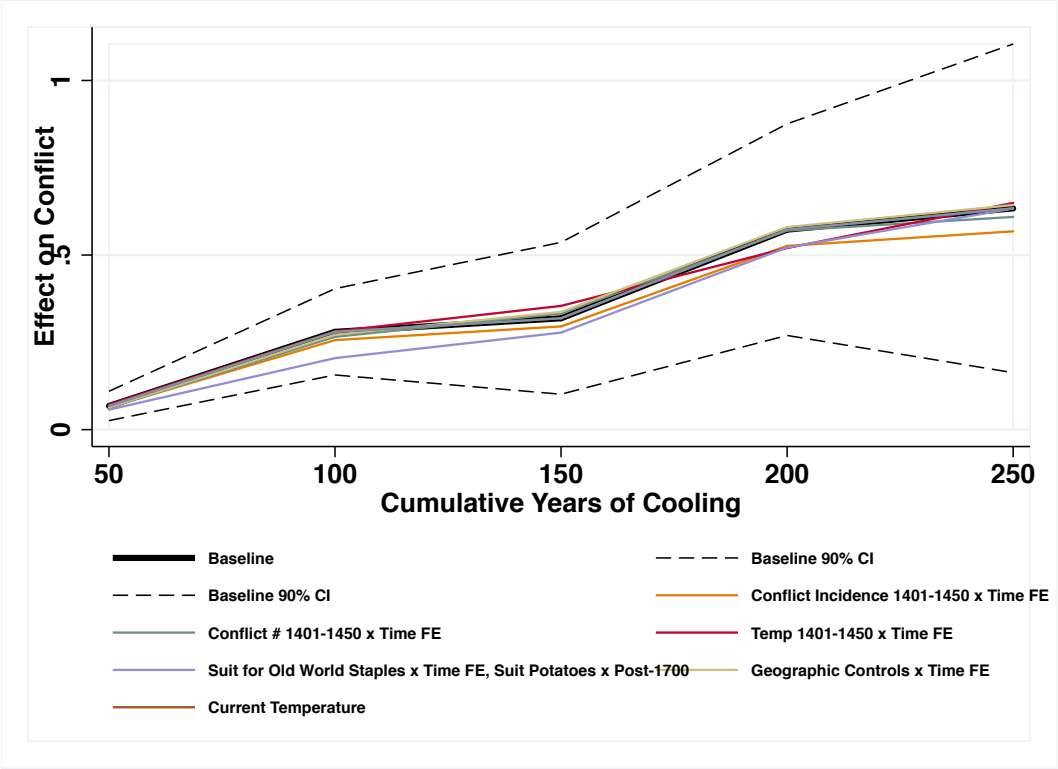
Notes: The figures plot the relative rankings of the amount of cooling over the specified fifty-year period. Dark blue indicates the most cooling. Orange indicates the least cooling (i.e., warming).

Figure 5: The Cumulative Effect of Cooling on Conflict using the Fully Flexible Specification



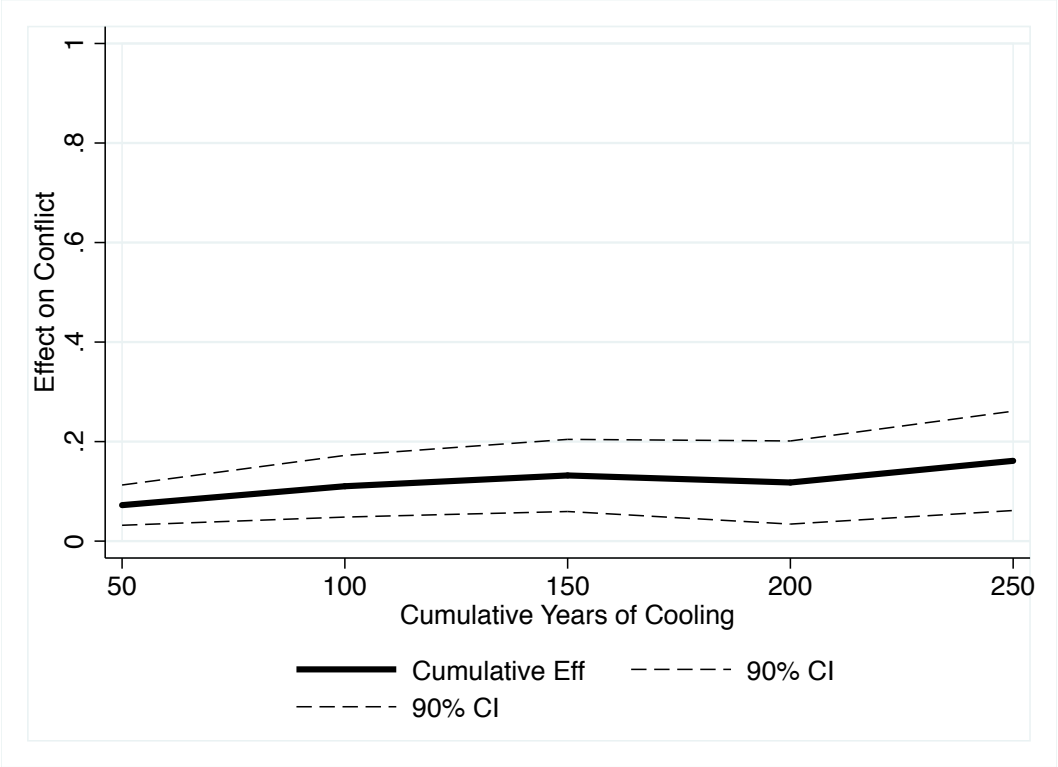

Notes: The y-axis plots the predicted effects of cooling on conflict for a given number of years. The x-axis states the duration of cooling. The predicted effects are based on coefficients from equation (6), which are shown in table A.3 column (4).

