# Toward a Global Conflict Heat Map Informed by Climate Change Stressors

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**Abstract:** Climate change and a rising global average temperature are likely to dramatically reshape the world as we know it over the coming decades. A statistical median of 2.7°C increase in global temperature by the turn of the century seems to be a reasonable prediction. Among other impacts, this corresponds to a significant increase in the heat stress experienced around the world. These conditions may bring forth food shortage, health and development issues, mass migration, civil unrest, and political instability, all of which could create conditions ripe for conflicts. It may be possible for governments to act preventatively to adapt and stabilize areas that have a high potential for climate-induced conflicts through infrastructure development, agricultural changes, treaties, agreements, or other means. However, systematically anticipating where conflict is most like to arise across borders and within states and measuring the risk reduction potential of various conflict prevention solutions is currently a gap. To that end, we are proposing to amend existing environmental models to include a probabilistic model relating conditions to conflict potential and create a global conflict likelihood map. Such a map will open up the possibility for action, and allow for the development of risk-based strategies to minimize the risk of, and ideally, avoid conflict.
Conflict in and of itself is difficult to model because of the lack of historical precedence and data needed to refine modern-day algorithms, and large uncertainties inherent in the problem. There has been some effort in the proposed direction, but the existing models have their shortcomings. Specific geographical locations have been studied in detail to check for various stressors causing conflict. In the other direction, there have been global mapping efforts which have not been able to richly address the stressors. There is room to bridge these shortcomings and make a "global heat map of conflict $n$ years from now." We are proposing a probabilistic approach which starts in the abundant and well-studied field of making global heat maps. We map out a multi-level multi-modal Bayesian network to understand the different hierarchies of causal factors. We explore micro- and macroeconomic factors, civil and political factors, issues of both internal and external security, and health and safety factors. Finally, we propose a path forward in constructing such a model and mapping the global potential for climate-induced conflict.

**Keywords:** Climate change, security, risk, conflict, Bayesian Network

## 1. INTRODUCTION

Human conflict can stem from myriad sources, including political disagreements, perceived social injustices, and economic disparity [1]. Researchers have postulated that the effects of climate change may have an increasing effect on the potential for human conflict by creating environmental conditions that exacerbate existing sources of conflict or create new ones. Resources to prevent or address the impacts of potential climate-driven human conflicts are likely to be limited, leading to difficult decisions on how best to deploy them. As such, governments and global development efforts require a clear understanding of where the most potential for human conflict in the future may exist, what preventative measures can be taken (such as investments in infrastructure and the development of cooperative plans, treaties, and agreements), and how to plan for sufficient resources to absorb and mitigate the consequences.
We seek an estimate of conflict risk for specific locations, at a global scale, tied to specific climate projections, using probabilistic risk methods. Such an analysis would result in a global "heat map" of conflict potential for some time, $t$, in the future. This map would need to account for and incorporate uncertainties in climate change projections along with uncertainties in the response of physical, social, and economic systems to those projections. Rather than taking a purely statistical or econometric view, this approach would also incorporate expert judgement and insights when that is the only information available. Estimates of conflict potential would be location specific and, in some cases, differ from estimates of climate change impacts because of local non-climate factors, such as cultural, financial, or societal features. That is, we hypothesize that just because a

place gets hotter or drier doesn't necessarily mean that it becomes more violent. Conflict potential will also depend on the resiliency of the underlying social and economic systems and on factors that involve neighboring nations – thus, a broader systems view is needed. We propose a risk-based, probabilistic mapping which looks at multiple factors without assigning causality to any one of them in particular. This paper lays out an approach to perform such an analysis, and documents the first steps in that effort.

## 2. BACKGROUND

There have been numerous efforts to identify relationships between conflict and climatic factors over the past few decades. A number of studies have focused on both potential climate drivers for conflict in specific locations [2] and overall impacts to factors globally [3]. In general, we find that there is no standard definition of violent conflict throughout literature due to the diversity of perspectives used. It covers all aspects, from interpersonal conflict [4] to larger mobility events like riots or even war [5]. Ideally, there needs to be a standardized definition with vertical scalability that can be utilized from local to more global levels of conflict. There are also various sociological hypotheses to explain intrastate conflict-initiation mechanisms [6], and it is widely acknowledged that these theories are not mutually exclusive.

