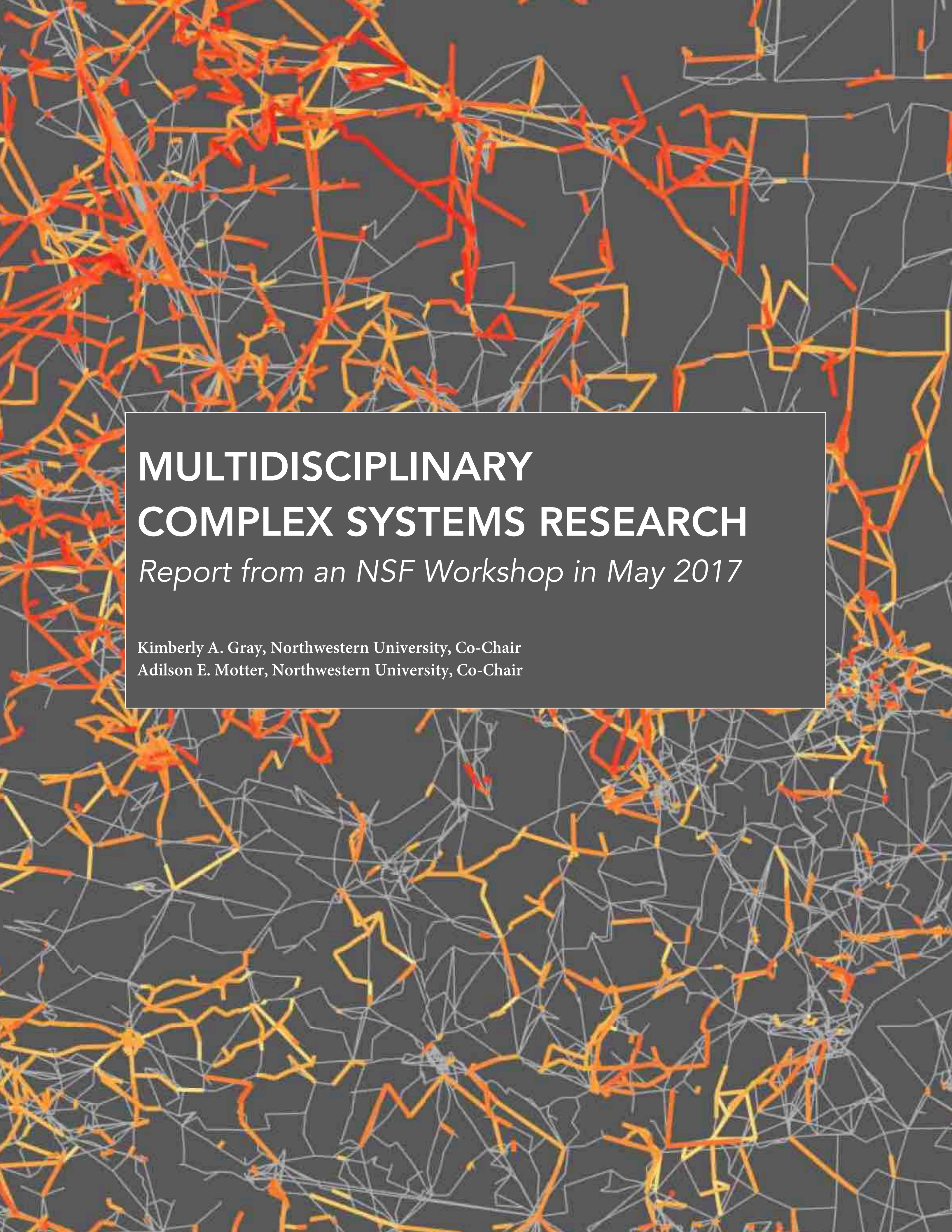

MULTIDISCIPLINARY COMPLEX SYSTEMS RESEARCH

Report from an NSF Workshop in May 2017

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INTRODUCTION

About

This workshop brought together a diverse group of experts in complementary areas of complex systems and was preceded by a series of weekly webinars (see references W1 to W6). The overarching goal of the activity was to address scientific issues that are relevant to the research community and reveal possible areas of opportunity for multidisciplinary research in the study of complex systems. The specific goals of the workshop included:

- identifying the most substantive research questions that can be addressed by fundamental complex systems research;
- recognizing community needs, knowledge gaps, and barriers to research progress in this area;
- identifying future directions that cut across disciplinary boundaries and that are likely to lead to transformative multidisciplinary research in complex systems.

The workshop was held at the National Science Foundation on May 1-3, 2017, supported by Award # **DMS**-1647351, and was attended by 48 scientists, mathematicians, and engineers.

The workshop was motivated by the observation that many processes in natural, engineered, and social contexts exhibit emergent collective behavior and are thus governed by complex systems. Because challenges in understanding, predicting, designing, and controlling complex systems are often common to many domains, a central objective of the workshop was to facilitate the exchange of ideas across different fields and circumvent disciplinary boundaries typical of many traditional scientific meetings. The workshop participants included experts in both theory and applications, as well as a selection of postdoctoral researchers and graduate students from various domains. Because of the cross-disciplinary nature of the workshop, the participants themselves had the opportunity to become aware of the latest developments in fields related to, but different from, their own. The inclusion of early-career researchers will help promote the transfer of this expertise to the next generation of researchers. The environment fostered discussions on the state of the art, potential issues, and most promising directions in multidisciplinary complex systems research.

This report includes outcomes of the workshop that can help inform the scientific community at large of the current status and challenges as well as future opportunities in multidisciplinary complex systems research as perceived by the participants of the workshop.

Multidisciplinary Needs and Opportunities

One of the identified needs is **scientific community development**. Examples include areas at the interfaces between fields such as chemistry, physics, biology; energy production, storage, and conversion; and medicine, nanotechnology, and materials engineering. Primary to this is a continued strong connection between theory, experiments, and simulations. Indeed, many of the systems lacking theoretical explanation were discovered through careful experiment. For example, tools to experimentally study and perturb molecular systems are remarkably advanced as compared to other scales. This includes tools to manipulate experimental parameters and system components, and to perform measurements with single molecule resolution. This level of control provides a unique opportunity for iteratively building and testing complex models that describe such systems. Future experimental directions include using microfluidics to control and probe scale effects on systems and to continue to explore the differences in observed collective behavior depending on the source and type of driving of the system components. The types of driving that need continued experimental exploration range from classical hydrodynamic effects to chemical, biochemical, and quantum interactions, which in turn requires properly trained personnel and hence well-structured communities around these topics.

