Giabbanelli *Security Informatics* 2014, **3**:2
http://www.security-informatics.com/content/3/1/2

Security Informatics
a SpringerOpen Journal

RESEARCH **Open Access**

Modelling the spatial and social dynamics of insurgency

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Abstract

Insurgency emerges from many interactions between numerous social, economical, and geographical factors. Adequately accounting for the large number of potentially relevant interactions, and the complex ways in which they operate, is key to creating valuable models of insurgency. However, this has long been a challenging endeavour, as insurgency imposes specific limitations on the data that could speak to these interactions: quantitative data is limited by the difficulties of systematic collection in war, while qualitative data may include vague or conflicting insights from direct observers. In this paper, we designed a computational framework based on Fuzzy Cognitive Maps and Complex Networks to face these limitations. A software solution fully implements this framework and allows analysts to conduct simulations, in order to better understand the current dynamics of insurgency or test 'what-if' scenarios. Two approaches are presented to guide analysts in developing models based on our framework, either through a nuanced reading of the literature, or by aggregating the knowledge of domain experts.

Keywords: Civil war; Complex networks; Fuzzy Cognitive Maps; Terrorism informatics

Introduction

Initially of interest primarily to soldier-scholars seeking to systematise their experiences as counter-insurgents in wars of decolonisation [1,2], insurgency (and its cognates) increasingly became the subject of several landmark studies by political scientists [3-5], historians [6], and economists [7]. Together with this considerable renaissance in the study of insurgency, computational research into the dynamics of terrorism and rebellion has grown in prominence [8]. One of the drivers of this growth is the ability of computational approaches to account for the many complex interactions between the factors that shape a conflict, which makes such approaches a valuable complement to the associational analyses stemming from economics and seeking to identify 'root causes'. Computational models have indeed been able to systematise and articulate many of the key processes which define insurgency as a particular type of conflict. For example, a recent model used 19 factors and over 80 parameters, accounting for processes such as the consequences of intelligence gathering on the insurgent's organization or the impact of outside support on the insurgents' actions [9]. The task of populating the model's parameters with real-world data is often left to the analysts [9] but this task can be particularly challenging as models require specific numerical values despite sources mostly providing qualitative data from empirical evidence. While the challenge of creating quantitative models of insurgency when given qualitative data has already been thoroughly addressed in the political methodology from a statistical perspective [10], this challenge remains relatively unexplored from a computational perspective.

In this paper, we develop a novel computational method that can be used to model how an array of interacting factors come together to determine loyalty or rebelliousness. This method involves two computational techniques whose synergies are essential to address the specific needs of modelling in insurgency. The artificial intelligence technique of *Fuzzy Cognitive Maps* (FCMs) has a proven track record in allowing for the development of models when supporting data is vague or conflicting. Using this technique will allow us to address one of the main shortcomings of current models as aforementioned. While FCMs have been used to model complex political phenomena, such as crises in the Republic of Macedonia [11] or Cyprus [12], this technique is not designed to

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capture the spatial dynamics that play a very important role in conflicts (*c.f.*, [13] for the role that urban geography plays in terrorism). For example, not adequately capturing the diffusion of civil wars over space [14] or the localized nature of attacks [15] would significantly lower the relevance of models to analysts. We previously demonstrated that FCMs could be used to model social processes but that they would have to be combined with another technique for local dynamics [16]. Our early work combined FCMs with *Cellular Automaton* [17], which have a long history of being used to model spatial dynamics [18] but suffer from having to rigidly divide the space into equal square cells. Therefore, we propose to represent the space as a *Complex Network* (CN), which offers several advantages over the early version of this framework: the space can be arbitrarily divided, standard generators can be used to test how a strategy would unfold in different types of space, and the analyses tools developed for complex networks can be used to explore the relationship between the structure of that space and the dynamics of insurgency.

Contribution of the paper

The principal contributions of the present work can be summarized as follows:

- We propose a computational framework to support researchers in mathematically expressing the important but often hard-to-formalise relationships spanning social and physical geography.
- We present a novel software solution that guides modellers and analysts in designing a model of insurgency in an interactive manner and then simulate it.
- We show two different approaches for the practical development of a model of insurgency based on our framework. One approach relies on a nuanced reading of a large corpus by a domain expert, while the other focuses on synthesizing the knowledge of an international group of experts.

Organization of the paper

We start by providing the technical background to our computational framework, and we formally specify it. Then, we detail the first and key step in building a model based on this framework: how to design a conceptual map articulating the interactions between several factors contributing to insurgency. We further highlight the functioning of the framework through our software implementation, with a focus on how it enables experts to interactively and efficiently set up computer models of insurgency tailored for the context they are interested in. Finally, we discuss the strengths and limitations of this framework.

Computational framework

Background

Insurgents can be mobile and difficult to identify, which limits the potential of terrain-centric and enemy-centric approaches for counterinsurgency (COIN) operations. In contrast, the population is easy to identify and often less mobile. Unlike conventional warfare, opposing forces in counterinsurgency warfare thus do not only seek to reduce each other's military capability but are also competing for the support of the population [1]. In societies with tribal power structures such as Iraq, winning the 'hearts and minds' of local opinion leaders is critical to secure support. Once opinion leaders are clearly identified (*e.g.*, using the Tactical Conflict Assessment Framework in Iraq) the question becomes: *who* among them should be targeted [19]? This question can also be approached from a geographical standpoint. Leaders must not only be persuaded that their interests are in line with counterinsurgents, but also that their interests will be protected. Given that forces cannot be deployed everywhere, the question becomes: *where* can protection be guaranteed in return for political support? Whether it is approached from a social-network perspective (*who*) or a geographical-network perspective (*where*), this is often studied as a variation of an influence maximization problem. The *influence maximization* problem posed by Domingos and Richardson [20] and modelled by Kempe and colleagues [21] asks, for a parameter k, to find the set of k nodes that provide the maximum influence. This needs to be extended in the case of insurgencies, since both insurgents and counterinsurgents want to spread their influence while blocking that of their opponent. This leads to an *influence blocking maximization* problem, which is different from the *competitive influence maximization* problem where forces are solely interested in maximimizing their influence instead of limiting others'. In the context of insurgency, these problems have often been modelled using complex networks (which account for the great variation in ties between people or places) and agent-based systems (which highlight the reasoning behind a switch in allegiance).

In [19,22], each node of the network represents a person. The attitude of a person with respect to the competing forces is represented by a value ranging from -0.5 (favourable to Taliban) to +0.5 (favourable to the US). Individuals are also categorized by their level of influence, which includes head of household or village leader. Individuals change attitude solely based on pairwise interactions between them. The outcome of interactions depend on set probabilities, and can lead to both individuals changing to their average attitude, retaining the original attitudes, or having one change to become more like the other based on a parameter. The model in [23] also propagates opinions through social links using probabilistic rules. One noteworthy simplification in these models was the absence of the context, that is, the set of political, economical, and social aspects that shape leaders' attitudes. For example, a village leader's loyalty to the government may wither as a larger number of young men in the village become unemployed. These aspects also mitigate the influence exerted during COIN operations or by the insurgent. While tribal relationships have been taken into account in some models [24], aspects such as the trustworthiness of institutions or the discrimination of counter-insurgent violence would impact the outcome of interactions with forces supportive of the government.

