The Spatial Ecology of War and Peace
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Abstract—Human flourishing is often severely limited by persistent violence. Quantitative conflict research has found common temporal [1], [2] and other statistical patterns in warfare [3], but very little is understood about its general spatial patterns. While the importance of topology in geostrategy has long been recognised [4], [5], the role of spatial patterns of cities in determining a region’s vulnerability to conflict has gone unexplored. Here, we show that global patterns in war and peace are closely related to the relative position of cities in a global interaction network. We find that regions with betweenness centrality above a certain threshold are often engulfed in entrenched conflict, while a high degree correlates with peace. In fact, betweenness accounts for over 50% of the variance in number of attacks. This metric is also a good predictor of the distance to a conflict zone and can estimate the risk of conflict. We conjecture that a high betweenness identifies areas with fuzzy cultural boundaries [6], whereas high degree cities are in cores where peace is more easily maintained. This is supported by a simple agent-based model in which cities influence their neighbours, which exhibits the same threshold behaviour with betweenness as seen in conflict data. These findings not only shed new light on the causes of violence, but could be used to estimate the risk associated with actions such as the merging of cities, construction of transportation infrastructure, or interventions in trade or migration patterns.

I. INTRODUCTION

Throughout history, most conflicts have been local and between culturally or ethnically distinct groups [7]–[9]. Whilst cultural diversity does not in itself cause violence, it can exacerbate existing vulnerabilities [10]. In particular, conflicts have been observed to occur at fuzzy cultural boundaries (i.e. interstitial or transitional regions between homogeneous communities) [6], [11], and clear boundaries have often been used to manage cultural conflict [12], [13]. One way of collecting data on cultural communities is through social interaction networks [14], and interaction networks between communities have been used to model the projection of cultural influence/threat [15]. However, although it is known that physical geography underpins community formation and influence/threat projection in conflicts [4], [14], there is no universal model able to quantify the role of spatial patterns in war and peace.

In this study, we consider both non-state terrorism and conventional warfare from 2002 to 2014, for which there is a spatially accurate reporting of violent events. We use a simple connectivity law to connect cities to their neighbours to reflect multiplexed interactions. We go on to show that the spatial network of cities is closely related to violence in our datasets, and propose a simple model to account for the phenomenon.

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Fig. 1. Complex network of cities and cultural interaction links. a-i) Cities’ spatial location is used to form an interaction network via the gravity law and a hard-disk constraint - the links enable the flow of cultural influence, a-ii) Top-down network model can detect high betweenness cities using shortest-path energy propagation, and a-iii) Bottom-up agent simulations can reveal fuzzy culture boundary cities and cohesive culture cores. The high betweenness metric relates to fuzzy culture and high degree relates to cohesive cultured cities. b) Global interaction network of cities v ∈ V (colour indicates country and size indicates population). c) Example of high degree cities (size ∝ D(v)) in Europe, which are far from any major conflicts. d) Examples of high betweenness cities (size ∝ B(v)) in the Middle East, which are close to major conflicts and international terrorist groups.

II. RESULTS

Using the spatial data from city locations worldwide, we infer a global interaction network via the gravity law, as shown in Fig. 1a-i (see Methods-B). This top-down network abstraction uses shortest-path energy propagation (Fig. 1a-ii – see Methods-C) to mirror the complex culture interactions
strategic centrality has a high probability of being in major conflict (Fig. 2). The results indicate a strong correlation ($R^2 = 0.51$) and is close to existing conflict zones (Fig. 2).<ref>Fig. 2. Scatter plot of number of attacks versus the network metrics of the top populated zones $z$; with smaller panel plots on the probability of suffering a major attack and the distance distribution to the nearest major conflict site. Subplots are divided in accordance to the top 250, 500, and 1000 populated zones (representing 15%, 27%, and 45% of the total modelled population). The colour gradient of the scatter plots indicate the mortality rate, with darker spots indicating a disproportionately higher mortality rate. Subplots a)-c) show the threshold relationship for the degree of a zone – high degree ($D(z) > 10^3$) experiences almost no attacks and is > 1200 km away from the nearest major conflict. Subplots d)-f) show the threshold relationship for the betweenness of a zone – high betweenness ($B(z) > 10^7$) has a high probability of major conflict ($P(A(z) > 100) > 0.7$), and is close to existing conflict zones (<150 km). Combining degree and betweenness, we propose strategic centrality $S(z) = B(z)/D(z)$. Subplots g)-i) show the relationship between the strategic centrality and the number of attacks. The results indicate a strong correlation ($R^2 < 0.82$). A zone with high strategic centrality has a high probability of being in major conflict ($P(A(z) > 100) > 0.7$) and is close to existing conflict zones (<50 km). Subplot j) shows conventional battle death-toll vs. strategic centrality, demonstrating a similar threshold behaviour. Mortality rates can be found in subplot k) and a summary of the findings can be found in subplot l).