Support for **interactions between theoreticians and experimentalists** and for training researchers to approach a problem from multiple spatial and temporal scales was identified among the main strategies for progress. For example, in contemporary studies of animal behavior, new tools and approaches for data-driven discovery may arise at the intersection of neuroscience and data sciences. In that context, a major challenge is the development of tools for representing and integrating data collected at different scales across the various embedded complex systems associated with neural systems and their behavior. Likewise, many other complex systems can benefit from model-driven experimental design drawing from interactions between theory and experiments. These interactions can in fact take many different forms, of which a formal collaboration is one of them. As an increasing number of researchers receive interdisciplinary training and develop research competency across disciplines, many advances in multidisciplinary complex systems research are expected to continue to come from projects pursued by individual researchers. Mechanisms for funding should acknowledge this plurality of research team compositions. They should also favor longer-term projects (*e.g.*, 5-year as opposed to 3-year initiatives), giving the researchers the necessary time to expand their base of knowledge beyond their primary discipline, interact across fields, and explore their discoveries in depth.

Some evidence was presented that opportunities for significant progress currently exist in both **emerging topics and in classic topics** within complex systems. One example is the area of self-organization, which has generated increasing interest over the past few years in connection with biological systems and active matter. At the same time, fundamental questions continue to exist and generate valuable discoveries in the now well-established area of pattern formation. Pattern formation is an example of self-organization, in which system components experience local interactions that lead to the emergence of global structures. Familiar examples include lane formation in traffic flows, Turing patterns, residential segregation by race and ethnicity, and phase transitions in multicomponent fluids. Figure 1 illustrates the case of Turing patterning with two kinds of diffusible molecules (activators and inhibitors), which mechanistically explains the color structure in the skin or coat of animal species. Research progress necessitates the creation of a framework for predicting what classes of patterns result from particular sets of interaction rules, and vice versa. In systems where the rules are tunable, this would allow for control of the types of self-organized patterns that would emerge, which is a research question of current interest.

Figure 1

Emergence of patterns and colors in the skin of salmon, which is ultimately dictated by the morphology of the developing embryo and modeled as Turing patterning (adapted from Miyazawa *et al*. 2010).

The group also identified and discussed **challenges associated with the evaluation** of multidisciplinary complex systems research and researchers. This included structural barriers that pose difficulties to the evaluation of young faculty and human factors that pose challenges to the assessment of papers submitted for publication or research proposals submitted for funding. For example, it is broadly recognized that it is more difficult to identify reviewers with expertise in all parts of a piece of scholarly production when the work is multidisciplinary. It was noted that while much progress on these fronts has been made—both by individual practitioners and by the institutions involved—significant difficulties inherent to the multidisciplinary nature of the field still remain. Part of the solution comes from acknowledging these issues and adopting practices to mitigate their effects. But the ultimate solution appears to lie in expanding the training of the next generation of multidisciplinary researchers and educators, which should be another priority of the field.

It was also noted that complex systems have a unique potential to contribute to **undergraduate education**. Numerous U.S. universities and institutes have rich research programs in complex systems, and many such institutions offer undergraduate education and/or research training in complex systems; some also produce online educational materials, such as courses and syllabi (*e.g.*, programs at the Santa Fe Institute, the University of Michigan, and Northwestern University). But this richness is not available to the average U.S. undergraduate student because of understandable constraints on student time and department resources. To address this, U.S. colleges could benefit from the development of educational materials that would illustrate aspects of complex systems phenomena in the individual STEM disciplines. One example would be the development and distribution of modular educational activities on complex systems that could be adopted into a professor's lab or lecture schedule in any standard course (organic chemistry, thermal physics, microeconomics, *etc.*) at low time and resource costs. This content could be created by drawing from the materials that already exist and by collaborations between experienced professors in traditional disciplines and complex systems experts, and reside in a repository for free use by academics across the country (and world). More broadly, the field should put emphasis behind the development of complex systems curricula.

Finally, it was argued that aside from its fundamental contribution to research in STEM fields, further development of complex systems research will provide powerful new **methods and insights for policymakers, managers, and stakeholders**. For instance, one might imagine a model of a metropolitan area that integrates multiple aspects of the social, natural, and built environment. Such a model, which is now conceivable within the frameworks of agent-based modeling and network science, could be continually updated with streaming data drawn from administrative sources, social media, and the Internet of Things. Policymakers could use such a model to determine how a new infrastructure policy would affect residents' access to services, what kind of financial resources would be required, and its environmental impact.

METHODS AND PRINCIPLES

Agent-Based Modeling

Agent-based modeling (ABM) is a powerful computational approach that enables the modeling of complex interactions of a large number of autonomous individual entities that produce system-level consequences (Wilensky & Rand 2015). A defining characteristic of ABM is that the models are simulated at the individual rather than the aggregate level, which allows fairly realistic representations of systems that are too complex to be represented with closed-form equations. ABM can serve as an *in silico* laboratory for assessing the global impact of local properties and understanding the dynamics resulting from different mechanisms; in addition, ABM is useful in performing theory exploration, intervention analyses, and general experimentation in many areas in natural, engineering, and social sciences (Miller & Page 2009).

Although early ABM focused primarily on the study of emergent behavior determined by simple rules, current frontiers are centered on realistic data-driven modeling and very large-scale simulations while accounting for model validation, integration of disparate methodologies, and reproducibility. For ABM to be useful in studying real-world phenomenon, it is important to advance the use of models that are drawn from empirical data (Bruch & Atwell 2015). Many methods are currently being explored in this space, of which the automatic generation of agent-based rules directly from observed data is an example. Future research into methods for assessing a model's sensitivity to assumptions, the (near-)automatic creation of models from theory and data, and robust validation approaches could provide powerful tools for the multidisciplinary study of complex systems. As ABM becomes more detailed, a related challenge concerns the development of computational techniques for implementing large-scale ABM (*e.g.*, Collier & North 2013, Cordasco *et al.* 2013) that can take advantage of recent advances in high-performance computing resources.

Another frontier concerns the integration of disparate research methodologies. For instance, lab experiments can be used to help generate agents' behavioral rules (Smith & Rand 2017); qualitative research can be used to ground the models; and traditional econometric analysis can complement ABM by providing ways to parameterize, analyze, and validate large-scale model outputs (Chen *et al.* 2012). One can further the current efforts to combine research approaches by developing best practices (*i.e.*, by using cases and frameworks) for method integration. There has also been increased recent interest in developing and applying tools for the advanced exploration of the outputs of agent-based models (*e.g.*, Thiele *et al.* 2014, Stonedahl 2011, Ozik *et al.* 2016). A central problem in ABM is understanding which model components have the largest effects on model outcomes; developing new tools for sensitivity analysis and causal inference would allow researchers to better capture these dependencies.