A large fraction of the existing work has focused on statistical analysis of historical events in an attempt to make inferences about the potential for future impacts (see for example [7]). Many researchers have applied regression analyses in various forms, based on the idea of examining extreme weather or climate events correlations to conflict actions. However, there is no clear consensus on how these factors interact with each other. [8] Further, various studies have pointed that only one factor, like heat or agriculture, does not often yield statistical significance when it comes to mapping out causative factors for conflict [9]. The primary drawback with these methods is the existence of reliable data. Often, there is simply not enough historical data when describing conflict in the appropriate conditions at the global level, so researchers tend to focus on areas where data is available ([10]).

Some scholarly articles and popular press publications examine conflict from a game theoretic perspective by postulating incentives for some behaviors and penalties for others. Collier and Hoeffer discuss a possible expression of the utility of conflict for rebel factions and how it is influenced by various economic factors [1], building on previous efforts that established a theoretical framework that serves as a foundation [11, 12, 13]. Using such an approach allows us to build parameterized solutions for simple cases.

However, it is well established that game theoretic models are difficult to scale when incorporating many players, and the numerous simplifying assumptions may not capture the reality of our state of the world. Some of these ideas have, in fact, inspired us to take up a related approach and move along the lines of probabilistic modeling.

Further dissecting the existing state of literature, we look at the time frame of the analysis. As mentioned above, most of the analysis looks at immediate past effects of climate variability or change in weather patterns like an extreme climate event or recent temperature changes [14]. While these analyses are helpful in adaptation and planning, they do not fully capture the consequences of climate change. Climate change is a phenomenon we observe over a longer period of time in a large-scale setting as a result of multiple interactions of these short-term weather changes and some underlying causes like carbon emissions. It is critical to look at a longer period to inform the full body of the analysis [15, 7]. It is also important to note the temporal lag and inconsistencies in predictions as we face accelerated, not just faster, climate change.

There has also been a great deal of study into the root causes of conflict, which can inform our modeling approach. The Greed and Grievance theory of internal conflict acknowledges the role of various drivers of inequity and how inequitable distribution of resources can move a population toward a rebellion [15]. Greed, or economic inequity, gives rise to conflict by being a direct economic motivation for individuals and/or groups. There is an opportunity cost associated with carrying out said rebellion which is weighed against the financial incentives up for grabs at the end of the conflict. Rebels are incentivized by these financial possibilities. The other half of the theory focuses on grievances which are real or perceived socio-political inequities between groups, such as marginalization, or deep-seated ethnic and religious biases. Systemic inequities like human rights violations, oppressive governance, or economic inequalities leading to hatred or feelings of injustice are all candidates for grievances. Greed and grievances go hand in hand, and their interaction can lead to complex emergent phenomena which lead to mobilization toward rebellion. We examine both greed and grievances as

exacerbated by climatic stressors, not ascribing particular importance to any one of the arms but allowing for the importance of variables to reveal themselves based on probabilistic relationships.
The scientific community has made immense progress on the climate-prediction front. While there exists a deep uncertainty in the realization of the future state of the world, there is a reasonable expectation by which to anchor our analysis [16]. The climate model that we use as a basis of our analysis is related to the adaptivity limit with increase in temperature [17]. To quickly recap related concepts, wet bulb temperature (WBT) is a measure of the combined impact of temperature, wind speed, humidity, and solar radiation. WBT effectively talks about the ability of a body to cool off in a said environment. Humans cannot tolerate WBT beyond 35°C (or 95°F), which means the body starts to experience hyperthermia beyond these temperatures. Under these circumstances, when the body cannot regulate the temperature, heat stress is observed, which is comprised of exhaustion, heat stroke, and even death. It is not difficult to see that, in addition to ecological considerations, an increase in heat stress has a wide range of economic, human, and societal consequences, including, but not limited to loss of labor productivity, an increase in healthcare cost, higher energy requirements to facilitate cooling, etc.

## 3. PROPOSED APPROACH

Our goal is to estimate, for a specific location $l$ at time $t$, the probability of conditions conducive to conflict $C$, $Pr\left(C|l,t\right)$. We argue that the factors that influence $C$ are, in some way, relatable to climate factors commonly predicted in current models, such as WTB. We would like to estimate $Pr\left(C|l,t\right)$ for many locations and create a map of the probability that conditions are conducive to conflict that can indicate hot-spots and inform decisions for management. It is worth noting that we are not seeking to predict where and when conflict will occur, or directly addressing the probability of conflict itself. Instead, we are mapping when economic, social, and other factors could create a local environment such that a population might be incentivized to begin fighting.

