Computational Social Science

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Overview

Computational social science

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The social sciences investigate human and social dynamics and organization at all levels of analysis (consilience), including cognition, decision making, behavior, groups, organizations, societies, and the world system. Computational social science is the integrated, interdisciplinary pursuit of social inquiry with emphasis on information processing and through the medium of advanced computation. The main computational social science areas are automated information extraction systems, social network analysis, social geographic information systems (GIS), complexity modeling, and social simulation models. Just like Galileo exploited the telescope as the key instrument for observing and gaining a deeper and empirically truthful understanding of the physical universe, computational social scientists are learning to exploit the advanced and increasingly powerful instruments of computation to see beyond the visible spectrum of more traditional disciplinary analyses.

Computational social science is a fledging interdisciplinary field at the intersection of the social sciences, computational science, and complexity science. The purpose of this article is to provide a brief overview of the field, including its scope and relation to the social sciences, and the main areas of theory and research. Although young by historical standards, computational social science already covers many areas and topics that were previously beyond the realm of scientific investigation in human and social dynamics, as the growing literature illustrates.[1] Given the range of topics and space constraints, this survey focuses on some of the main recent developments, with due attention to earlier foundations, with a view toward orienting the reader, not to provide in-depth technical details on each area of computational science.

The next section begins with a background introduction for readers who may be unfamiliar with the social sciences in general, in order to situate computational social science within the broader family of human sciences. The sections cover the main clusters of computational social science methods and models. A summary concludes this overview.

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BACKGROUND

The social sciences or social science disciplines investigate all forms of human and social dynamics and organization at all levels of analysis (or 'consilience,'[2]), including cognition, decision making, behavior, groups, organizations, societies, and the world system. The traditional social science disciplines are five: social psychology, anthropology, economics, political science, and sociology, each of which comprises several specialized branches. For example, anthropology comprises physical anthropology, cultural anthropology, and archaeology. Political science comprises comparative politics, international relations, public policy and administration, and research methods. Statistics as a scientific method plays a prominent role across all the social sciences and their specialties,[3,4] as well as in geography (human and social geography), history (social science history and cliometrics), linguistics, management science, communication, and other human sciences disciplines.

Over the past two centuries—since the Enlightenment initiated the scientific study of society—the social sciences have acquired the three main methodologies that characterize contemporary science: statistics, mathematics, and computation. Moreover, these scientific methods have been acquired for similar reasons as in the physical and biological sciences: primarily for purposes of description and induction (statistics); analytic theoretical development (mathematics); and simulation of complex systems (computation). Social statistics and mathematical social science are by far the oldest of the three approaches and have long traditions with roots in 'political arithmetic'[5] and probability theory.[6,7]. Interestingly, 'statistics' was the original name of political science, as the science of the state,[8] similar to economics as the science of the economy and linguistics as the science of language.

Computational social science is a more recent development that can be dated to the second half of the 20th century and the invention of electronic computers. During the1960s social scientists began using computers for conducting statistical data analysis—those were the early days of SPSS, SAS, and punched-card jobs.[9] The founders of the more theoretical orientation in computational social science during the first generation included Herbert A. Simon (1916–2001), Karl W. Deutsch (1912–1992), Harold Guetzkow (1915–2008), and Thomas C. Schelling (1921). Computational social science is the integrated, interdisciplinary investigation of social systems as information-processing organizations and through the medium of advanced computational systems. Therefore, the computational paradigm in social science has dual foundations: substantive (as a theoretical perspective) and instrumental (as a methodological approach). The former information processing and cybernetic orientation is grounded on earlier foundations by Ross Ashby, Norbert Wiener, Claude Shannon, and Ludwig von Bertalanffy. The emphasis here is on the latter (methods in computational social science), given the purpose of this overview.

Just like Galileo exploited the telescope as the key instrument for observing and gaining a deeper and empirically truthful understanding of the physical universe, computational social scientists are learning to exploit the advanced and increasingly powerful instruments of computation to see beyond the visible spectrum of more traditional disciplinary analyses. Accordingly, computational social science is an instrument-enabled scientific discipline, in this respect scientifically similar to microbiology, radio astronomy, or nanoscience—new scientific fields of investigation that were enabled by the microscope, radar, and electron microscope, respectively. In each of these instrument-enabled disciplines—including computational social science—it is the instrument of investigation that drives the development of theory and understanding.