In the long-term, one can imagine a world in which ABM becomes a common technique in the toolkit of every researcher working in complex systems, as statistics is now for many disciplines. Getting to that point requires the development of tools, methodologies, and frameworks that can explore the boundaries of multidisciplinary research, and also the adoption of practices to facilitate use of these techniques. In particular, given the variety of platforms and languages currently used for ABM, future research should encourage adoption of specification methods, such as ODD (Grimm *et al.* 2010), and of code archives, such as OpenABM (Janssen 2017), to enable reproducibility and facilitate collaborations across fields.

Network Science

Networks are tools for analysis in many domains, letting us represent complex systems and data with an emphasis on interactions between their constituents. This "network lens" allows us to probe multi-scale social interactions rather than just homogeneous populations, explore integrated metabolic networks rather than focusing on individual pathways, and model epidemics using contact networks rather than low-dimensional models. Many phenomena cannot be understood without understanding the structure of their underlying networks—networks are not a choice. In addition to being useful representations, networks are objects of study in their own right, with common phenomena and properties across domains. While networks in each domain (*e.g.*, social, metabolic, and infrastructural) have unique properties, we can gain insights into all of them using shared language and techniques.

Topological structure is a good first glimpse of a system, but "networks" are not just graphs. Nodes and/or edges are often dynamical systems; edges may have weights, capacities, and lengths; nodes may have locations, demographics, and content; networks can change over time, often have multiple types of links, and may include higher-order interactions in addition to pairwise ones. Network science embraces all of these types of structure and dynamics, and we are actively extending our tools to capture them.

The early days of network science focused on simple statistics: degree distributions, clustering coefficients, "motif" or subgraph counts, centralities, and so on. But we have come a long way since then, and our colleagues in other sciences can gain enormously by connecting with current work. Here are some of the current frontiers and outstanding problems in network science:

Dynamics, both on the network and of the network (Motter & Timme 2018, Holme & Saramäki 2012). Numerous applications involved coupling dynamics *on* the network (*e.g.*, voltages on a power grid, neuronal oscillations, or populations in a food web) with dynamics *of* the network (changing topologies due to breakdowns, learning, or the introduction of invasive species, respectively). The coupling between these two types of dynamics creates many new phenomena, and requires new mathematical tools to be properly addressed.

New techniques in statistical inference (Clauset *et al.* 2008, McAuley & Leskovec 2014). Networks are high-dimensional datasets that are globally correlated, making many concepts from classical statistics inapplicable. Popular network analysis algorithms offer no guarantees of statistical significance and do not guard against overfitting. Moreover, real datasets are often biased samples of larger networks, violating statistical assumptions like independence and exchangeability. As a result, there are now many open questions about how to perform statistical inference on networks in a mathematically principled way.

Connections with statistical physics (Decelle *et al.* 2011, Mossel *et al.* 2015, Radicchi 2014). Just as a block of iron loses its magnetic field at a critical temperature, there are phase transitions where community structure and other features suddenly become impossible to find if a network is too sparse or too noisy. Identifying these phase transitions, making them mathematically rigorous, and designing optimal algorithms has led to a lively interaction between physicists, mathematicians, and computer scientists, in which open theoretical questions remain.

New control theory (Motter 2015, Gao *et al.* 2014). Standard control theory mostly addresses small-scale deterministic systems, in which a small number of components interact within a well-defined architecture under the effect of small disturbances. Networks demand control approaches that can scale up to large assemblies of dynamic units, which are often nonlinear and only partially accessible to intervention. Remote synchronization, cell reprogramming, and control of cascades are exemplary applications. While recent progress has been made under simplifying assumptions, the broad problem of controlling networks under realistic conditions is an evolving topic of current research.

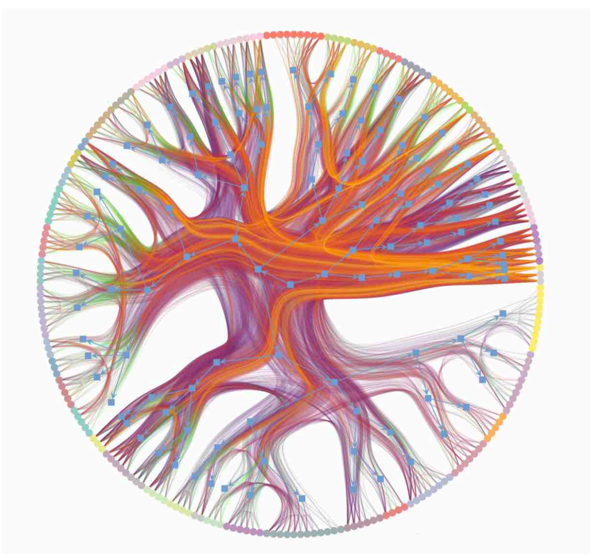

Figure 2

Modular structure of a weighted social network inferred from data using a nonparametric method (adapted from Peixoto 2018).

Dealing with uncertainty and noise (Martin *et al.* 2016, Platig *et al.* 2013). Measurement uncertainty includes missing links (*e.g.*, unobserved connections in an ecological network), false positives (*e.g.*, when two proteins are annotated as interacting even though they don't work together in the cell), as well as the very nature of the interactions themselves (*e.g.*, inhibitory or excitatory). How can we predict missing links, flag likely false positives, and disentangle properties of the interactions? How does dynamical noise affect our ability to infer network structure (*e.g.*, from correlations in time series)?

Finally, the overarching goal of network science—understanding the relationship between structure and function—is still an enormous challenge, despite significant progress that has been made in this direction (as illustrated in **Figure 2**). What can the connectome of the brain tell us about its functional architecture? How does the protein interaction network translate into phenotype and physiology? Conversely, how do network functions, resource limitations, and selection pressures modulate the topology of interactions among components?

Dynamical Systems

Dynamical systems is an area of mathematics that comprises a collection of techniques used to analyze and understand the time-dependent behavior of a system, typically through use of ordinary, partial, delay, and stochastic differential equations as well as differential-algebraic equations, difference equations, and discrete-time models. Dynamical systems tools are important for helping understand a variety of properties and phenomena in complex systems, including stability, bifurcations, invariant sets, and chaos. Experimental studies in this area cover a broad range of interests and methods and include studies of fluids, engineering systems, model population systems, biological systems, and chemical reactions, just to name a few. A closely related area of research is that of control theory (Murray 2003), which provides the principles and methods used to design engineering systems that maintain desirable performance by automatically adapting to changes in the environment.