### 3.1. Defining Terms

Our first task is to define what is meant by *conflict* for the purposes of this analysis. We have chosen to specifically focus on intrastate conflict such as civil wars and rebellion, and not interstate conflict, for reasons we will explain in subsequent sections. There are many possible definitions of conflict that could be employed. For example, the threshold of intrastate conflict has been defined in some literature as at least twenty-five battle-related deaths [18]. Credibly using such a definition would require additional model complexity and data on conflict outcomes that is not readily available at the scale and scope required for a global conflict "heat map." Instead, we adopt a combination of group motivation hypothesis and private motivation hypothesis to define the threshold of conflict as the set of conditions when factions would prefer conflict over peace. Put together, these hypotheses address initiation of discord over various dimensions like political, economic, and social factors. Additionally, we are able to explain the reasons for civil conflict to continue once it has been initiated. Some motivating factors for this behavior may include opportunities to loot, trade arms, and other illicit activities. These activities seem lucrative as a new opportunity for utility maximization which would otherwise not have been possible in peace time. All said, we are relying on a strong rational-choice theory argument to map from environmental conditions to conflict potential.

### 3.2. Assumptions and Scope

Our initial modeling focus is on intrastate conflict and associated factors as opposed to interstate conflict. This is based on an assumption that local economic and unrest are factors that are likely more immediately sensitive to heat and labor disruptions. We posit that global economic factors like trade lane access, access to resources, and others, are more likely to be reasons for interstate conflict when domestic conditions for actors demand conflict responses because of desperation. This is based on the argument that there must be a direct security benefit for a nation to create war with another nation. Therefore, we also posit that outside of an acute political grievance, a nation is less likely to invade a neighbor just because of heat stress, and more likely to suffer conflict within its own borders because of exacerbated local conditions.

In our current proposal, we assume the smallest unit of geographical measurement to be a country. In doing this, we take an average measurement for the entire country for a given year in the future. We are also assuming that the internal conflict of a country is due to the internal conditions at that particular location in a given time. In this model, we are assuming no changes in intrastate conflict due to interstate conflict.
The assumptions and scope limitations discussed above may seem overly narrow. We are making these assumptions as a matter of creating an initial framework for the model, which we will revise as we move forward. As we build and successfully utilize the initial framework, we will work to relax some of these assumptions and expand the scope to account for more factors. That said, we believe that the assumptions and scope limitations are still consistent with our understanding of the literature.

### 3.3. Modeling Approach

As discussed above, we define the conditions conducive to conflict as the state where the utility for a population to engage in civil conflict or uprising less the the utility lost in duration of the conflict, $D$, is greater than zero. That is, when the dissatisfaction with the conditions at a location reaches some critical threshold, then the marginal utility of rebellion jumps to a high value, creating conditions conducive to conflict. We argue that a greed-and-grievances framework drawing from sociology literature here is appropriate[15]. Borrowing directly from [1], we utilize the expression in Equation 1 which summarizes the contributions to utility for conflict, $U$ from various factors. As described in the original work, in the expression in Equation 1, $W$ is the taxable capacity of the local economy, $P$ is the size of the population, $Pr\left(\cdot\right)$ is the probability of a victory by the uprising population, $G\left(\cdot\right)$ is economic gain conditioned on victory, $Y$ is the per capita income, $C$ is the cost of coordination, $f\left(\cdot\right)$ is the disruption to income flow due to conflict, and $r$ is an economic discount rate such as that used in a net present value calculation.

$$U_C = \int_{t=D}^{\infty} \frac{Pr\left(W\right) \cdot G\left(W, \rho\right)}{\left(1+r\right)^t} dt - \int_{t=0}^{t=D} \frac{f\left(Y\right) + C}{\left(1+r\right)^t} dt \tag{1}$$