The main computational social science methods in use today can be classified in five areas:

- Automated information extraction
- Social network analysis (SNA)
- Geospatial analysis [socio-GIS (geographic information systems) or social GIS]
- Complexity modeling
- Social simulations models

In turn, each of these has several specialized branches. For example, computational social simulations (see subsection below) comprise a variety of models that include system dynamics, microanalytical models, queuing models, cellular automata, multi-agent models, and learning and evolutionary models, including some hybrids [e.g., combining system dynamics and agent-based models (ABMs)]. Several combinations among the main five methods are also common, as in power law models of social complexity when simulated by ABMs; others have yet to be explored. As the field is so young, not all synergies have been tried.

In the future, data visualization[10–12] and 'sonification'[13–15] will also likely become distinct specializations of computational social science. What matters most is that each computational method contributes new and distinct scientific insights for seeing beyond the visible spectrum of traditional social science methods, or even beyond earlier statistical and mathematical approaches.

Computational social science is currently organized in an internationally distributed and active community of learned societies, including the North American Association for Computational Social and Organizational Sciences (NAACSOS), the European Social Simulation Association (ESSA), and the Pacific Asia Association for Agent-Based Social Systems Sciences (PAAA). Each of these regional associations holds annual conferences, publishes proceedings (and post-proceedings in some cases), and a joint world congress of regional associations is held every few years (Kyoto Institute of Technology, Japan, 2004; George Mason University, USA, 2006; University of Kassel, Germany, 2010). The main peer-reviewed specialized periodicals include the *Journal of Artificial Societies and Social Simulations* (*JASSS*, available free and online), *Computational and Mathematical Organization Theory* (CMOT, published by Springer), *Social Science Computer Review* (*SSCR*, published by Sage), *Advances in Complex Systems* (published by World Scientific), and *Journal of Economic Interaction and Coordination* (published by Springer). Computational social science research is also increasingly visible in many social science journals (e.g., *American Journal of Sociology*, *American Political Science Review*, and other mainstream journals), as well as interdisciplinary journals (*IEEE Transactions on Systems, Man, and Cybernetics*).

AUTOMATED INFORMATION EXTRACTION

Content analysis—the unobtrusive method of parsing and coding documents to extract information from data[16,17]—has recently evolved into the computational analysis of multiple all-source media (text, audio, images, video), in both academia and governmental domains (e.g., the online OpenSource Center). A quantum improvement in the efficiency of these methods occurred in academia—but not yet in other application areas—with the introduction of computational methods from artificial intelligence (AI) and other computational algorithms,[18] an effort that continues today[19,20] and is likely to yield significant breakthroughs in the future.

One of the primary uses of automated information extraction methods is the production of *events data*[21–23] which can then be analyzed through various methodologies (time series analysis, semantic analysis,[24,25] hidden Markov models, wavelet analysis, and event life-cycle modeling.[26]) These methods often interact with others, such as the complexity-theoretic methods mentioned in the subsection below. In addition, many applications of automated text mining[27] produce network data structures, making methods from graph theory or SNA a natural combination. However, data from automated information extraction algorithms and systems are used by social scientists for developing a broad variety of models.[28]

In the area of applied analysis, methods of automated information extraction should be used not only for anomaly detection and early warning, but also for monitoring trends and evaluating intervention or program performance. This is because automated information extraction can sometimes be used for mining real-time data streams, such as in news broadcasts or other electronic reports. Ideally, the exploitation of automated information extraction systems should take place in specialized facilities, or at least be part of an upgraded operations center or situation room supported by specialized visualization and sonification functionality.