The area of dynamical systems has established a broad repertoire of tools for studying complex systems. This includes the classical field of geometric singular perturbation theory, which remains very active, but new directions have also been explored in recent years. For example, tools have been developed to detect coupling or causal relationships in a system (Butail *et al.* 2016, Sugihara *et al.* 2012). Analysis and determination of bifurcations are well-developed for low-dimensional systems, but more research is needed to determine how to make best use of them in very large-scale, heterogeneous, high-dimensional systems. This research is particularly relevant in the context of tipping points discussed in the section on regime changes.

Recently, data assimilation techniques have been successfully developed that allow the incorporation of real-time data into predictions of future behavior (Law *et al.* 2015, Abarbanel 2013). These tools are being used with enormous success in weather forecasting as well as in related problems such as solar and wind prediction. Further development of data assimilation techniques can be applied to a variety of other fields, such as feedback-based neuromodulation, power system load forecasting and dynamic line rating, and personalized medicine. More generally, there are ample opportunities for data-driven modeling and analysis (including machine learning) given the increasing availability of very large-scale data sets, especially in biomedical fields (Murdoch *et al.* 2013). Topological data analysis methods are related approaches for examining both numerical and experimental data exhibiting complex patterns (Carlsson 2009), which provide an alternative to some of the standard techniques, such as correlation or spectral analysis. There have been a number of successes in this area, such as in brain (Giusti *et al.* 2015) and genomics (Camara *et al.* 2016) research, and broader dissemination of these methods is likely to yield relevant results in other areas of complex systems.

Another area of expanded activity is in the use of computer-assisted proofs that might allow researchers to move beyond numerical simulation and establish more rigorous and potentially general conclusions. Combining interval arithmetic with analysis could allow for exact validation with a mathematical proof. For example, one can guarantee that certain types of periodic orbits occur or that a bifurcation structure exists. While research in this area has a long history, which can be traced back to the computer-assisted proofs of Feigenbaum conjectures (Lanford 1982), this research remains timely because of the potential it has to address multidisciplinary complex systems problems.

To take advantage of the opportunities in the expansion of dynamical systems tools for the study of complex systems, it will be important to enable interdisciplinary research that promotes both intra- and inter-institutional interactions, and to disseminate research results and techniques across disciplines. Some examples of research gaps and promising directions include: 1) better methods for linking fidelity and detail in models to the intended uses of those models (*e.g.*, when implementing dimensionality reduction methods, what is the appropriate reduced dimension to retain?); 2) better approaches to study systems with only partially known dynamics, of which biological systems are prime examples; 3) better tools for probing complex systems to build mathematical models (*e.g.*, to reconstructing the network structure from data); and 4) scalable approaches to manipulate and control the behavior of complex systems, possibly in combination with tools from network science (Zañudo *et al.* 2017).

APPLICATIONS AND IMPLICATIONS

Nervous Systems and Behavior

The subject of brain and behavior spans a broad range of systems, from genes to cells to neural systems to organisms to groups of organisms to the cultures that those organisms develop. Each of these systems exhibits complex dynamics while being embedded in the systems at levels above and below it. In many cases, these systems have network structures that change over time (from synaptic remodeling to cultural change) as a result of activity in the network itself and those above and below it. A major challenge for this field is to understand how each of these complex dynamical systems relates to the other.

Neural systems encompass a wide range of spatial and temporal scales—from small organisms with hundreds of nerve cells, to tissues of thousands of nerve cells, to brains of higher organisms comprising billions of cells. At the subcellular level, synapses mediate communication between cells; at the cellular level, individual neurons may be quiescent or autonomously active, and the activity can be regular, irregular, or bursting; at the whole brain level, activity patterns reflect metabolic changes tied to activity at finer scales as well as the social context of the organism; at the cultural level, the cognitive biases of learners shape the structure of language. At all scales, problems concerning the function, structure, and dynamics of the system continue to challenge researchers, and data sets are rapidly increasing in size and coverage (Sejnowski *et al.* 2014). The complexity of the system makes it difficult to identify the right scale to begin exploration of a problem, and most existing techniques are unable to connect multiple scales. Addressing the many challenges in characterizing and understanding systems spanning multiple spatial and temporal scales, which cut across diverse research areas and require technical advances, will have far-reaching impacts.

New technologies for studying brain activity have exposed the critical need for new theoretical and analytical approaches that can capture the most pertinent features of these complex systems (Churchland & Abbott 2016). The time is ripe for concerted application of the tools of complex systems analysis to brain and behavior. New and emerging technologies enable stimulation and recording of activity over a range of spatial scales simultaneously. These recordings involve a variety of imaging techniques, including imaging at the molecular level using fluorescent dyes sensitive to individual molecules, voltage, and calcium concentrations associated with sub- and super-threshold nerve activity (*e.g.*, Yang & Yuste 2017), extracellular recordings using multi-electrode arrays (*e.g.*, Jun *et al.* 2017), and functional magnetic resonance imaging covering activities of millions of nerve cells in distributed brain regions (*e.g.*, Craddock *et al.* 2013). To complement these technological advances, we advocate for the research and development of theoretical, mathematical, and analytical tools for representing, integrating, and characterizing data from embedded complex systems across spatial and temporal scales. Major contributions are likely to come from the sciences of dynamical systems (Breakspear 2017) and complex networks (Bassett & Sporns 2017).

There are numerous examples that illustrate the challenges to be addressed: 1) understanding the changes in the nervous systems of language learners where brain changes drive changes in language function, which in turn alters the nervous system at multiple scales; 2) deciphering the role of localized and large-scale activity in modifying synaptic structure, which in turn alters the network over which the activity takes place; 3) understanding how system dynamics can route information flow in the functioning of distributed neuronal networks (Palmigiano *et al.* 2017); and 4) determining how the network structure of the brain is tied to the structure of the individual's social network. For a specific example of the latter, we refer to the study illustrated in **Figure 3**, where two embedded complex systems (brain networks and social networks) influence one another dynamically: an individual's connectivity in a social network affects their patterns of brain connectivity, which in turn may affect the individual's social interactions (Schmälzle *et al.* 2017).

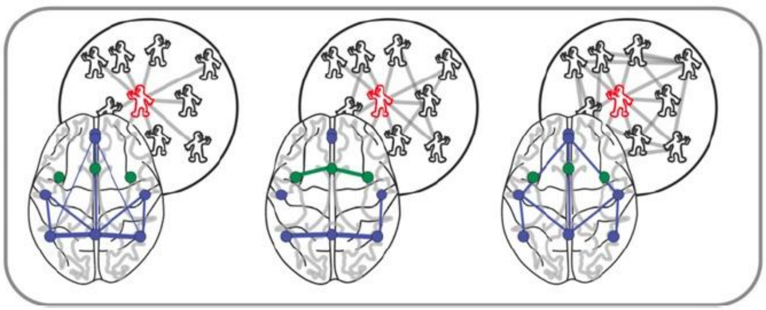

Figure 3

Interaction between brain networks and social networks as an example of multiscale analysis (adapted from Schmälzle *et al*. 2017).

