Civil armed conflicts: the impact of the interaction between climate change and agricultural potential (Work in progress)

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January 24, 2019

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Abstract

The goal of this paper is to examine the impact of rising world temperatures on the incidence of civil armed conflicts, focusing on a specific mechanism: the interaction between variations in annual temperatures and variations in agricultural potential. We assemble a dataset from various sources for 172 countries from 1946 till 2014. Agricultural potential is based on the Food and Agricultural Organization's definition of a country land suitability for growing basic crops. Annual temperature data come from the Climate Research Unit of the University of East Anglia. Data on civil armed conflicts is from the Uppsala Conflict Data Project. Using a fixed-effect approach, our identification strategy is akin to a natural experiment where the exogenous interaction between the temporal variation in temperature within a country and the cross-country variation in agricultural potential allows identifying the effect of this interaction on conflict incidence. The findings indicate that temperature and agricultural potential are substitutes and have offsetting effects on conflict incidence. We find that in a country with low agricultural potential a one degree increase in temperature is associated with a 3% increase in conflict incidence. However, when agricultural potential is high, a one degree increase in temperature is associated with a 5% decrease in conflict incidence. The results are tested against various robustness checks.

JEL codes:

Keywords: armed conflict, civil war, climate change, crop suitability, water scarcity, food security

1 INTRODUCTION

According to (Pettersson and Wallensteen, 2015), 2014 has been the most violent since the end of the cold war using the most recent available data on armed conflicts. At the same time, the past decade has seen the three warmest years on record (WMO, 2018). Is this just a mere correlation? According to a growing literature, climate change will have many adverse consequences on human kind, one of which is potential increases in violence. Indeed, Burke *et al.* (2015) show that an increase of one-standard deviation in contemporaneous temperature increases the probability of interpersonal and inter-group conflicts by 2.4% and 11.3% respectively. In parallel, many case studies have noted that the impact of a poor endowment in natural resources, and more particularly in resources related to agricultural potential, i.e., water scarcity, land suitability to grow crops, on violence could be exacerbated by temperature (Mukhar, 2006; Raleigh and Urdal, 2007; Kameri-Mbote, 2007; Lecoutere *et al.*, 2010; Petitjean 2016). However, there seems to be no study, to the best of our knowledge, which examine systematically this mechanism using a broad panel of countries over a long time period.

This is exactly the goal of this paper. We examine the impact of the interaction between variations in annual temperature and variations in agricultural potential on the incidence of civil armed conflicts using a panel of 172 countries from 1946 to 2014. The conflict data is taken from the Uppsala conflict data project (UCDP). The UCDP defines a conflict as a contested incompatibility involving the government and/or a territory. According to the UCDP classification, a minor conflict has 25 or more annual battle-related deaths and a war has 1000 or more annual battle-related deaths. The UCDP dataset contains information on various types of conflicts, i.e, interstates and intrastate. Given the decrease in the occurrence of interstates conflicts and the prevalence of civil conflicts since the end of the cold war, we focus on civil and civil-internationalised (when other countries contribute troops) conflicts.[1] Focusing on civil conflicts also limits the number of methodological issues generated by international conflicts (mi-

[1] Gleditsch *et al.* (2002) gives an in-depth description of the methodology of the UCDP.

gration flows, number of countries involved, to what extent, etc.). We find that 100 countries were engaged in a conflict between 1946 and 2014 with an average incidence of 15%. However, there is a lot of variations in conflict incidence across regions. Europe has the lowest level of incidence (5%) while the middle-East has the highest level of incidence (24%).

Data on temperature at the country level come from the Climatic Research Unit (CRU) of the University of East Anglia. The CRU provides a global and high resolution dataset, with monthly climatology observations, covering all land masses (except Antarctica) between 60S and 80N with a 0.5 x 0.5 resolution. There are ten climatology variables available but the main results of the paper focus on annual temperature. This choice of focus is based on Burke *et al.* (2009)'s argument that variations in rainfall or other climate variables have an impact on conflict through rises in temperatures. The dataset covers a period going from 1901 to 2014.[2] The average annual temperature for 1946-2014 is 18.5 Celsius with a peak around 20 Celsius around 1990. Canada and Russia face lowest average annual temperature (around -7C) and Mali, the highest average temperature (30C).

We define agricultural potential as land suitability for growing cereals with a rain-regime and low inputs in a given country. To develop this variable, we use information from the Food and Agricultural Organization (FAO)'s project for global agricultural and ecological zones (GAEZ). GAEZ runs an inventory of land potential agricultural productivity, identifying specific exogenous biophysical limitations of a country's land surface in order to classify it into various indexes of suitability (SI) to grow cereals or other types of cultures, depending on regime (rain, irrigation,etc.) and quantity of inputs used. We focus on cereals grown on a rain-fed regime and a low-level of inputs. This makes the agricultural potential variable exogenous from human interventions, i.e., irrigation, fertilization. GAEZ classifies land surface in a country using eight categories, from not suitable to highly suitable. In this paper, we use the ratio between the surface with a suitability index (SI) above a medium level of suitability according to GAEZ,

[2]For the interested reader, the methodology is fully described in Harris *et al.* (2013).

and the total surface in a given country as an indicator of a country's agricultural potential.[3] On average, 24% of the world's land surface exhibit a suitability index above GAEZ medium threshold. Europe has the highest endowment (35%) and the middle-East, the worst (9%).

We use a fixed-effect panel approach to analyze the data and we regress conflict incidence over temperature and its interaction with agricultural potential. According to Dell *et al.* (2012), a panel analysis exploits climate fluctuations as an exogenous variable, which heightens its identification power. Furthermore, Burke *et al.* (2015) argue that geography do not differ significantly across time, making it an interesting tool for the identification of causal effects. In this paper, we use both variations in a dynamic difference-in-difference analysis. Our approach is akin to a natural experiment where the first difference in annual temperature is across time and the second difference in agricultural potential is across countries. The interaction between temperature variation and agricultural potential variation is thus exogenous and allows identifying a causal effect on the incidence of conflict. We are evaluating the degree to which countries are resilient conflict-wise to climate change due to their agricultural potential. We control for omitted variables by including fixed effects at the country level, thus controlling for institutions, history and geography.[4] We also include time fixed effects, thus controlling for events and time trends which might have affected specific countries, regions or the world all over.

One concern with the use of long time-series for conflict incidence and temperature is whether these variables exhibit a non-stationary data generating process. We conduct a series of econometric tests in order to examine this issue (Im *et al.* (2003), Pesaran (2004)). We find that our main variables, i.e., conflict incidence and temperature exhibit some cross-dependence across panel units. However, these two variables taken in levels do not exhibit a unit-root and are thus stationary.[5]

Having shown that our main variables are stationary, we then examine the effect of tem-

[3] We follow Nunn and Qian (2011) in this choice of threshold but the results are not affected by this choice.

[4] Agricultural potential is controlled for with country fixed effects. There is however enough variation in this variable such that its interaction with temperature allows identifying an effect.

[5] We do find however that temperature taken in first-difference or in second-difference temperature is potentially non-stationary.

perature and its interaction with agricultural potential on the incidence of civil conflicts using a fixed-effect approach. The baseline results show that when agricultural potential is low, i.e., none of the land surface in a country has a suitability index above GAEZ medium threshold, a one degree increase in temperature is associated with a 3% increase in conflict incidence. However, when agricultural potential is high, i.e., all land surface in a country is above the medium threshold, a one degree increase in temperature is associated with a 5% decrease in conflict incidence. Hence, temperature and natural resources act as substitutes. In other words, a better [worst] endowment in agricultural potential mitigates [exacerbates] the effect of temperature on conflict incidence.

We run various robustness checks. We further examine issues related to persistence and auto-correlation. The results are robust to the introduction of a lagged dependent variable or the introduction of lagged temperature. We use standardized temperature at the country level and the results are not qualitatively affected. A long run analysis, using decade averages, does not alter the results qualitatively. However, the detrimental effect of temperature on conflict incidence is more important in the long run than in the short run for countries with a poor agricultural potential with an increase in conflict incidence of 9% (instead of 3%) and the mitigating effect of better agricultural potential is not as strong in the long run as in the short run with a decrease in conflict incidence of 3% (instead of 5%).