Automated information extraction and text mining is also a promising computational strategy in areas of social science that are, so to speak, text-rich and numbers-poor. For example, ethnography is a field of social anthropology that relies primarily on the production of written records through 'qualitative research.'[29] Large depositories of ethnographic records are now available online (e.g., the Human Relations Area Files, HRAF, Yale University) and increasingly available for text mining and other methods of automated information extraction. Combining object-oriented algorithms based on encapsulated objects and operations might one day accomplish significant breakthroughs in the computational investigation of social relations.

SOCIAL NETWORK ANALYSIS

The foundations of modern SNA are found in the much earlier and pure mathematical theory of graphs.[30,31] A network consists of a set of nodes and a set of relations, each defined by a set of attributes. Alliances, terrorist organizations, trade regimes, cognitive belief systems, and the international system itself are common examples (instances) of networks of interest to social scientists. The 'small world' model was pioneered by Stanley Milgram through his famous experiment.[32] (see also Refs 33,34).

SNA has many computational applications across the social science disciplines—not just for visualizing network structures—and is supported by a large family of metrics and exact methods.[35–39] For example, SNA can provide insightful information and inferences on the functionality of an organization, given its structural pattern of nodes and relations. Properties such as resilience, vulnerability, decomposability, functionality, and others provide insightful information and knowledge not available through plain observation or through more traditional methods. In addition, SNA can be applied to the design of more robust and sustainable networks relevant to public policy (e.g., transportation, homeland security, and public health).

An operational principle of networks is that the structure S of a given network N—the way the relations among nodes are organized or connected in N—is related to the main mission or function F of the network in question, such that ideally there is a unique one-to-one correspondence between function F and structure S.[40] For instance, the structure of a terrorist organization (cellular network), or that of a human trafficking organization (chain network) will differ from that of an alliance (clique network)—because their functionality differs. Whereas terrorist and trafficking networks operate as clandestine organizations, an alliance must be overt to produce deterrence. Observation, research, distribution, communication, lobbying, transporting, protection, and innovation are examples of specific functions that require different types of organizational structures. A challenging goal is to identify each organizational functional structure in terms of well-defined statistics and distributions.

SNA has numerous applications across the social sciences by providing a deeper understanding of:

- Belief systems, including extremist ideologies and processes such as radicalization;
- Alliance and treaty systems, including their historical evolution in time;
- International and transnational organizations, including terrorist networks[41–43]; and
- Network games, for instance among proliferators versus counter- proliferators, and illicit traffickers versus government agents.

SNA can also leverage other computational social science methods (e.g.,visualization and data-mining from events data) to exploit synergies. It is difficult to imagine scientific investigations of social systems or processes of any significance that do not include networks—they are ubiquitous in the social world and a constituent feature of many policy issues.

In addition to professional organizations and journals in computational social science mentioned earlier (Section on Background), the SNA community also counts with its own organization, the International Network of Social Network Analysis (INSNA), as well as several peer-reviewed journals, such as *Connections* and *Social Networks*. The INSNA website is recommended for useful information on theory and methods of SNA.

SOCIAL GIS

GIS pertaining to specifically social phenomena were first introduced by social geographers and cartographers as tools for visualizing and analyzing spatially referenced data about the social world.[44] Social GIS has found many social science applications of interest across the social sciences and related disciplines, such as through criminology[45,46] and regional economics.[47,48] Applications of social GIS to quantitative conflict analysis have also been combined with other quantitative techniques to produce unique new insights about spatial patterns that are otherwise unavailable through other statistical or mathematical models.[49–51]

Social GIS is also closely related to the vast field of spatial statistical analysis,[52,53] but with a greater emphasis on visualization of layers of social data.[54]

A significant trend in this area has been the movement toward geospatial science,[48,55] concomitant with the development of Google Earth and other computational resources. Another significant institutional development in this area of computational social science has been the establishment of the National Center for Geographic Information and Analysis as an independent research consortium dedicated to basic research and education in geographic information science and its related technologies, including GIS.

The analysis of many forms of social phenomena could leverage much more from social GIS modeling and analysis, by developing additional cartographic projections and transformations that are more suitable for social data.[49,56] For example, the capability of social GIS for rendering complex Boolean expressions with many data layers is an advanced computational method that awaits exploitation. In addition to cartographic developments, historical GIS[57,58]) is another important area of significant computational developments, thanks to increased computational power and spatio-temporal data sets. The development of Google Earth and its data facilities add yet another dimension to social GIS, offering new methods of investigation.