Taking into account the broader context in which individuals make decisions can be very challenging due to the complexity of this context and the difficulty of collecting data about it. Focusing on the counterinsurgency environment, Upshur and colleagues wrote that "researchers are not impartial but rather armed actors in a conflict; thus there is a 'combatant observer effect'. The interviewer's obvious association with a combatant organization affects the openness and honesty of respondents, as does the power disparity between a member of an occupying military force and an unarmed local population" [25]. Consequently, data corruption results in uncertainty and bias. Furthermore, disagreements on the mechanisms are not only found between the reports of direct observers but also in the analyses of scholars. For example, Fearon and Laitin reported that "the effect of primary commodity exports is considerable: [...] a country with no natural resource export only has a probability of warstart of 1%" compared to 22% when exporting" [7], but Ross considered that "the claim that primary commodity exports are linked to civil war appears fragile and should be treated with caution" [26]. Therefore, there is a need for computational models that can use the qualitative data provided by process-tracking and ethnographical studies, and have specific mathematical ways to address the uncertainty and conflicts found in the data.

Many frameworks have been proposed to model diffusion in networks [27], and they account for uncertainty in different ways. In the Weighted Generalized Annotated Program (wGAP) framework, changes are expressed by rules whose probability reflects the certainty [28]. For example, the rule $supportInsurgents(A) \overset{0.75}{\leftarrow} supportInsurgents(B) \wedge leader(B, A)$ states that if the village leader B for inhabitant A supports insurgents, then A will support the insurgents with 75% certainty. Similarly, the Linear Threshold Model (LTM) and the Independent Cascade Model (ICM) have rules for changes in the nodes' attitudes, and random thresholds are associated with these rules to model uncertainty [21]. The Multi-Attribute Networks and Cascades (MANCaLog) framework provides more flexibility, the properties of nodes and edges have a weight whose uncertainty is represented by an interval that can be open or closed [27]. However, a key distinction is that these frameworks are designed to operate once the values for the uncertainty have been specified: they are not made to take in (possibly contradictory) qualitative assessments and turn them into values based on the uncertainty.

Fuzzy Cognitive Maps

Fuzzy Logic Theory is a valuable mathematical technique to deal with the conflicting and uncertain evidence found in the wealth of testimonies, media reports, and other forms of 'thick description'. As described by Li, Fuzzy Logic Theory [29]

> resembles human reasoning under approximate information and inaccurate data to generate decisions under uncertain environments. It is designed to mathematically represent uncertainty and vagueness, and to provide formalized tools for dealing with imprecision in real-world problems.

When trying to evaluate the strength (and thus the existence of) a mechanism, straightforwardly assigning a score to each source and simply computing the average or the mode would address neither vagueness nor conflicts. Instead, Fuzzy Logic Theory allows us to summarize opinions via linguistic terms (*e.g.*, a mechanism may have a "weak" or "medium" effect) and consider that each term is associated to a range of values. A *membership function* represents the range of each term, and ranges can overlap to account for the possibility that an expert judges a relationship to be "strong" while actually thinking the same as the expert who calls the relationship "very strong". The choice of a membership function depends on the problem. Triangular membership functions (Figure 1) are often used [30,31], and a plethora of alternatives exists (*e.g.*, Z-shape, Gaussian, and S-shaped membership functions [32]).

Once the evidence is summarized via a linguistic term, a set of IF-THEN rules is produced. For example, we asked experts to evaluate the extent to which an inhospitable terrain would contribute to the government's institutional weakness. Two experts judged the effect to be 'medium' while two saw it as 'high' and one called it 'very high'. The IF-THEN rules associate a crisp antecedent (*e.g.*, whether the terrain is inhospitable) to a fuzzy consequent (*e.g.*, a 'medium' or 'high' impact on the government's institutional weakness) and a confidence factor (*e.g.*, number of experts who produced that rule). In this example, we obtain:

R_1: IF (*Inhospitable terrain* is PRESENT) THEN the impact on the (*Government's institutional weakness*) is *medium* (2/5)

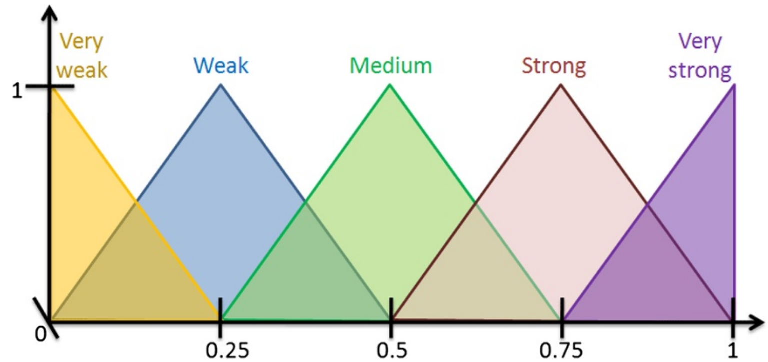


Figure 1 Triangular membership functions. Perceptions for concepts of strength correspond to membership functions, which can overlap. This particular shape is known as a *triangular* membership function.

R_2: IF (*Inhospitable terrain* is PRESENT) THEN the impact on the (*Government's institutional weakness*) is *high* (2/5)

R_3: IF (*Inhospitable terrain* is PRESENT) THEN the impact on the (*Government's institutional weakness*) is *very high* (1/5)

These rules are combined to formulate a Fuzzy Inference Systems that yields one quantitative value. Fuzzy Set Theory is repeatedly applied to obtain one crisp value from the evidence supporting each relationship in the model. These relationships are connected: for example, an inhospitable terrain can impact the ability of insurgents to control the population which in turns affects the socio-economic advantage to insurgency. Therefore, these connections can be viewed as a network named a *Fuzzy Cognitive Map* (FCM). The *nodes* of the network represent fuzzy domain concepts (*e.g.*, trustworthiness of institutions, baseline tension). The *edges* stand for causal connections, and their values are obtained via Fuzzy Set Theory. Edges are either positive or negative to indicate that the target concept respectively increases or decreases with the source concept. Since the introduction of FCM by Kosko in 1986 [33] and its initial application as an artificial intelligence tool to public policy [34], FCMs have been used successfully in critical situations where accuracy has to be obtained despite vagueness [35], such as evaluating the vulnerability of facilities to terrorism [36].

Formally, the number of concepts in the FCM is denoted by n and the matrix $S_{i,j}, i = 1 \ldots n, j = 1 \ldots n$ denotes the **s**trength of the relationships from concepts i to concept j. The vector $C_i(t)$ stores the values of all **c**oncepts at time t. For example, if *inhospitable terrain* is the third concept and the *government's institutional weakness* is the fifth one, then $S_{3,5}$ represents the link from the latter to the former, and their initial values are stored in $C_3(0)$ and $C_5(0)$ respectively. The simulation of the FCM consists of updating the values stored in V until a subset of them stabilizes (*c.f.*, algorithm in [30]). For example, if the analyst is interested in knowing how the rise in unemployment and household poverty will ultimately impact the socio-economic advantage to insurgency, then the FCM will be updated until the socio-economic stops fluctuating. The following equation is used to perform one update:

$$C_i(t+1) = f\left(C_i(t) + \sum_{j=1, j \neq i} C_j(t) \times S_{j,i}\right) \tag{1}$$

where f is a threshold function (also known as *transfer* function) that bounds the output in the interval [0, 1]. It is common practice to use such function in order to keep concepts within a specific range [37]. This function can be, for instance, a sigmoid function such as the hyperbolic tangent $f(x) = \tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$ [31].