simulated by the bottom-up agent-based model (Fig. 1a-iii – see Methods-D). We use two standard network measures: degree $D$ (number of neighbouring connected cities) and betweenness $B$ (number of shortest paths which pass through the city in question).

We find a robust empirical relationship between conflict and network measures: high degree cities are peaceful and far from the nearest conflict zones, whereas high betweenness cities are often engulfed in persistent violence. Strikingly, there is a threshold effect such that only cities above a certain betweenness are at risk. These results seem consistent with the interpretation that dense cores of high degree nodes in the network correspond to culturally cohesive regions, while high betweenness nodes (which usually link such cores) signify fuzzy cultural boundaries associated with violence. Examples of the highest degree cities are in Western Europe and are far from the nearest conflict zones (Fig. 1a). Examples of the highest betweenness cities are in the Middle East, and have experienced high levels of terrorism and conventional violence (Fig. 1b). A simple agent-based model of cities which can adopt different states (cultures) and exert an influence on the states of their neighbours reinforces this view: a similar pattern arises, such that nodes in the cores maintain their states while those above a threshold of betweenness tend to flip at high frequency from state to state.

A. Top-Down Network Results

Conflicts often occur across regions which include several cities. We therefore group cities into small zones $z$, each covering 0.5% of the global land surface area (500km radius). Fig. 2 shows scatter plots of the number of terrorist attacks $A(z)$ against the network metrics, with panel plots for both the probability of being a major conflict zone, and the distance to the nearest major conflict zone. A major conflict zone
is one that experiences persistent conflict, which is defined as having suffered over 100 attacks between 2002 and 2014 (equivalent to at least 78% of the years being under attack – see Supplementary Information (SI)). Isolated high profile terrorist attacks (e.g. 9/11 in New York and 7/7 in London) do not necessarily indicate major conflict zones. This is because the death-toll variance for individual attacks depends on certain on-the-day factors, which do not reflect the general level of threat faced by a region (Fig. 2).

1) Degree and Betweenness Centrality: The results for degree and betweenness centrality indicate a threshold behaviour, whereby if the zone has high degree ($D(z) > 10^8$) links – see Fig. 2a-c) or low betweenness ($B(z) < 10^7$) shortest paths – see Fig. 2d-f), then there are very few attacks (<1/year). Conversely, if the zone has low degree ($D(z) < 10^4$) or high betweenness ($B(z) > 10^7$), then there is a high probability that the zones will experience major conflict (see Fig. 2a-f). We also show that the average distance from any zone to the nearest top-100 major conflict zone rises with increasing degree. High degree zones are at least 1200 km away from the nearest conflict zone, whereas high betweenness zones are usually less than 150 km away.

2) Strategic Centrality: In order to further refine the statistical prediction of conflict, we define the strategic centrality of a zone $z$ as $S(z) = \frac{\theta(z)}{\theta(z) + \beta}$, which normalises the betweenness of a city by its number of neighbours. It captures the path importance of a city, since a low degree means fewer alternative paths. The results indicate that zones with a high strategic centrality suffer both a high number of attacks and a dispassionately high mortality rate (see Fig. 2g-i).