The expression in Equation 1 relates the utility gain from a positive outcome to the conflict to the utility loss from the disruption of the status quo over the duration of the conflict. Such a model is conservative, and simple, and makes some strong assumptions. For example, this model assumes that the portion of the population considering rebellion is making a rational choice as a unitary actor, which may or may not actually be true. In keeping with our focus on determining when and where conditions are conducive to conflict, we argue that this model simply points out when conditions are such that a population would likely a benefit from rebelling. Our assumption is simply that the population would perceive such a benefit in the same way the expression in the equation captures it.
We must map from climate factors, such as heat stress, to the terms required for Equation 1. For this task, we propose the use of a Bayesian network (BN) to capture key factors that relate climate model outputs and the probability of conditions conducive to conflict [19]. This will allow us to capture the probabilistic dependency relationships between key variables, as well as the uncertainty in each variable that result from both epistemic (i.e., knowledge uncertainty) and aleatory sources (i.e., characterizable randomness). Existing models will be used to estimate climate factors that drive the BN for a specific location. Specifically, heat stress in the form of WBT will serve as the proxy for climate factors in this initial model. Given a climate factor estimate and other factors for a specific location and time, we should be able to then estimate the probability the local conditions are conducive to conflict, $Pr\left(C|l,t\right)$. If the set of all locations in the map is noted $L$, the BN model will be evaluated for a specific location, $l$, at a specific time, $t$, and repeated for all locations, $l \in L$. The resulting, location-specific estimates of $Pr\left(C|l,t\right)$

### 3.4. Mapping Concepts

Figure 1 illustrates a proposed BN model mapping causal factors as interdependent uncertainties from heat stress to conflict conditions. The root (or unconditional node) in the network is Heat Stress, $H\left(l,t\right)$, which is a function of location, $l$, at a specific time, $t$. Estimates of localized heat stress will be generated by existing climate impact models, which are based on studies, experimentation, and modeling of WBT as a function of temperature increase [17].

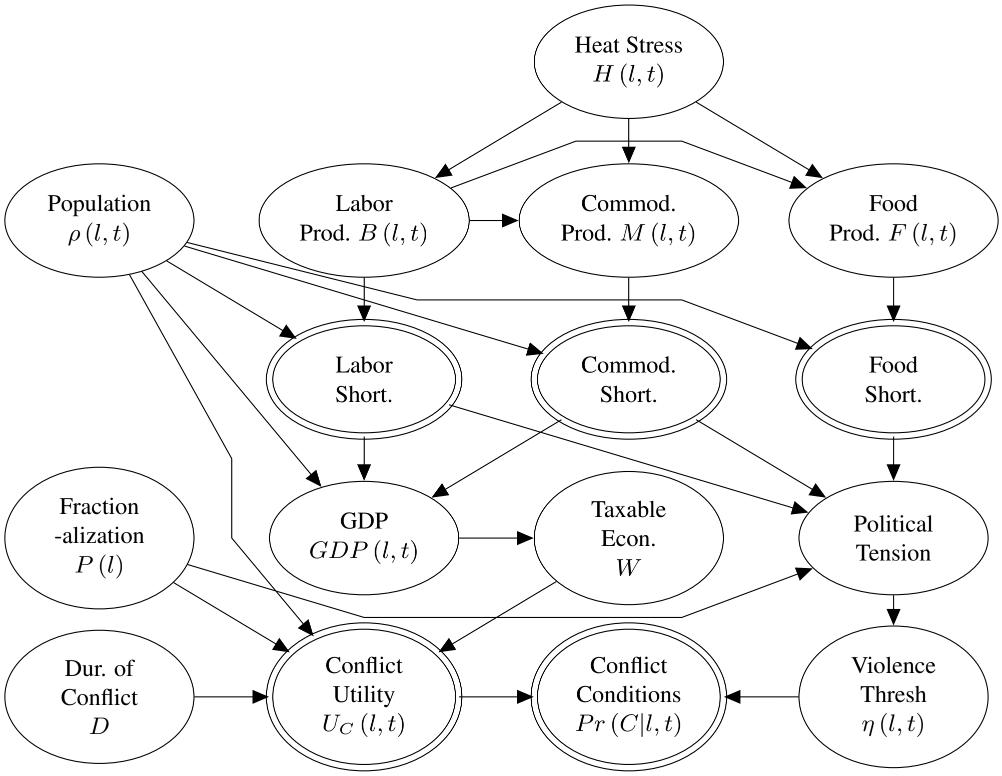


Figure 1: Preliminary Bayesian Network Model for Conflict Conditions

Several other components in the model are tied to exogenous variables like location, $l$, and time, $t$, and will be estimated based on the best available data. For example, we must consider population estimates for specific locations, $\rho(l,t)$, which will be modeled using existing data and projection methods. For now, we are not allowing Heat Stress to have a direct impact on Population, $\rho(l,t)$ as a simplifying assumption, but it's possible that this assumption will be relaxed in future versions.