Complex networks

In our framework, the geographical space over which an insurgency takes place needs to be discretized. A straightforward approach would be to map the space to a grid, that is, to partition it into squares [17]. However, this approach raises several issues. If the squares are too large, then important local differences are ignored; for example, two districts may end up merged under one cell despite tremendous discrepancies in terms of socio-economic status and, ultimately, propensity to support an insurgency. Squares could be made smaller to ensure that different contexts are represented by different cells, but the larger number of squares would negatively impact the performances of a simulation, and redundancy could occur frequently as taking too small a resolution can lead to subdividing a space that has a homogeneous context. Thus, the difficulty is to avoid redundancy in order to keep performances satisfactory, while adequately representing local differences. Using networks provides the flexibility required for this situation. In a network approach, each region deemed homogeneous with respect to factors of interest to the analyst (*e.g.*, unemployment, use of explosive device, daily murder rate) is represented as one vertex, and this vertex is connected to all adjacent regions by an edge (Figure 2). Networks have long been used to understand the properties of various phenomena in space. A recent review of research results on this approach is provided in [38], while several complete study cases can be found in [39]. Formally, locations are expressed by the set of vertices $\mathbb{V}$ while adjacency is given by the edges $\mathbb{E}$.

As our framework aims to support analysts, the space must be represented in a way that is not only efficient for calculations: analysts should also be able to navigate this space in an intuitive way. The primary reason to use cellular automata in our previous work was that their straightforward mapping of space onto a grid could easily be navigated [17]. However, this came at the expense of the aforementioned issues in efficiency. Using networks addresses the issue of efficiency, but questions are then raised regarding the ease of use by analysts. While navigating a *general* network can be a challenge, this task is simple in our case since a geographical division of space into neighbourhoods or regions produces *planar* networks. Indeed, the sub-spaces represented as vertices are linked by edges only when they are adjacent, and thus edges do not need to cross in order to display the network. A wealth of research has been conducted to display planar graphs, initially motivated by the need to display electrical schemes of large circuits for engineering purposes. Therefore, a number of algorithms such as surveyed in [41] offer convenient displays that can support analysts in exploring the geographical dynamics of insurgency. Furthermore, additional support is provided through ongoing research in natural interaction techniques for networks (*c.f.*, the work of Nathalie Henry Riche).

Coupling

Each location contains an FCM that expresses the social dynamics within that location. The FCMs all have the same structure, as the concepts and mechanisms contributing to insurgency are selected for the entire event (*e.g.*, war in Baghdad, insurgency in Syria) rather than for a specific neighbourhood. However, the values of these concepts depend on the location. For example, we might consider that a lack of political representation contributes to both the weakness of a government and the exclusion of an ethnic group, which in turn favour insurgency. However, the level of political representation might differ across neighbourhood; in the case of Iraq and Baghdad (Figure 2), the Sunni neighbourhoods of Azamiyah and Doura would have a different level of political representation compared to the Shia neighbourhoods of New Baghdad and Kazimiyah. Some of the concepts are influenced by the values of concepts in surrounding locations, as defined by the network in the previous section. Figure 3 illustrates this influence: all locations (circles) have the same concepts linked in the same way, but one concept is influenced by neighbours. Focusing on the dotted orange circle, the ability of insurgents to control population movements at that location is influenced by the control that is exerted in the surrounding four locations. Network influences are applied first, and then the FCMs are updated to reflect how such influences would turn out based on the local context. It is possible for such influences to be cancelled out because of opposing forces (*e.g.*, inhabitants in the target neighbourhood are politically well-represented and have a high level of trust in institutions), or they could be reinforced due to the presence of factors fuelling insurgency (*e.g.*, household poverty and number of unemployed young men). This coupling allows to accurately represent local dynamics through FCMs, and asssess the spread of influences over larger areas using a network.

Formally, we extend the notation of FCMs to express the value of a concept i at time t in a location $v \in \mathbb{V}$ by $C_{i,t,v}$. The extent to which a concept a of the FCM is influenced by a (not necessarily distinct) concept b is given by $W_{a,b}$. The influence function f takes in two concepts, where the first is under the influence of the second, and computes

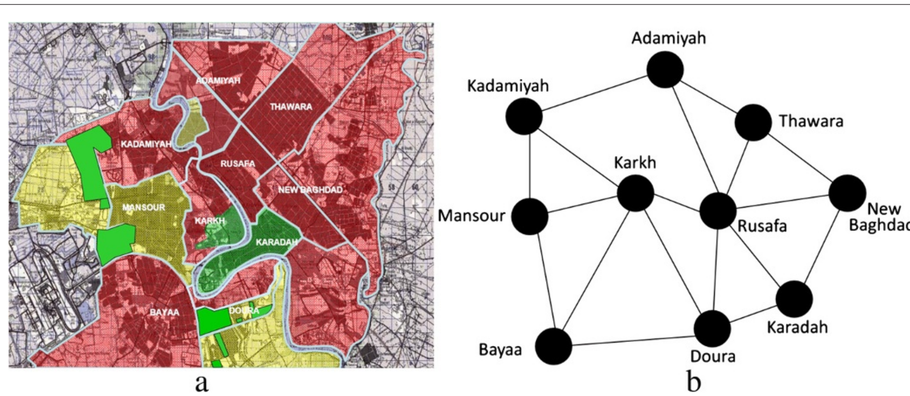


Figure 2 Geography of Baghdad. Map of Baghdad used in Operation Together Forward [40] **(a)** and its abstraction using a network **(b)**.

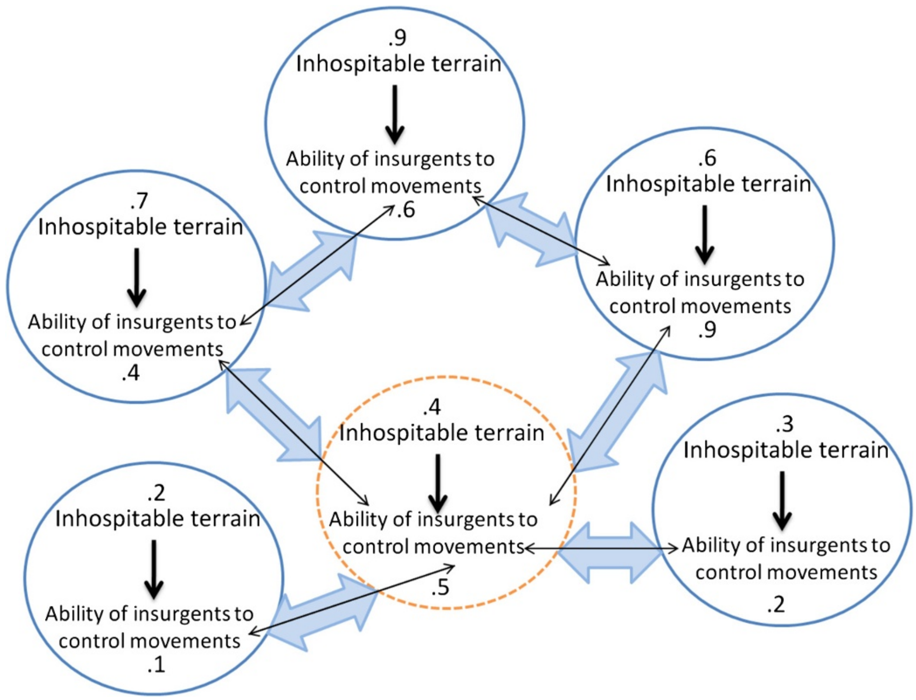


Figure 3 Impact of neighbouring influences mediated by local context. All locations (circles) have the same concepts and mechanisms (large black arrows), but neighbouring influences (blue arrows) will impact some concepts (thin black arrows). In this situation, the hostility of the terrain follows a North-South gradient, while the insurgency has a stronghold in the North-East.

the the impact of the influence. One time step of the simulation is given in Algorithm 1. The Algorithm has two parts. First, it applies the influence of neighbouring locations: for each location $i \in \mathbb{V}$ and each neighbour $j \in \mathbb{V}$, all concepts of i will be influenced by the concepts of j. While we previously used dedicated functions to specify which concepts were either influenced or influencing [16], this new formalism simply encodes such roles in $W_{a,b}$ since $W_{a,b} > 0$ states that b is an influencing concept and a the concept under influence. The second part uses the local context to mediate the influences that were received, by independently updating each FCM using the standard procedure in the literature [30].

