Studying Social Processes Underlying the Persistence of Female Genital Mutilation Using Agent-Based Modeling

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Discipline

Sociology [D1]

Sub-discipline

Sociology of Health, Illness and the Body [SD-Soc-14]

Academic Level

Postgraduate

Contributor Biography

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topics. His PhD research focuses on the incidence of female genital mutilation (FGM) in populations in the developing world.

Abstract

This methods case covers three areas. Many researchers have not heard of agent-based modeling, so I first explain how agent-based modeling research works, what it involves, and what it is for. My PhD research project has been about applying agent-based modeling to a real-world topic: the occurrence of female genital mutilation in populations in the developing world. I briefly provide an overview of this topic. It might sound counter-intuitive to apply abstract modeling to the study of female genital mutilation. Yet, I explain why this can provide useful and informative insights on the subject. Finally, I talk about the practicalities of applying the methodology of empirical agent-based modeling research to the topic of female genital mutilation. I focus on what was helpful and what was challenging in designing and evaluating a preliminary agent-based model of female genital mutilation.

Learning Outcomes

By the end of this case, students should be able to

- Explain the difference between macro-structures (or patterns) and social processes and give an example of each
- Describe how agent-based models simulate social processes to generate macro-structures (or patterns)
- Describe how agent-based models are evaluated and identify one of the challenges in doing this

- Identify a macro-structure (or pattern) in society that interests them and imagine how they might explain it in terms of social processes

Case Study

The Distinct Agent-Based Modeling Approach: Micro-Specifications and Macro-Structures (Patterns)

When people first hear of "agent-based modeling" (ABM), they may think of computer code, equations, or even machine-learning techniques—in other words, technical wizardry. They are right in a way. ABM research often involves technical elements. However, at its heart, I do not think this is what is distinctive about ABM. I want you to think of ABM, at its core, as a strategy or approach to research. Epstein (1999) describes this strategy in terms of two key concepts: micro-specifications and macro-structures. In social research, micro-specifications are descriptions of social processes. Social processes are the thoughts, decisions, actions, and interactions that individuals (or sometimes organizations or groups) in populations engage in as they go about their lives. Gumerman, Swedlund, Dean, and Epstein (2003) reported a study with a now well known agent-based model of the population of Long House Valley in Arizona. In Gumerman et al.'s model, the social processes of interest were the decisions by Kayenta Anasazi households (between 200 AD and 1450 AD) about where to live, their actions in terms of either staying where they were or moving somewhere else (including, potentially, out of the valley), and their interactions: how the decisions of a given household about where to settle depended on where other households farmed, and so on. Understood in this way, any story about a decision you made, an action you took, or an interaction you had with someone else is a story about the

operation of a social process. Macrostructures are the overall outcomes within populations that come about because of the operation of social processes over time. In Gumerman et al.'s model of the Long House Valley, the macro-structures of interest included the size of the settlements in the valley over time and the spatial distribution of households across the valley over time. Macrostructures (or patterns) are everywhere and they are a central concern of social research. Think of patterns in wealth, inequality, political opinion, labor markets, or racial segregation, to name a few. The ABM approach is about representing a set of social processes (in a micro-specification) and then studying the patterns that are generated at the macro-level when these processes operate over time. This is different from other popular approaches to social research. Take, for example, regression analysis in which macro-structures, like wealth inequality, are typically modeled in terms of their associations with other patterns at the macro-level, such as ethnicity and educational status.