We then compare subsets of countries for which we expect different responses to climate change due to their difference in institutions, sectoral composition, or endowment in other natural resources such as oil. Using a rough measure of agricultural intensity, we find no difference between countries with an agricultural share of GDP above 10% and countries with a share below 10%, i.e., the interaction coefficient remains negative and significant for both type of countries.[6] Parting countries based on their OCDE membership, the interaction coefficient is not significant for OCDE countries. Hence, temperature and agricultural potential are substitutes in countries with a lower level of institutional development than OCDE countries. Interestingly, parting

[6] Using other thresholds to part agricultural and industrial countries does not change this result.

countries in terms of their OPEP membership, the interaction coefficient is not significant for OPEP countries.

As a further robustness check, we use a measure of water scarcity from GAEZ as an alternate measure of agricultural potential. This variable does not exhibit much variation compared to the Suitability Index for cereals. This raises the risk of co-linearity issues between temperature and its interaction with water scarcity. This is why we do not use water scarcity in the main regressions. This variable measures the global distribution of water scarcity by major river basin. Even if water basin are not an exhaustive measure of hydrological resources, they serve as a proxy for water availability in a given country. The results are not qualitatively affected by this alternate measure, subject to aforementioned caveat.

Finally, there is a debate in the literature between the use of fixed-effects or the use of specific co-variates to control for omitted variables in a panel analysis involving temperature (Buhaug (2010), Collier and Hoeffler (2002) and Fearon and Laitin (2003)). Although, we feel more confident in a fixed-effect approach, we check whether the alternative suggested in the literature affects the results of this paper. Keeping year fixed-effects and introducing GDP per capita, education, openess to trade, population growth and inflation (from the Barro and Lee (2013) dataset and World development Indicators), the main result of this paper remains unaffected: temperature and agricultural potential are substitutes.[7]

The rest of the paper is organised as follows. The next section present a brief review of the literature. Section 3 focuses on a description of the data and an examination of the properties of the main variables, namely whether these are stationary or not. Section 4 presents the model, the identification strategy as well as the main results and robustness checks. Section 5 concludes.

[7]The number of observations drops significantly as data on most of these other covariates is not available before 1960. Also, the results hold using various number of lags for these additional controls (results available upon request). If, on top of these additional controls, we also introduce country fixed-effects, resulting in what Dell *et al.* (2009) calls overcontrolling, we indeed find that the main result does not hold anymore.

2 Literature review

There is a long tradition of scholarly thinkers who have examined the relationship between climate, geography and human societies. As noted by Gates (1967), Ibn Khaldoun's *Al-Muqaddima* and Montesquieu's *L'esprit des lois* are heirs of Hippocrate's theory of *Air, water and places*. More recently, Jared (1997), Easterly (2001) and Sachs (2005) argue that climate and geography have played and still play a major role in explaining inequalities across societies. Recent studies tend to corroborate these theories.

In a report which has received international attention, Stern (2007) argues that climate variability has an impact on the economy with increasingly notable effects. Indeed, more and more quantitative findings corroborate Lord Stern. Dell *et al.* (2009) show using cross-sectional data for 2000 that an increase of one degree Celsius decreases GDP per capita by 8.5% and that variations in temperature could explain up to 23% of the cross-country variation in revenues. Hsiang (2010) shows that domestic production declines by 2.5% for each degree Celsius of warming. The review of the climate-economy literature asserts that climate events have a significant influence on a variety of economic outcomes including agriculture, labor productivity, industry and services, health and mortality, energy and conflict and political instability (Dell, Jones and Olken, 2014). This paper focuses on the effect of temperature and geography on conflict.

Temperature and Violence Studies in psychology have shown that excessive heat appears to cause increases in aggression in many settings (Anderson, 2001). Anderson (1989) shows that there are 2.6% more murders and assaults in the United States during the summer. Kenrick and MacFarlane (1986) find that in Phoenix, Arizona, aggressive horn honking increases at hotter temperatures. According to Reifman *et al.* (1991), baseball pitchers are more likely to hit batters on hot days.

Do these consequences observed in micro settings translate to a more global scale? The answer is that they do. Burke *et al.* (2009), in a panel study of sub-Saharan countries between

1981 and 2002, found that a temperature rise of one Celsius resulted in a 4.5% increase in the incidence of civil war in the same year and an increase of 0.9% in conflict incidence the year after. Hsiang *et al.* (2011) show that conflict probability doubles in tropical regions during El Niño (higher temperatures) in comparison to La Niña (colder temperatures). These authors argue that El Niño-Southern Oscillation (ENSO) has a role in 21% of civil conflicts during the 1950-2004 period.[8] Wetherley (2014) shows that riots and looting intensify one year after a typhoon in the Philippines. Hsiang and Burke (2014) do a meta-analysis on 55 countries, focusing on studies which use natural experiments to examine the effect of temperature on violence, and find that an increase of one degree in contemporaneous temperatures increases the probability of interpersonal and inter-group conflicts by 2.4% and 11.3%, respectively.

Not all findings on temperature and conflict are black and white however. Burke *et al.* (2009) argue that variations in rainfall have an impact on conflict through rises in temperatures as these two climatic variables are negatively correlated. Moreover, in a study of sub-Saharan Africa between 1980 and 2012. O'Loughlin *et al.* (2014) conclude that warm extremes of temperature are associated with additional conflict. They, however, suggest a more nuanced perspective on their results by specifying the lack of consistency of the results across different types of conflicts and different sub-regions. Divergences in parametrization, i.e., temperature averages, deviations from the average or the use of extremes explain some of the discrepancies in the literature. Burke *et al.* (2015) focus on this issue: identifying non-linearities when going from micro to macro results. They attempt to unify the data by taking into account nonlinearity at a macro level and show that the link between temperature and overall economic productivity is non-linear, with a peak at 13 degree Celsius and a sharp decline for higher temperatures for all countries.

Nevertheless, conflict cannot be explained solely by variations in temperature and is dependent on a various array of complex interactions with other factors, such as geographic conditions and/or economic/political conditions (Burke *et al.*, 2015). This limits the scope of the determin-

[8] Grove (2006) highlights late 18th centurys El Niño contribution to triggering subsequent economic, intellectual, and social events at that period of time (e. g., the French Revolution of 1789).

istic views that regard climate as the main key factor in generating conflicts. A more realistic approach sees climate as a "threat multiplier for instability" (CNA Board, 2007). Hence, the research agenda should focus on specific mechanisms linking climate variables to conflict and other political/economic outcomes.

Mechanisms Political gain, greed and grievances generate and aggravate conflicts (Montalvo and Reynal-Querol (2005), Glaeser (2005), Theisen (2012)). Migratory flows might also play a role in the onset and duration of conflicts (Bohra-Mishra *et al.*, 2014). Competition over resources is considered a key determinant of conflict. Economists analyze conflict with a rational cost/benefit analysis (Collier and Hoeffler, 2002). As a consequence of a negative income shock, agents are more likely to engage in conflict because their opportunity cost has decreased (Hissler, 2010). Miguel *et al.* (2004) show that a 5% negative growth shock increases the probability of conflict in the following year by 12%. In this paper we focus on the role of natural resources in exacerbating the impact of temperature on conflicts.

Natural resources and conflicts There is whole strand of literature devoted to the so-called resource curse whereby well-endowed countries resource-wise have economically failed to meet the expectations generated by their resources' bounty. For example, Collier and Hoeffler (2005) show that the probability of conflict increases with the degree of dependence of a country towards natural resources. However, these cursed countries are generally rich in exportable natural resources such as oil, diamonds, etc. In this paper, we focus on another curse at the opposite of the endowment spectrum, i.e., a poor endowment in natural resources, such as water scarcity, unsuitable lands to grow cereals, etc. Kameri-Mbote (2007) study the historical conflict related to the Nile between Egypte, Ethiopia, Sudan. Mukhar (2006) examines the conflict over water between Israel, Palestine and their neighbors. Maystadt and Ecker (2014) find that droughts generated the conflict in Somalia through an escalation of livestock prices. Sinai (2015) argues that Syria, between 2006 and 2011, experienced its worst drought and harvest losses in history and that this might have contributed to the onset and duration of the conflict during the subsequent years. Most studies examining the interaction between climate variables and resources have focused on case studies of one or a few specific countries. The objective of this paper is to examine the impact of this interaction for a wide panel of countries during an extended period of time.