Heat stress will have an impact on all biotic spheres and as a consequence, the abiotic components as well [17]. Biotic components such as labor production and abiotic components like commodity and food production systems are influenced by changes in the heat stress conditions. We specifically consider three primary factors as potential impacts of heat stress: labor, food, and commodity production. We capture several of those impacts by allowing for dependencies between heat stress, $H(l,t)$ and Labor Production, $B(l,t)$, Commodity Production, $M(l,t)$, and Food Production, $F(l,t)$.

High heat stress can reduce labor production, $B(l,t)$, especially in outdoor or non-climate-controlled environments. The acute impacts of heat stress on human health include heatstroke, exhaustion, cramps, dehydration, and syncope, among others. The chronic impacts of heat stress in humans include physical symptoms like cardiovascular diseases, respiratory obstructions and kidney damages, and mental health issues such as stress, anxiety, and depression. By impacting available labor performance, these health stressors can decrease the capacity for a population to be economically productive.

Heat stress can also have an impact on the ability for a society to produce the commodities that drive economy, $M(l,t)$. Commodity production is arguably dependent on labor production, $B(l,t)$. However, heat stress can also lead to other infrastructure issues like power outages and transportation disruptions. Refrigeration systems can become less efficient, as can other machines that require cooling to operate such as engines and electrical power transmission and transformer equipment. Further, heat stress may have impacts on commodity production capacities by causing disruptions on any part of the supply chain.

Finally, heat stress can also have an impact on the production of food, $F(l,t)$. Here again, labor production, $B(l,t)$, will directly impact food production as people may be less able to do the demanding tasks of planting, cultivating, and harvesting crops. Agriculture production could also be impacted impacted by reduced crop yields, total crop failures, and increased livestock mortality. Further, extreme weather events and drought may create exacerbated soil erosion and land degradation leading to a reduction in long-term productivity.

As these individual factors start producing lower outputs, we may see shortages manifested as labor, food, and energy shortages as they are unable to support the anticipated load. We utilize a simple demand function for each measure of production, $D.\left(\rho\left(l,t\right)\right)$ that scales population to units compatible with the production uncertainties, $B$, $M$, and $C$. For example, if $DB\left(l,t\right) > B\left(l,t\right)$, then we assert that there is a shortage condition for Labor – likewise for Commodity Production and Food Production. Labor shortages can cause economic distress and social unrest, thereby increasing political tension. Food shortages can lead to mental distress and dissatisfaction in addition to having lasting physical health impacts on the people. Further, daily life and economic activities are disrupted by basic commodities and energy shortages. Note that in this initial version of the model, we are not considering the magnitude or duration of a shortage, just the existence of one. It could be argued that the magnitude or duration of the shortage could lead to more extreme reactions or impacts more quickly. However, our current intent is to get a basic model running, so we leave this refinement to future work.

A shortage in labor or commodities can have dramatic impacts on a nation's economic performance, modeled here as an estimate of gross domestic product, $GDP(l,t)$. Population also impacts GDP, and hence we use a per-capita calculation in our model. Per-capita taxable capacity is a measure of the potential tax revenue that can be generated from each individual in a population, hence pointing to the economic capacity for taxation. A higher GDP also means a higher taxable economy which is a measure of the economic disparity in the population. Thus, it also contributes to a change in the taxable economy which is a measure of the economic disparity in the population. Taxable economy also serves as an indicator of the level of funds available.