Figure 6: The Cumulative Effect of Cooling on Conflict using the Fully Flexible Specification — Robustness to Controls



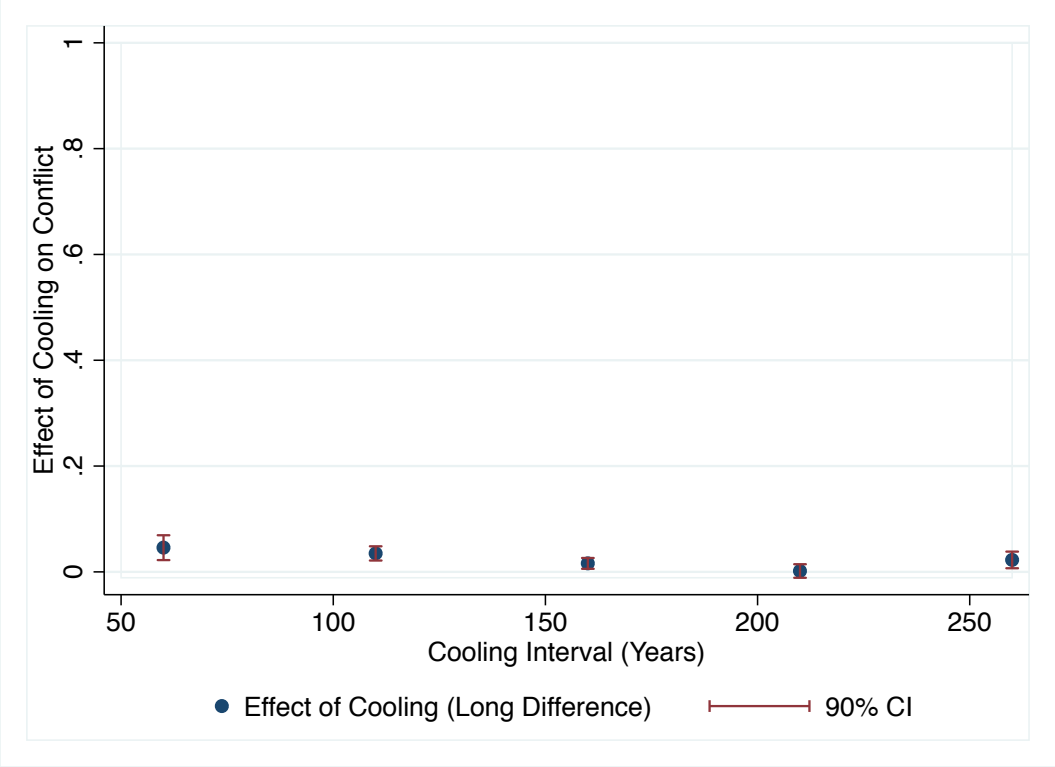

Notes: The y-axis plots the predicted effects of cooling on conflict for a given number of years. The x-axis states the duration of cooling. The predicted effects are based on coefficients from equation (6) with additional controls. The coefficients and standard errors are shown in Table A.4.

Figure 7: The Cumulative Effect of Cooling on Conflict using the Uninteracted Specification




Notes: The y-axis plots the predicted effects of cooling on conflict for a given number of years. The x-axis states the duration of cooling. The predicted effects are based on coefficients from equation (5), except that the interaction effects are assumed to be zero. They are shown in table A.6 column (4).

Figure 8: The Cumulative Effect of Cooling on Conflict using the Long-Difference Specification




Notes: The y-axis plots the predicted effects of cooling on conflict for a given number of years. The x-axis states the duration of cooling. The predicted effects are based on coefficients from equation (2), except that region and decade fixed effects are include. They are shown in table A.7. Each coefficient is estimated from a separate regression.

# A Data Appendix

Following Nunn and Qian (2011), we construct measures of suitability using the *FAO*'s Global Agro-Ecological Zones (*GAEZ*) data base. We differ in using a more recent version than was unavailable to Nunn and Qian (2011). The data include information on 154 different crops and the physical environment of 2.2 million cells spanning the whole world, with each cell covering an area of 5 arc minutes by 5 arc minutes, or roughly 10km$\times$10km cells. Using nine climate characteristics of each cell, such as frequency of wet days, precipitation, mean temperature, etc., *FAO* calculated an estimate of the potential yield of each crop in each cell, given an assumed level of crop management and input use. With some additional data processing, the *FAO* then calculated the constraint-free crop yields and referenced the potential yield of each cell as a percent of this benchmark. The index ranges from 0 to 100. The *GAEZ* cells are 10km$\times$10km and finer than the cells used in our analysis. Thus, we measure suitability at the cell level as the average suitability measure of land with the cell.

It is important to note that in calculating suitability, the FAO's agro-climatic model explicitly avoids taking into account factors that are easily manipulated by human intervention. For example, the fact that Europe has been significantly de-forested over time does not affect the suitability measure because the amount of forests does not factor into suitability. Instead, the model focuses on agricultural inputs that are difficult to manipulate such as climate and the average hours of sunshine in each season. Similarly, the GAEZ model allows us to choose inputs for factors such as mechanization and irrigation. To the best of our ability, we choose inputs to approximate for the level of technology available during our historical period of study (e.g., rain-fed and low input intensity).

Table A.1: Correlates of Climate Change across Different Time Periods

| | Temp (decade mean) | Temperature drops | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | | A. Long differences | | | |
| Temperature drop | | t-50 to t | t-100 to t | t-150 to t | t-200 to t |
| t-50 to t | -0.188* | | | | |
| t-100 to t | -0.094* | 0.5687* | | | |
| t-150 to t | -0.0909* | 0.4613* | 0.6576* | | |
| t-200 to t | -0.0704* | 0.3522* | 0.4902* | 0.6813* | |
| t-250 to t | 0.017 | 0.2690* | 0.1759* | 0.3919* | 0.5736* |
| | | B. 50-year intervals | | | |
| | | t-50 to t | t-100 to t-50 | t-150 to t-100 | t-200 to t-150 |
| 50-year temperature drops | | | | | |
| t-50 to t | -0.188* | | | | |
| t-100 to t-50 | 0.0438* | -0.1561* | | | |
| t-150 to t-100 | 0.0538* | -0.0724* | -0.1346* | | |
| t-200 to t-150 | 0.1177* | -0.1237* | -0.0820* | -0.1124* | |
| t-250 to t-200 | 0.0447* | 0.0469* | -0.1735* | 0.0183 | -0.1474* |

Notes: Observations are at the 10-year period and $400^2$km cell level. A positive value for temperature drop means that temperature has declined over time. Correlation coefficients are presented in the table.
* indicates statistical significance at the 90% level.