The Method: Simulating Social Processes

If the ABM approach is to study macro-structures in terms of micro-specifications, then ABM as a method is about how we generate macro-structures from micro-specifications. First, we create the micro-specification. This is a clear and explicitly laid out description of the social processes that we think are operating in the population that we are interested in. This description needs to be precise so that it can be worked through in an exact, step-by-step, way. It will need to include an account of the relevant social actors (e.g., people) in the population, how they make decisions and behave, and so on. To find out what patterns this specification generates, we need to consider each social actor in the described population and have him or her act, interact with others, and so on according to the rules specified in our model specification. In principle, we

could do this by hand with a pen and paper (and possibly a set of dice), but I would not recommend it. In practice, the model specification is almost always worked through using specially designed computer programs. In my own research, I use a free and open-source program called NetLogo (Wilensky, 1999). When I use NetLogo, I describe my population, and the social processes at work within it, in simple computer code (this is the micro-specification). When I "run" the program, the computer works through my described social processes in a methodical, step-by-step, way. Think of this as "simulating" the micro-specification. ABM in the social sciences is often called social simulation. By observing what happens in the population as a whole when I run the simulation, I find out what patterns are generated at the macro-level.

What Is It For? The Role of ABM in Research

At the heart of much ABM research is the goal of studying, and therefore understanding, how social processes bring about macro-structures. Why are we interested in this? I focus here on two prominent and distinct reasons why people do ABM research in the social sciences, although there will be others. The first is that they are interested in understanding families of social processes. The second is that they are interested in understanding some specific real-world phenomenon. Those in the first camp will often take some plausible or theoretically motivated idea about social processes, such that people interact in social networks and exchange opinions and then try to characterize and understand a broad range of possible models of such processes. They might ask, for instance, under which social process specifications will opinions in a group converge on a single opinion or diverge, polarizing on different views? The hope is that developing typologies of related models will, in the long run, identify robust properties of certain social situations which can be generalized to human populations. The second camp starts from an

opposite perspective. Researchers in the second camp are interested in building specific models to help them understand a particular phenomenon observed empirically. Often, their aim is to offer a model as an explanation for a specific empirical pattern, or patterns, at the macro-level and to study the model to better understand how that pattern came about. Gumerman et al.'s model offered an explanation for the macro-patterns in the Long Horn valley in terms of social processes. A wider aim, in this case, was to gain specific insights into why the Anasazi population abandoned the valley around AD 1300. Their model suggested that this was due to something in addition to environmental variation. There is, of course, some overlap between the aims of the two camps. We need to understand a model thoroughly to learn about the real world from it. Similarly, any modeler is interested in the relevance of his or her model to real-world scenarios. Nevertheless, my research falls largely into the second camp, which I will call empirical ABM research.

This still leaves unanswered, of course, the wider question of why we should want to understand macro-structures in terms of social processes. There are many possible answers. The two that I find most persuasive are these:

1. *Social processes are intelligible*. A central goal of much social research is to understand the world. That means making it intelligible to us, people. Think of grand narratives, like Marxist theory. This explains the world through vague historical forces, like capital. Also, think of statistical methods, like regression, which model the world in terms of ambiguous aggregate variables, like class, whose causal status is uncertain. To borrow an expression from Goldthorpe (2015), neither necessarily succeeds in making the social world "transparent" to us. By contrast, ABM helps us to understand phenomena in a way

that is more directly relevant to our experiences: in terms of how people bring about phenomena through their actions and interactions, and so on.

2. *Social processes frequently matter*. There are some situations in which trying to analyze the social world without explicitly considering social processes at the micro-level may lead to us to false conclusions. Nobel Prize winning economist Thomas Schelling (1971) famously showed, counter to our strong intuitions, that a macro-pattern of extreme racial segregation could potentially arise from relatively weak discriminatory preferences in a population in which everyone was willing to live in a racially diverse neighborhood because of the complex way that certain moving decisions aggregate together. Demonstrating this was only possible with a formal abstract model.

The Methodology of Empirical ABM Research

It is still early days for empirical ABM research in the social sciences. However, texts such as Gilbert and Troitzsch (2005), Epstein (1999), and Railsback and Grimm (2011) are beginning to develop some of the core principles that researchers can adopt to help guide our efforts. Often the phrases model calibration, model verification, and model validation are used. I use the terms model design, model verification, and model evaluation here instead. This is to avoid overlap with other meanings of the terms calibration and validation. As a simplification, think of these terms as parts in a sequence of steps. First, we design a model, we verify it, and then we evaluate it. Throughout, of course, we study it. Model verification is essentially the process of documenting a model and checking that it was implemented in computer code in the way actually intended by the researcher. I do not talk more about model verification, although it is

indispensable to ABM research. Instead, I focus on model design and evaluation. I have found these to be the most challenging and contested aspects of empirical ABM research.