Algorithm 1 Updates the simulation for one time step

Require: The FCMs at each location have initial values, time $t > 0$

//Applies the geographical dynamics in parallel
for $i \in \mathbb{V}$ **do**
  for $j \in \mathbb{V} | (j, i) \in \mathbb{E}$ **do**
    //for each location j influencing a location i
    for $a = 1 \ldots n$ **do**
      for $b = 1 \ldots n$ **do**
        //for each combination of concepts in the FCMs
        $C_{a,t+1,i} \leftarrow C_{a,t,i} + W_{a,b} \times f(C_{a,t,i}, C_{b,t,i})$ *//updates the value of concept a*
//Standard procedure to update each FCM until stabilization [30]
for $i \in \mathbb{V}$ **do**
  update(i)

Creating conceptual maps

The first step in designing models based on our framework is to create a conceptual map that uses expert knowledge to assess which factors are relevant to insurgency in a specific context and how these factors can be articulated. The product of this step is a network consisting of representative factors (*i.e.*, vertices) whose interactions (*i.e.*, edges) are either positive (*i.e.*, the presence of a factor increases another) or negative and are given a strength. Two broad approaches support the elicitation of knowledge from an expert in order to construct maps [42]: *direct* approaches assist the experts in constructing maps (*e.g.*, Novak's concept mapping [43]) for example by asking them which concepts are important and how they are related, while *indirect* approaches infer the maps from written documents or interviews (*e.g.*, Trochim's concept mapping [44]). Both approaches can be used to create the conceptual map used by our framework, and the choice depends on the availability of experts on the different aspects of the insurgency. A direct approach may be taken when modellers and experts can meet several times to iteratively construct maps, while an indirect approach may be necessary when experts on the field communicate by sending intelligence reports. This section illustrates both approaches for a typical example of a "revolutionary war" [1] or of a terrorist campaign [45], in which insurgents are engaged in a population-centric war by shattering the confidence of the local communities in their government.

Indirect approach

Two steps were used for this approach, which was previously reported in [17]. First, a scholar in insurgency assessed which factors and interactions were deemed most important in a body of literature relevant to the example of revolutionary war. Then, each interaction was weighted by using a nuanced reading to extract the overall opinion of each peer-reviewed articles speaking to that interaction, and then combining the opinions using Fuzzy Logic. This process was resulted in Figure 4. In this section, we first report on the three groups of factors and relationships that compose the map. Then, we detail the technical choices that allowed Fuzzy Logic to be applied on each edge.

The **rebelliousness** of a community indicates the level of its participation in insurgent activities. It is thus the most closely monitored factor for this scenario. It is determined by two factors: *motive* and *opportunity*. The motive is determined by the socio-economic advantage to insurgency, which collectively incorporates the social, political, and economic reasons for which an individual or community would want to rebel. Opportunities consist of the mechanisms and material conditions that make rebellious acts possible on an incidental basis. This model also accounts for the self-reinforcing effect of rebellion, in which existing rebelliousness facilitates further rebelliousness though mechanisms such as insurgent recruitment networks and the solidification of ascribed political loyalties [3].

The **socio-economic advantage to insurgency** depends on several factors. The ability of insurgents to control the population and to use discriminating violence determines the extent to which they can offer enticements and coercion to the local community, as does the power of the government to employ discriminate violence. Indeed, "control - regardless of the 'true' preferences of the population - precludes options other than collaboration by creating credible benefits for collaborators and, more importantly, sanctions for defectors" [3]. Community economic factors also play a powerful role. The rate or level of economic development determines the opportunity costs of participation, where economic recession makes participation in rebellion less risky or costly in comparison to times of economic boom [46]. Natural resources vulnerable to looting or military capture present a tantalising incentive to join armed groups [47]. For example, in the developing world, "conflict diamonds" or the drug trade influenced the development and proliferation of militias [48] described as a class of 'feral' insurgent [49], since their activism is a means of survival instead of an institutional mechanism to secure popular support. High unemployment among young men produces a likely

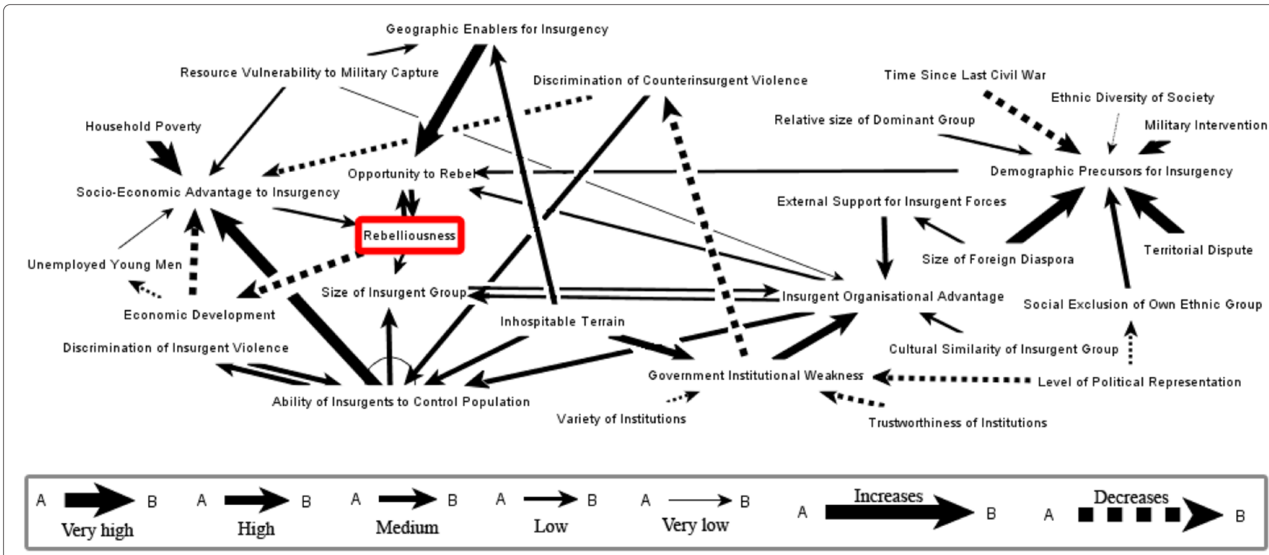


Figure 4 Map from the indirect approach. Each edge is either positive (full line) or negative (dashed line). Edges' weights have been discretized as "very high" (0.9 and above), "high" (0.76 and above), "medium" (0.7 and above), "low" (0.5 and above), or "very low" (less than 0.5).

pool for insurgent recruitment, as it provides them with opportunities to advance economically and socially [7]. On a more micro level, a household so poor that its members have little means to sustain themselves is particularly likely to join whichever group happens to offer the best immediate chance of survival [50]. For example, while Pakistani rebels often had better education than their Afghani counterparts, both came from large, impoverished households [51].