The relationship again displays a threshold effect, which can nevertheless be approximated quite well with a power law for the purpose of prediction. The best-fit power law for the number of attacks $A^\ast$ with respect to the strategic centrality of zones is given by $\log_{10}(A^\ast(z)) \approx a \log_{10}(S(z)) + b$, where the parameters are $a = 4$ and $b = -9$. The corresponding adjusted R-squared value is 0.82 for the top 250 populated zones. The results show that strategic centrality is a better predictor of conflict than either degree or betweenness. A low strategic centrality zone ($S(z) < 10^5$) will experience almost no attacks. On the other hand, high strategic centrality zones ($S(z) > 10^5$) are on average less than 50 km away from the nearest major conflict zone. A summary of the findings can be found in the table in Fig. 2. To demonstrate the wider applicability of the approach to conventional conflicts (approx. 150 over the time period compared to 30,000 terrorist and insurgency attacks), Fig. 2 shows conventional battle death-toll vs. strategic centrality, demonstrating a similar threshold behaviour.

To confirm that these results are not spurious, we perform two analyses (see SI). First, we show that similar statistical results to Fig. 2 for different zone sizes and flow weights, demonstrating model robustness. Second, we show that the network centrality metrics presented here are not proxies of key geopolitical or socio-economic metrics. The results indicate that strategic centrality is a far superior predictor of conflict (adjusted $R^2 = 0.51$) than any established geopolitical or socio-economic metric considered here (adjusted $R^2 = 0.00–0.13$) and strategic centrality itself is not related to any of these indicators (adjusted $R^2 = 0.01–0.30$). The results show that zones and their cities that are simply near the equator or between densely populated sub-continents do not always have a high betweenness or strategic centrality. Simplified country or county/state connection maps are therefore not as informative as city level network descriptions. The metrics developed in this paper cannot be obtained without considering the city network, and do not appear to be direct proxies for established socio-economic or geo-political metrics.

3) Effect of Cities Merging or Fragmenting: We further expand the analysis by considering how different aspects of city development would affect strategic centrality. We consider a high betweenness city that connects $M$ cohesive city cores, each with $N$ cities (see Methods-C and Fig. 2?). Its strategic centrality is therefore proportional to $(M - 1)N$. If the high betweenness city fragments from 1 to $K$ smaller cities, its strategic centrality $S(v)$ decreases in proportion to $(M - 1)N/2K$, suggesting that the emergence of new cities around existing high betweenness cities, with connecting links to the cohesive cores, would effectively reduce vulnerability to conflict.

B. Bottom-Up Agent-Based Simulation Results

The empirical results described above suggest that cities exert an influence on their neighbours, and that geography
can determine to a large extent whether a city will converge in some way with its neighbours, or find itself torn between competing influences. In order to study this mechanism, we propose a simple bottom-up agent-based model (ABM). This is an extension of a model previously used to show how governments can influence each other with a view to achieving global cooperation on issues such as climate change [16]. We assume that each city is characterised at each moment by a 'state', which could represent the reigning government or the dominant culture. Cities are connected by a spatial network, as in the empirical case above, and each city has the capacity to influence the states of its neighbours. This influence, which might represent cultural diffusion or military threat, is such that a city will tend to make its neighbours adopt the same state as itself.

Each city’s capacity $C_i$ to project influence scales linearly with its population and inversely with the number of neighbours currently in different states to itself (see Fig. 3a). At each time step of the simulation, cities update their states according to the sum influence towards each possible state. This model is similar to others used to study social interaction, such as Axelrod’s model for the dissemination of culture [17], or the well-known voter model [18]. The main difference is that in our model each agent must divide its influence among all neighbours not in the same state, which is more realistic for the case of interacting cities.

