AI & Soc
DOI 10.1007/s00146-013-0527-2

ORIGINAL ARTICLE

The emergence of attractors under multi-level institutional designs: agent-based modeling of intergovernmental decision making for funding transportation projects

Asim Zia · Christopher Koliba

Received: 28 February 2013 / Accepted: 28 November 2013

Abstract Multi-level institutional designs with distributed power and authority arrangements among federal, state, regional, and local government agencies could lead to the emergence of differential patterns of socioeconomic and infrastructure development pathways in complex social–ecological systems. Both exogenous drivers and endogenous processes in social–ecological systems can lead to changes in the number of "basins of attraction," changes in the positions of the basins within the state space, and changes in the positions of the thresholds between basins. In an effort to advance the theory and practice of the governance of policy systems, this study addresses a narrower empirical question: how do intergovernmental institutional rules set by federal, state, and regional government agencies generate and sustain basins of attraction in funding infrastructure projects? A pattern-oriented, agent-based model (ABM) of an intergovernmental network has been developed to simulate real-world transportation policy implementation processes across the federal, the state of Vermont, regional, and local governments for prioritizing transportation projects. The ABM simulates baseline and alternative intergovernmental institutional rule structures and assesses their impacts on financial investment flows. The ABM was calibrated with data from multiple focus groups, individual interviews, and analysis of federal, state, and regional scale transportation projects and programs. The results from experimental simulations are presented to test system-wide effects of alternative multi-level institutional designs, in particular different power and authority arrangements between state and regional governments, on the emergence of roadway project prioritization patterns and funding allocations across regions and towns.

Keywords Institutional design · Intergovernmental relations · Infrastructure development · Agent-based modeling · Complex systems · Basins of attraction · Network governance

A. Zia (✉) · C. Koliba
Department of Community Development and Applied Economics, University of Vermont, 146 University Place, Burlington, VT 05405, USA
e-mail: Asim.Zia@uvm.edu

C. Koliba
e-mail: Christopher.Koliba@uvm.edu

A. Zia
Department of Computer Science, University of Vermont, 146 University Place, Burlington, VT 05405, USA

1 Introduction

Multi-level institutional designs that investigate the distribution of power and authority arrangements among federal, state, regional, and local government agencies are at the core of many public policy theories and frameworks, such as the Institutional Analysis and Development (IAD) framework (Ostrom 2005), Multiple Streams Framework (MSF) (Kingdon 1984), Policy Subsystem and Punctuated Equilibrium framework (Baumgartner and Jones 2002), Advocacy Coalition Framework (ACF) (Sabatier and Jenkins-Smith 1993), Policy Network framework (Marsh and Rhodes 1992; Rhodes 1997), and Governance Network framework (Koliba et al. 2010). The IAD framework, for example, draws on institutionalism and neo-institutionalism theories, game theory, transaction cost theory, and common resource pool theory to create a description of multi-institutional systems that explains the crafting of public policy as an institutional design problem within and

Published online: 11 December 2013

across complex "action arenas." Ostrom (2005) emphasizes the roles that institutional rules play in structuring governance arrangements. Many of these frameworks impose homogenous assumptions about human decision-making behaviors, such as expected utility maximizing behaviors in IAD, while others assume more unpredictable, chaotic decision-making behavior, such as those found in the MSF. Another difference that arises across these frameworks concerns the balance between individual behavior and institutional norms and rules. While ACF focuses on the role that common belief networks play in powerful advocacy coalitions, IAD focuses more on the role that operational, collective choice, and constitutional rules play in shaping multi-institutional arrangements. In contrast, the network-based frameworks (e.g., Rhodes 1997; Kickert et al. 1997; Milward and Provan 1998; Agranoff and McGuire 2003; Koliba et al. 2010) account for the multi-scalar dimensions of multi-level policy networks, meaning they account for the fact that these networks are populated by individual people, groups, organizations, and networks of organizations. The ties between these agents are informed by the types of resources that flow between them (Rhodes 1997), the kinds of managerial strategies employed (Agranoff and McGuire 2003), and the mixed structures of administrative authority (Koliba et al. 2010) that persist within and across them.