We model the utility of a rebellion or uprising, $U_C$, as a function of the taxable economy, a measure of coordination costs for the rebels, and the duration of the conflict. Collier and Hoeffler 1998 argue that the coordination costs can be proxied by an Ethno-lingusistic fractionalization (ELF) Index which is an indication of the diversity of a country. ELF measures the probability that two randomly selected people would belong to two uncorrelated ethnic groups [1]. Thus, the higher the ELF index value, more fractionalized the population is said to be. We do not directly use Fearon's analysis to get these country-wise ELF indices as we acknowledge that the pace of globalization makes a fractionalization index a time-dependent variable [20]. To this end, we believe that Historical Index of Ethnic Fractionalization (HIEF) Index is a better dataset to use as it captures data up to 2013 as a time series for over 160 countries. We start with HIEF index to get data unitl 2013, then use a simple prediction model which takes population density as an input to get 2050 estimates.

In our research so far, we have found that such a fractionalization index is dependent on numerous factors. Kaufamnn discusses the Ethnic fractionalization (EF) as a dependent variable [21]. It looks at many dependent and independent variables from a robust statistical sense. Further building upon this idea, Marson [22] suggests and tests the idea of using a 40-year lagged population density as a proxy for EF. We employ simple predictive model which is informed by UNDP predictions [23] of population densities and use this to capture coordination costs. It is important to underscore here that ELF, HIEF, EF and even the fractionalization factor that we are proposing are all closely clustered ideas and a finer examination is required in future iterations of this work.

Social struggles include cultural and economic factors which contribute to intrastate conflict, and are captured in this model as Political Tension. This could manifest by fractionalization over different axes like religion, ethnicity, languages etc. Further, a shortage of labor, commodity, or food can create domestic political tensions as they create grievances that citizens can hold against the ruling government. As these tensions rise, they may lower a threshold for political violence. Thus, the level of political tension modulates the threshold for rebellion, in that higher degrees of tension may lower the threshold for which a population would be willing to incite violence.

In the model we are proposing, there are very few exogenous uncertainties like duration of conflict, which for now, is treated as an unconditional variable. It might actually be that the duration that a populous is willing or capable of fighting depends on factors that are impacted by shortages in food supply or commodities, as captured elsewhere in the model. However, we make the simplifying assumption that those factors are independent for the sake of getting a first version of the model together. This will be revisited in future work.

The utility for conflict, $U_C\left(l,t\right)$ is calculated using Equation 1 and values of its parent nodes. That utility value is compared to the threshold value for violence. When this utility of rebellion crosses the peace threshold, $\eta$, we say that there are conditions for conflict, thereby saying that there is some potential for conflict, $C$. Finally,

we can directly calculate the probability of conflict conditions, $Pr\left(C|l,t\right)$ within the BN.
The full BN is then recalculated for geographic region (or location), $l$ defined in the analysis, for a given time, $t$. This will result in a set of values of the probability of conflict conditions, $Pr\left(C|l,t\right)$, over space and time. Visualizing the results provides our goal: a global map of future conflict potential resulting from climate change, and a valuable tool for informing policy and investment decisions on how to best to mitigate or adapt to those risks. Examining such a map, we might conclude that a specific nation has a high potential for intrastate conflict in the year 2050 because we see a high likelihood that shortage conditions combined with intermediate fractionalization create a condition where the cost of an uprising is low with high potential gains. Comparatively, another state might have a higher threshold for rebel violence and so lower probability of conflict conditions. On the other hand, affluent countries have a very high threshold for violent conflict or the a very low utility of rebellion due to high fractionalization rates not allowing for favorable intrastate conflict conditions.