Figure A.1: Average number of conflicts per decade in the Jacques data

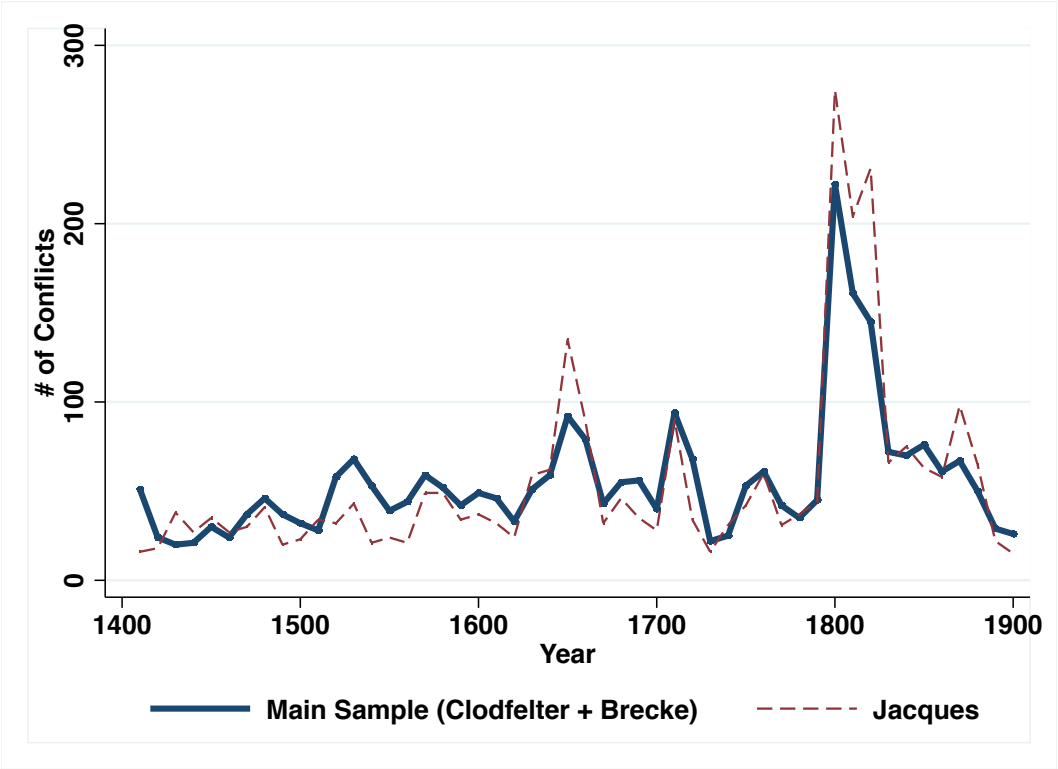


Table A.2: The Effect of Cooling on Conflict — Robustness to the exclusion of the 25 largest wars

| | | Dependent Variable: $\Delta Conflict_{t,50}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Size (# of Conflicts) | $\Delta T_{t,50}$ | | $\Delta T_{50,100}$ | | $\Delta T_{t,50} \times \Delta T_{50,100}$ | | | | Cumulative Effect | |
| | of Omitted War | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Obs. | R-sq. | **100 years** | Std. Err. |
| (1) | No Omission | 0.0414*** | (0.0134) | 0.0872** | (0.0375) | 0.00442 | (0.0119) | 12669 | 0.016 | **0.133** | 0.0403 |
| (2) | 74 | 0.0437*** | (0.0136) | 0.0891** | (0.0377) | 0.00458 | (0.0119) | 12669 | 0.015 | **0.137** | 0.0406 |
| (3) | 70 | 0.0409*** | (0.0133) | 0.0913** | (0.0377) | 0.00152 | (0.0120) | 12669 | 0.019 | **0.134** | 0.0407 |
| (4) | 66 | 0.0410*** | (0.0134) | 0.0729** | (0.0368) | 0.00228 | (0.0121) | 12669 | 0.015 | **0.116** | 0.0401 |
| (5) | 63 | 0.0411*** | (0.0135) | 0.0886** | (0.0375) | 0.00424 | (0.0119) | 12669 | 0.015 | **0.134** | 0.0404 |
| (6) | 55 | 0.0426*** | (0.0134) | 0.0844** | (0.0373) | 0.00401 | (0.0119) | 12669 | 0.015 | **0.131** | 0.0401 |
| (7) | 48 | 0.0395*** | (0.0134) | 0.0903** | (0.0378) | 0.00204 | (0.0120) | 12669 | 0.015 | **0.132** | 0.0403 |
| (8) | 43 | 0.0392*** | (0.0132) | 0.0714** | (0.0358) | -0.00740 | (0.0109) | 12669 | 0.015 | **0.103** | 0.0378 |
| (9) | 42 | 0.0395*** | (0.0134) | 0.0900** | (0.0376) | 0.00347 | (0.0120) | 12669 | 0.015 | **0.133** | 0.0404 |
| (10) | 35 | 0.0416*** | (0.0134) | 0.0888** | (0.0376) | 0.00331 | (0.0120) | 12669 | 0.017 | **0.134** | 0.0404 |
| (11) | 32 | 0.0386*** | (0.0133) | 0.0949** | (0.0377) | 0.00289 | (0.0119) | 12669 | 0.015 | **0.136** | 0.0407 |
| (12) | 31 | 0.0435*** | (0.0137) | 0.0795** | (0.0359) | 0.00249 | (0.0119) | 12669 | 0.016 | **0.126** | 0.0395 |
| (13) | 31 | 0.0414*** | (0.0134) | 0.0872** | (0.0375) | 0.00442 | (0.0119) | 12669 | 0.016 | **0.133** | 0.0403 |
| (14) | 28 | 0.0423*** | (0.0134) | 0.0928** | (0.0380) | 0.00439 | (0.0119) | 12669 | 0.016 | **0.139** | 0.0408 |
| (15) | 27 | 0.0393*** | (0.0133) | 0.0926** | (0.0374) | 0.00627 | (0.0119) | 12669 | 0.014 | **0.138** | 0.0404 |
| (16) | 24 | 0.0412*** | (0.0134) | 0.0860** | (0.0375) | 0.00378 | (0.0119) | 12669 | 0.016 | **0.131** | 0.0403 |
| (17) | 23 | 0.0405*** | (0.0134) | 0.0834** | (0.0372) | 0.00323 | (0.0120) | 12669 | 0.016 | **0.127** | 0.0402 |
| (18) | 23 | 0.0413*** | (0.0134) | 0.0889** | (0.0376) | 0.00431 | (0.0119) | 12669 | 0.015 | **0.134** | 0.0405 |
| (19) | 23 | 0.0409*** | (0.0135) | 0.0871** | (0.0374) | 0.00370 | (0.0120) | 12669 | 0.016 | **0.132** | 0.0403 |
| (20) | 22 | 0.0413*** | (0.0134) | 0.0880** | (0.0374) | 0.00484 | (0.0119) | 12669 | 0.015 | **0.134** | 0.0403 |
| (21) | 20 | 0.0384*** | (0.0133) | 0.0932** | (0.0374) | 0.00289 | (0.0118) | 12669 | 0.015 | **0.135** | 0.0406 |
| (22) | 19 | 0.0411*** | (0.0132) | 0.0814** | (0.0357) | 0.00556 | (0.0119) | 12669 | 0.015 | **0.128** | 0.0387 |
| (23) | 19 | 0.0409*** | (0.0134) | 0.0837** | (0.0373) | 0.00454 | (0.0119) | 12669 | 0.016 | **0.129** | 0.0401 |
| (24) | 19 | 0.0417*** | (0.0134) | 0.0857** | (0.0373) | 0.00345 | (0.0118) | 12669 | 0.016 | **0.131** | 0.0402 |
| (25) | 18 | 0.0417*** | (0.0134) | 0.0916** | (0.0379) | 0.00532 | (0.0119) | 12669 | 0.016 | **0.139** | 0.0408 |
| (26) | 18 | 0.0407*** | (0.0133) | 0.0857** | (0.0373) | 0.00447 | (0.0119) | 12669 | 0.016 | **0.131** | 0.0401 |