The **opportunity to rebel** is strongly linked to the strength of the insurgent organisation, which affects whether recruitment mechanisms, arms [52], information [3], and logistical capacity make it possible to rebel in an organised or meaningful way. The strength of an insurgent organisation increases in the presence of weak government institutions, limited in their ability to identify and neutralise insurgent agents [2,3,49,53]. Demographic precursors for insurgency establish conditions of instability that can be exploited by insurgent groups to provide political justifications and normative space for rebellion. An existing territorial dispute can evolve into an enduring ethnic or sectarian rivalry, providing the fault-lines for civil conflict and increased fractionalisation [54]. The presence of foreign military forces staging an intervention can inhibit the power of any party to achieve significant political progress through force of arms, paradoxically often making conflict longer-lasting and more intractable [55]. A recent previous civil war can ensure that the population has both lurking hostilities and access to weapons. The Balkan wars are one example of the facilitating effect that weapons-saturation has upon making participation in civil wars feasible [56]. A supportive foreign diaspora can make funding insurgent activities easier, while the social exclusion of certain groups makes conflict increasingly easier to justify and prosecute as the excluded group grows in size.

We capture the precise strength of the 44 discrete relationships between factors by giving each edge a weight (Figure 4). To determine the weight of a given edge, evidence was gathered from nuanced readings of peer-reviewed articles. Following a standard procedure (e.g., see word bank in [30]), the parts of selected articles that spoke to the relationship under study were examined by a field expert and categorized using a fuzzy linguistic term from the set *{Very Weak (VW), Weak (W), Medium (M), Strong (S), Very Strong (VS)}*. For example, the selected parts quoted in the Section on the Fuzzy Cognitive Map were used to estimate the relationship from *Resource Vulnerability to Military Capture* to *Geographic Enabler for Insurgency*; Fearon and Laitin were categorized as strong as they saw the effect of commodity exports as "considerable" [7], while Ross was categorized under weak since he sees the link as "fragile" [26]. The different categories assigned to the evidence constitute a knowledge base which is combined using Fuzzy Logic Theory. The membership functions used in this process (Figure 1) are described by the following standard equations [57]:

$$\mu_{VW}(x) = max(min(0, \frac{0.25 - x}{0.25}), 0) \tag{2}$$

$$\mu_{W}(x) = max(min(\frac{x}{0.25}, \frac{0.5 - x}{0.5 - 0.25}), 0) \tag{3}$$

$$\mu_{M}(x) = max(min(\frac{x - 0.25}{0.5 - 0.25}, \frac{0.75 - x}{0.75 - 0.5}), 0) \tag{4}$$

$$\mu_{S}(x) = max(min(\frac{x - 0.5}{0.75 - 0.5}, \frac{1 - x}{1 - 0.75}), 0) \tag{5}$$

$$\mu_{VS}(x) = max(min(\frac{x - 0.75}{1 - 0.75}, 1), 0) \tag{6}$$

The process was carried out for each edge, using the Mamdani algorithm, the *sum* method of aggregation, and the *centroid* method for defuzzification. These technical choices are common practice, and we refer the interested reader to [37] for the technical aspects.

Direct approach

In a direct approach, a purposeful sample of experts is assembled and guided through a three step process. First, experts are given a question that will prompt them to iteratively identify concepts (*e.g.*, writing them on sticky notes), arrange them (*e.g.*, creating clusters or hierarchies by moving the notes), link them and re-arrange them to facilitate the display of links [43]. This step results in the map's structure. While that step can be carried on straightforwardly for simple problems when experts are all available in one place, it can be challenging for complex problems where a panel of international experts is needed in order to account for each part of the problem [31]. Thus, the map's structure may be set based on a sub-committee of experts. The second step is to ask all experts about the strength of each relationship, and the final step combines their knowledge using Fuzzy Logic Theory as in the previous section.

To illustrate these steps, we asked international experts about the contributors to rebelliousness. Due to the complexity of the problem and the wide range of expertise required to achieve a comprehensive understanding of insurgency, we structured the map as a set of 24 concepts and 44 relationships based on the feedback obtained about Figure 4. Experts were then asked to evaluate the strength of each relationship, by categorizing it as 'non-existent', 'very low', 'low', 'medium', 'high', or 'very high'; experts were also given the possibility of choosing 'unsure' in order to skip evaluating relationships about which they did not feel confident. Finally, expert opinions were combined using Fuzzy Logic Theory for each relationship using the standard procedure aforementioned (*i.e.*, membership functions specified by equations 1 to 5, Mamdani algorithm, *sum* method of aggregation, and *centroid* for defuzzification). The result is shown in Figure 5.

Software solution

Three steps process

Software was built to support the development of models of insurgency via our framework. While our framework is first and foremost mathematical, it can be mostly used via a graphical user interface that aims at making the modelling process as intuitive as possible so that modellers can focus on the few equations that require a fine tuning. The modelling process is divided into three steps (Figure 6), and each step has a dedicated software component that supports both design and analysis.

A Fuzzy Cognitive Map (FCM) can be created via either the direct or indirect approaches outlined in the previous section. Then, it is provided to our software using the *Concept Map editor* (Figure 7) which guides modellers in creating their FCM via a series of steps. In our experience, some structures typically arise when experts are asked to think about what contributes to an insurgency. One such structure is the star, where all factors point to one; this arises when experts list all the contributors to insurgency but do not yet zoom out to consider second-order contributors as well as interactions. Another structure is the cycle, which typically represents how insurgencies either grow or are sustained despite interventions. Therefore, such a structure can directly be built as the first step (Figure 7-1); alternatively, modellers can create or alter structures by directly interacting with the workspace (Figure 7-2). Then, the map is operationalized (Figure 7-3) by weighting the links, designating the factors that must stabilize for the FCM to stop evolving, designating the factors that can influence or be influenced by others (for integration with the second software component), and providing initial values. Since an FCM is assigned to one geographical area, initial values can either depend on the area, be randomly generated based on either probability distributions (*e.g.*, normal, inverse gaussian) or conditional distributions (*e.g.*, the value of a concept may depend on the value of another concept), or be populated from real-world data. As data is entered on the map, modellers can use different layouts to automatically rearrange the display (Figure 7-4). Once the map is ready, its structure can be analyzed (Figure 7-5) to find out influential factors, which was can lead to insight in how the model was conceived [30]. Finally, the map can be simulated (Figure 7-6) to show what would happen independently of spatial factors or which trajectories could be obtained based on different initial values.