Model Design

In designing an ABM, we typically aim to find a balance between simplicity/abstraction and realism/description. All models must involve some abstractions and simplifications. These are necessary for a model to be useful. To adapt an analogy from Gilbert and Troitzsch (2005), the most realistic map of the London Underground would be the London Underground itself, but we would not find this informative or useful. Like a good model, a good map offers a simpler, but structurally realistic, representation of the underground. Like map-making, the challenge of a model design is to decide which aspects of the structure of a phenomenon are important and where simplifications and abstractions are acceptable to help make a model that is understandable and useful. It is a common view in ABM research that certain features of social situations, such as variation within populations (aka population heterogeneity) and local interaction (e.g., I talk to my friends more often than I talk to a stranger a county away), are crucial to explaining and understanding them. When it comes to other things, like how abstract our representation of individual decision processes should be, there is currently little consensus on what details matter. Individual decision-making in ABM ranges from behavioral contagion (blindly copying other's behavior) to decisions based on complex predictions of the future. Ultimately, empirical models contain whatever the modeler thinks is necessary or helpful in explaining and understanding the phenomenon under study. In addition to choosing what to put in our models, we have to decide on what the specific details of the components of the model will be. Gumerman et al. (2003) had to decide, for instance, how big the initial population in

their model was, under exactly what circumstances social actors would decide to move elsewhere, and so on. Many researchers, such as Chattoe-Brown (2014), advise that we tie design decisions directly to existing theory, data, or knowledge of the phenomenon under study to improve our models' credibility. I have heard this called "independent empirical calibration." This kind of calibration is very important. Unfortunately, resources, data, and knowledge are often limited. Often, there are important aspects of ABM design that are hard to "nail down" in this way. Currently, it is commonplace for published ABM not to be calibrated empirically at all.

Model Evaluation

The question of how we evaluate (or "validate") an empirical ABM is perhaps the least worked out of the current issues in ABM methodology. There are two concepts that I have been concerned with in my research in particular. The first is the idea of model fit. If we want to learn about some macro-structure in the real world from an ABM, then, as a minimum, we need to show that the macro-patterns simulated by the model have some level of "fit" with patterns in the real world. Epstein (1999) called having models that can account for empirical macro-structures in terms of a social process micro-specifications "an embarrassment of riches," noting that this kind of explanation is rare in the social sciences. However, Epstein also noted that reproducing empirical macro-structures only shows that a model is a candidate explanation for those patterns. There might be alternative, contradictory, models that could also account for them. This is another important concept in model evaluation, sometimes called the problem of equifinality. Many current methodological developments in ABM research may help to address this problem. One approach, mentioned before, is using independent empirical calibration to rule out alternative models at the model design stage. A second is testing and refining one's model

against multiple macro-patterns. Railsback and Grimm (2011) call this pattern-oriented modeling (POM). A final option is to compare the fit of one's model with the fit of plausible alternative models. In my opinion, all of these approaches are promising, although they may be challenging to implement in practice. Perhaps because of the current challenges involved in model evaluation, a study of agent-based models in the social sciences by Angus and Hassani-Mahmooei (2015) showed that only a small minority of published ABM articles contain tables or figures in their results which directly report empirical data or which directly compare simulated output with empirical data.

The Real-World Phenomenon: Female Genital Mutilation

The real-world target of my ABM research so far has been the incidence of female genital mutilation (FGM) in populations in the developing world, especially Africa. In this section, I describe what FGM is, how prevalent it is, and how it is viewed by international decision makers. I also acknowledge that FGM is a varied practice whose meaning is highly contested. Against this backdrop, I suggest that ABM can contribute to the understanding of the topic by offering useful insights into how social processes underlying FGM generate macro-patterns in the persistence of the practice in local populations.