In this paper, we aim to advance modeling of multi-level institutional mechanisms that can ultimately be used to improve both the real-world multi-level institutional arrangements (e.g., intergovernmental relations) and evidence-based public policy decision-making processes. Within this broader set of goals, we focus on modeling alternative multi-level institutional designs that can use the virtual power of artificial intelligence and computer simulation modeling to enable a better understanding of power and authority arrangements among federal, state, regional, and local government agencies. Differential power configurations among intergovernmental agencies typically result in vastly different social, economic, political, and ecological outcomes over various spatial and temporal scales. Traditional policy research methods (e.g., case studies, regression models, system dynamic models) have produced useful insight into the role of multi-level institutional designs on complex public policy outcomes. Case studies, interviews, and surveys have been used for analyzing the functions, capacities, and dynamics of intergovernmental decision-making processes deployed by so-called governance networks (Klijn 1996; Jones et al. 1997; Kickert et al. 1997; O'Toole 1997; Ingram et al. 2005; Koliba et al. 2010; Zia and Koliba 2011). Markovian process models provide another strategy for modeling the transitions in the policy outcomes induced by multi-level institutional mechanisms over multiple time periods. While these approaches are useful in analyzing multi-level institutional designs, we use agent-based modeling as a tool to model policy systems in a "bottom-up" methodological and theoretical architecture. Through the use of agent-based modeling, we can examine alternative intergovernmental institutional designs and their effects on the allocation of resources across regions and towns. One advantage of ABMs over other methodologies is the explicit representation of agents' behaviors via their decision rules. Furthermore, agents within an ABM interact with each other as well as their environments. The ability of ABMs to model "institutional rules" as "decision rules" in empirically based models of social–ecological systems has opened up new vistas of interdisciplinary research between computer and policy sciences (e.g., see Janssen and Ostrom 2006). Most importantly, from a mathematical standpoint, ABMs enable the modeling of an n-dimensional state space of complex systems, which is further described below.

In this study, we postulate that multi-level institutional designs with distributed (versus non-distributed) power and authority arrangements among federal, state, regional, and local government agencies lead to the emergence of differential patterns of socioeconomic and infrastructure development pathways. We address the question: *how do intergovernmental institutional rules set by federal, state and regional government agencies generate and sustain "basins of attraction" in funding transportation projects?* Walker et al. (2004) explain that both exogenous drivers and endogenous processes in policy systems can create dynamic changes in the number of basins of attraction, changes in the positions of the basins within the state space, and changes in the positions of the thresholds between basins. We define a system's "state space" or "phase space" as the state variables that constitute the system under consideration. If, for example, a transportation system is defined by the amount of energy consumed per vehicle mile and vehicle miles traveled, then the state space is the two-dimensional space of all possible combinations of these two state variables. More complex systems could have an n-dimensional state space. A system's state at any time is defined by its current values in the n-dimensional state space. Broadly speaking, a "basin of attraction" is an area in state space in which the system tends to remain over time. Further, as expostulated by Walker et al. (2004), "For [social-ecological] systems that tend toward an equilibrium, the equilibrium state is defined as an 'attractor', and the basin of attraction constitutes all initial conditions that will tend toward that equilibrium state…the various basins that a system may occupy, and the boundaries that separate them, are known as a 'stability landscape.'"

The basins of attraction are also linked with alternate stable states and the resilience of systems under consideration (e.g., Scheffer et al. 2001). The conditions of dynamic systems, such as integrated transport land use and environmental systems, are never constant. Stochastic events, such as economic downturn (e.g., housing market crash of 2008), economic upturn (e.g., IT boom of the 1990s), political agendas, and climatic and weather extremes (e.g., more or less intense floods and droughts), can cause fluctuations in the basins of attraction of a state space, which in turn can trigger the systems to move from one stable state to another stable state. In "fragile" systems, small endogenous changes or exogenous shocks can induce changes in the system (stable) states. In contrast, as argued by Holling (1973), more resilient systems remain in the same stable state despite internal endogenous changes or exogenous shocks. The size of the basins of attraction in an n-dimensional state space is thus linked with the fragility or resiliency of dynamic systems (Walker et al. 2004).