Community-Based Systems

Community-based systems (CBSs) are inherently complex. Communities include cities, villages, large organizations, nations, and any system in which individuals either self-describe as members of the community or are allocated to a community by a third party. CBSs include all of the complex systems that affect members of those communities such as infrastructural, health, political, industrial, economic, and environmental systems. Thus, CBSs are inherently a multi-layered network of multiple systems, many of which were not designed to work together and all of which are continually changing. Pervasive and dynamic interdependencies greatly contribute to the behavior of the CBS. Complex systems research enables the study of CBSs because it provides tools and methods for the interdisciplinary integration of different domains or fields, such as epidemiology, public health, economics, urban planning, sociology, policy, transportation, anthropology, engineering, political science, networks science, *etc.* Advances needed include improving the understanding of and informing decisions about the design and management of CBSs, as well as expanding contributions to the current scholarship by adopting novel methods and promoting interdisciplinary collaborations.

Traditionally, CBSs are evaluated from (or at least favor) one perspective, such as that of the policymaker, the landowner, *etc.* In reality, the perspectives of all inhabitants in a community should be taken into account. Accordingly, an integrated perspective can provide a more comprehensive framework for the construction of CBS models.

In addition, it is often a challenge to understand what interdependencies are relevant to particular research and decision-relevant questions, so methods for ascertaining what to include and how to integrate it would be appropriate. For instance, we observe the rapidly increasing impact of interconnections among technology and social systems (so-called cyber-physical-social systems). Such systems provide an important example of the challenges of understanding, modeling, and integrating information from many sources and fields. This includes addressing the impacts of the use of social media, the democratization of technology, and the burgeoning of capabilities like gig economy environments (*e.g.*, Uber and Lyft) and advanced logistics (*e.g.*, near-free delivery of goods). In addition to being an area of research in its own right, this work can add significant value to the existing efforts of smart, connected cities (Gray *et al.* 2011).

In most CBSs, we have one instantiation of the real world that we can observe, and so validating a model or theory against that instantiation can be difficult. Moreover, determining the appropriate level of modeling for these systems, and determining how to best integrate multiple scales of modeling, are not well understood. Complex systems research also integrates capabilities from dynamical systems, agent-based modeling, and network science (noted in this report) that directly apply to CBSs and provide frameworks that enable sensitivity analysis, testing of model robustness, and using uncertain or ambiguous model results to usefully inform decision making. However, work still needs to be done to satisfactorily develop and integrate these frameworks and to validate the associated models.

Finally, advances are needed in the evaluation of success. In many cases, there is an explicitly stated goal of studying a CBS to understand how to make the system "better." However, CBSs are made up of numerous stakeholders with different and sometimes opposing needs, thus no solution will address all needs. Moreover, as CBSs typically operate for extended time periods, concepts related to interoperability, upgradability, extensibility, sustainability, *etc.*, must also be considered in system improvements. The goal of some innovative research into CBSs may be not to incrementally modify the current system, but rather to foment a transformative revolution that essentially redesigns these systems from the ground up, such as in the development of an urban system in which human behavior and the natural environment are coupled sustainably. Since complex systems research embraces dynamic, non-equilibrium measures, it will be useful to build on these measures in developing rigorous notions of success for CBSs. (For additional information on CBSs, see references CBS1 to CBS6.)

Collective Behavior Arising from Molecular to Micro Scale Interactions

Numerous topics have emerged from studying the collective behavior that results from primarily local interactions between particles of a system, where particles may be individual atoms, molecules, or microscale entities (*e.g.*, colloids or bacteria). This perspective forms the basis of various fields, including meta-materials, active materials, responsive chemical systems, and synthetic biology. Efforts have focused on characterizing these systems and engineering new systems with desired behaviors. To foster these efforts, an improved understanding of non-equilibrium statistical mechanics is needed, as is the adaptation of computational and experimental approaches used in other contexts, such as agent-based modeling, network science, single-molecule measurements, microfluidics, and imaging techniques.

A prominent emerging domain is active matter, which concerns systems (biological or not) composed of agents that consume energy and are thus out of thermal equilibrium. Such systems require non-equilibrium statistical characterization as they include physical or chemical driving forces acting on each system component separately, and energy cascades from small to large scales. An area of particular interest in the field of complex molecular behavior lies in harnessing non-equilibrium processes to enable the engineering of self-organizing materials capable of autonomous motion and programmed tasks. Driving matter out of equilibrium makes it possible to synthesize materials with bio-inspired functions, including autonomous motility, self-replication, force generation, and adaptive mechanics. The ultimate goal is to design non-equilibrium processes to achieve desired functions. This will be possible by developing a new framework to process and encode information in heterogeneous materials.

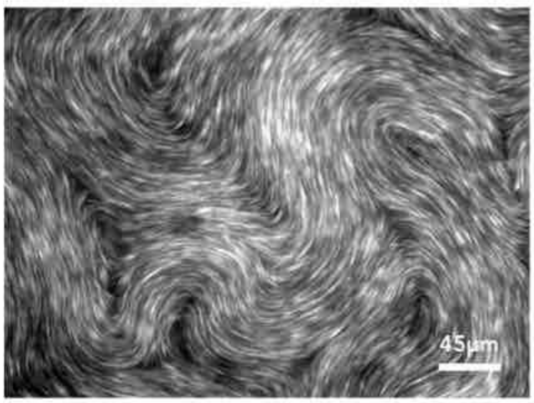

Figure 4

Active nematic liquid crystal exhibiting patterns similar to those that emerge from flocking birds and schooling fish (adapted from Sanchez *et al*. 2012).

The coupling of experiment and theory at the molecular or micro-scale is now making it possible to build an understanding of self-organization at this scale that can be applied at much larger scales to engineer biomimetic materials and meta-materials. For example, DNA origami demonstrates that it is possible to design the subunits necessary to produce a desired self-assembled structure (Praetorius & Dietz 2017), and adaptive materials have been synthesized to assemble responsive and self-healing gels (Stukalin *et al*. 2013), membranes for filtration and sensing (Šarić & Cacciuto 2013), magnetically-driven polymers and membranes, and self-replicating colloids (Dempster *et al*. 2015). In addition, fluid dynamic effects on driven colloids continue to produce surprising behavior (Driscoll *et al*. 2017), including the clustering and propulsion of particles. The presence of molecular-scale particles can perturb an environment, such as a membrane, in a way that feeds back and facilitates the self-organization of those very particles (Liu *et al*. 2015). An intriguing new quantum physics example of a system with non-equilibrium, emergent properties is time crystals, a class of materials that exhibit ordered repetition in time, rather than in space (Zhang *et al*. 2017, Choi *et al*. 2017). Collaboration between experimentalists and theorists has also produced a breadth of knowledge on fundamental hydrodynamic physics in soft matter (Marchetti *et al*. 2013). Work on cytoskeletal filaments, motors, and energy demonstrates (Schaller *et al*. 2010, Sanchez *et al*. 2012) the biological relevance of active matter systems and how computational modeling can describe these systems (Keber *et al*. 2014). An example of the latter are structures formed by the self-organization from biological filaments (microtubules) and molecular motors that use ATP as an energy source (Sanchez *et al*. 2012), as shown in **Figure 4**.