COMPLEXITY MODELING

Complexity-theoretic models provide mathematical systems based on concepts and principles for the analysis of nonequilibrium dynamics.[59–66] Such conditions that are far from equilibrium (in general, non-Gaussian distributions) are quite often found in the most challenging research problems across the social sciences.[67–74] Observed patterns in terrorist attacks, wealth and poverty in developing societies, political instability, foreign aid distributions, and aspects of domestic and international conflicts are instances of nonequilibrium dynamics. By contrast, equilibrium systems are characterized by state variables that approximate a Gaussian or 'normal' (i.e., 'bell-shaped') distribution, with infrequent departures from their central tendency (see Figure 1a).

- Power laws are among the best known complexity-theoretic models in Computational Social Science (CSS), having first been discovered in economics by Pareto.[75] A power law describes the probability density function (p.d.f.) of a given variable X as $p(x) \sim 1/x^a$, where $a > 0$ is the so-called Pareto exponent.

For example, computational social science examines how the distribution of several conflict variables of interest follows a power law (Fig. 1b), rather than a normal distribution (Fig. 1a): war fatalities in both interstate and civil wars[76–79] insurgency fatalities[80]; and terrorism fatalities.[81] By

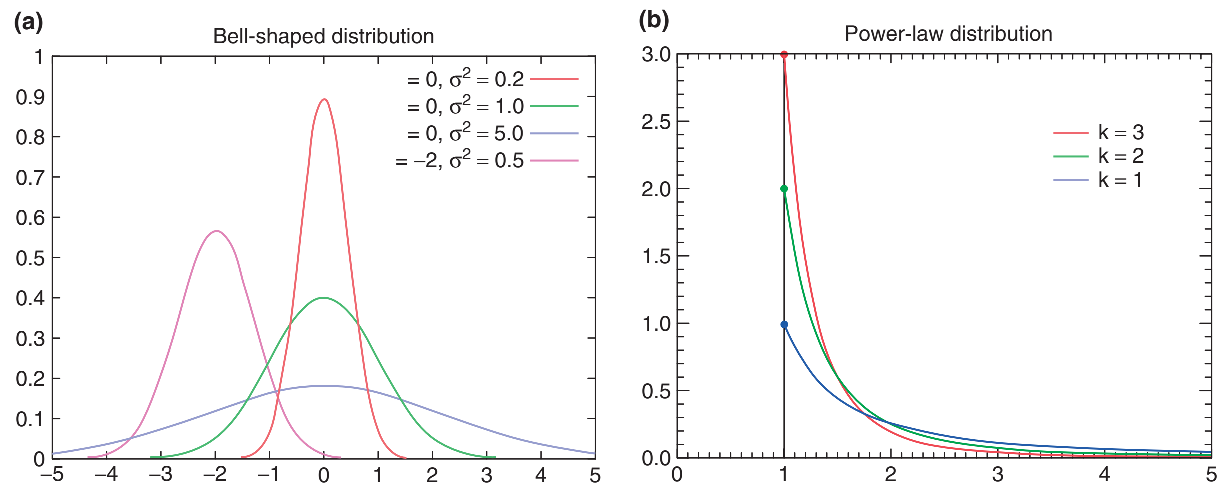

FIGURE 1 | A normal (bell-shaped) distribution (a) and a power law (b). Besides differing in the lower range (left tail), the power law (b) also produces much more likely extreme events (right tail), such as severe terrorist events, political collapse, or other extreme social events. Source for the graphs: Wikipedia.

contrast, earlier statistical approaches attempted to transform the data to obtain Gaussian distributions suitable for regression models. However, from a complexity perspective transforming data represents a loss in information by eliminating skewness, kurtosis, and other natural and informative features.