In earlier work, solid-state physicists applied basins of attraction to study the dynamics of "spin-glasses," theoretical magnetic materials in which the interdependencies between the orientations of dipoles in a lattice create a complex dynamic system. Other applications exist in evolutionary biology, computer sciences, game theory, ecology, and economics. In evolutionary biology, for example, Kauffman et al. (2004) present methods for calculating the number of attractors in Boolean networks. In computer sciences, Wuensche (1999) describes the emergence of attractor basins in cellular automata-based computational models. In game theory, Page and Wooders (2009: 462) address the question, "given preferences of individuals and rules governing network formation, what networks are likely to emerge and persist?" Using an induced abstract game as their basic analytic tool, they demonstrate that for any set of primitives, the following results hold: first, "The feasible set of networks contains a unique, finite, disjoint collection of non-empty subsets each constituting a *strategic basin of attraction*. Given preferences and the rules governing network formation, these basins of attraction are the absorbing sets of the process of network formation modeled via the game" (2009: 463). Second, "A stable set (in the sense of Von Neumann Morgenstern) with respect to path dominance consists of one network from each basin of attraction" (Page and Wooders 2009: 463).

In ecology, Vandermeer et al. (2004) analyzed a data set accumulated over a 12-year period subsequent to the catastrophic disturbance of a Nicaraguan rain forest by a hurricane. They analyzed the data to determine whether the observed trajectories corresponded to expectations from an equilibrium or non-equilibrium model of community structure. The equilibrium case, implying a single basin of attraction, suggests that trajectories should become ever more similar over time. The non-equilibrium case, implying multiple basins of attraction, suggests the opposite. Vandermeer et al. (2004) demonstrated that the data from this particular forest strongly supported the multiple basins hypothesis. Earlier, the multiple attractors' hypothesis was also confirmed through an experimental study by Henson et al. (2002) to account for insect population growth dynamics. Further, Scheffer et al. (2001) reviewed the linkage between basins of attraction and alternate stable states in ecological systems including lakes, coral reefs, woodlands, deserts, and oceans.

In economics, based on the earlier work of Neary (1978), Krugman (1994: 412–413) asked the question, "How complex is the economic landscape…that represents the dynamics of resource allocation across activities and locations[?]" Krugman (1994: 412–413) analyzed this question in the context of foundational questions in international trade, such as the "relative importance of increasing returns versus comparative advantage in causing specialization and trade, the prevalence of multiple equilibriums, [and] the extent of path dependence." In this context, he characterized complex landscapes as being complex because they contain many basins of attraction, noting "which equilibrium the economy ends up in depends on which basin of attraction it started in." Krugman (1994) uses an economic-geographical theoretical context to explain how countries starting in different basins of attraction in a two-dimensional state space of resource allocation and labor location can eventually have differential market shares in international trade.

In this study, we extend Krugman's (1994) theoretical work on basins of attraction in complex economic and policy systems. We apply it to understand the effects of intergovernmental decision-making processes and rule structures on the differential allocation of transportation funds across regions and towns. Attractors on a landscape can be represented by the amenities that draw human populations to congregate in clusters of different sizes, ranging from small towns to large metropolitan areas. Through complex feedback loops between societies and governments, some of these towns and cities continue to attract substantial government funds over time to sustain their transportation, energy, and housing infrastructures. Batty (2007) uses bottom-up cellular automata and agent-based modeling to demonstrate the "fractal" emergence of rural to urban land use patterns over time through the interplay of complex dynamics. Within this broader scope of land use, transportation, and economic interactions, we focus our study on investigating the effects of intergovernmental institutional rules on generating basins of funding attraction across regions and towns/cities.

In the specific context of US transportation policy, we use an agent-based modeling approach to explore baseline and alternative intergovernmental institutional rule structures and how they attract the increasingly scarce, even "sequestered," governmental transportation funds for various regions and towns/cities. Since 1991, US federal transportation laws have emphasized two primary policy goals. First, the US Congress is interested in developing an intermodal transportation system where citizens can safely use multiple forms of private and public transit: "It is the policy of the United States to develop a National Intermodal Transportation System that is economically efficient and environmentally sound, provides the foundation for the Nation to compete in the global economy, and will move people and goods in an energy efficient manner" (Intermodal Surface Transportation Efficiency Act [ISTEA] of 1991). Second, to qualify for federal transportation funds, projects need to be carried out with the cooperation of state and local governments: the planning process needs to be *continuing, comprehensive, and cooperative*. This principle of *"3C's"* has been in place since the Federal Aid Highway Act of 1962. The planning system intertwines municipalities, state transportation agencies, and the US Department of Transportation (USDOT). It is not clear whether and how the principle of "3C's" is implemented in practice. The circular framework requires a hierarchal planning system supplemented by federal funding for infrastructure development. Decisions concerning which transportation projects to scope, plan, and build are made by a complex latticework of intergovernmental networks of organizations ranging from the Federal Congress to USDOT, state DOTs, Municipal Planning Organizations (MPOs), Regional Planning Commissions (RPCs), and municipal governments.