3 Empirics

3.1 Data

Armed conflicts Data on armed conflicts is taken from the UCDP/PRIO Armed Conflict Dataset, developed by the International Peace Research Institute of Oslo (PRIO) and the department of Peace and Conflict Research at the University of Uppsala which manages the Uppsala conflict data program (UCDP). This dataset is deemed more transparent than other similar datasets such as The Correlates of War (Miguel *et al.*, 2004). The UCDP data constitutes the main reference in terms of data on organized violence and civil war from 1946 and on.

According to the UCDP definitions, a conflict consist in fighting for an incompatibility related to power and/or territory. A minor conflict has 25 or more annual battle-related deaths and a war has 1000 or more annual battle-related deaths (Gleditsch, Wallensteen, Eriksson, Sollenberg et Strand, 2002). The UCDP uses three sub-definitions of conflict/war. First, a state-conflict involves two parties of which at least one is the state. Second, a non-state conflict is defined by two parties not related with the state. Finally, the third category of conflicts is related to unilateral violence exerted by the state or a formal group against civilians without any incompatibility related to power and/or territory.

State conflicts are then divided into four sub-categories. First, an extra-systemic conflict pits the State against a non-state group outside its territory. Second, inter-state conflicts involve two or more states. The third category is concerned with conflicts where the State fights against one or many internal groups without other countries intervening. Finally, internal-internationalized conflicts involve the State against one or more internal groups and other countries intervening on one side or the other (UCDP, 2017).

Pettersson et Wallensteen (2015) show that the number of exta-systemic and interstate conflicts has significantly decrease over the last 40 years. Since the beginning of the 21st century, only one conflict can be categorized as such, involving Pakistan and India in 2014 with less than 50 battle-related deaths. However, since 2004, there is an increasing trend in internal and internal-internationalized conflicts, with 2014 the most lethal year since the end of the cold war. We thus focus in this paper on those last two categories. This implies that we do not take into account non-state conflicts and unilateral violence by a government. For example, conflicts involving pastoral groups in Northern Kenya or the Arab springs, are not taken into account in this analysis.

Conflict incidence, the dependent variable for this study, is a binary variable which takes a value of 1 in all years and all countries where there is an active conflict (internal or internal-internationalized), and a value of 0 otherwise.

Temperature We use the high resolution dataset on climate variables from the Climatic Research Unit (CRU) from the University of East Anglia. The data is based on time-series of monthly observations from meteorological stations across the world, interpolated in 0,5 latitude / longitude grid cells covering earth surface between 60 S and 80 N (except Antartica). The CRU dataset compares well with other similar datasets. For example, regional correlations with data from the University of Delaware are .73 (for South-East Asia) up to .98 for other continents. The main reason behind the discrepancy for South-East Asia is the lack of available raw data. The temperature variable in this paper is an annual average based on monthly averages per country in the CRU dataset.

Agricultural potential: crop suitability index GAEZ was developed over the past 30 years by the FAO and the International Institute for the analysis of applied systems. Its portal is an interactive tool which grants access to data on various themes, from agro-climatic resources, related to water and soil, to agricultural production (FAO, 2018).

Agricultural potential is defined by intrinsic characteristics at the country level which do not vary across time. We focus on an index of suitability to grow cereals but we have also examined other variables such a water scarcity among major river basins (see robustness section below). The suitability index is based on yearly observations from 1961 to 1990 on various characteristics related to soil quality which change very slowly across time.[9]

The index is based on cartographic data with a resolution of 5 minutes of an arc. The evaluation of the agricultural potential is based on potential yields for more than 280 types of cereals and soil uses and it is an inventory of natural resources, their biophysical limitations and their productivity potential (FAO, 2018). Note that the suitability index represents a potential and differ from real returns which vary according to specific climatic conditions.

We focus on cereals dependent on a simple rain regime and a low level of inputs. Focusing on cereals follows from the fact that many conflicts occur and persist in regions where food security is an issue. The focus on a rain regime is privileged over other regimes (rain with water conservation, irrigation by gravity, by aspersion or by dripping) to avoid endogeneity issues caused by human interventions, i.e., irrigation. Similarly, we focus on a scenario with a low level of inputs, because it corresponds to traditional agriculture, i.e., high labor intensity and few or no human intervention in terms of nutriments and/or chemicals. The other levels of inputs (intermediate or high) assume more advanced management and exploitation systems oriented towards markets and commercial goals.[10] These choices (cereals, rain regime, low level of inputs), we believe, give a clearer picture of the basic potential to grow cereals across the

[9] Nunn and Qian (2011) use a similar variable, soil quality, as an exogenous variation across countries to examine the impact of the introduction of the potato on economic outcomes in Europe during the 1800s.

[10] Production under these other levels of inputs uses high-yields crop varieties and is operated with manual tools and animal or mechanical traction.

world without human interventions.

GAEZ classifies land area into eight categories, from not suitable (SI=0) to highly suitable (SI=100). The surface of a country is therefore divided into areas which fit one of the eight categories. In our analysis, we take the ratio of the area of a country with a suitability index of 40 or more over the total land area of this country. Using any other threshold does affect the results but for the sake of brevity we focus only on GAEZ medium threshold (results with other thresholds available upon request).

3.2 Descriptive statistics

The main sample is an unbalanced panel of 172 countries over the period 1946 to 2014. Following Gleditsch (2012)'s definition of an independent state, some countries appear and other disappear throughout the period. Table 1 presents some descriptive statistics for the main variables under analysis.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Incidence	0.151	0.358	0	1	9344
Average Incidence per year	0.151	0.043	0.037	0.238	69
Number of conflicts per year	20.420	9.644	3	35	69
Number of years in conflict	8.186	13.834	0	67	172
Average temperature (Country)	18.623	8.26	-7.3	29.6	172
Average temperature (World)	18.318	1.473	15.088	20.119	69
Surface with $SI > 40$	0.24	0.226	0	0.985	172

Average incidence is 0.15 with a standard deviation of 0.36 for the whole period and a standard deviation of 0.04 using yearly averages. The average number of civil conflicts per year is close to 25 with a maximum of 35 civil conflicts in 1990, 1991 and 1992. The average number of years a country was in conflict is 31.4 with a maximum of 67 years for Myanmar. Average world temperature between 1946 and 2014 is 18.6 with a minimum at 15 and a maximum around 20. Canada faced a minimum average temperature of -7.3 and Mali a maximum of 29.6. In terms of the suitability to grow cereals, 24% of the land worldwide have a Suitability Index above 40 with 18 countries having no land classified with an SI above 40 and with Moldova having 98.5% of its land classified with an SI above 40.[11]

Figure 1 exhibits the correlation between average conflict incidence and crop suitability (LHS panel) or temperature (RHS panel). The correlation between average conflict incidence and crop suitability is negative with a coefficient of -0.1. The correlation between average conflict incidence and average temperature is positive with a coefficient near 0.2.

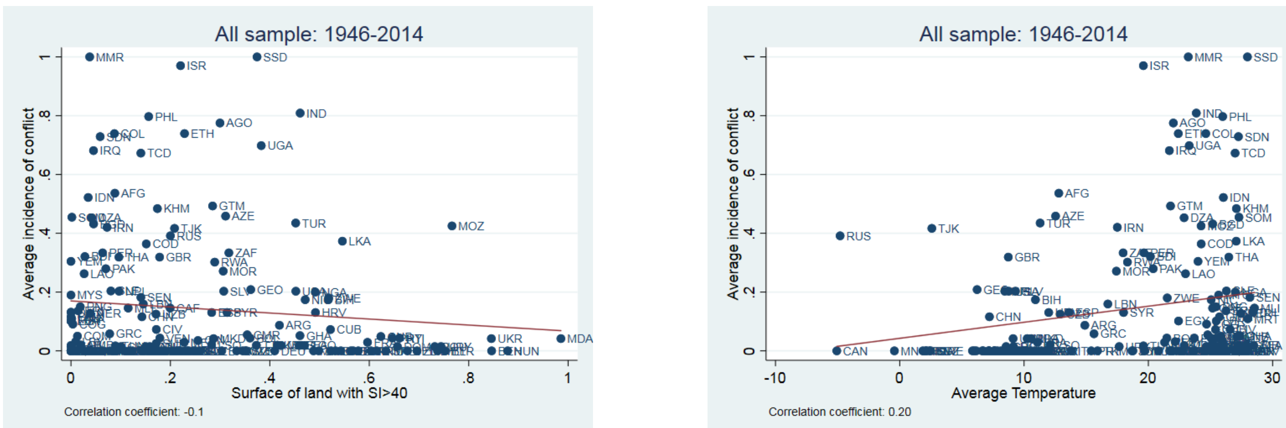

Figure 1: Average conflict against agricultural potential or temperature

Figure 2 presents time series for temperature and conflict incidence for the whole sample. Average world temperature is steadily on the rise for the whole time period. Civil conflict incidence presents an upward trend until the end of the cold war, drops until early 2000's but as argued by Pettersson and Wallensteen (2015) the trend has been steadily on the rise for the past decade.