Importantly, the difference between bell-shaped (Figure 1a) and fat-tailed (Figure 1b) distributions means that extreme values of these variables (e.g., large fatalities) are to be expected with significantly greater frequency, so policy makers should plan accordingly—both for prevention and mitigation—when dealing with social (or natural) nonequilibrium phenomena susceptible to the realization of extreme values. (Policy planning would differ significantly if the upper tail of these distributions followed a normal distribution). Data transformations obscure such properties and can facilitate misunderstanding.

Besides conflict, other patterns of interest to social scientists also obey power laws and related 'fat-tailed' distributions[74,82,83]:

- Extremist religious opinions[84]
- market fluctuations[85,86]
- Size of organizations[87–89]
- Foreign and military aid programs
- Natural disasters, including earthquakes, flood, and landslides[90]

Important inferences that researchers can draw from power law analyses and related complexity-theoretic models include, but are not limited to: the risk of extreme events, the fragility of unstable conditions, or the early-warning indicators of impending abrupt change. Such inferences are neither available nor reliable on the basis of data or plain observation unassisted by complexity-theoretic models.[64] For instance, computing the exponent of a given power law (say, of terrorism fatalities in a given region) provides potentially insightful information on the criticality of social conditions in terms of expecting extreme events. This is because the mean value (first moment) of a power law distribution is proportional to $1/(1—a)$, so as $a \to 1$ the mean value 'blows up' $[E(X) \to \infty]$. In sum, given a policy issue domain (e.g., climate change, terrorism, insurgency, political instability, illicit trafficking, counter-proliferation inspection violations), monitoring and computing the power law parameters of relevant state variables in real-time or near-real-time can provide actionable information that is unavailable by other research methods.

Although significant foundations already exist for complexity-oriented investigations in social science, much more of the extant concepts, models, and methods are yet to be explored. Moreover, combinations of complexity, networks, and simulations provide a rich potential for further scientific discovery.

SIMULATION MODELS

Some of the earliest simulations in computational social science originated in the domains of national security and domestic social policies[91–103] However, simulation models appeared across the social sciences within a relatively short time after the initial utilization of computers for data analysis purposes, thereby establishing foundations for contemporary computational social science research.[104–112] Among the most recent and salient types of simulation models today—as well as in terms of integrative interdisciplinary potential across areas of social science—are those based on system dynamics models and ABMs.[113–115a] As with all formal models, however, simulation models must meet proper standards of internal and external validity.[110,116b]

A particularly valuable feature of computational simulation models for both basic social research and for policy analysis is their ability to run current and alternative policies to observe their effects (alternative scenarios), assuming a sufficiently well-developed base model of a given 'target system.' For example, to estimate the effects of various social stressors on patterns of political instability.[117] Another valuable feature of simulation models is the ability to conduct sensitivity analysis in large parameter spaces to explore robustness and other properties of policies or hypothetical (e.g., counterfactual) events.[118,119]

The two principal types of computational simulation models involved in basic social research are arguably systems dynamics models and ABMs. Hybrid models also exist but are less common.[120]

System Dynamics

System dynamics models are computational simulations that model a given target or referent system as a set of state variables (stocks) and their associated rates of change (flows), based on the method pioneered by Jay Forrester,[121] Randers,[122] Sterman[123] and his collaborators at Massachusetts Institute of Technology (MIT). Today the system dynamics bibliography counts many thousands of entries, including numerous industrial, managerial, and natural science applications.

Whereas earlier system dynamics models were written in DYNAMO code, the most recent implementations of system dynamics models are in the Stella software or in the Vensim software, for both Windows and Mac OS. The object-based approach has also been implemented. Nonetheless, the ontology of system dynamics models is primarily equation-based, not object-based, because of its roots in systems of difference equations with feedback loops and its model-building methodology.