The grand challenges for future research stem from the fact that harnessing non-equilibrium processing to transform matter into performance materials requires an understanding of the ways in which various energy forms (chemical, optical, thermal) are converted into motion. That is, how is the energy injected at the microscale converted into organized motion and function at the large scale? A key challenge is thus learning to encode, process, and act on information within highly fluctuating and complicated environments, as occurs so effectively in living organisms. In particular, the range of research challenges include: 1) classifying active systems based on modes of energy input, symmetry, and interaction with the environment; 2) formulating the continuum mechanics of growing and reproducing materials with states that may depend on deformation, external perturbations, or chemical signals; 3) developing a theoretical framework to describe the adaptive mechanics of active materials in response to external forces; 4) formulating a framework that explains information storage, transmission, and processing in the context of non-equilibrium statistical mechanics; and 5) developing a theoretical understanding of biological organization as a far from equilibrium process. Ultimately, advances in theory and computation are expected to enable a new paradigm of *in silico* materials design and testing.

Food, Energy, and Water Systems

How can nine billion people thrive and prosper equitably on one planet? The health and security of humans and the environment rely on highly interconnected food, energy, and water (FEW) systems. These systems are both complex and complicated, with multiple interdependencies and feedback processes (Pereira *et al.* 2017). Questions on food, water, energy, and human health security are urgent, as illustrated by the concept of "Planetary Boundaries" (Rockström *et al.* 2009). The nine boundaries identified in this seminal work are all directly or indirectly related to the FEW nexus: climate change, ocean acidification, stratospheric ozone depletion, the nitrogen and phosphorous cycles, global freshwater use, land use change, biodiversity loss, atmospheric aerosol loading, and chemical pollution. Many of these boundaries have already been crossed and others are approaching critical thresholds, indicating that FEW systems are in danger of either failing themselves or endangering key earth system processes (as characterized in **Figure 5**). Furthermore, since these systems are interconnected, stress in one area reduces resilience in other areas. A central goal of FEW systems management is to understand how to build and manage resilience, preserve ecosystems' functions, inform decision making under uncertainty, understand the limits of prediction, and investigate effective systems of governance (*e.g.*, Hannam *et al.* 2015).

Given the nature of the FEW nexus, complex systems science is uniquely positioned to advance FEW systems knowledge and management. Here, we discuss how multidisciplinary complex systems approaches provide insight into three key areas: (1) food and water security; (2) energy supply and sustainability; and (3) crosscutting "nexus" questions.

Food and water security. We consider food and water security together, as these systems are highly interlinked and can be described with similar approaches. Food and water systems encompass everything from food production and the hydrological system to allocation, distribution, trade, governance, consumer choice, and social norms, with multiscale feedbacks among these processes (Leck *et al.* 2015, Nesheim *et al.* 2015, Acharya *et al.* 2014, Ingram 2011). They have their own internal dynamics, are subject to external forces (*e.g.*, both are highly influenced by the Earth's climate system) and stochastic variations, and are strongly dependent on ecosystem health. While climate processes are largely determined by the laws of physics and chemistry, the processes that make up food and water systems are also strongly influenced by cultural and societal norms, governance, and social conflict (Acharya *et al.* 2014, Beddington *et al.* 2012, Brown *et al.* 2015, FAO 2017, Ng *et al.* 2014, Raworth 2017, Rockström *et al.* 2009, Wilson 2006). Tackling these interconnections requires integrating models for the behavior of agents in socio-economic systems with resource dynamics in ways that go beyond patching together disciplinary models.

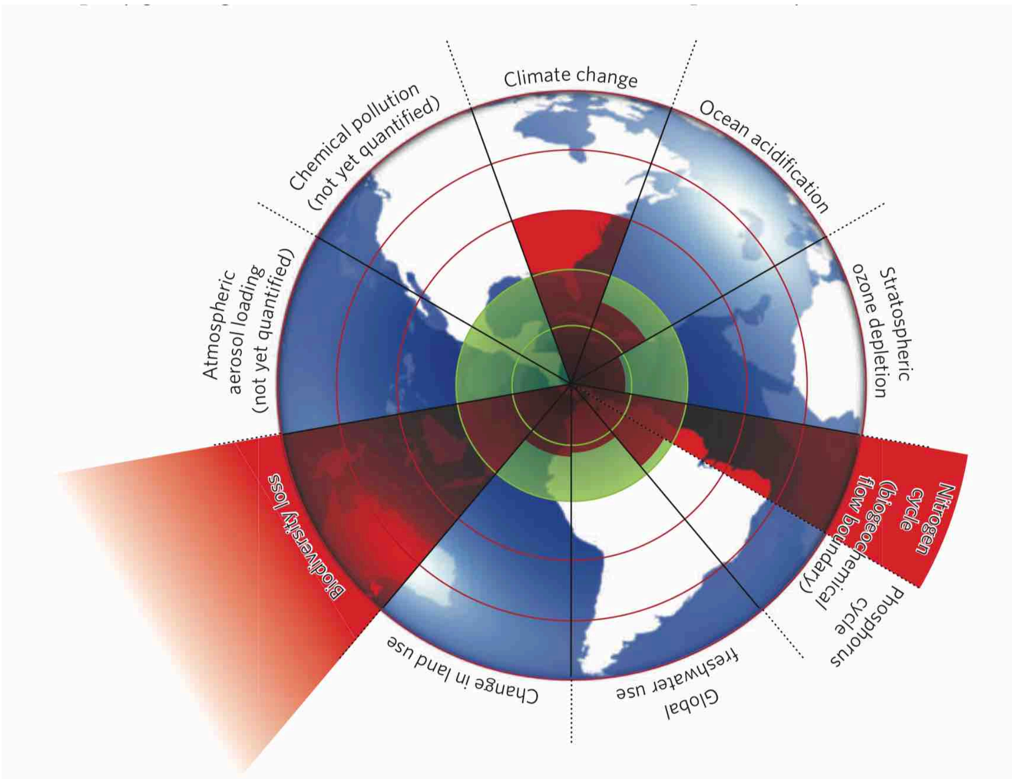

Figure 5

The nine planetary boundaries and their current status (Rockström *et al.* 2009).