## 4. DISCUSSION AND NEXT STEPS

We believe the modeling approach discussed above has advantages. Utilizing a probabilistic modeling approach, such as a Bayesian network allows for us to explicitly capture dependencies between a multitude of factors, and proposes a logical structure for those dependencies. Such an approach treats variables probabilistically, allowing for current uncertainties to be represented and accounted for in the analysis. If new data is discovered that updates our understanding of a variable or component, we can easily update the model and rerun most analyses. As discussed above, we anticipate the results of the analysis to be a map of the probability of intrastate conflict conditions that can indicate where we may be more likely to see civil uprising and instability as climate change exacerbates conditions for citizens. We expect these results to be useful in planning in the international community on where aid and support might be most useful at reducing the risk of conflict, as well as planning at the national level to begin making sure that investments in stabilizing and risk-reducing efforts are sufficiently undertaken.
Utilizing a structured model and probabilistic information enables us to provide prospective analysis for conflict conditions and allows for systematic sensitivity analysis on those results. This will allow us to understand how estimates of the probability of conflict conditions changes based on perturbations to the component variables. The results of these sensitivity analyses can provide additional insights beyond the prospective assessment of likely conflict conditions. Sensitivity analysis results can also indicate what factors are most likely to lead to the most risk reduction, providing decision makers with an ability to prioritize mitigation actions and develop strategies with improved efficiency. We will explore different sensitivity analysis approaches in future work.
It's worth discussing why the results we hope to generate could be different from simple heat stress or other projections. Put another way, why might this work provide added insight? We argue that heat stress or other projections of potential climate change impacts are indeed critical tools to understanding how humanity will be affected by climate change and help guide how we adapt. However, we believe that the factors that translate between human impacts like heat stress to societal and national impacts are more complicated, and need further study. A map of heat stress projections over time is good indicator of what locations and populations will be subject to hazards from climate change, but we must consider economic, cultural, and political factors (among others) and how those factors modulate a population's response to understand how climate-change-induced stressors could lead to outcomes such as conflict.
The current approach develops a map of intrastate conflict potential that has the resolution of current political boundaries between nations. This is largely a function of the resolution of the current data sets that we are utilizing, such as the data set for fractionalization. We do realize that conflict can be regional and localized within a state where cultural, economic, or other divides exist within a nation's borders. Our hope is that as we discover higher resolution data on economic and political factors for all nations (detailed data does exist in some cases), or as such data becomes more available, that we would be able to include it in the analysis and simply replicate the BN calculations on a higher geographic resolution. This could produce results at the provincial level, or perhaps even on a regular grid over the map in the same way that current heat stress projection data is organized.
We are also considering the idea that some of the factors we are utilizing in this work may have cumulative effects that would change the projections. For example, if we use basic methods for population projection, we

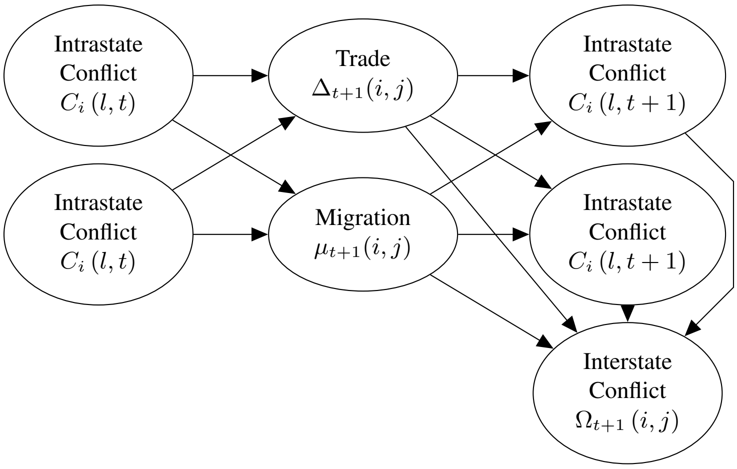


Figure 2: Preliminary Bayesian Network Model for Conflict Conditions

would effectively be assuming that future population estimates were independent of the influence of the events we are seeking to understand and vice versa. That is, if there was a large civil conflict resulting from unrest due to a severe shortage of nutrition, then it's reasonable that the shortage of nutrition and the conflict itself (along with other factors such as refugee migration) would impact the population estimates. Conversely, an increase in the population could make shortages to labor, commodities, and food more likely as well. Our current approach, in effect, assumes that projections of population, fractionalization, and potentially other factors are not influenced by the events we seek to model, but instead only influence them.

Another issue is that our model implicitly assumes that the factors that influence intrastate conflict are not directly influenced by the same factors in neighboring states. In other words, we are currently assuming any influence is embedded in the underlying root variable estimates of factors like fractionalization, population, and heat stress. It's reasonable to assume that adverse conditions in one nation would lead to some pressures on geographically neighboring states. For example, economic hardship could lead to mass migrations of populations toward neighboring nations that are perceived to have better prospects, thus altering the neighboring nation's core factors, like increasing fractionalization and population.