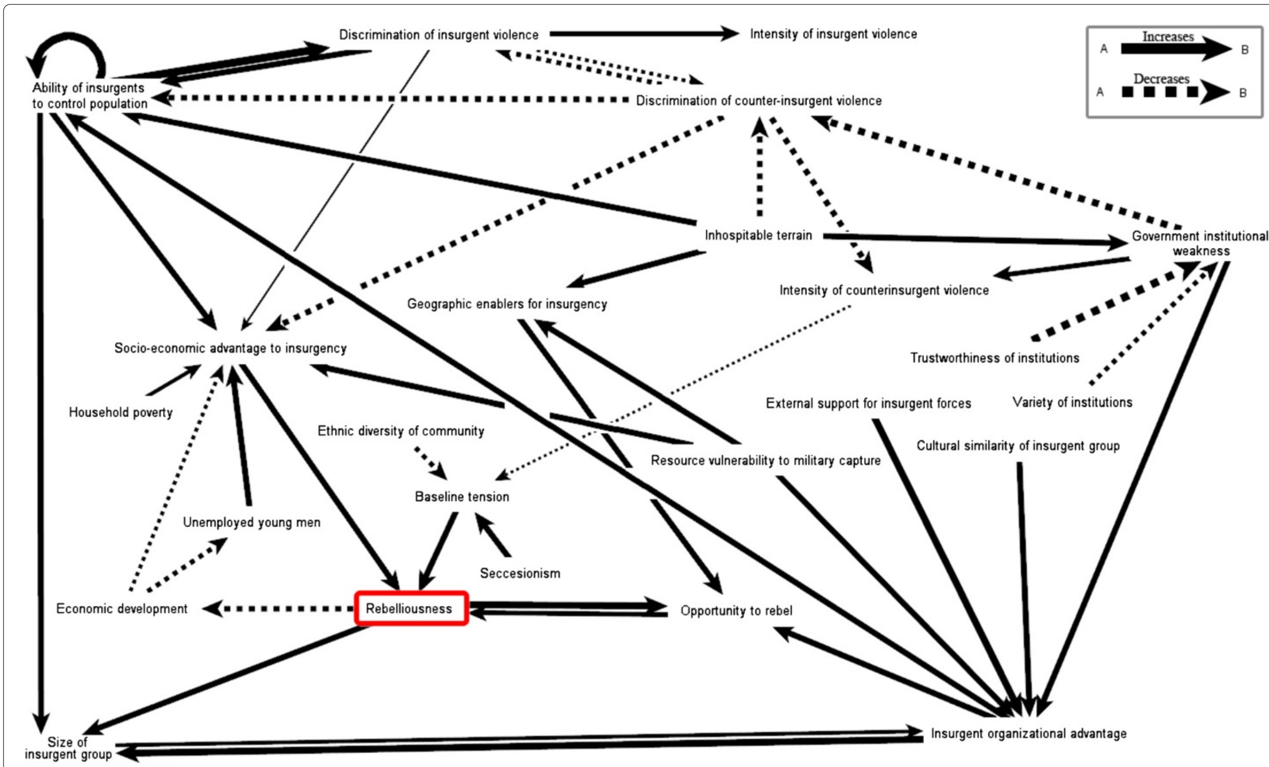


Figure 5 Map from the direct approach. Each edge is either positive (full line) or negative (dashed line). Edges' weights are proportional to their value on a scale from 0 to 1.

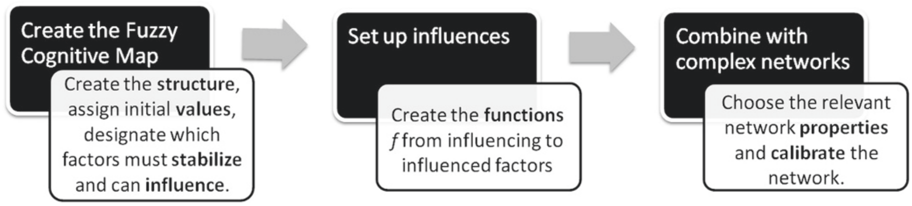


Figure 6 Modelling process. Models can be developed by following a three steps process.

Once the Fuzzy Cognitive Map has been finalized, the Coupling Editor is used to provide the mathematical equations governing influences between FCMs. This is achieved by first connecting influencing factors (in white on Figure 8a) to influenced factors (in black on Figure 8a), and assigning a function to each connection. Such functions can be designed from scratch in Java, or they can be selected from a set of templates which then only need to be parameterized. For example, modellers can consider that a slight difference in the level of economic developments in neighbouring locations is not important, but when that difference goes over a given *threshold* then it will *impact* local economic development. To input this into the model, modellers would select the 'threshold and impact' template (Figure 8a) and provide the values of both threshold and impact. Similarly, modellers may notice that a relationships is stronger at the beginning of the conflict (*e.g.*, demographic precursors) so they would use the 'decaying impact' template and specify both the impact and rate of decay. Offering access to functions commonly used in modelling complex social problems (*e.g.*, threshold and impact [58], fractional and majority votes [59]) also simplifies the process of modelling development, thereby making it accessible to participants with limited mathematical background.

The final step is to generate the spatial network. During the early phases of model development, an exact mapping might not be available to modellers. Consequently,

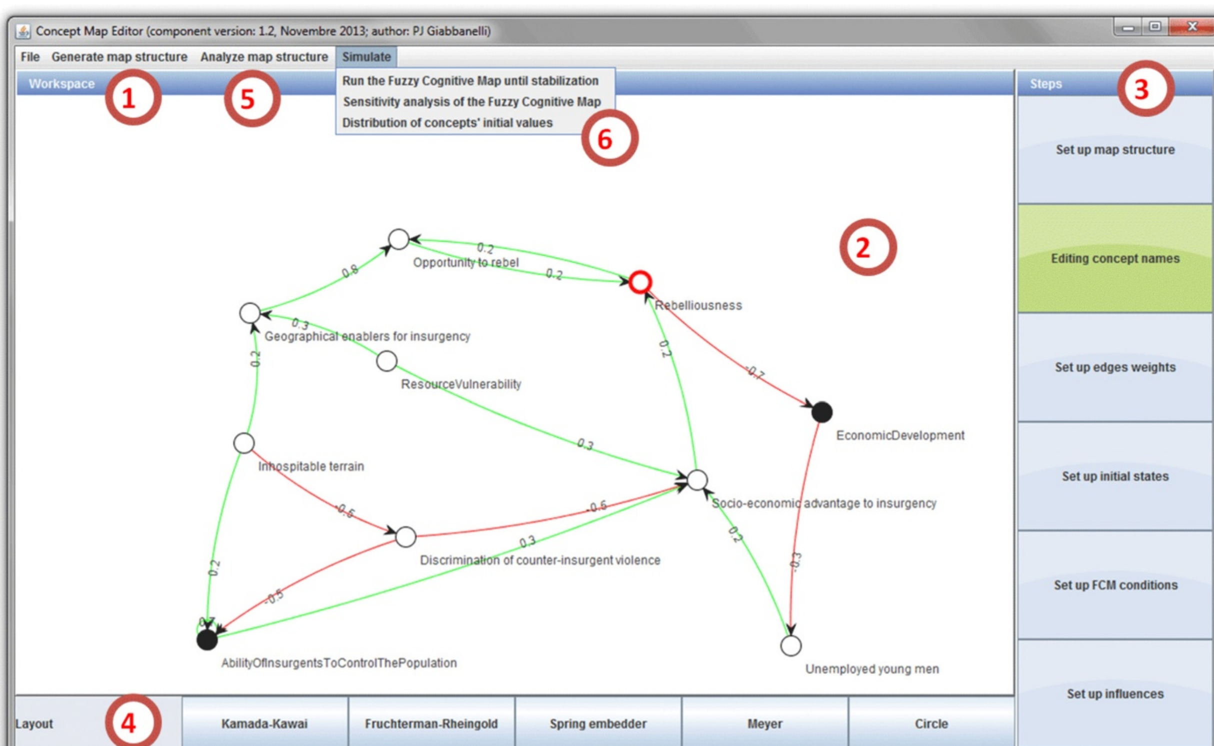
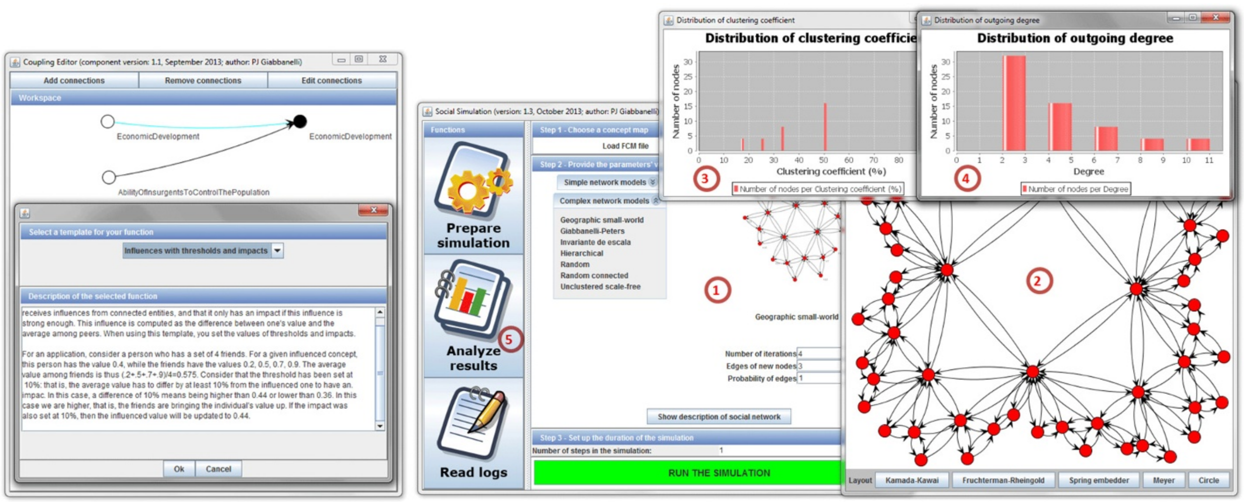