To understand the institutional rules of intergovernmental planning systems in the USA, we present a pattern-oriented, agent-based model (ABM). Pattern-oriented models are described by Grimm et al. (2005) as "bottom-up" models that emphasize the applicability of models to real problem solving. Grimm et al. (2005: 987) describe pattern-oriented models this way:

In [this approach to modeling], we explicitly follow the basic research program of science: the explanation of observed patterns. Patterns are defining characteristics of a system and often, therefore, indicators of essential underlying processes and structures. Patterns contain information on the internal organization of a system, but in a "coded" form. The purpose of [pattern-oriented models] is to "decode" this information…A key idea [in these models] is to use multiple patterns observed in real systems to guide design of model structure. Using observed patterns for model design directly ties the model's structure to the internal organization of the real system. We do so by asking: What observed patterns seem to characterize the system and its dynamics, and what variables and processes must be in the model so that these patterns could, in principle, emerge?"

This ABM is calibrated to simulate the allocation patterns of federal funds for roadway projects in the state of Vermont under baseline intergovernmental institutional rule structures. The ABM simulates complex, inter-twined parallel decision making by ten regional governments and six hundred towns/cities in the state of Vermont. Our intention is to expand this ABM to study the diffusion of transportation funds across the states and eventually across different countries.

In Sect. 2, we present research methods that were used to elicit roadway project prioritization processes and decision heuristics of multi-level agents in the simulation model. We also describe the federal and state transport policies that govern this network's dynamic operations in the specific context of intergovernmental project prioritization. In particular, we present the observed patterns of funding allocations for the study region of the state of Vermont. In Sect. 3, we present the fundamental structure of the stochastic, multi-level agent-based model. Sect. 4 presents findings from experimental simulations of alternative multi-level institutional designs. Section 5 presents conclusions and discusses the limitations of the current simulation model and possible next steps to further improve and generalize it.

2 Research methods and the observed patterns of roadway project prioritization and funding allocations in the state of Vermont

To surface the patterns of interaction and resource flows occurring in this network, we conducted a series of in-depth interviews and two focus groups with multiple stakeholders in the fall of 2010 to understand the legal and policy context of intergovernmental transportation policy implementation networks, both generally and specifically in Vermont. The stakeholders included local government officials, MPO staff and board members, staff of other RPCs in Vermont, state agency of transportation (VTrans) officials, Federal Highway Association (FHWA) representatives, USDOT officials, federal and state senate office representatives, and local NGOs. The focus groups and interviews were recorded, transcribed, coded, and analyzed for major and minor themes. To understand how projects were prioritized, we examined various source documents related to project funding, including major pieces of federal legislation (such as the Intermodal Surface Transportation Efficiency Act [ISTEA], the Transportation Equity Act for the 21st Century [TEA-21], and the Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users [SAFETEA-LU]), planning and policy documents developed by VTrans and the MPO, meeting minutes, and project databases. We obtained the project prioritization data for all transportation projects in Vermont between 1998 and 2011 and analyzed it using statistical analysis. The data included the classes of project, the scoring data from VTrans and the MPO, the location of the project, and the amount of funds that went into the roadway projects.

In Vermont, VTrans is delegated the tasks assigned to States by the federal government. Also, the Chittenden County MPO (CCMPO), the only Vermont MPO (which recently merged with the Chittenden Country RPC), and ten other RPCs collaborate with the State to incorporate the regional transportation planning needs. The planning process and financial structure developed in federal legislation (ISTEA, TEA-21, and SAFETEA-LU) create both a complementary and competitive partnership between the RPCs and VTrans. We consider the competitive nature of the relationship between the state and regional agencies to be an essential feature to model: it directly affects the flow of transportation investments to different regions and local towns.