Overview of the Topic

The phrase FGM usually means any cutting or alteration of female genitalia for non-medical reasons. FGM happens to women and girls all over the world and is typically arranged by family members. The extent of FGM varies considerably. At its most severe, it may involve the cutting

of most, or all, of the external female genitalia. Women and girls usually undergo FGM sometime between infancy and adolescence.

FGM is enormously prevalent. At least 200 million women and girls (alive today) around the world have been mutilated (UNICEF, 2016). The occurrence of FGM is concentrated in particular African nations. At least 87% of the women and girls in Egypt (between 15 and 49 years old) have been mutilated, for instance. However, it is also highly prevalent in other parts of the world, such as parts of Indonesia and Iraq. There are efforts by the international community, as well as non-governmental organizations (NGOs) around the world, to end FGM. These have had some success in reducing the occurrence of the practice. However, according to a recent forecast, the absolute number of women or girls subjected to FGM is about to increase (unless a far greater change in the rate of FGM occurs). This is because population growth is about to outstrip the relative decline in the rate of practice (UNICEF, 2016).

Some prefer to use the phrase female genital cutting (FGC), female genital surgery, and female circumcision. I adopted the phrase FGM because it conforms to the terminology of major organizations working to prevent the practice, such as the World Health Organization (WHO). That the phrase FGM should be used has also been strongly advocated by the authors and signatories of a "Feminist Statement on the Naming and Abolition of Female Genital Mutilation" (Burrage, 2016). Regardless of the terminology used, all forms of FGM are considered violations of human rights by the agencies of the United Nations (WHO, 2008). A recent systematic review of the health consequences of FGM by Berg, Underland, Odgaard-Jensen, Fretheim, and Vist (2014) provides good evidence that FGM is harmful to health. Nevertheless, the status of FGM as a harmful violation of human rights is highly contested by some. Some view explicit criticisms of FGM as ethnocentric or hypocritical. They point to the, often unchallenged,

existence of "Western" cosmetic genital surgeries. Others are critical of what they perceive to be a treatment of FGM analytically as a single homogeneous phenomenon. Instead, they emphasize the variety of forms of FGM and the variety of meanings attached to the practice. They point out that the reasons given for practicing FGM vary considerably across different local populations.

How Can ABM Contribute to the Study of FGM?

How can an abstract model of social processes contribute to the study of FGM? The answer is that despite the many ways in which the meaning and circumstances surrounding FGM vary across populations, there are certain common macro-patterns (i.e., regularities) in the occurrence of FGM across some local populations in the developing world. Moreover, there are good reasons to think that there are certain features of the social processes underlying these macro-patterns that are common across these populations and that using an abstract model to help us understand the relationship between the two can be both informative and useful.

The persistence of FGM in parts of the developing world, despite increasing globalization, is hard to explain on its face. After all, the practice is painful, harmful, and conveys no benefits to health. Perhaps even more surprising are certain patterns in survey data across countries where FGM is practiced. These show that the proportion of women and girls, and the proportion of men, who say that FGM should continue (which I will call "popularity"), is consistently lower than the proportion of women and girls who say that they have been mutilated (which I will call "prevalence") in populations where FGM happens (UNICEF, 2013). Also notable is the trend of "local universality" in the practice of FGM across populations, first documented by Mackie (1996). It is commonly reported that in most local populations where FGM is practiced, all girls are mutilated. There are few communities where only some women

and girls are mutilated. Understanding the causes of these macro-structures is an important theoretical question and one that is highly relevant to those wanting to design policies to prevent FGM.