Figure 7 Concept Map editor. The Concept Map editor allows the creation, analysis, and simulation of a Fuzzy Cognitive Map.



a b

Figure 8 Coupling editor and simulation tool. The Coupling Editor allows modellers to apply commonly used functions for the influence of the surroundings **(a)**. The simulation tool provides a set of network generators that can be analyzed and tuned to match the desired topology **(b)**.

the model might have to operate on assumptions regarding the broad characteristics of the space, and only if the model proves useful then partnerships can support the acquisition of accurate data. Our software provides extensive support for the early phase by allowing modellers to choose network generators with a desired set of properties (Figure 8b-1), such as creating planar power-law networks (Figure 8b) which represent a densely connected urban centre linked to increasingly isolated settlements. Since such generators require a fine tuning, analysis tools are provided both for visual inspection (Figure 8b-2) as well as for the quantification of key metrics (*e.g.*, clustering coefficient in Figure 8b-3 or degree distribution in Figure 8b-4). Once the right network has been generated, the simulation can be performed and analyzed to see how factors of the FCM changed over time (Figure 8b-5).

Sample scenario

The simple model used in this section does not aim to make accurate recommendations regarding counterinsurgency strategies. Rather, the experiments focus on demonstrating the ability of our framework to easily represent complex dynamics and handle 'what-if' scenarios. We use the model represented in Figure 7, which articulates how geographical (*e.g.*, inhospitable terrain), economical (*e.g.*, economic development and unemployment of young men), and political factors come together in shaping rebelliousness. The values were obtained by aggregating expert knowledge using Fuzzy Logic, as in Figure 5. In this sample scenario, an insurgency has begun in a resource-based economy. Consequently, the following assumptions were made on the initial values of concepts:

- the presence of *resources* is drawn from a normal distribution with mean 0.7 and standard deviation 0.4. That is, regions are resource-rich on average but significant inequalities are present. Given that the scenario abstracts a resource-based economy, the level of *economic development* is set to match the presence of resources, whereas the level of *unemployment* is inversely proportional to the presence of resources.
- since recently started, the level of *rebelliousness* is still very low (set to 0.1). It is fueled partly by a slight *socio-economic advantage to insurgency* (set to 0.1) and the presence of some *opportunities to rebel* (set to 0.2). As the insurgency is only nascent, insurgents have a limited *ability to control the population* (set to 0.2).
- clear ethnic differences are present and occasional skirmishes are followed by a large *discrimination of counter-insurgent violence* (set to 0.7).
- the country has a wide variety of terrains with a minority deemed inhospitable. Consequently, the extent to which is *terrain is inhospitable* is drawn from a normal distribution with mean 0.3 and standard deviation 0.5.

Once these hypotheses have been implemented using the Concept Map Editor, the dynamics of the Fuzzy Cognitive Map can be simulated to see how events would unfold independently of geographical influences between regions (Figure 9). The simulation of this toy model of insurgency confirms the expectations of experts, as insurgency gradually arises (Figure 9a) and impairs economic development (Figure 9b), thereby providing further ground for insurgency. Given that the values of some concepts are drawn from probability distributions, the outcome of several runs of the simulation can be different. To explore the range of possible outcomes, Figures 9 (c-d) provide histograms of the final values. Two equally probable outcomes appear for insurgency, either by sustaining it at an intermediate level or by having a high level of conflict. Geographical enablers are high in most cases.

Two factors are involved in influences across regions: the economic development, and the ability of insurgents to control the population (black in Figure 7). The Coupling Editor is used to formaly specify these influences (Figure 8a). A region's level of economic development is impacted by the level of economical development of neighbouring regions, as they are potential trade partners. The relationship is modelled using the 'threshold and impact' template (Figure 8a), such that a (positive or negative) difference of at least 5% between the level of economical development of a region and its trading partners will lead to a difference of 5% in that region (c.f., [58] for the equations). The control exerted by insurgents can hinder trades, which is accounted for by decreasing the level of economical development based on the insurgents' control at a rate of 0.1. Finally, the geography was abstracted using a planar small-world graph generated using the method proposed by Zhang et al. [60]; parameter values and properties of the networks are displayed in Figure 8b.

In the absence of any intervention, the system stabilizes with high values of insurgency as would be expected from the aforementioned dynamics. To illustrate the framework's ability in handling 'what-if' scenarios, three possible counterinsurgent interventions were modelled: direct support for *economic* development (*e.g.*, by restoring the infrastructure and building local economic capacity), direct support for *security* (*e.g.*, by holding areas and training governmental security forces), and a *combination* of the two. In each case, the intervention was modelled by adding a concept in the Fuzzy Cognitive Map via the Concept Map editor, and linking that concept to the ones that are directly impacted. Consequently, the economic intervention increases the level of economic development (with weight 0.5) whereas the security interventions decreases the ability of insurgents to control the population (with weight 0.5), and the combination does both. The impact of these three possible interventions is summarized in Table 1 by showing the improvements in terms of increase in economic development and decrease in rebelliousness, unemployment, and insurgent control. Results highlight that, in isolation, economic or security interventions have little impact on rebelliousness. However, combining them can achieve a reduction of almost 10%. This is in line with recent military strategies such