Energy supply and sustainability. Energy balance, dissipation, and storage are examples of a set of physical constraints on complex systems. The global energy balance has profound effects on climate dynamics and the flow of water resources. Energy accumulates in food resources, is transferred through various food chains, and is stored and dissipated in living organisms (including humans). Energy resources govern the growth of the human population, where the overabundance and undersupply of food resources determines the health or malnutrition of the population. Advances on accounting for such conservation principles will help establish connections with other areas, such as climate and human health, that impact or are impacted by food, water, and the environment.

Crosscutting nexus issues. Development of multiscale theory and models for the food-water-health-energy-security nexus is in a more primitive state than, for example, modeling climate systems or the energy grid. Until recently, the main food systems analysis tools involved statistical models based on linear techniques or detailed process models (*e.g.*, of soil fertility) designed to address specific questions but not designed to integrate into a larger system. The very fact that food and water are now viewed as vivid examples of interdependent complex systems in which the flow of natural resources is coupled to human decisions and behavior is a novel and transformative achievement of complex systems science. (Ingram 2011, Ingram & Zeeman 2015, Levin & Clark 2010, Wilson 2006). Addressing "nexus questions" requires a new framework to translate system function at various levels of complexity, organization, and heterogeneity into state variables and observables. Major crosscutting questions that will benefit from the development of common frameworks and methodologies include: 1) can we characterize the speed and magnitude of failure propagation in the global and regional FEW systems due to sudden shocks or chronic stresses? 2) What are signatures of approaches to critical transitions in the global food-water-health system? What governance systems best address decisions, interventions, adaptations, and mitigations at multiple scales? 3) How might we initiate, facilitate, value, inform and/or further advance cooperation in responses and sustainable governance of the commons? 4) How might we structure connections between FEW components to minimize vulnerability and confer system resilience? 5) Are we making necessary progress in regions where FEW system instability represents an urgent and growing threat?

A persistent challenge across these research areas concerns the availability of data of sufficient quality, which can inform monitoring, evaluating, and modeling of the relevant aspects of these systems. Data sources are numerous and diverse, including private owners, government agencies, and publicly funded research projects in various domains, and data rights can be complex. It is therefore essential that monitoring campaigns, data collection, and analysis are conducted with explicit knowledge of how the data will be used and, when used as part of a modeling effort, that the model helps drive data collection to ensure that the data will be of sufficient quality and appropriate type. In addition, in the spirit of generating rich datasets that are open and shared, monitoring, collection, and analysis efforts must be supported by a strategy for data and model curation that ensures the availability and continuity of datasets that retain all necessary information (metadata) for their ongoing use in new applications.

Core approaches of complex system modeling remain open problems—and opportunities—for gaining traction of key questions in FEW nexus research. Critical challenges include dimensionality reduction in multiscale models, model simplification through coarse-graining of dynamics, embedding of the system of interest within proper boundary conditions, identification of energy balance, dissipation, and storage, and decoupling of nonlinear feedbacks to drive systems based off observations.

Regime Change and Resilience

Many of the most urgent and compelling problems faced by science and society entail critical transitions in evolving, multicomponent systems under cumulative perturbations (see, *e.g.*, **Figure 6**). These systems and problems cross scale and disciplinary boundaries. They include cellular and physiological studies of transitions from healthy to diseased states (Rikkert *et al.* 2016, Boettiger & Hastings 2013); ecological transitions from productive, biodiverse scenarios to population collapse (Scheffer & Carpenter 2003); and transitions in glacial cycles on geologic timescales (Scheffer *et al.* 2009). The transitions we wish to describe may also involve a new state that is more desirable than the previous one (*e.g.*, transition to a carbon-free economy). Yet, our ability to understand and describe such systems—

let alone predict their behavior—is limited. An important challenge associated with the study of transitions in large-scale systems is that such systems are often unique (*e.g.*, there is only one Earth, and its evolution will follow only one out of many possible paths), which disallows us from relying on large N experiments.

Here we describe three key areas where work is needed to further develop experimental, theoretical, and modeling approaches for such systems: 1) designing effective experiments; 2) reducing dimensionality while maintaining fidelity to essential system features; and 3) using adaptive management to extract information about system behavior (learning from low N). One potentially useful framework for the latter is provided in March *et al.* 2003, where (while focusing on historical inference in organizations) the importance of independently considering the reliability and validity of a particular history is highlighted.

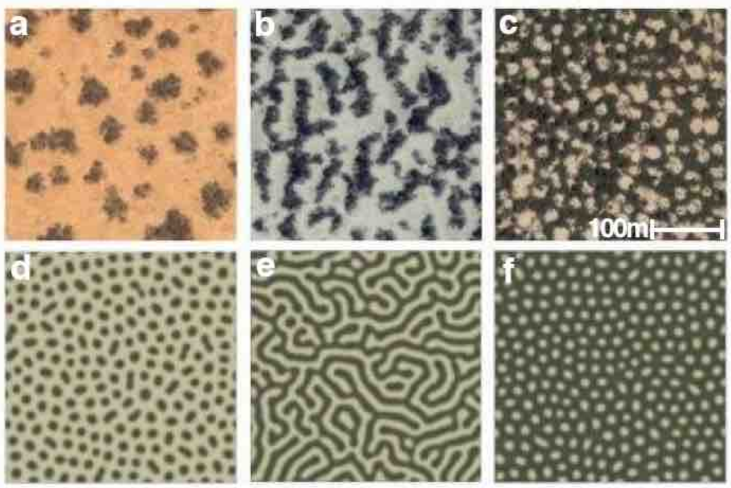

Figure 6

Observed (top) and predicted (bottom) vegetation patterns along a gradient of precipitation from arid to semi-arid (adapted from Gowda *et al*. 2014).

A fundamental question concerns how to predict the approach to a transition (or "tipping point") with sufficient warning time (Dai *et al.* 2012). While progress has been made on identifying markers or indicators for transitions (*e.g.*, oscillations), substantial gaps remain in our ability to assess how far away a particular system is from a transition (Lim & Epureanu 2011, D'Souza *et al.* 2015, Lade & Gross 2012). Once a transition occurs, additional work is needed to characterize the possible existence of hysteresis in the system, including whether and how return to a previous state is possible.