In order to address interstate conflict, such an approach should also incorporate dependencies between adjacent locations. Nations could be geographical neighbors, or neighbors in any relevant network sense, such as trading partners, alliance partners, or cultural relatives. A connective dependency structure would need to be developed to indicate which nations were neighbors to each nation. The exact details of that structure are beyond the scope of this paper, but would imply certain factors that govern those dependencies and the potential disputes. This could involve factors such as trade, migration, or disputes over access to resources. Those interstate dependencies likely depend on intrastate factors, which implies intrastate evolutions can have downstream interstate conflict effects, which we are not yet capturing.

In order to address the issues above, we are considering a multi-level modeling approach that calculates intrastate conflict potential, and then updates models that are adjacent temporally and spatially. Figure 2 illustrates a rough concept for such an approach. The intrastate conflict model that is location specific, and an interstate conflict model that considers interactions between nations. Consider two nations, $i$ and $j$. The intrastate conflict models described in this paper would be calculated for each individual nation at time step $t$, $C\,(i,t)$ and $C\,(j,t)$. The intrastate model factors would then update interstate model factors like trade and migration at the next time step, $t+1$. Those interstate factors would in turn influence intrastate factors like economics, social and cultural elements, and population. The intrastate conflict models would then be calculated again for each individual nation at the next time step $t+1$, $C\,(i,t+1)$ and $C\,(j,t+1)$. A separate interstate conflict calculation would then estimate the conflict conditions between nations $i$ and $j$, or $\Omega\,(i,j,t+1)$, likely using a similar BN approach as intrastate conflict but with a different structure. This process would be repeated from a set of initial conditions at $t=0$ through to the desired time step, for all sets of neighboring nations.

Finally, because we are using BN methods to capture the dependency structure and uncertainty information, observations of outcomes, such as conflict itself or causal factors like labor shortages, can be used to update

projections. Those realized events would update our beliefs about the conflict drivers we are considering, and it's reasonable to expect that, in turn, our expectations about conflict in the future would also update, especially given the interconnectedness of nations. For example, if we observe conflict eruption due to shortages or political grievances exacerbated by climate issues, we can note that as evidence in the model and rerun the projects to understand the cumulative impacts. We may update our beliefs that the conflict would lead to refugee migration thereby putting extra pressures on neighboring nations, and possible raising the potential for conflict in and among those nations.
Our next steps include implementing a first version of the core model using existing data. For example, a more accurate understanding of fractionalization and the factors that could influence it, while keeping heat stress fluctuation as a prior is needed to build a better projection model. This is also true for other factors in the model that rely on projections in space and time. In the longer term, we will be addressing many of the issues and concepts we have discussed above in this section. Specifically, we will be working to expand the framework to incorporate interstate conflict while considering intrastate conflict.

## 5. CONCLUSIONS

The effort described in this paper represents a first step in an attempt to develop a richer basis for understanding the potential for conflict and how those might be exacerbated as a result of climate change and a warming planet. We focused on capturing the potential impacts of heat stress have on labor, commodity, and food production, and map potential shortages in those areas to political unrest and the potential for intrastate confict. This work represents a departure from traditional approaches that attempt to infer correlations between climate change and conflict through statistical analysis of historical data. Our proposed approach distinguishes itself in two primary ways. First, it acknowledges and incorporates local factors like economies and social factors that could change the response to rising temperatures in specific locations. Second, it treats the problem probabilistically, capturing the dependencies and uncertainties that describe the relationships between factors based on accepted models, principles, and data. The relevant factors in this approach likely involve a great deal of uncertainty, and a probabilistic treatment allows to capture that uncertainty as it is – to characterize our current state of information. By characterizing the uncertainty and capturing it logically in the model, we can better inform decisions and prioritize efforts to reduce that uncertainty through data collection and research where possible. Validation of the model as a whole in any rigorous sense will also be challenging, because we may never have sufficient data or an opportunity to statistically compare the model to the history we have yet to live. Instead, we must focus on ensuring that the components of the model are as verified as possible and that the composition of the model is logically sound. As we further develop this approach and model, our hope is insights derived from the model can help governments and philanthropic organization make improved decisions about how to prioritize and utilize resources to avert conflict risk, and manage an increasingly uncertain future.

## ACKNOWLEDGEMENTS

We would like to acknowledge Dr. Matthew Huber, Dr. Stacey Connaughton, and Dr. Andrew Reddie for their ideas and feedback as we developed the ideas and concepts presented in this paper. We would also like to thank Kean Fernandes for his support in finding and analyzing relevant data.

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