By regions, European countries account for 25 % of the sample, 9 % for middle-East, 20 % for Asia, 25 % for Africa and 22% for the Americas. Table 2 presents the descriptive statistics by regions.

Figure 3 exhibits time series for temperature and conflict for each of these regions. One important thing to note is that conflict incidence varies by regions and time periods. Europe

[11]Countries with no land classified with an SI above 40 are: Bahrain, Brunei, Cape Verde, Djibouti, Gabon, Iceland, Kuwait, Liberia, Maldives, Mauritius, Malaysia, Oman, Qatar, Saudi Arabia, Singapore, Solomon Island, United Arab Emirates, Yemen.

Table 2: Summary statistics 1

Variable	Mean	Std. Dev.	Min.	Max.
Europe				
Incidence	0.043	0.203	0	1
temp	8.986	4.934	-6.600	20.8
Surface with $SI > 40$	0.342	0.259	0	0.985
N		2106		
Middle East				
Incidence	0.242	0.428	0	1
temp	21.439	4.637	9.700	29
Surface with $SI > 40$	0.091	0.139	0	0.452
N		943		
Asia				
Incidence	0.233	0.423	0	1
temp	18.2	8.763	-2.5	28.6
Surface with $SI > 40$	0.129	0.141	0	0.603
N		1856		
Africa				
Incidence	0.183	0.387	0	1
temp	24.184	3.444	11.3	29.6
Surface with $SI > 40$	0.237	0.224	0	0.846
N		2601		
South, North and Central America				
Incidence	0.098	0.297	0	1
temp	20.777	7.389	-7.3	27.2
Surface with $SI > 40$	0.317	0.2	0.064	0.744
N		1838		

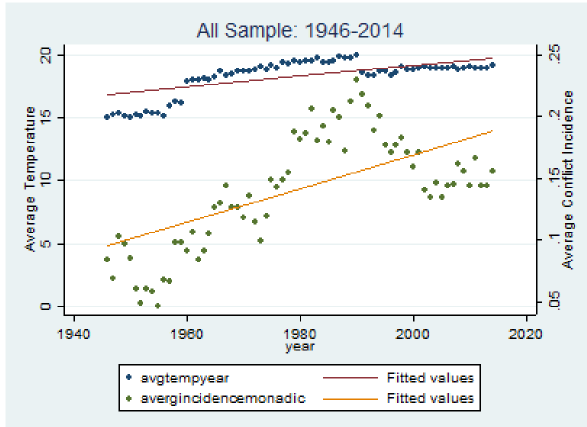

Figure 2: Time series for temperature and conflict incidence, whole sample

sees a surge in conflict incidence during the 1990's with the dismantling of former Yugoslavia. The Americas present higher incidence during the 1980's because of the various conflicts in central and latin America. Note that the U.S. is the main driver of the recent trends, being involved in 13 internal-internationalized conflict in 2014. Since the wave of African countries' independence in the 1960's, Africa has shown an unflinching trend towards more increased civil strife.

3.3 Persistence and stationarity

One major concern when working with long time-series is related to stationarity. Put bluntly, if some variable exhibits a unit root, i.e., behavior at time t-1 would fully explain behavior at time t and there would be nothing left to be explained by our analysis. In this section, we conduct a series of tests to check whether our main variables exhibit a unit-root. First, we examine cross-dependence across panel units, i.e., countries. Indeed, some subsets of the sample might share common sources of heterogeneity and this requires the use of specific unit-root tests. Second, we explore a few unit-root tests to check whether non-stationarity is an issue or not.

Cross-dependence As argued by Eberhardt and Teal (2011), cross-dependence among panel units is more a norm than an exception in macro panels. For example, a common exogenous shock (e.g., the 2008 financial crisis, a shared colonial past, a common set of institutions, etc.)

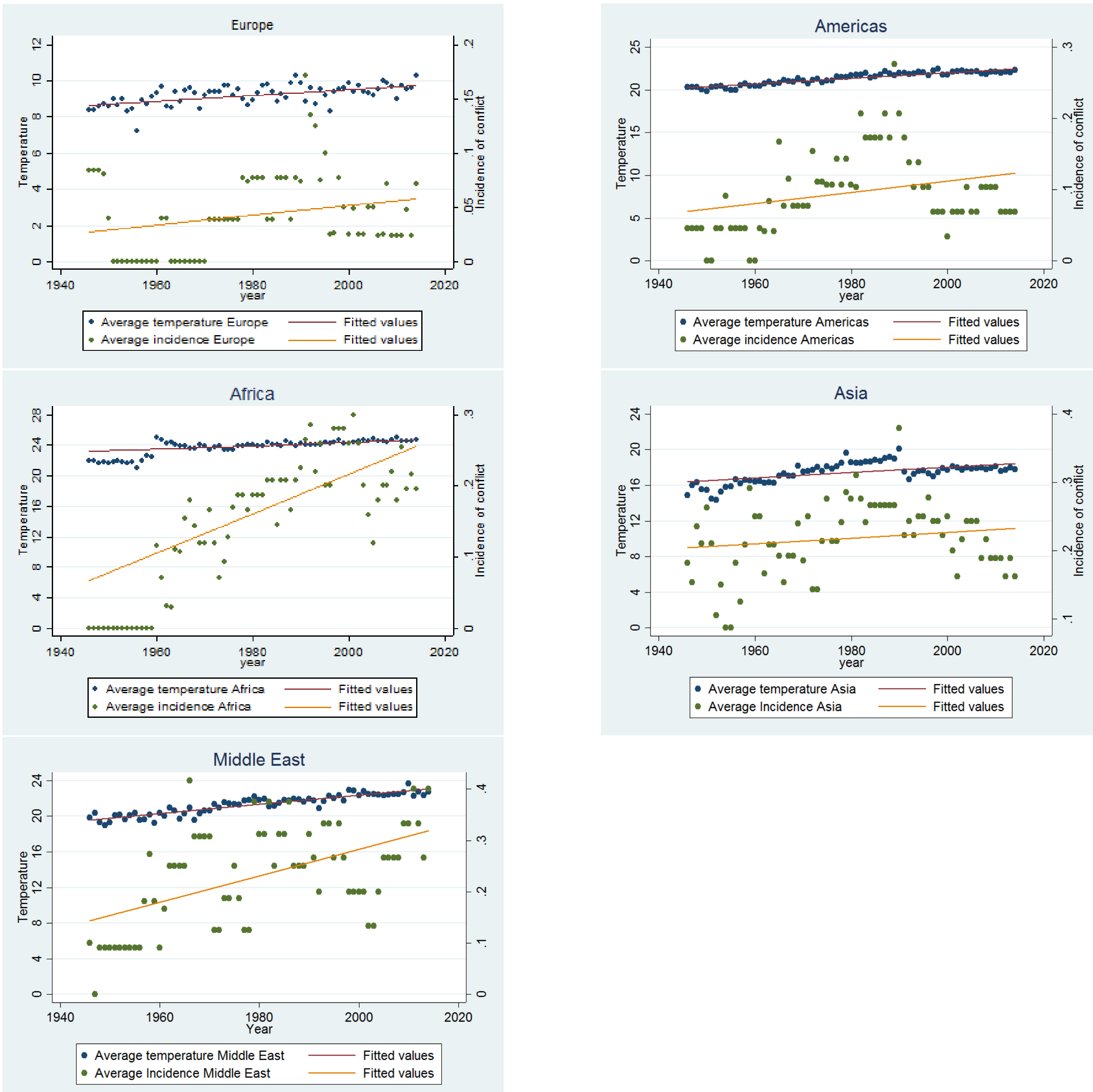

Figure 3: Time series for Temperature and Conflict incidence, by regions

or the result of an externality (e.g. a change in trade policy affecting neighboring countries) may result in heterogeneous effects across the panel units of a subgroup. It is thus of interest to test for such cross-dependence and use estimation methods robust to this type of correlations.