Notes: The regression controls for cell and time fixed effects. Observations are at the decade and $400^2$km cell level. Standard errors are clustered at the cell level. Each row is estimated with a sample where all battles from a given war are omitted. This does not affect the number of observations since the sample includes observations with zero conflicts.

Table A.3: The Very Long-run Effect of Cooling on Conflict using Fully Flexible Specification

| | Dependent Variable: $\Delta Conflict_{t,50}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\Delta T_{t,50} \times \Delta T_{50,100}$ | 0.0872** | 0.0848** | 0.112** | 0.157*** |
| | (0.0375) | (0.0394) | (0.0469) | (0.0575) |
| $\Delta T_{t,50}$ | 0.0414*** | 0.0496*** | 0.0335* | 0.0678*** |
| | (0.0134) | (0.0166) | (0.0179) | (0.0255) |
| $\Delta T_{50,100}$ | 0.00442 | 0.00385 | 0.0127 | 0.0555** |
| | (0.0119) | (0.0126) | (0.0181) | (0.0219) |
| $\Delta T_{t,50} \times \Delta T_{100,150}$ | | -0.0154 | -0.0366 | 0.0207 |
| | | (0.0482) | (0.0543) | (0.0741) |
| $\Delta T_{50,100} \times \Delta T_{100,150}$ | | 0.00687 | -0.0179 | -0.00250 |
| | | (0.0390) | (0.0435) | (0.0490) |
| $\Delta T_{100,150}$ | | -0.00467 | -0.00667 | 0.0205 |
| | | (0.0165) | (0.0161) | (0.0186) |
| $\Delta T_{t,50} \times \Delta T_{150,200}$ | | | 0.0552 | 0.0802 |
| | | | (0.0465) | (0.0679) |
| $\Delta T_{50,100} \times \Delta T_{150,200}$ | | | 0.101** | 0.147*** |
| | | | (0.0454) | (0.0512) |
| $\Delta T_{100,150} \times \Delta T_{150,200}$ | | | -0.00119 | 0.0445 |
| | | | (0.0442) | (0.0557) |
| $\Delta T_{150,200}$ | | | -0.0366** | -0.0176 |
| | | | (0.0165) | (0.0165) |
| $\Delta T_{t,50} \times \Delta T_{200,250}$ | | | | 0.00734 |
| | | | | (0.0388) |
| $\Delta T_{50,100} \times \Delta T_{200,250}$ | | | | 0.0178 |
| | | | | (0.0774) |
| $\Delta T_{100,150} \times \Delta T_{200,250}$ | | | | -0.0258 |
| | | | | (0.0640) |
| $\Delta T_{150,200} \times \Delta T_{200,250}$ | | | | 0.0169 |
| | | | | (0.0657) |
| $\Delta T_{200,150}$ | | | | 0.0448** |
| | | | | (0.0196) |
| Observations | 12669 | 11124 | 9579 | 8034 |
| R-squared | 0.016 | 0.018 | 0.021 | 0.027 |
| **Predicted Cumulative Effects (each 50-year cool by 1 degree)** | | | | |
| **Cool 100 Years** | **0.133** | **0.138** | **0.158** | **0.280** |
| Std. Err. 100 | 0.0403 | 0.0430 | 0.0559 | 0.0751 |
| **Cool 150 Years** | | **0.125** | **0.0972** | **0.319** |
| Std. Err. 150 | | 0.0773 | 0.107 | 0.132 |
| **Cool 200 Years** | | | **0.215** | **0.573** |
| Std. Err. 200 | | | 0.136 | 0.184 |
| **Cool 250 Years** | | | | **0.634** |
| Std. Err. 250 | | | | 0.286 |

Notes: All regressions control for cell and time fixed effects. Observations are at the decade and $400^2$km cell level. Standard errors are clustered at the cell level.