In building models and designing useful experiments, another fundamental question concerns how to distill the behavior of large systems to more manageable smaller systems (or how to use small systems in one field to describe large systems in other fields). Although there is a substantial body of literature on dimensional reduction, it is not yet known how to successfully capture the behavior of complex systems in general. This is especially true when there is no clear separation of time scales. Moreover, the presence of time-dependent interactions, non-conservative fields, interacting feedback mechanisms, and far-from-equilibrium conditions challenge our ability to theoretically describe regime changes. To capture the behavior of such complex systems, we need to extend methods and concepts of statistical physics (*e.g.*, phase transitions) and dynamical systems (*e.g.*, bifurcation theory).

Finally, given the existing uncertainties regarding system structure, system dynamics, and system response to perturbation, how can we effectively combine available information sources to manage systems on which our well-being depends? Often, the goal of management (*e.g.*, in ecosystems and societal systems) is to nudge the system towards more favorable paths. Even the process of identifying the right measurements to characterize these paths remains an open theoretical problem, which requires integrating expertise from data science, control theory, optimization, dynamical systems, and information theory.

Of particular interest to this area of study are biological and ecological systems, which contain multiple redundancies and structural principles that give rise to resilience (Adler *et al.* 2017). Also of interest is to consider the various classes of engineered systems whose designs are increasingly inspired by those of living systems. Current trends in adaptation and resilience are in fact shifting away from a paradigm of (over)engineering to avoid catastrophic failures to adopt instead a paradigm of engineering systems to fail gracefully (Nemeth *et al.* 2009).

DEVELOPMENTS SINCE THE 2008 NSF WORKSHOP

The previous NSF workshop on complex systems was held in 2008 and centered on the Foundations for Complex Systems Research in the Physical Sciences and Engineering (Guckenheimer & Ottino 2008). The 2008 workshop report and recommendation emphasized cross-cutting fundamental research on complex systems that transcended individual complex systems. The NSF made some modest efforts at implementing the recommendation, including one call for collaborative proposals—Building Engineered Complex Systems (BECS)—and a set of awards.

The most significant development since the publication of the 2008 report has been the considerable expansion of the scope of the field of complex systems. While that report was focused primarily on the intersection of mathematics and engineering and on a common foundation in the mathematical theory of dynamical systems, the current report is significantly broader and includes examples of complex systems from the physical, chemical, biological, and social sciences, in addition to engineering and computer science. This is a positive development, since it reflects the broad awareness in the scientific community that the traditional reductionist approach may need to be complemented by a more contemporary systems approach. However, it is less clear that there is a trend toward a science of complex systems, which was the assumption underlying the convening of the previous workshop.

Four questions were posed in the previous report. We assess briefly the research progress that has occurred since 2008 in addressing those questions.

1. *What are the best models for representing and analyzing the properties of complex systems?* Noticeable progress has been made in the formulation and analysis of data-driven models. Approaches such as "equations-free modeling" and "dynamic-mode decomposition" produce low-dimensional dynamical models from observational data. In addition, there have been significant efforts in the application of data assimilation techniques to models across many research areas in physical and life sciences systems. Examples include intracellular networks, systems and synthetic biology, biophysical modeling of neurons and functional networks, neuromorphic engineering, electrical and chemical engineering, hydrological models of streams and lakes, flows and transport of toxic products, identification of oil and gas reservoirs, and, of course, for decades, numerical weather prediction. In various areas, complex systems are still often modeled by first-principle approaches, but even in those areas, increasing effort has been geared toward the development of data-driven models. The validation of such models is a topic of current research.

2. *What is the relationship between the structure of a complex system and its dynamics?* The area of network science has expanded tremendously over the past decade, and there has been progress in understanding the role of network structure in shaping the dynamics of complex network systems. Network science has placed substantial emphasis on the role of the graph topology and the impact of structural properties such as degree distribution, clustering coefficient, and centrality and spectral

properties of the network. Nonetheless, progress has also been made beyond purely topological analysis. For example, in the study of networks of signal transduction and gene regulation, a number of network models with parameterized dynamics have been constructed and experimentally validated over the past decade; the connection of structure and function has been explicitly explored in such models, and computational tools to identify this connection have been developed. Some progress has been made on the interaction of the structure of a complex network and its dynamics in the important case in which not only the dynamics of individual nodes and/or links depend on the network structure but also the structure of the interaction network depends on the node and link dynamics.

3. *What are the consequences of evolution and adaptation in complex engineered systems?* This section of the 2008 report discussed the power grid as an archetype for an evolving engineered system. The changes in the grid have accelerated substantially, and there has been a qualitative increase in research on the effects of this evolution. More generally, the field of cyberphysical systems—including smart grids, the Internet of Things, and autonomous vehicles—has advanced as a discipline and provides many new examples of evolution and adaptation of complex and engineered systems. Progress has also been made outside engineered systems, particularly in social sciences, owing to the increased availability of high-quality temporal data (from mobile phones, social networking sites, and other sources). This has allowed researchers to empirically track evolution and adaptation in complex social systems and has enabled reliable model validation.

4. *How do we calibrate complex systems and predict their behavior?* Theoretical advances in data assimilation and uncertainty quantification have led to significant improvements in our ability to make weather forecasts that are valid for longer periods of time and have reliable probabilistic estimates associated with them. This has been facilitated by progress in using large-scale computation for model-based predictions and forecasting, including applications in climate modeling, as well as changes in the amount of data available and the ability to perform data analytics. But mathematical development has also been noticeable, as illustrated by progress in the characterization of tipping points in various systems. In particular, methods are currently being developed for the identification of imminent transitions and for managing of complex systems to avoid undesirable transitions.

Despite the major advances in theory, computation, and the use of data, progress in the context of the vision of the 2008 report has been modest and uneven. The rapid development of machine learning in computer science has seen some application to the study of complex systems, though many of the most advanced methods (*e.g.*, deep neural networks) have not yet progressed to the point where they provided structured representations that are amenable to mathematical analysis. The combination of models at various levels of description, large-scale data sets, and advanced computation (*e.g.*, to perform calibration, prediction, and analysis of complex systems) is still an area with many challenges and opportunities.

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CBS2, Array of Things (City of Chicago).
https://arrayofthings.github.io/

CBS3, Smart & Connected Communities: A vision for the 21st century.
https://www.nsf.gov/cise/scc/

CBS4, US Department of Transportation Smart City Challenge.
https://www.transportation.gov/smartcity

CBS5, NIST IoT-Enabled Smart City Framework.
https://pages.nist.gov/smartcitiesarchitecture/

CBS6, Cyber-Physical Systems Virtual Organization: Fostering collaboration among CPS professionals in academia, government, and industry.
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Iain Couzin – Max Planck Institute for Ornithology
Daniel Diermeier – University of Chicago
Ian Dobson – Iowa State University
Alan Hastings – University of California, Davis
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Cover Image

The cascade vulnerability map of a portion of the U.S. power grid network (adapted from Yang *et al.* 2017).