Pesaran (2004) and Pesaran (2015) develop a test for cross-dependence. Consider a simple model:

$$y_{it} = \alpha_i + \beta' X_{it} + u_{it}, \quad i = 1, ..., N \quad and \quad t = 1, ..., T \tag{1}$$

The correlation between two panel units will be given by:

$$\rho_{ij} = cor(u_{it}, u_{jt}) = \frac{\sum_{t=1}^{T} u_{it} u_{jt}}{\left(\sum_{t=1}^{T} u_{it}\right)^{1/2} \left(\sum_{t=1}^{T} u_{jt}\right)^{1/2}} \tag{2}$$

and the test hypotheses are then given by:

$$\begin{cases} H0 : \rho_{ij} = \rho_{ji} = cor(u_{it}, u_{jt}) = 0 \quad for \quad i \neq j \\ H1 : \rho_{ij} = \rho_{ji} = cor(u_{it}, u_{jt}) \neq 0 \quad for \quad i \neq j \end{cases} \tag{3}$$

Pesaran (2004) shows that the test-statistic follows a normal distribution under the null. In table 3, we examine cross-dependence for conflict incidence and temperature. The statistics for conflict incidence and temperature are significant at the 1% level, rejecting the null of independence between panel units in our sample.

Table 3: Cross-dependence

Variable	**CD stat**	**p-value**
Conflict Incidence	5.34***	0.0
Temperature	376.38***	0.0

Note: *** significant at 1%

Unit root tests We next examine whether conflict incidence or annual temperatures exhibit a non-stationnary process by testing for the presence of a unit-root for these variables. We focus on second generation unit-root tests because these tests account for cross-dependence.

Im *et al.* (2003) consider the presence of heterogeneity across panel units to conduct a unit root test. Hence, the results from the unit root test may differ across panel units, avoiding to reject (or failing to) stationarity for the whole panel. Consider the following model:

$$\Delta y_{it} = \alpha_i + \beta_i y_{it-1} + \mu_{it}, \quad i = 1, ..., N \ \ and \ \ t = 1, ..., T \tag{4}$$

where $\beta i = -(1 - \phi)$. We are interested to check if $\phi_i = 1$. The hypotheses for this test are:

$$\begin{cases} H0 : \beta_i = 0 \quad for\ \imath = 1, ...N \\ H1 : \beta_i < 0 \quad for \quad i = 1, ...N_1 \\ AND \\ H1 : \beta_i = 0 \quad for \quad i = N_1 + 1, ..., N \end{cases} \tag{5}$$

where $0 < N_1 < N$. The alternate hypothesis thus admits two sets of panel units, i.e., N_1 units with a stationary variable and $N - N_1$ units exhibiting a unit root. The Im *et al.* (2003) statistic is an average of the N statistics of individual ADF tests (first generation tests, see Levin *et al.* (2002)). The authors show that the normalized statistic under H0 follows a normal distribution asymptotically. A rejection of the null of Im *et al.* (2003) statistic indicates that at least one panel unit exhibits at least one stationary variable.

To execute Im *et al.* (2003)'s unit root test, one needs to take into account the auto-correlation generated by the introduction of lags of the dependent variable among the regressors. The optimal number of lags is specific to each panel unit and is done based on various criteria (AIC, BIC, HQIC).

Table 4 presents the results of various test using or not a trend and various numbers of lags (0, 1 and 2 lags) and all tests use demeaned variables. From Table 4, we can never reject the presence of a stationary panel unit for conflict incidence. The null is always rejected for conflict incidence using or not a common trend, using 0, 1 or 2 lags and no matter which criterion (AIC, BIC or HQIC) we use in conjunction with those lags (results available upon request). For temperature, the null is rejected when there is no common trend introduced and this, no matter the number of lags being used for the estimation. However, with both a common trend and lags (1 or 2), the null that all panels contain a unit root cannot be rejected. Hence, first-difference and second-difference in temperature are non-stationary. Nonetheless, conflict incidence and temperature in levels do not exhibit non-stationary processes (not for all panel units). This guides us in our analysis below as we focus on a regression in levels.

Table 4: Unit root tests, Im *et al.* (2003)

Variable	**No lags**		**1 lag**		**2 lags**	
	No trend	Trend	No trend	Trend	No trend	Trend
Conflict Incidence	-23.1***	-26.1***	-21.8***	-15.3***	-12.7***	-5.1***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Temperature	-14.9***	-15.5***	-10.5***	-0.38	-9.2***	1.1
	(0.00)	(0.00)	(0.00)	(0.35)	(0.00)	(0.86)

Note: p-value in parenthesis; *** significant at 1%; In all tests, cross-sectional means are subtracted; Z-t-tilde-bar stat: no lags; W-t-bar stat: 1 lag; Number of panels: 169; Average number of periods: 55.2

4 The model

In order to examine the main question of the paper, we use the following model:

$$CI_{i,t} = \beta_0 + \beta_1 Temp_{i,t} + \beta_2 AP_i + \beta_3 Temp * AP_{i,t} + \nu_{i,t} \tag{6}$$

where CI_{it} represents conflicts incidence for country i during year t, $Temp_{it}$ is temperature, AP_i is agricultural potential, $Temp{*}AP_{it}$ is the interaction between temperature and agricultural potential for country i at time t, and $\nu_{i,t}$ is the error term.

Now, the error term can be expanded to capture unobservables at the country level as well as across time, i.e., we can introduce fixed effects in our analysis. Let us identify country fixed effects and time fixed effects by α_i and γ_t respectively. Note that AP_i does not vary across time and is thus captured by α_i. Rewriting equation 6, we have:

$$CI_{i,t} = \beta_0 + \beta_1 Temp_{i,t} + \beta_3 Temp * AP_{i,t} + \alpha_i + \gamma_t + \varepsilon_{i,t}$$

(7)

We present below the results of a linear probability model. The reason for this choice are as follows. Even if non-linear probability models such as Probit or Logit generate coefficients with the right sign, these models are problematic when it comes to the interpretation of the coefficient of the interaction variable. Ai and Norton (2003) show that with these non-linear models: (1) there could exist a positive or negative effect of the interaction term even if the coefficient is zero; (2) the significance of the effect of the interaction term cannot be tested with a standard t-test; (3) the effect of the interaction term is conditional on the set of control variables; (4) more specifically, the effect of the interaction term can change sign depending on the set of controls.

It is however possible to estimate the average effect with an OLS, i.e., a linear probability model (LPM). Angrist and Pischke (2008) show there are three advantages in using a linear over a non-linear probability model. First, linear probability model are more efficient at taking into account fixed effects (Caudill, 1988). Second, Probit and Logit models make an explicit assumption about the functional form of the distribution of the error term (normal and exponential, respectively). Third, the coefficient of the LPM are readily interpretable. There are however limitations to LPM (Gujarati, 2004). First, the dependent variable follows a Bernoulli distribution which implies heteroskedasticity of the error term. This can be in part corrected using robust standard errors. Second, errors are not normally distributed. However, asymptotic theory shows that OLS follows a normal distribution for large sample which we have here. Third, predicted values may fall outside the [0,1] interval. However, we are concerned with the average treatment effect and Davidson and MacKinnon (2004) show that LPM gives more precise estimates for average treatment effect.

4.1 Identification

This study aims at establishing the causal link between temperature and conflicts through the magnifying lens of agricultural potential. There are obvious issues related to endogeneity in conducting such an analysis, namely reverse causality and omission bias.

First, concerns about reverse causality are attenuated by the choice of the main variables of interest. Temperature can be taken as exogenous in our model or, at least, cannot be impacted by conflicts. As argued, agricultural potential based on cereals grown from a rain regime and low inputs does not vary over the period under analysis. A concern could arise if the component of culture irrigation was affected by human activity in the construction of this variable. However, as argued earlier, GAEZ makes a clear distinction between the various irrigation regimes and inputs.