Table A.4: The Very Long-run Effect of Cooling on Conflict using the Fully Flexible Specification — Robustness to Controls

| | Dependent Variable: $\Delta Conflict_{t,50}$ | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Baseline | Conflict Incidence 1401-1450 x Time FE | Conflict # 1401-1450 x Time FE | Temp in 1401-1450 x Time FE | Suitability for Old World Staples x Time FE, Potatoes x post-1700 | # of Cities in 1401-1450 x Time FE | Geography$^{+}$ x Time FE | $Temp_t$ |
| $\Delta T_{t,50} \times \Delta T_{50,100}$ | 0.157*** | 0.139** | 0.144** | 0.163*** | 0.109* | 0.152*** | 0.157*** | 0.157*** |
| | (0.0575) | (0.0567) | (0.0564) | (0.0609) | (0.0590) | (0.0562) | (0.0575) | (0.0575) |
| $\Delta T_{t,50} \times \Delta T_{100,150}$ | 0.0207 | 0.0157 | 0.0253 | 0.0267 | -0.00570 | 0.0350 | 0.0207 | 0.0207 |
| | (0.0741) | (0.0727) | (0.0729) | (0.0802) | (0.0821) | (0.0725) | (0.0741) | (0.0741) |
| $\Delta T_{t,50} \times \Delta T_{150,200}$ | 0.0802 | 0.0978 | 0.0840 | 0.0627 | 0.138* | 0.0739 | 0.0802 | 0.0802 |
| | (0.0679) | (0.0664) | (0.0657) | (0.0733) | (0.0722) | (0.0667) | (0.0679) | (0.0679) |
| $\Delta T_{t,50} \times \Delta T_{200,250}$ | 0.00734 | 0.0330 | 0.0312 | 0.0102 | 0.0463 | 0.0209 | 0.00734 | 0.00734 |
| | (0.0388) | (0.0375) | (0.0383) | (0.0411) | (0.0406) | (0.0380) | (0.0388) | (0.0388) |
| $\Delta T_{50,100} \times \Delta T_{100,150}$ | -0.00250 | 0.00243 | 0.0161 | -0.000232 | 0.0297 | 0.00937 | -0.00250 | -0.00250 |
| | (0.0490) | (0.0464) | (0.0474) | (0.0507) | (0.0492) | (0.0488) | (0.0490) | (0.0490) |
| $\Delta T_{t,50} \times \Delta T_{150,200}$ | 0.147*** | 0.118** | 0.130*** | 0.141** | 0.107* | 0.144*** | 0.147*** | 0.147*** |
| | (0.0512) | (0.0504) | (0.0499) | (0.0577) | (0.0565) | (0.0500) | (0.0512) | (0.0512) |
| $\Delta T_{t,50} \times \Delta T_{200,250}$ | 0.0178 | 0.0171 | 0.00560 | -0.00789 | 0.0398 | 0.0264 | 0.0178 | 0.0178 |
| | (0.0774) | (0.0762) | (0.0760) | (0.0827) | (0.0837) | (0.0762) | (0.0774) | (0.0774) |
| $\Delta T_{100,150} \times \Delta T_{150,200}$ | 0.0445 | 0.0319 | 0.0411 | 0.0233 | 0.0370 | 0.0437 | 0.0445 | 0.0445 |
| | (0.0557) | (0.0526) | (0.0536) | (0.0559) | (0.0548) | (0.0545) | (0.0557) | (0.0557) |
| $\Delta T_{100,150} \times \Delta T_{200,250}$ | -0.0258 | -0.0153 | -0.0141 | -0.0447 | -0.0232 | -0.0127 | -0.0258 | -0.0258 |
| | (0.0640) | (0.0613) | (0.0615) | (0.0679) | (0.0719) | (0.0639) | (0.0640) | (0.0640) |
| $\Delta T_{150,200} \times \Delta T_{200,250}$ | 0.0169 | -0.0357 | -0.0258 | 0.0705 | -0.0192 | -0.0133 | 0.0169 | 0.0169 |
| | (0.0657) | (0.0613) | (0.0624) | (0.0707) | (0.0660) | (0.0644) | (0.0657) | (0.0657) |
| $\Delta T_{t,50}$ | 0.0678*** | 0.0639** | 0.0632** | 0.0718** | 0.0571* | 0.0636** | 0.0678*** | 0.0678*** |
| | (0.0255) | (0.0257) | (0.0257) | (0.0343) | (0.0324) | (0.0258) | (0.0255) | (0.0255) |
| $\Delta T_{50,100}$ | 0.0555** | 0.0538** | 0.0585*** | 0.0464 | 0.0388 | 0.0560*** | 0.0555** | 0.0555** |
| | (0.0219) | (0.0219) | (0.0216) | (0.0327) | (0.0245) | (0.0215) | (0.0219) | (0.0219) |
| $\Delta T_{100,150}$ | 0.0205 | 0.0211 | 0.0255 | 0.0465 | 0.0490* | 0.0207 | 0.0205 | 0.0205 |
| | (0.0186) | (0.0184) | (0.0183) | (0.0303) | (0.0250) | (0.0186) | (0.0186) | (0.0186) |
| $\Delta T_{150,200}$ | -0.0176 | -0.0167 | -0.0177 | -0.0617* | -0.0387 | -0.0184 | -0.0176 | -0.0176 |
| | (0.0165) | (0.0161) | (0.0163) | (0.0365) | (0.0237) | (0.0164) | (0.0165) | (0.0165) |
| $\Delta T_{200,150}$ | 0.0448** | 0.0427** | 0.0424** | 0.101*** | 0.0679*** | 0.0417** | 0.0448** | 0.0448** |
| | (0.0196) | (0.0190) | (0.0190) | (0.0361) | (0.0256) | (0.0192) | (0.0196) | (0.0196) |
| Observations | 8034 | 8034 | 8034 | 8034 | 6994 | 8034 | 8034 | 8034 |
| R-squared | 0.027 | 0.060 | 0.059 | 0.030 | 0.048 | 0.045 | 0.027 | 0.027 |
| **Predicted Cumulative Effects** | | | | | | | | |
| **Cool 100 Years** | **0.280** | **0.256** | **0.266** | **0.281** | **0.205** | **0.272** | **0.280** | **0.280** |
| Std. Err. 100 | 0.0751 | 0.0745 | 0.0740 | 0.0879 | 0.0835 | 0.0737 | 0.0751 | 0.0751 |
| **Cool 150 Years** | **0.319** | **0.296** | **0.333** | **0.354** | **0.278** | **0.337** | **0.319** | **0.319** |
| Std. Err. 150 | 0.132 | 0.129 | 0.129 | 0.143 | 0.144 | 0.130 | 0.132 | 0.132 |
| **Cool 200 Years** | **0.573** | **0.526** | **0.570** | **0.520** | **0.522** | **0.580** | **0.573** | **0.573** |
| Std. Err. 200 | 0.184 | 0.175 | 0.177 | 0.200 | 0.192 | 0.178 | 0.184 | 0.184 |
| **Cool 250 Years** | **0.634** | **0.568** | **0.609** | **0.650** | **0.633** | **0.643** | **0.634** | **0.634** |
| Std. Err. 250 | 0.286 | 0.283 | 0.284 | 0.312 | 0.306 | 0.283 | 0.286 | 0.286 |