Ever since Gerry Mackie published his seminal article in 1996, a number of scholars and development agencies, such as UNICEF, have emphasized that there are important commonalities in the social processes underlying FGM. The core idea is that in many populations, decisions about FGM are interdependent within local groups. Families and individuals face social costs if they do not participate in FGM (loss of marriage, loss of status, etc.) and social benefits if they do (social capital, increased status). Therefore, social actors face incentives to practice FGM if others do and will only abandon it if enough others do so too. Some refer to this as a process of "social coordination," as a "social convention," or as a "social norm." I use the first phrase. Mackie (1996; see also UNICEF, 2007) used an abstract model, based on simple game theory, to demonstrate that a process of individuals "coordinating" their decisions with others could lead to "universality" within a local coordinating group and the persistence of FGM when it is unpopular. Mackie also used his model to derive specific recommendations for policy-makers about how FGM might be brought to an end—through coordinated collective declarations of abandonment within local populations. It is important to emphasize that in building his abstract model, Mackie was not making essentialist claims about FGM as a homogeneous practice. Rather, he was highlighting certain commonalities across populations that could be usefully studied by representing them abstractly.

ABM enters the picture as a way of extending and strengthening efforts, originating in Mackie's article, to build abstract models to study the social processes underlying FGM. Mackie's model did not represent variation within populations directly and did not represent

local interaction. Instead, Mackie's model treated all social actors as similar in their willingness to abandon FGM and treated all actors as interacting globally (with everyone) in the local population. Population variation and local interaction are known to have important effects on social processes. Efferson, Vogt, Elhadi, Ahmed, and Fehr (2015), as part of their recent study of FGM in Sudan, demonstrated that representing all social actors as homogeneous prevents models like Mackie's from adequately "fitting" macro-patterns in empirical data. They demonstrated that the assumption of homogeneity also had a strong influence on the implications of Mackie's model for policy. Using ABM, it is possible to represent internally varied populations in which interaction is local. Such ABM can, therefore, potentially, "fit" macro-patterns more effectively. They can also be used to re-examine the robustness of the policy implications of Mackie's model. Furthermore, ABM can be used as an alternative framework to construct, compare, and evaluate alternative social process specifications as explanations for macro-patterns related to FGM. These are the goals of my PhD research project.

Research Practicalities: Designing and Evaluating ABM of FGM

As the focus of this case is methodological, I do not go into much detail about my findings to date, which are, in any case, still being developed. Instead, I talk about my experiences in applying two aspects of ABM methodology: model design and model evaluation. I talk about what has been helpful and challenging in putting these concepts into practice for a particular, preliminary, ABM of FGM. I also talk briefly about what I see as promising avenues for strengthening these aspects of my research.

Model Design in Practice

Part of the reason that I chose to apply ABM to the topic of FGM was that there was already a formal abstract model of the social processes underlying the practice. This was Mackie's 1996 (updated in UNICEF, 2007) game theory model of FGM as a "social convention." This was enormously helpful for two reasons. First, it provided me with an initial theoretical framework to represent individual decisions and interactions. Social actors' decisions about whether to participate in FGM could be represented as a process of interactive and interdependent social coordination. Moreover, this framework was already recognized by some in the field as legitimate and useful. Second, it was clear how ABM could contribute to this existing model. Namely, the ease with which population heterogeneity and local interaction can be represented and explored within an ABM is one of its main strengths.

One of the major challenges in designing the model came from trying to specify the details of population variation and local interaction. Designing a model in which actors vary in their willingness to practice FGM is quite straightforward when building an ABM. Also, local interaction can be introduced by connecting actors in a kind of network structure (a social network) and having them interact with those they are connected to. The challenge comes in deciding on the details of these elements, such as what the "distribution" of willingness to abandon FGM across the whole population should be or how densely connected the network of social interaction should be. This is especially important as the behavior of the model is quite sensitive to such details. The resource limits of my PhD project make investigating such questions directly quite challenging. One solution that I explored was a technique called parameter estimation. This involved trying a large number of combinations of possible settings

for these unknown features and choosing the combination that produced the best quantitative fit between the model and real empirical data at the macro-level. Briefly, the model I built and the experiment I used to fit the parameters are described below.