Second, to diminish concerns related to omitted variable bias and unobserved heterogeneity, we use a fixed-effect approach, to control for country and time unobservables. Controlling for country-fixed-effects conditions the analysis on the characteristics intrinsic to a country, thus purging out these idiosyncrasies and country-specific shocks (Dell *et al.*, 2014). For example, colonial legacy, institutional capacity, geography, which explain baseline differences across countries and could potential drive the results, are thus controlled for by country-fixed effects.[12] This allows focusing the analysis on the average causal effect of the interaction between temperature and agricultural potential on civil armed conflicts. Time-fixed-effects allow controlling for time trends and variables evolving across time such as economic performance which impacts conflict incidence (Burke *et al.*, 2009). Time-fixed-effects take also into account common trends across

[12]Salehyan and Hendrix (2014) have shown that democracies are indeed less likely to suffer from armed violence, contrary to other political regimes.

the sample and thus allow identifying a causal link through idiosyncratic perturbations at the individual level (Dell *et al.*, 2014). In summary, the fixed-effect model implies that all variables are evaluated against their time-average (within estimator), i.e., individual deviations are subtracted from their time-average. Hence, individual effects which are a source of endogeneity, are eliminated.

4.2 Results

4.2.1 Baseline results

Table 5 presents the baseline estimates.[13] In the first column, temperature does not enter significant. However, in column 2, when the interaction between temperature and agricultural potential is introduced, we observe a larger and significant coefficient for temperature and an interaction term which is both significant and negative.

From equation 7, the total effect of temperature on conflict incidence is $\beta_1 + \beta_3 * AP_i$ where AP_i is called the moderator variable. If the moderator variable (agricultural potential) is set to zero, say a country without any land with a SI above the medium threshold, the effect of a rise of one degree in temperature increases the incidence of conflict by 3%. Instead, if the moderator variable is set to one, the effect of a rise of one degree Celsius is -5%.

In the following columns of table 5, we examine other likely causes for these results and run a set of robustness checks. First, we examine the persistence of conflict incidence, i.e., conflicts tend to linger and conflict at time t-1 may explain conflict at time t. We thus introduce a lag of the dependent variable in column 3. The coefficient on this lag is highly significant and has a large magnitude. Nevertheless, the coefficients on temperature and its interaction with crop suitability remain significant with a somewhat smaller magnitude however. Introducing a second lag for conflict incidence in column 4, the coefficient for temperature remains significant but not for the interaction term. In column 5, we introduce lagged temperature and this does not alter the

[13]We present in the appendix the results based on a probit estimation with a random effect model. The signs of the coefficients on temperature and its interaction are unaffected.

coefficients for temperature and its interaction term. In column 6, we use an alternate measure for temperature, i.e., its standardized distribution with mean zero and a variance of one. Climate variables more often than not present anomalies and normalizing such variable allows examining variations around the mean, controlling for the sample variation over the period of study, see for example Barrios *et al.* (2010). We note from column 6 that standardizing temperature does not affect the results qualitatively. Finally, in column 7, we use decade averages for conflict incidence and temperature examining long differences. The results are not affected qualitatively. However, we see a stronger effect of temperature when countries have an extremely poor endowment in agricultural potential with conflict incidence increasing by 9%. In the opposite case, the mitigating effect of a good endowment in agricultural potential is not as strong in the long run as in the short run with conflict incidence decreasing by 3%.[14]

Interaction figures In the previous subsection, we have analyzed the effect of temperature according to extreme values of the moderator variable. In this section, we present a somewhat rough graphical depiction of the effect of the interaction between temperature and agricultural potential on conflict incidence. In order to construct Figure 4 below, we first run an OLS using average conflict incidence between 1946 and 2014 for the dependent variable, and where the independent variables are average temperature between 1946 and 2014, agricultural potential and the interaction between average temperature and agricultural potential. Figure 4 is then built using the predicted values for conflict incidence. On Figure 4, there are two red zones which corresponds to the highest predicted conflict incidence.[15]

In order to understand Figure 4, take two countries with a similar average temperature, say

[14]We have also tested for the inclusion of fixed-effect at the regional level in order to account for regional unobservables. This does not affect the results which are available upon request. This should not be surprising as country and year fixed effects are already controlling for common trends across the sample. Examining regions separately, the results hold only for Africa or Europe depending on the specification. This is due to a change in sample size and also a weakening of the identification strategy. Indeed, the identification strategy relies on comparing countries in terms of their suitability to grow cereals. Variation at the regional level is much lower than at the global level which reduces the variation in the data, therefore limiting the scope for identification.

[15]These temperature intervals also correspond to the highest densities observed in terms of number of countries with these average temperatures (see Figure 5 in the appendix).

Table 5: Main results

	Panel estimates, dependent variable: Conflict incidence						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	(T only)	(Main)	(Persistence)		(Lag T)	Standardized T	Long-Diff
Temp	0.0121	0.0327**	0.0159**	0.0137*	0.0285**	0.021**	0.092**
	(1.24)	(2.17)	(2.16)	(1.88)	(1.98)	(2.57)	(2.01)
Interaction		-0.0802**	-0.0311*	-0.0242	-0.0797**	-0.047*	-0.129*
		(-2.10)	(-1.96)	(-1.65)	(-2.05)	(-1.92)	(-1.83)
Incidence_lag1			0.643***	0.521***			
			(26.24)	(20.57)			
Incidence_lag2				0.186***			
				(8.38)			
Temp_lag1					0.00919		
					(1.11)		
adj. R^2	0.030	0.031	0.432	0.449	0.030	0.031	0.078
N	9344	9344	9172	9000	9172	9344	990

t statistics in parentheses; Robust standard errors clustered at the country level;

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$;

All regressions include a constant, year and country fixed effects;

Column 6 uses standardized annual temperature at the country level.

Column 7 uses decade averages.

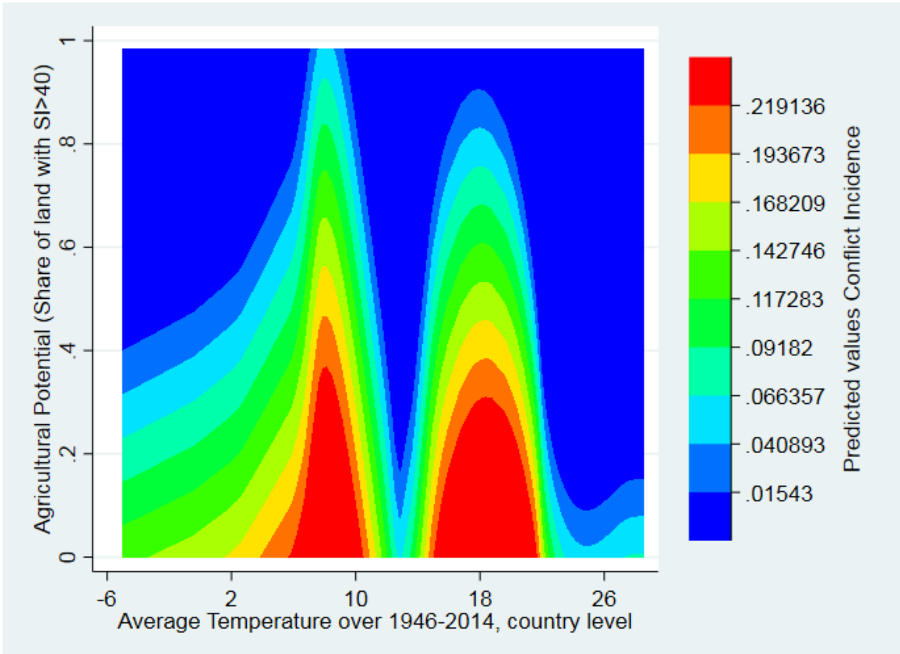

Figure 4: Predicted conflict incidence against Average Temperature and Agricultural potential

between 21 and 22 Celsius, which corresponds to Iraq and Swaziland in our sample. Now, Iraq has only 5% of its surface with a Suitability Index above 40 whereas Swaziland has 33% of its land surface with a SI above the medium threshold. Figure 4 shows that predicted incidence of conflict for Iraq (0.21) is about 1.5 times that for Swaziland (0.14). Actual conflict incidence data indicate that Iraq has been in conflict 68% of the time during the 1946-2014 period, while Swaziland has not seen one year of conflict from 1968 (year of its independence) till 2014 (based on UCDP definitions).[16]

4.2.2 Subgroups

Table 6 examines the effect of the interaction between temperature and agricultural potential depending on various subgroups.[17] In column 1, we examine groups with an agricultural share of GDP above and below 10%. Indeed, one preliminary intuition at the source of this paper

[16]Figures for each year taken separately present similar results (available upon request).