Notes: The regression controls for cell and time fixed effects. $^{+}$Geographic controls include latitude, longitude, elevation, slope and the distance to the nearest coast. Observations are at the decade and $400^2$km cell level. Standard errors are clustered at the cell level.

Table A.5: The Very Long-run Effect of Cooling on Conflict using the Fully Flexible Specification — Alternative Measures of Conflict

| | Dependent Variable: | | |
|---|---|---|---|
| | (1) | (2) | |
| | Conflict Incidence | Ln # Conflict | Ln # Onset |
| $\Delta T_{t,50} \times \Delta T_{50,100}$ | 0.157*** | 0.498*** | 0.596*** |
| | (0.0575) | (0.168) | (0.198) |
| $\Delta T_{t,50} \times \Delta T_{100,150}$ | 0.0207 | 0.0457 | 0.0271 |
| | (0.0741) | (0.207) | (0.241) |
| $\Delta T_{t,50} \times \Delta T_{150,200}$ | 0.0802 | 0.352* | 0.434** |
| | (0.0679) | (0.179) | (0.207) |
| $\Delta T_{t,50} \times \Delta T_{200,250}$ | 0.00734 | 0.0404 | 0.0444 |
| | (0.0388) | (0.106) | (0.125) |
| $\Delta T_{50,100} \times \Delta T_{100,150}$ | -0.00250 | 0.0307 | 0.0700 |
| | (0.0490) | (0.136) | (0.159) |
| $\Delta T_{t,50} \times \Delta T_{150,200}$ | 0.147*** | 0.519*** | 0.605*** |
| | (0.0512) | (0.153) | (0.178) |
| $\Delta T_{t,50} \times \Delta T_{200,250}$ | 0.0178 | 0.0880 | 0.125 |
| | (0.0774) | (0.217) | (0.252) |
| $\Delta T_{100,150} \times \Delta T_{150,200}$ | 0.0445 | 0.203 | 0.245 |
| | (0.0557) | (0.170) | (0.198) |
| $\Delta T_{100,150} \times \Delta T_{200,250}$ | -0.0258 | -0.0739 | -0.0901 |
| | (0.0640) | (0.180) | (0.205) |
| $\Delta T_{150,200} \times \Delta T_{200,250}$ | 0.0169 | 0.171 | 0.167 |
| | (0.0657) | (0.181) | (0.215) |
| $\Delta T_{t,50}$ | 0.0678*** | 0.187** | 0.230*** |
| | (0.0255) | (0.0737) | (0.0859) |
| $\Delta T_{50,100}$ | 0.0555** | 0.164*** | 0.211*** |
| | (0.0219) | (0.0619) | (0.0719) |
| $\Delta T_{100,150}$ | 0.0205 | 0.0832 | 0.102* |
| | (0.0186) | (0.0505) | (0.0578) |
| $\Delta T_{150,200}$ | -0.0176 | -0.0424 | -0.0468 |
| | (0.0165) | (0.0469) | (0.0545) |
| $\Delta T_{200,150}$ | 0.0448** | 0.109* | 0.131** |
| | (0.0196) | (0.0566) | (0.0665) |
| Observations | 8034 | 8034 | 8034 |
| R-squared | 0.027 | 0.031 | 0.031 |
| **Predicted Cumulative Effects** | | | |
| **Cool 100 Years** | **0.280** | **0.849** | **1.037** |
| Std. Err. 100 | 0.0751 | 0.218 | 0.257 |
| **Cool 150 Years** | **0.319** | **1.009** | **1.236** |
| Std. Err. 150 | 0.132 | 0.378 | 0.440 |
| **Cool 200 Years** | **0.573** | **2.040** | **2.473** |
| Std. Err. 200 | 0.184 | 0.552 | 0.658 |
| **Cool 250 Years** | **0.634** | **2.374** | **2.851** |
| Std. Err. 250 | 0.286 | 0.837 | 1.000 |

Notes: The regression controls for cell and time fixed effects. Observations are at the decade and 4002km cell level. Standard errors are clustered at the cell level.