Two pioneering applications of system dynamics modeling in the political science and policy domain during the Cold War were the simulation of strategic rivalry processes between the United States and the USSR,[126] based on L.F. Richardson's theory (1960) of arms races, and the simulation of guerrilla insurgency during the Soviet intervention in Afghanistan.[127] More recently, system dynamics models of polity dynamics—for analyzing governance capacity, stress, state failure potential, and stabilization policies—are also being developed.[125]

System dynamics models used in social science and policy research contribute new understanding by using their ability to draw valid inferences from a complex system of human and social dynamics that can be specified primarily by variables and relations at least in qualitative form; better yet when they can be quantified. For example, important properties such as short- and long-term effects, feedback and feedforward effects, stability properties (or lack thereof), fluctuations, and other interesting features for understanding social dynamics and designing better policies. For example, in the MIT model of polity dynamics (N. Choucri and collaborators, Figure 2c), simulation analysis has identified a range of policies that mitigate insurgency—a potentially valuable insight not available through traditional data analysis or other research methods.

Similar to the SNA community, the system dynamics community is also supported by its own institutional organization, called the System Dynamics Society (established in 1983), and a peer-reviewed journal, the *System Dynamics Review*.

Agent-based Modeling

ABMs are computational simulations that model a given target system based primarily on representing classes of actors and other social entities that interact through a variety of relations (associations) in a given environment. The basic ontology or landscape of an ABM typically includes a set of actors/agents, a set of interaction rules, and an environment with features that may be static or dynamic, organizational and/or spatial. The general class of problems addressed by ABMs is that of explaining—through a simulation model—the emergence of collective or macroscopic behavior based on the individual behavior of agents or actors. Alliances, norms, public moods, spheres of influence, international or transnational networks, distributions in regional or global systems, and other forms of collective behavior are considered emergent phenomena produced by individual actors—issues of central interest to the social sciences. The UML (Unified Modeling Language) is a powerful method for developing the initial design stages of an ABM.[128,129] Gilbert[130] provides a succinct introduction to ABMs in social science, including helpful references and URLs for online content.