Overview of the Model

- Name: FGM as a coordinated practice V1
- Components: A "local population" of 500 social actors connected in a social network
- Qualities of the agent population: Each social actor has a behavior (participate in FGM or not), an attitude (support FGM or not), and a "coordination threshold" of willingness to practice FGM (how many other social network contacts had to practice FGM before they would do so).
- Initial state of the model: At the beginning of the simulation, there is a minimum level of support for FGM (all those who approve of it, practice it).
- Processes in the model: At each time step, that is, between 10 and 50 time steps, social actors decide to practice FGM, or not, depending on whether their coordination threshold has been exceeded.
- Simulated macro-pattern: For an individual simulation run, the output of interest is the overall prevalence of FGM that emerges in the population.

Parameter Estimation Experiment

I used secondary data made available by United States Agency for International Development's (USAID) Demographic and Health Survey (DHS) program that collects nationally representative survey data on countries around the world. This included information on the incidence of FGM. These surveys were based on hundreds of small samples, roughly at the level of a village or city block. These small groupings are called Primary Sampling Units (PSUs). Although the samples

are very small (so subject to high sampling error), they can be used to give a rough indication of the prevalence (% women mutilated) and popularity (% women who say FGM should continue) of FGM within a local population. I relied on trends across hundreds of these estimates to help get a better idea of patterns in the occurrence of FGM. I used the 2005 Senegalese DHS Survey for the following (Centre de Recherche pour le Développement Humain/Sénégal and ORC Macro, 2006).

I estimated the key parameters in my model by finding the combination of settings which caused my model to reproduce a stable rate of FGM which most closely matched the estimated prevalence of FGM in the survey PSUs. The experiment worked like this:

1. I chose a "training sample" of 100 PSUs at random from the 376 PSUs in the survey.
2. For each PSU in the training sample, I treated the popularity of FGM in the PSU as the initial state (initial level of support, see model overview) of the model. I then compared the resulting simulated prevalence of FGM with the real prevalence estimate from the survey PSU.
3. I repeated Step 2 for a large range of possible model parameter settings.
4. I worked out, overall, which parameter settings produced simulated prevalence predictions that were closest to the estimates from the PSUs, on average.

Using this approach gave me a way of estimating important qualities of my model empirically. Other promising avenues for strengthening the design of this preliminary model may come from using additional empirical patterns for parameter estimation or from obtaining data relating to these parameters directly. Both are an ongoing task for my research. Other important ongoing questions relating to the design of this model include whether it is appropriate to treat

popularity as an initial state and the extent to which the prevalence of FGM in survey PSUs is really comparable with the simulated percentage of social actors "participating" in FGM in an abstract sense.

Model Evaluation in Practice

Having designed a model and estimated its key parameters, here I consider what was challenging and what was helpful when evaluating it empirically. Recall the first question is whether the model was actually able to reproduce the key macro-patterns of interest. It was very helpful that I had access to secondary data on the incidence of FGM that I could use to characterize these patterns more precisely. In particular, I was able to characterize the relationship between popularity and prevalence of FGM across PSUs from the DHS survey data. Figure 4 shows the distinctive relationship between the two. Except where it is very unpopular, FGM is much more prevalent than popular in most PSUs in the 2005 Senegalese DHS survey. I was also able to characterize the related, but logically distinct, pattern of the distribution of the prevalence of FGM across the PSUs. Figure 2 shows that there is a strong trend of local universality of FGM across the PSUs. Evaluating the fit of the model involved producing a simulated prevalence estimate for each of the 376 PSUs and then comparing patterns in the simulated and real data. Figure 3 shows that a pattern of greater practice than popularity of FGM was reproduced in the model's simulation runs. Figure 1 shows that the model also reproduced a pattern of local universality in the occurrence of FGM across simulation runs. A visual comparison of Figures 1 to 4 shows that the model was able to reproduce key qualitative features of the data at the macro-level. It can, therefore, be considered a *candidate explanation* for these structures.