Table A.6: The Very Long-run Effect of Cooling on Conflict using an Uninteracted Specification

| | Dependent Variable: $\Delta Conflict_{t,50}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\Delta T_{t,50}$ | 0.0447*** | 0.0532*** | 0.0435*** | 0.0723*** |
| | (0.0135) | (0.0164) | (0.0167) | (0.0246) |
| $\Delta T_{50,100}$ | 0.000815 | 0.00112 | 0.00297 | 0.0380* |
| | (0.0122) | (0.0125) | (0.0163) | (0.0193) |
| $\Delta T_{100,150}$ | | -0.00644 | -0.00590 | 0.0217 |
| | | (0.0163) | (0.0152) | (0.0162) |
| $\Delta T_{150,200}$ | | | -0.0319** | -0.0142 |
| | | | (0.0154) | (0.0166) |
| $\Delta T_{200,150}$ | | | | 0.0436** |
| | | | | (0.0199) |
| Observations | 12669 | 11124 | 9579 | 8034 |
| R-squared | 0.015 | 0.018 | 0.020 | 0.027 |
| **Predicted Cumulative Effects** | | | | |
| **Cool 100 Years** | **0.0455** | **0.0543** | **0.0464** | **0.110** |
| Std. Err. 100 | 0.0180 | 0.0206 | 0.0239 | 0.0377 |
| **Cool 150 Years** | | **0.0479** | **0.0405** | **0.132** |
| Std. Err. 150 | | 0.0252 | 0.0287 | 0.0441 |
| **Cool 200 Years** | | | **0.00863** | **0.118** |
| Std. Err. 200 | | | 0.0337 | 0.0508 |
| **Cool 250 Years** | | | | **0.161** |
| Std. Err. 250 | | | | 0.0607 |

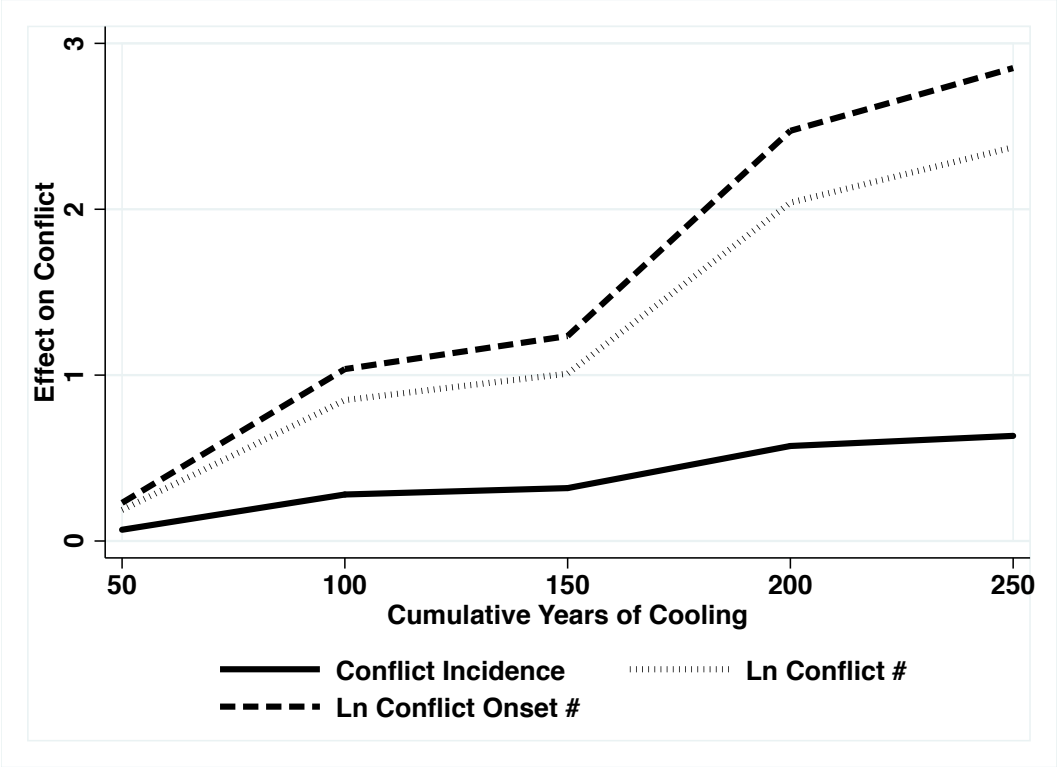
Notes: All regressions control for cell and time fixed effects. Observations are at the decade and $400^2$km cell level. Standard errors are clustered at the cell level.

Table A.7: The Very Long-run Effect of Cooling on Conflict using the Long Difference Specification

| | Dependent Variable: $\Delta$Conflict$_{t,50}$ | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| $\Delta T_{t,50}$ | 0.0457*** | | | | |
| | (0.0143) | | | | |
| $\Delta T_{50,100}$ | | 0.0349*** | | | |
| | | (0.00818) | | | |
| $\Delta T_{100,150}$ | | | 0.0160** | | |
| | | | (0.00622) | | |
| $\Delta T_{150,200}$ | | | | 0.00162 | |
| | | | | (0.00779) | |
| $\Delta T_{200,150}$ | | | | | 0.0226** |
| | | | | | (0.00957) |
| Observations | 14214 | 12669 | 11124 | 9579 | 8034 |
| R-squared | 0.015 | 0.294 | 0.290 | 0.292 | 0.293 |
| **Predicted Cumulative Effect (1 degree of cooling each 50 years)** | | | | | |
| **Cool 100 Years (Coef x 2)** | | **0.0698** | | | |
| **Cool 150 Years (Coef x 3)** | | | **0.048** | | |
| **Cool 200 Years (Coef x 4)** | | | | **0.00648** | |
| **Cool 250 Years (Coef x 5)** | | | | | **0.113** |