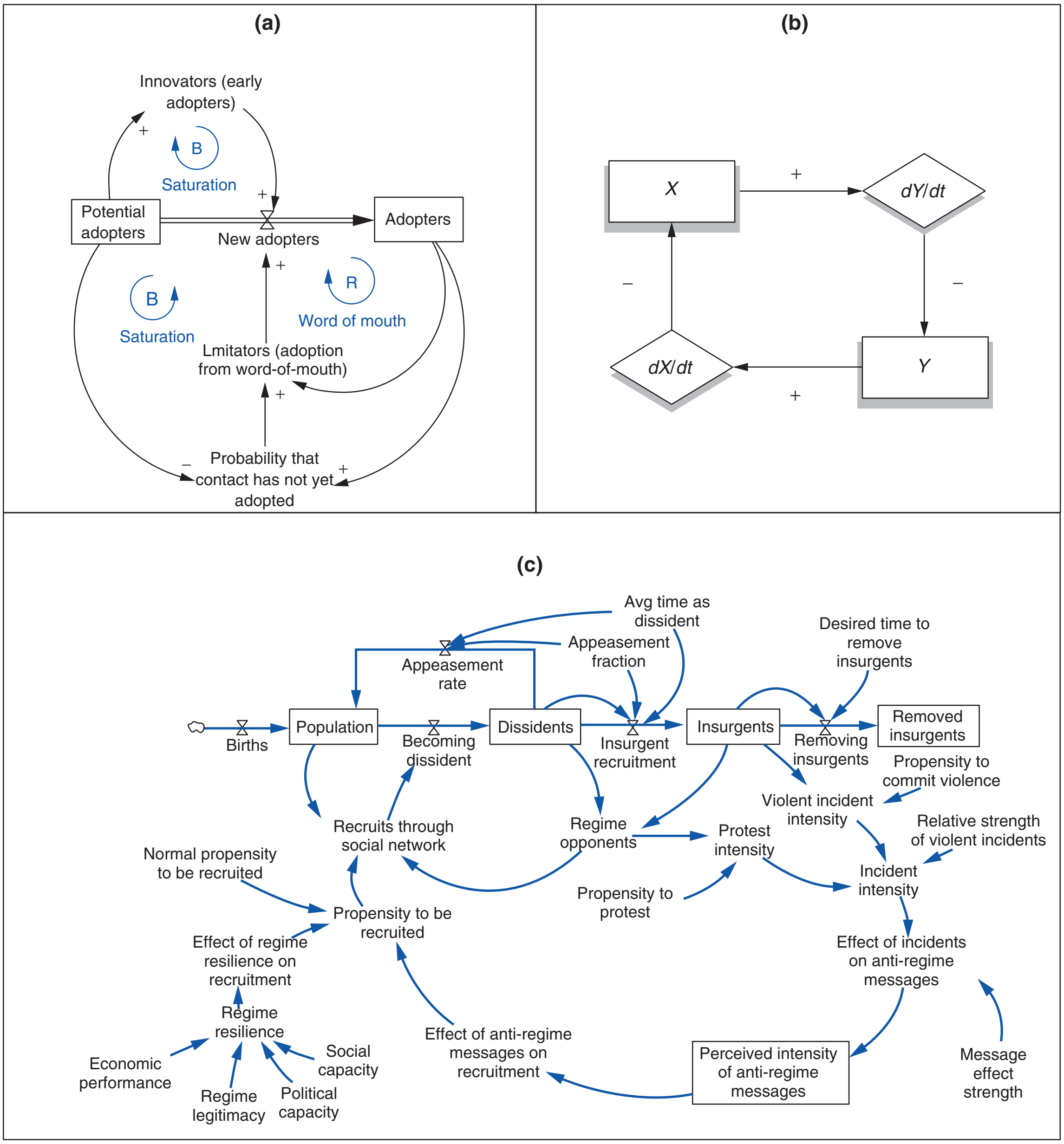

FIGURE 2 | System dynamics models of (a) innovation processes, (b) strategic rivalry, and (c) the MIT model of polity dynamics. Sources: (a) System Dynamics Society website, (b) prepared by the author based on the Richardson's[124] arms race model, and (c) Choucri et al.[125]

Warfare, political unity and disintegration, ethno-sectarian segregation, competition for resources, land-use patterns, environmental change, and other domestic and international issues have been of central interest since the first ABMs were developed.[100,115,134–137] Today, more realistic ABMs are becoming increasingly feasible and valuable for policy analysis. Some examples include:

- The Nomad-Darfur regional model[138]
- An Islamic terrorism model[139,140]
- A Rwandan genocide model[141]
- A cyberwarfare model (DeJong and Hunt, in Lawlor[142])
- An irregular warfare model.[117]

Examples of the potential contribution of ABM simulations to policy analysis and production include the following:

- Unlike econometric models, ABMs are rendered primarily in terms of the main social entities