[17]The results of this subsection remain qualitatively unaffected using the interaction term AND the interaction interacted with one category of the various subgroups in the same regression.

was that countries highly dependent on agriculture might be more impacted by variations in temperature. Interestingly, the coefficients for the interaction of both type of countries is very similar in magnitude and significant at the 5% level. However, this result must be taken with caution as the sample size is dramatically reduced.

In column 2, we examine the impact of institutional quality, by parting countries based on their OECD membership. The results show that temperature and agricultural potential are substitutes for non-OECD countries. The effect is non-significant for OECD countries, thus confirming that institutions play also a role as a mechanism in limiting the effects of a variation in temperature.

In column 3, countries are divided based on their OPEP membership as large endowments in oil might override agricultural potential in the curse of natural resources. Indeed, the coefficient for the interaction for OPEP countries is not significant.

4.3 Robustness checks

Table 7 presents other robustness checks. We have examined the use of an alternate measure of agricultural potential, i.e., water scarcity by major river basins; and the use of additional socio-economic co-variates.

Alternate measure of agricultural potential: water scarcity As an alternate measure of agricultural potential, we use the intrinsic hydrological characteristics of a country which do not vary (or very little) across time as opposed to water resources which could be affected by sudden variations in temperature. To measure this hydrological potential for each country, we use the dataset on the level of water scarcity across major water basins from the Global Agro-Ecological Zone (GAEZ) project of the FAO. The global distribution of physical water scarcity by major river basin represents the ratio of consumed water through cultures irrigation over renewable resources in fresh water in a given water basin. Even if water basin are not an exhaustive measure of hydrological resources, they serve as a proxy for water availability in a

Table 6: Subgroups estimates

	(1)	(2)	(3)
temp	0.0387*	0.0326**	0.0316**
	(1.93)	(2.12)	(2.12)
c.ILand with $SI > 40$c.Agr_10	-0.111**		
	(-2.06)		
c.ILand with $SI > 40$c.non_Agr_10	-0.110**		
	(-2.02)		
c.ILand with $SI > 40$c.ocde		-0.0776	
		(-1.58)	
c.ILand with $SI > 40$c.non_ocde		-0.0818*	
		(-1.79)	
c.ILand with $SI > 40$c.opep			0.234
			(0.90)
c.ILand with $SI > 40$c.non_opep			-0.0804**
			(-2.12)
_cons	-0.332	-0.174	-0.216
	(-1.32)	(-0.78)	(-1.20)
adj. R^2	0.025	0.031	0.032
N	5532	9344	9344

t statistics in parentheses
All regressions include a constant, year and country fixed effects
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

given country. The variable lends itself however to potential endogeneity issues as irrigation is affected by humans. The aim of GAEZ is to define the intrinsic characteristics of a country with regard to its agro-ecological zones. As such, GAEZ makes a clear distinction between physical water scarcity (the variable used here) and infrastructure or institutional water scarcity (FAO, 2011). The data we are using is supposed to reflect water availability independently of man-made infrastructures.

This variable is made of four intensities from low to very high scarcity. For the sake of brievity and clarity, we present the results based on the threshold of moderate scarcity. Hence all land with an index of water scarcity below 20% is accounted as having a moderate level of water scarcity.

The results are shown in column 1 of Table 7. The coefficient on the interaction term is negative and significant at 5%. In a country with very high water scarcity, a one degree Celsius increase in average temperature increases conflict incidence by 15% whereas in a country with no water scarcity, a one degree Celsius increase in average temperature increase conflict incidence by a mere 0.4%.[18]

Other controls We control, on top of year fixed effects, for a number of potential socio-economic covariates which are potentially related to conflicts. According to Buhaug (2010), these covariates have more explicative power than temperature. As a robustness check, we thus examine the impact of including these additional controls on our results.

These potential covariates are taken from the World Development Indicators. We control for log GDP per capita (Miguel *et al.*, 2004). We control for inflation (Gupta *et al.*, 2004).

Population growth is also a control with ambiguous effect on conflicts. According to Humphreys

[18]The correlation between temperature and the interaction terms is really high for the water scarcity variable. Correlation is and 0.89 between temperature and the interaction for water scarcity. There are thus obvious concerns about colinearity. The correlation coefficient between temperature and the interaction variable for crop suitability is 0.27. Concerns about colinearity are therefore much lower for the baseline estimates as there is enough variation in both temperature and crop suitability variables in order to capture some relevant information about the impact of their interaction on conflict incidence.

(2003), higher population growth rates are associated with lower revenues and a larger likelihood of conflict. This is because overpopulation increases the competition over resources (Tir and Diehl, 1998). We use the exponential rate from year t-1 to t, expressed in percentage.

Using the sum of exports and imports as a percentage of GDP, we control for openess to trade as many studies have shown that trade is usually associated with peace (Polachek, 1980). This is because trade entices parties to cooperate in a positive sum game whereas conflict is a zero sum game.

Finally, we control for education, using data from the Barro and Lee dataset (Barro and Lee, 2013) on 146 countries from 1950 until 2010. We use the average number of years of schooling for the population 15 years old or older. Education may reduce the risk of conflicts through various channels, e.g. by fostering economic growth or spreading values of tolerance and pacifism (Smith and Vaux, 2003).

Controlling for these extra-covariates on top of year and country fixed effects, the coefficients on temperature and the interaction term for crop suitability are no longer significant (results available upon request). This is because we are overcontrolling as argued by Dell *et al.* (2009). If we only introduce these covariates but do not include country fixed effects as in Buhaug (2010), the interaction term remains significant as shown in columns 3 to 7 of Table 7. However, giving up country fixed effects implies that their is a host of unosbservable characteristics we are no longer controlling for. We are thus more confident in the main results presented in the tables of this paper.

More specifically, column 2 reproduces the baseline result for the crop suitability index. In columns 3 to 7, covariates are introduced one by one (not controlling for country fixed effects). Temperature is no longer significant but the interaction term remains significant, albeit with a much a smaller magnitude. On top of the unobservables unaccounted for without country fixed effects, there are obvious simultaneity issues regarding the additional covariates. For example, conflicts most certainly impact the level of GDP per capita and vice-versa (Miguel *et al.*, 2004). Hence, in order to account for this, we have used lags of the controls, following Collier and Hoeffler

(2002) and Fearon and Laitin (2003) (results available upon request). Finally, when we control for country fixed effects on top of the additional covariates, temperature and the interaction term are never significant (results not shown) and this is most likely due from overcontroling as argued by Dell *et al.* (2009).

Table 7: Robustness checks estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
temp	0.151**	0.0327**	0.00189	0.00189	0.00356	0.00478*	0.00256
	(2.28)	(2.17)	(0.66)	(0.66)	(1.17)	(1.65)	(0.68)
Iwater$_{s}carcity$	-0.146**						
	(-2.10)						
ILand with $SI > 40$		-0.0802**	-0.0101**	-0.0101**	-0.0110**	-0.0117***	-0.0106**
		(-2.10)	(-2.37)	(-2.37)	(-2.57)	(-2.84)	(-2.39)
ln_pib			-0.0631***	-0.0631***	-0.0643***	-0.0512***	-0.0368
			(-3.02)	(-2.99)	(-3.01)	(-2.61)	(-1.45)
inflation				0.00000111	0.000000893	0.00000116	0.00000162
				(0.08)	(0.06)	(0.08)	(0.11)
croissancepop					-0.0166*	-0.0163*	-0.0191**
					(-1.72)	(-1.68)	(-1.99)
commerce						-0.00111***	-0.00109***
						(-2.84)	(-2.78)
education							-0.0169
							(-1.07)
R_2 within	0.0390	0.0385	0.0267	0.0267	0.0283	0.0308	0.0325
N	9344	9344	5311	5311	5311	5311	5311

t statistics in parentheses

All regressions include a constant, year FE; Columns 1 and 2 with Country FE also.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5 CONCLUSION

In this paper, we examine the impact of the interaction between variations in annual temperature and variations in agricultural potential on the incidence of civil armed conflicts using a panel of 172 countries from 1946 to 2014. The conflict data is taken from the Uppsala conflict data project (UCDP). Data on temperature at the country level come from the Climatic Research Unit (CRU) of the University of East Anglia.

To define agricultural potential we use information from the Food and Agricultural Organization (FAO)'s project for global agricultural and ecological zones (GAEZ). We focus on cereals which use a rain-fed regime and a low-level of inputs as this make our agricultural potential exogenous from human interventions such as irrigation and fertilization. We use, as an indicator of a country's agricultural potential, the ratio between the surface with suitability index above a medium threshold set according to GAEZ definition, and the total surface in a given country.