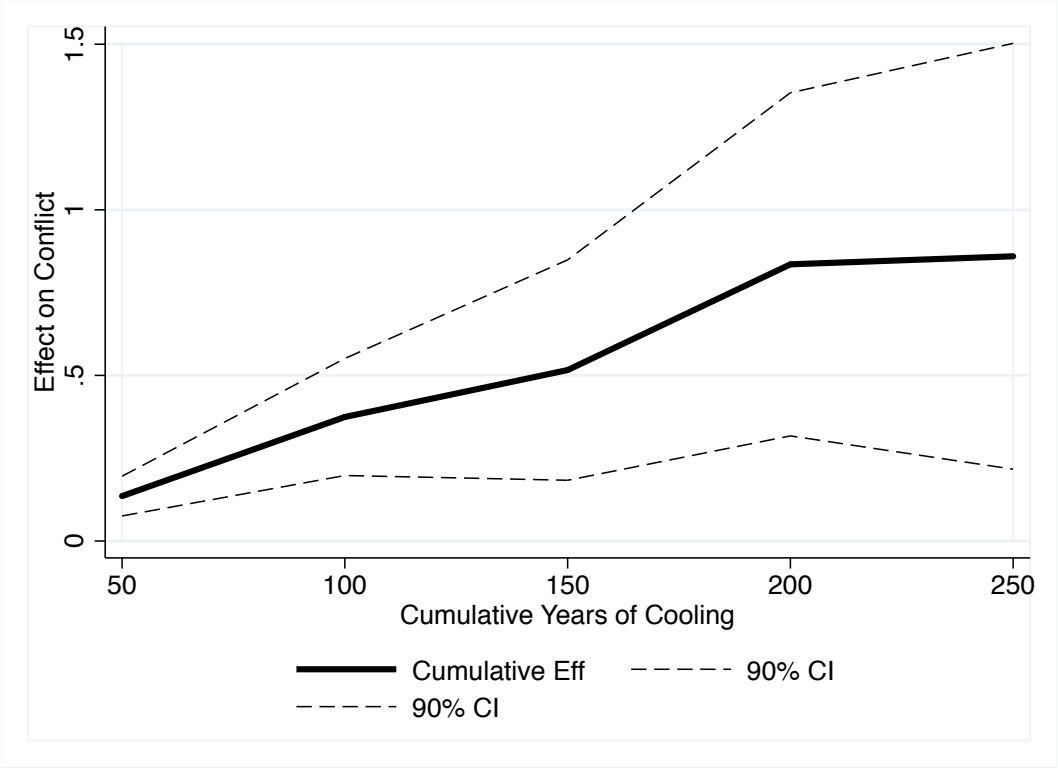
Notes: All regressions control for cell and time fixed effects. Observations are at the decade and 4002km cell level. Standard errors are clustered at the cell level.

Figure A.2: The Cumulative Effect of Cooling on Conflict using the Fully Flexible Specification — Robustness to Alternative Measures of Conflict



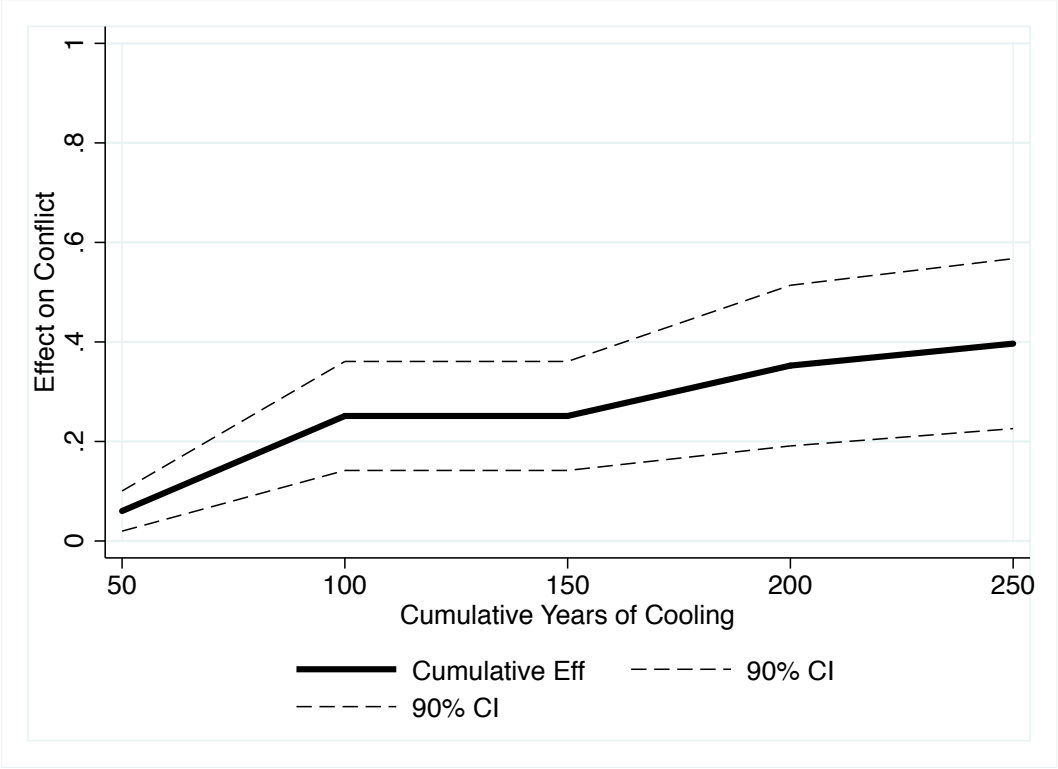

Notes: The y-axis plots the predicted effects of cooling on conflict for a given number of years. The x-axis states the duration of cooling. The predicted effects are based on coefficients from equation (6). The coefficients and standard errors are reported in Appendix Table A.5.

Figure A.3: The Cumulative Effect of Cooling on Conflict using the Fully Flexible Specification — Robustness to Clustering at the $800^2 km$ cell level.




Notes: The y-axis plots the predicted effects of cooling on conflict for a given number of years. The x-axis states the duration of cooling. The predicted effects are based on coefficients from equation (6). The coefficients and standard errors are available upon request.

Figure A.4: The Cumulative Effect of Cooling on Conflict using the Fully Flexible Specification — LASSO estimate




Notes: The y-axis plots the predicted effects of cooling on conflict for a given number of years. The x-axis states the duration of cooling. The predicted effects are based on coefficients from the LASSO model. The coefficients and standard errors are available upon request.