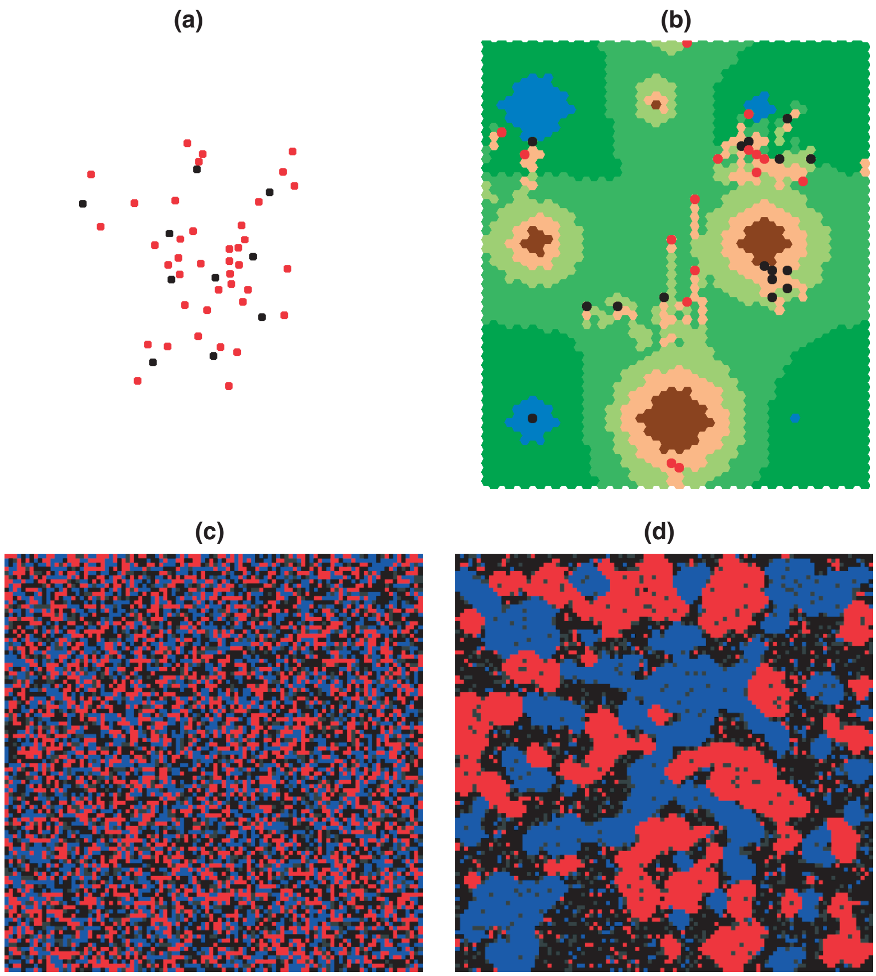

FIGURE 3 | Agent-based models. (a) Cooperative target observation; (b) group dynamics in a changing environment; (c) ethno-sectarian integration in a bicultural society; and (d) emergence of segregation caused by violence. Sources: (a) Sullivan et al.[131]; (b) Cioffi et al.[132]; and (c)-(d) Luke et al.,[133] based on Schelling.[100]

(actors, beliefs, goals, groups of various sizes, or composition) and relations of interest, rather than starting immediately with variables and equations (these are added later), so they are easier to develop in collaboration with analysts, planners, and subject matter experts (SMEs) that know the social entities well but are understandably less versant with computational models;

- In an ABM, the attributes and behaviors of actors are 'encapsulated' in the actors themselves, not added later 'as an afterthought,'[143] so after identifying relevant actors attention can then turn to attributes and eventually to behaviors;
- ABMs are modular, in the sense that they are composed of parts that can be used in other models or projects, thus ensuring progress and efficiency in terms of model development and analysis;
- Several free software toolkits exist for building ABMs,[144] including MASON,[133] RePast, and NetLogo, so these can be installed directly without purchasing additional software. MASON is also open source (available at http://www.cs.gmu.edu/~eclab/projects/mason/).

Finally, although agent-based modeling is experiencing major advances in terms of modeling and analysis of puzzles that once where well beyond the frontiers of feasible investigation, the field must nonetheless manage expectations while investigators gain more confidence in fast growing tools while continuing to pay attention to theoretical foundations and basic science.

SUMMARY

Analysis of the most complex issues confronting the social scientific and policy analysis community today and in the future could be boosted by advanced social science methods that are increasingly powerful and relevant for understanding social and human dynamics. This brief overview identified and described the main methods of computational social science: automated information extraction systems, SNA, social GIS, complexity modeling, and social simulation models. Just like Galileo exploited the telescope as the enabling instrument for observing and gaining a far deeper and empirically truthful understanding of the physical universe, social scientists and policy analysts should exploit the advanced and increasingly powerful instruments of computation to see beyond the visible spectrum available through the traditional disciplines.

NOTES

[a]Other types of social simulations include queuing models, micro-simulations, neural nets, and cellular automata. These and other simulations are surveyed in Gilbert and Troitzsch.[113] GLOBUS,[145] IFS,[146] and similar econometric models provided initial stimulus to the current generation of system dynamics and agent-based models.

[b]Translation: The modeling and simulation (M&S) community, especially in defense analysis and military operations research (MORS), uses the terms 'validation and verification' (V&V) to denote internal (i.e., formal) and external (empirical) validation, respectively. External validity includes calibration. Another distinction that is common in computational social science is between model 'fitting' (estimation, calibration) and model 'testing' (e.g., out-of-sample forecasting). On these and related issues of model validation, see, Refs 113 and 147.

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