In the hierarchically nested system of US transportation policy, USDOT apportions money to each state in accordance with the approved Statewide Transportation Improvement Plan (STIP). The FHWA authorizes the apportionment and certifies to the state that funding is available for each program. Then, depending on state regulations, the state completes federally funded projects by either distributing money to a municipality or completing the project itself. From the focus groups and interviews with MPO and RPC officials, we elicited the current institutional rule structure, i.e., criteria for project prioritization, that are followed by the state and MPOs/RPCs in prioritizing transportation projects in Vermont. Table 1 shows these rules for six project classes: roadways, paving, bridges, bike/pedestrian, traffic operations, and park and ride. These rules were instituted in 2006. Prior to 2006, transportation projects were prioritized through a more politically driven process of negotiation among the regional and state agencies. The introduction of these rules in 2006 was part of a broader "depoliticization" process, as stated by many focus group participants. Simultaneously, an asset management system was developed by VTrans to assign expected value scores to transportation projects under the specific criteria shown in Table 1. For example, for the roadway projects, VTrans evaluates each project on four criteria: highway system is assigned 40 % weight, cost per vehicle mile is assigned 20 % weight, regional priority is assigned 20 % weight, and project momentum is assigned 20 % weight. Both highway system and cost per vehicle mile are estimated from the VTrans asset management system. The CCMPO assigns equal weight (16.6 %) to six criteria in ranking the projects: economic vitality; safety and security; accessibility, mobility, and connectivity; environment, energy, and quality of life; preservation of existing system; and efficient system management. Remaining RPCs rank the projects on similar decision criteria but do not explicitly assign equal weights to all the decision criteria.

The observed patterns from the project prioritization data elicited from 1999 to 2012 STIPs reveal "basins of attraction" in terms of allocation of funding across the MPO/RPCs in the state of Vermont, as shown in Fig. 1. Noticeably, some RPCs/MPOs tend to receive more transportation funding for their projects than others over time. In particular, as shown in Fig. 1, Bennington County RPC, Chittenden County RPC, and Northwest RPC appear to consistently attract funding for their transportation projects during the observed 12-year time period. The dip in total monetary allocation for roadway projects in 2006, as shown in Fig. 1, is observed due to the change in the project scoring system. Further, the relatively higher peak of funding allocation in 2010–2011 occurred due to stimulus funding under the American Reinvestment and Recovery Act (ARRA), which is not a long-term transportation program.

Our intention here, however, is not to model "black swan" events, but to model operational intergovernmental decision processes, institutional rules, and the resultant funding patterns that emerge across the regional planning commissions and local towns. Taleb (2010) defines "black swan" events as events or occurrences that deviate beyond what is normally expected of a situation and that are extremely difficult to predict based upon historical data. The 2008 housing market crash and subsequent introduction of ARRA stimulus funding present an example of such a black swan event. Instead of modeling such events, we focus on modeling multi-level institutional rules, as described in Sect. 3.

3 The structure of the agent-based simulation model

The capacity of computer models of complex governance networks to lead to accurate forecasting and prediction of particular policy outcomes is predicated on a "deep uncertainty" that characterizes our current state of understanding of complex social systems. To cope with the inherent complexity and uncertainty of governance networks, we undertake a variation in "pattern-oriented" modeling (Grimm et al. 2005). In this study, a pattern-oriented, agent-based model (ABM) is designed to simulate the intergovernmental decision-making process of the transportation governance network, as shown in Fig. 2. The ABM is designed as a stochastic multi-level model that generates "emergent" patterns assessed through the mining of state agency records in the STIP database. Structurally in the ABM, shown in Fig. 2, a state agent (i.e., VTrans) contains ten nested RPCs and six hundred local towns that are nested within RPCs.

Table 1 Decision-making criteria for transport project prioritization at state and regional levels