Figure 1.

Caption: Simulated prediction: Local universality of FGM.

Figure 2.

Caption: Empirical: Local universality of FGM.

Figure 3.

Caption: Simulated predictions: Discrepancy between popularity and prevalence.

Figure 4.

Caption: Empirical: Discrepancy between popularity and prevalence.

A major challenge in undertaking this comparison was to account for the noisiness of the empirical data, evident in Figure 4. As the PSU estimates were based on small samples, we would expect lots of random noise in such estimates. To manage this to some extent, I followed the approach of Zurell et al. (2010) who discussed mimicking, within a simulation, the process whereby the empirical data were collected. As a preliminary attempt at this, I loosely imitated the DHS sampling procedure by calculating the simulated prevalence in my model based on a two-stage random sample of 50 of 500 social actors in the model.

Another major challenge in evaluating the model was finding a way to eliminate alternative explanations. As a starting point, I was able to show that an alternative explanation—that popularity will match prevalence based on a theory that FGM is not coordinated—fails to reproduce either of the two macro-structures recognizably. It also produces a worse fit quantitatively. A model that retained Mackie's model's assumption of population homogeneity performed similarly poorly. However, my evaluation of my own model would have been more

convincing if it had outperformed an alternative explanation which took into account potential issues with the empirical data, such as the *historical* nature of prevalence estimates (some women in the sample will have been cut decades ago) compared with the *current* nature of popularity estimates. The challenge comes in constructing such an alternative explanation. More generally, testing my model against additional macro-patterns would strengthen its evaluation and further resolve such questions. There may be opportunities to strengthen the operationalization of popularity and prevalence in the survey data by incorporating other variables, such as mothers' future intentions to practice FGM on their daughters. Overall, this evaluation of my model suggested that I was headed in the right direction. It enthused me about further efforts to refine and develop my model over time.

Exercises and Discussion Questions

1. Identify a macro-structure (or pattern) in society which you think could be usefully explained in terms of social processes and justify this view.
2. For the example you chose in the previous question, imagine that you had to build an agent-based model of those social processes. Explain what details you think would be important to put in the model, what details you could leave out, and why.
3. Download the free software NetLogo from https://ccl.northwestern.edu/netlogo/. Look in the "Models: Library" and open the model called "Rebellion" under "Social Science" (Wilensky, 2004). Read the "info" tab and then try running the model (press " go"). Try changing some of the sliders (parameters) and look at how that affects the model.

4. Once you are familiar with the "Rebellion" model, write a short description summarizing how you think the social processes in the model are generating macro-patterns in the outbreaks of rebellion.
5. Taking into account the methodological concepts described in this case, try to think of a way in which you might evaluate the Rebellion model as an explanation for real patterns in civil violence. What data would you need and how might you adjust the model to make it comparable with these data?

Further Reading

For accessible introductions to ABM as a research method:

Gilbert, N., & Troitzsch, K. (2005). *Simulation for the social scientist*. London, England: McGraw-Hill Education.

Railsback, S. F., & Grimm, V. (2011). *Agent-based and individual-based modeling: A practical introduction*. Princeton, NJ: Princeton University Press.

To find out more about the value of agent-based models for social research:

Chattoe-Brown, E. (2013). Why sociology should use agent based modelling. *Sociological Research Online, 18*, 3. doi:10.5153/sro.3055

For a brief overview of key facts on the global status of female genital mutilation:

UNICEF. (2016). *Female genital mutilation/cutting: A global concern* (pp. 1-4). Retrieved from https://data.unicef.org/resources/female-genital-mutilationcutting-global-concern/

Web Resources

Download the free and accessible ABM development toolkit: NetLogo

https://ccl.northwestern.edu/netlogo/

Browse open repositories for ABM on all kinds of topics:

http://modelingcommons.org/

https://www.openabm.org/

Find other links to lots of ABM-relevant resources:

http://ccl.northwestern.edu/netlogo/resources.shtml

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