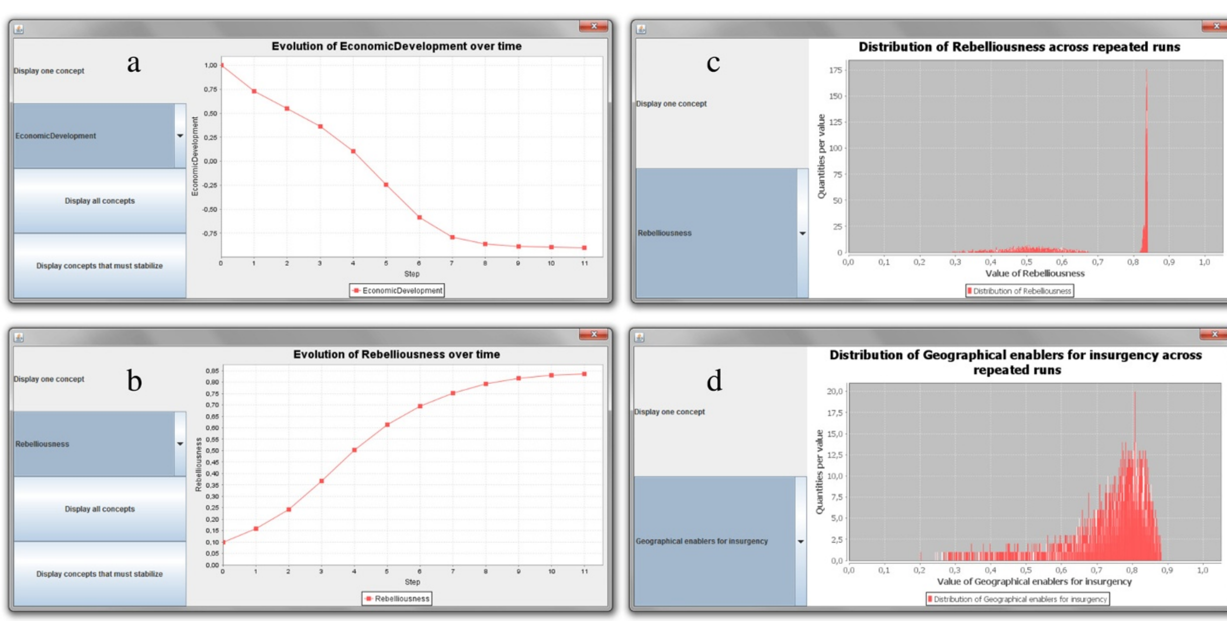


Figure 9 Simulation results. Simulations performed via the Concept Map editor show the evolution of economic development **(a)** and rebelliousness **(b)** over time. The final values of rebelliousness **(c)** and geographical enablers for insurgency **(d)** are displayed based on 10,000 runs of the simulation.

Table 1 Improvements (%) via different interventions

Intervention	Rebelliousness	Economic development	Unemployment	Ability of insurgents to control the population
Economic	2.05	56.57	29.91	None
Security	0.84	99.56	0.76	271.48
Combined	9.87	148.29	181.50	270.74

as the "US National Strategy for Victory in Iraq", which pointed out the importance of intervening simultaneously on political, economical, and security aspects [61]. Our results confirm that a combined strategy is far more powerful than the sum of its parts.

Discussion

In order to develop accurate models of conflicts that can support military analysis, computational techniques need to utilize vasts amounts of data to the best of its potential. However, uncertainty and conflicts abound in data collected by observers or synthesized by experts, making it challenging to effectively incorporate it into quantitative models. Furthermore, adequately capturing the spatial and social dynamics of insurgency tends to require different computational techniques. Our previous work proposed a novel approach to create models of insurgency from imperfect data while accounting for both spatial and social dynamics [17]. While this early framework addressed some of the needs for modelling insurgency, it also came with three limitations. First, the space had to be divided into a set of square cells, which could lead to either an over-simplification of key spatial features (*e.g.*, when cells are too large and cover very distinct neighbourhoods) or a computational burden (*e.g.*, when small cells unnecessarily partition a homogeneous space). Second, the process of model building was centred on the nuanced reading of scholarly articles, which could not be straightforwardly applied to gathering first-hand observations. Finally, the initial development of software highlighted the need for a more intuitive approach to model design, such that modellers could focus on key aspects while the modelling process would be transparent for stakeholders. This paper extends our previous work and addresses all three shortcomings aforementioned. The space is now represented using complex networks, and generators are also provided to create space when detailed maps are not available. We detail how models can be built directly from participants' experience, and provide a proof-of-concept that synthesizes the expertise of five scholars in insurgency. Finally, our focus on usability during software development has resulted in a set of tools that can effectively guide modellers and stakeholders through the process of building a computational model of insurgency.

Our framework supports the integration of data from different sources so that analysts can understand conflicts and run 'what-if' scenarios for counterinsurgency scenarios. It also provides methodological support for scholars of insurgency in two ways. First, it allows for military theories, individually or synthetically, to be tested for consistency by exploring the implications of their suppositions. Second, it allows for intriguing empirical phenomena to be encountered and explored as the disjuncture between the actual world and the world contained within the model. We expect that the use of our framework for these different endeavours will further drive its evolution, both through changes in software and refinement of its mathematical structure.

Our framework currently represents the space using an unweighted planar graph, such that influences either totally flow between two adjacent locations or do not. In practice, adjacency is dynamic: for example, a wall built for security purposes around the district of Adamiyah would virtually cut it off from neighbouring districts (Figure 2) once completed. Adjacency is also a social construct, as members of one ethnic group may rarely move to places populated by another ethnic group during a conflict. Our framework could be augmented to take these aspects into consideration, by having a dynamic network and weighting its edges depending on social factors. Furthermore, the assumption of a planar graph can be challenged due to the spread of violence in non-contiguous areas via tribal ties. This effect is particularly salient in Iraq, which has an estimated 150 tribes and 2,000 clans. While the Ba'athist ideology under Saddam Hussein emphasized the state over ethnic/sectarian divisions, tribal loyalties were nonetheless essential to maintain military support and continue to play a key role in Iraq [62]. Consequently, models often focus on tribal relationships and road network accessibility to link locations [24]. Capturing such relationships can be achieved in two stages. First, the requirement for planarity could be waived, as generating non-planar graphs is straightforward due to the availability of numerous graph generators [63]. Second, the requirement for a single edge between two nodes can also be waived. Frameworks such as wGAP already use multiple labelled edges between nodes [28], which would allow to connect places based on multiple criteria such as geographical and ethnic proximity. Such additions are virtually endless in a modelling endeavour, which highlights the need for a trade-off between the accuracy of the models and the additional complexity brought into the modelling process. Therefore, applications of our framework will prove instrumental in gradually establishing the guidelines for computational methods of insurgency and continuing to meet them via innovative frameworks.

Competing interests
The author declares he has no competing interests.

Acknowledgements
This work benefited from earlier collaborations with Piper Jackson (Simon Fraser University) on cellular automata, Vijay K. Mago (Troy University) on Fuzzy Cognitive Maps, and Simon Frankel Pratt (University of Toronto) on insurgency. The author is indebted to the scholars' whose expertise informed the design of the expert system under a direct approach: Bruce Bueno de Mesquita (New York University), Isabelle Duyvesteyn (Universiteit Utrecht), Samuel S. Stanton, Jr (Groove City College), Ethan Bueno de Mesquita (University of Chicago), and James Morrow (University of Michigan).

Received: 4 November 2013 Accepted: 6 February 2014
Published: 2 May 2014

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doi:10.1186/2190-8532-3-2
Cite this article as: Giabbanelli: **Modelling the spatial and social dynamics of insurgency.** *Security Informatics* 2014 **3**:2.