Project class	State level		Regional level			
	SDOT criteria	Wt.	Chittenden county		Other counties	
			MPO criteria (applied across all classes)	Wt.	RPC criteria since 2006	Wt.
Roadway	Highway system[a]	.40			The impact or the project on congestion and mobility conditions in the region	
	Cost per vehicle mile[a]	.20				
	Regional priority	.20				
	Project momentum	.20				
Paving	Pavement condition index[a]	.20				
	Benefit/cost[a]	.60				
	Regional priority	.20	Economic vitality		The availability, accessibility, and routes	
Bridges	Bridge condition[a]	.30				
	Remaining life[a]	.10	Safety and security			
	Functionality[a]	.05				
	Load capacity and use	.15	Accessibility, mobility and connectivity			
	Waterway adequacy and scour suspect.	.10			The functional importance of the highway or bridge as a link in the local, regional, or state economy	
	Project momentum	.05	Environment, energy and quality of life			
	Regional input and priority	.15		.166@		Ranked by priority from 1 (being the highest) to 5 (being the lowest)
	Asset-benefit cost factor	.10				
Bike/pedestrian	Land use density	.20	Preservation of existing system			
	Connectivity to larger bike/pedestrian network	.10				
	Multi-modal access	.05				
	Designated downtown/village center	.05	Efficient system management		The functional importance of the facility in the social and cultural life of the surrounding communities	
	Project cost	.20				
	Regional priority	.20				
	Project momentum	.20				
Traffic operations	Intersection capacity[a]	.40				
	Accident rate	.20				
	Cost per intersection volume[a]	.20				
	Regional input and priority	.20			Conformance to the local and regional plans	
	Project momentum	.10				

Table 1 continued

Project class	State level		Regional level			
	SDOT criteria	Wt.	Chittenden county		Other counties	
			MPO criteria (applied across all classes)	Wt.	RPC criteria since 2006	Wt.
Park and ride	Total highway and location[a]	.40				
	Cost/parking space	.20				
	Regional input priority	.20			Local support for the project	
	Project momentum	.20				

[a] Asset management system

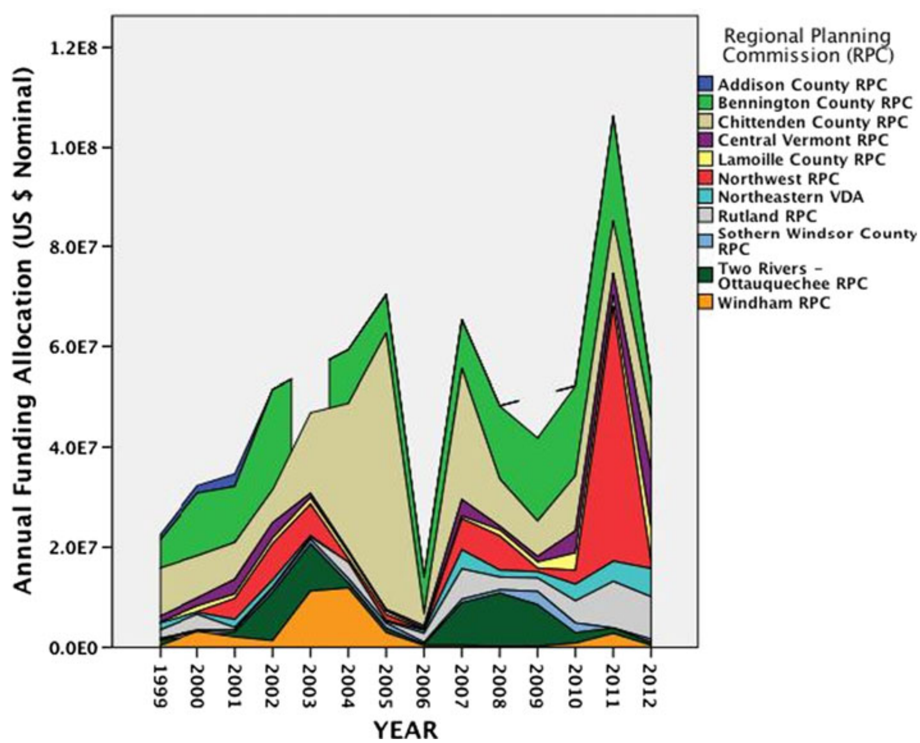


Fig. 1 Observed patterns of roadway funding allocations among MPOs/RPCs in Vermont, 1999–2012 (US$, nominal)

Further, transportation projects are modeled as an agent class at the bottom-most layer of this hierarchy. RPCs, local towns, and transportation projects are thus modeled as multi-level nested agents in this ABM contained within a state agent.

USDOT is modeled as a "dummy" parameter in the current model, due primarily to three reasons: First, our focus in this study is on understanding the intergovernmental tensions that arise between state agencies, RPCs, and local towns. Second, many participants in the focus groups literally described federal agencies as "dummies" that allocate funding for the projects prioritized by VTrans. Third, we are not focused on understanding *inter*-state funding allocation issues from a federal agency standpoint, rather our focus is on *intra*-state funding allocation issues that arise due to the intergovernmental decision-making processes. The federal agent is thus not explicitly modeled as an agent in the current ABM. Rather, the federal agent is represented through a parameter that sets the available funding in a given year. The ABM user can define and vary this parameter. The default value is set to 10 %, which is closest to the observed value for the VTrans agent from the project prioritization data observed between 1998 and 2012.