At the beginning of the simulation, each city is assigned a random state (see Fig. 3a). Over time their states are updated under each other’s influence until the whole network converges to quasi-stationarity, such that only a few states exist, each occupying a culturally cohesive core of nodes (see Fig. 3d). Such spatial patterns have been observed in empirical studies of human culture [14]. In between the aforementioned cohesive cores there exist isolated cities that constantly flip between different states, akin to fuzzy cultural boundaries (see red boxes in Fig. 3d). A city’s flip rate (i.e. the number of state changes per simulation iteration) can be interpreted as the magnitude of the tension attempting to change a city’s culture or government. We find that the flip rate correlates strongly with betweenness $B(v)$. Moreover, the modularity (a measure of how well-defined a network’s community structure is) associated with the clusters of equal state cities increases rapidly during the initial transient period and then settles at close to unity, indicating that the model detects the natural communities in the network. This is consistent with other dynamical models which have been found to reflect community structure in the same way [19, 20]. Despite this model’s simplicity, the fact that it displays the same threshold relationship between activity and betweenness as we have observed empirically supports the conjecture that it is the formation of fuzzy cultural boundaries between cohesive cores which mediates human conflict.

C. Predictions

One application of the model is to identify high risk areas that are currently relatively peaceful. Fig. 3 highlights cities whose strategic centrality predicts a significantly higher number of terrorist attacks than currently experienced as of 2015 (Fig. 4a). Two major geographic areas have been identified (yellow labels): i) Saudi Arabia and Iran, ii) southwestern China (Fig. 4b). Of particular interest is Saudi Arabia, which is surrounded by several major existing conflict zones, i.e. Yemen, Syria and Iraq (red labels). Fig. 4a shows that the prediction algorithm is also accurate for the American continent, where persistent violence between international criminal organisations dominates the genre of conflict. Island networks with a violent history such as Northern Ireland and the Southern Philippines can be detected as high strategic centrality by analysing the surrounding islands as isolated interconnected sub-networks. Using this method of prediction, 74% of the terrorist attacks in 2016 occurred within 50km of the high betweenness cities.

D. Discussion

Tolstoy once remarked that “individuals struggle between necessity and free-will, and the sum of individuals amounts to a general collective behaviour, which can explain war and peace.” We have shown that the spatial distribution of cities is statistically related to human violence. In particular, the bottlenecks of a global network of cities often display persistent conflict. We conjecture that this empirical pattern ensues from the fact that such bottlenecks often correspond to the “fuzzy cultural boundaries” identified in the conflict literature as risk factors. To test this hypothesis we propose a simple agent-based model of cities which can influence each other to adopt the same state as themselves (where states might represent the particular culture or government of the city). And indeed, in this model the cities in the cohesive cores of the network settle down to a single state, whereas the bottlenecks continue flipping indefinitely between states. In fact, the flip-rate exhibits the same threshold relationship to betweenness centrality as the number of attacks do in the conflict data.
Together, these results support the view that human violence is related to fuzzy cultural boundaries, which in turn reflect structural features of a network of interactions between populations. This is in keeping with previous findings: on the one hand, with the notion that fuzzy cultural boundaries cause ethno/cultural conflicts [6] (see Fig. 2a-i); and on the other, with the fact that conventional battles take place in central locations as in Mackinder’s The Pivot of History geopolitical theory [4, 5, 21] (see Fig. 2). However, while our agent-based model suggests that cultural interaction of some kind is the most likely mechanism behind the empirical findings, other potential causal explanations should not be dismissed out of hand.

Whilst it is true that the distribution of cities in any given region might be the result of complex historical dynamics, we should mention that the spatial bottlenecks are the result of intricate interactions among the whole connected world (i.e. the model loses predictive power when only a subset of nodes is considered). The statistical accuracy of our spatial network model does not in itself reveal causality, even if it serves as an elegant way of capturing the effects of such complex historical dynamics. However, unless history has caused both ancient and new cities to form in a particular spatial pattern leading to the observed close relationship between a city network and violence, it seems more likely that the simple cultural interaction model presented in the paper does indeed describe at least one dominant mechanism at work. But other mechanisms linking civilization-level network structure and ground-level human interactions should also be explored.

As urban population grows, the emergence of new cities, transport links, and other connected infrastructures and international trade networks [22] as interdependent multiplexed networks presents humanity with an opportunity to improve topological resilience. Dynamic effects such as mass human migration as a response to war and climate change [23] also deserve attention, and we encourage others to investigate more deeply the role of spatial networks in the hope of informing policies and interacting with the politics of anthropocentric resilience.

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