We conduct a series of econometric tests in order to examine cross-dependence and stationarity. We find that our main variables, i.e., conflict incidence and temperature exhibit some cross-dependence across panel units. However, these two variables taken in levels do not exhibit a unit-root.

We use a fixed-effect panel approach to analyze the data and we regress conflict incidence on annual temperature and its interaction with agricultural potential. Our approach is akin to a natural experiment where the first difference in annual temperature is across time and the second difference in agricultural potential is across countries. We control for omitted variables by including fixed effects at the country level, thus controlling for institutions, history and geography. We also include time fixed effects, thus controlling for events and time trends which might have affected specific countries, regions or the world all over.

The baseline results show that when agricultural potential is low, i.e., none of the land surface in a country has a SI above the medium threshold, a one degree increase in temperature is associated with a 3% increase in conflict incidence. However, when agricultural potential is high, i.e., all land surfaces in a country are above the SI medium threshold, a one degree increase in temperature is associated with a 5% decrease in conflict incidence. This main result holds against various robustness checks.

Temperature and natural resources seem to act as substitutes. In other words, a better [worst] endowment in agricultural potential mitigates [exacerbates] the effect of temperature on conflict incidence. This result has important policy implications, given global temperatures are on the rise. In order to reduce conflict incidence and the risk of future onset, international aid could be targeted to compensate countries with low agricultural potential. Such transfers could occur in times where temperature variations increase the risk of conflict and, ideally, in anticipation of the onset of a conflict in order to avoid it. International mechanisms to reduce price fluctuations for basic staples and cereals could also potentially reduce conflict incidence in these poorly endowed countries.

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6 Appendix

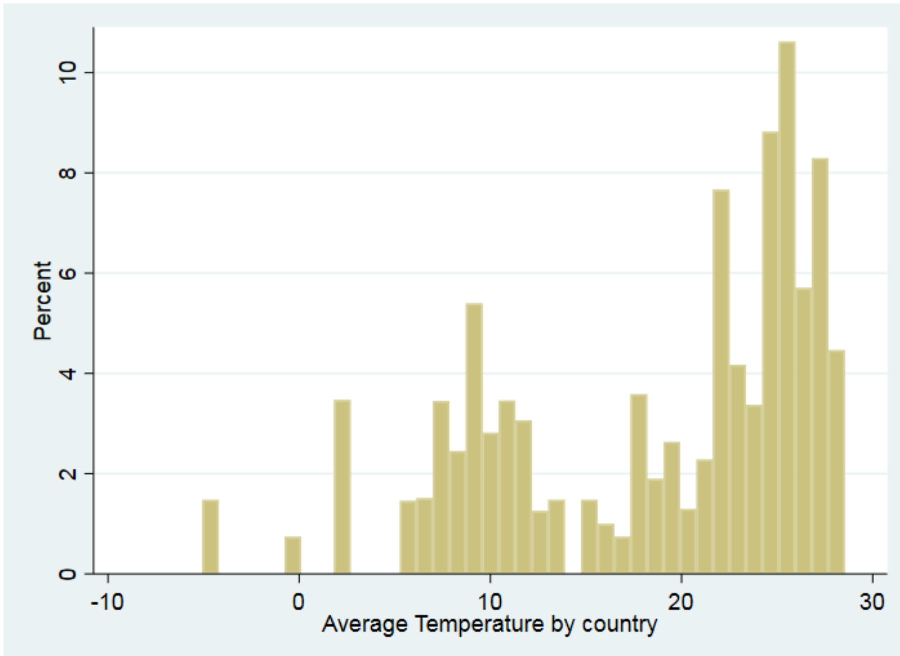

Figure 5: Distribution of average temperature over 1946-2014

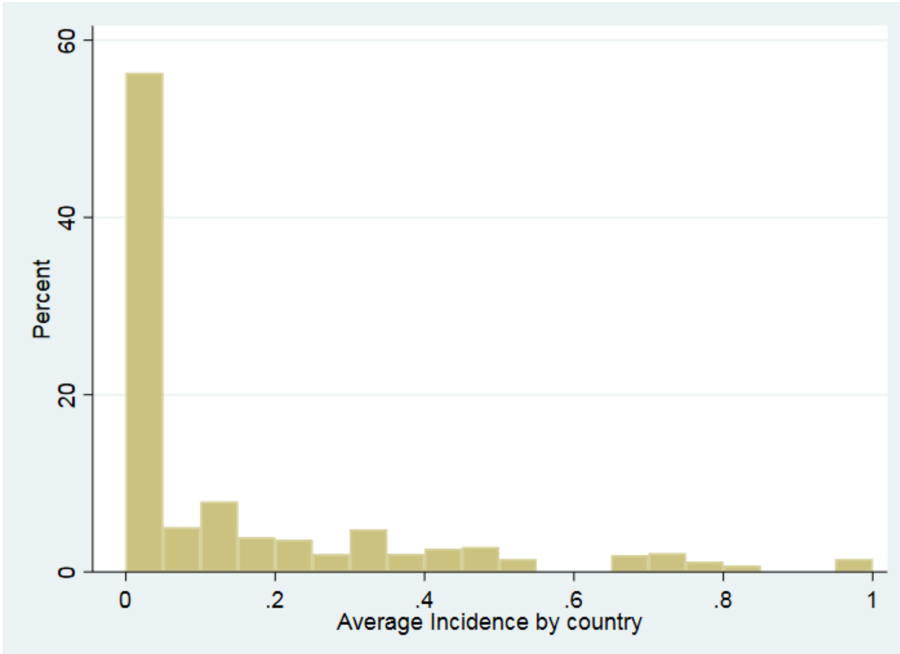

Figure 6: Distribution of average incidence over 1946-2014

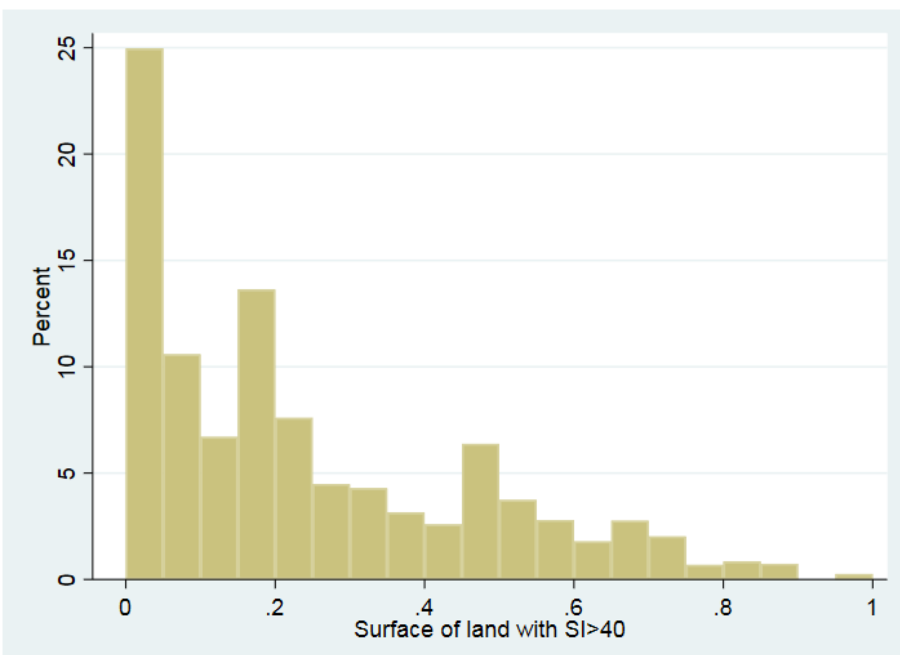

Figure 7: Distribution of SI above 40

Table 8: Probit regression, SI> 40

	(1)	(2)	(3)
temp	-0.0738***	-0.0601***	0.0859***
	(-8.78)	(-5.61)	(4.34)
ILand with $SI > 40$		-0.0619**	-0.0135
		(-2.17)	(-0.56)
_cons			-3.518***
			(-8.38)
/			
lnsig2u	1.241***	1.221***	0.802***
	(6.07)	(5.94)	(4.09)
N	9344	9344	9344

t statistics in parentheses; Columns 1 and 2, no constant

Column 3 with a constant; Random effect models

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$