Figure 2 shows the attributes, behaviors, and the simulated environment of each of the four agent classes in the ABM. The state agent ranks projects each time period using the state agency decision-making criteria shown in Table 1 for only roadway projects. The top-ranked projects are periodically chosen by the state agent depending upon the funding level made available by the federal "dummy"

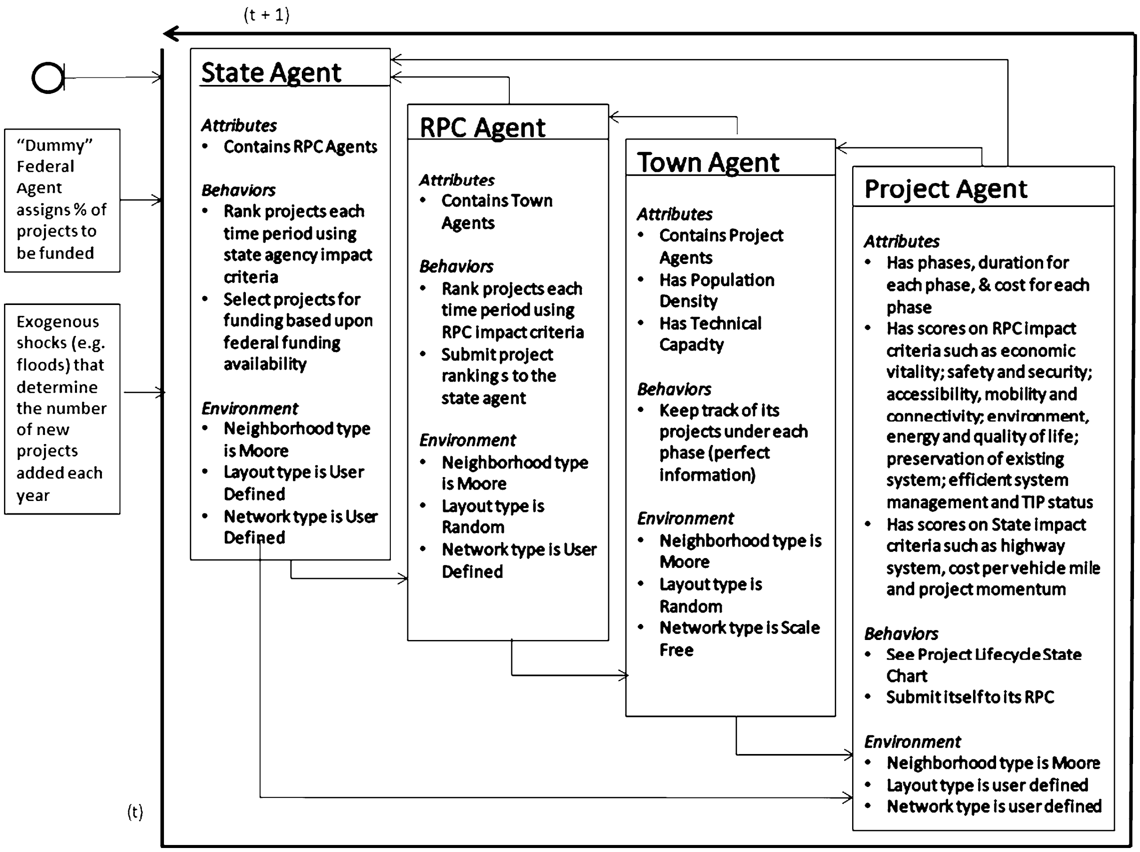


Fig. 2 The internal structure of the stochastic ABM showing attributes, behaviors, and the environment of four agent classes—state agency, regional planning commissions, local towns, and projects

agent. The state agent ranking is contingent upon the ranking of the projects performed by the RPCs in a given period. The RPC ranking of projects is partially determined by the complexity of the project phases as well as "backlogged" projects in any given time period. The project agent class, which is the innermost layer of this nested model, tries to represent the observed complexity of the backlogged projects in the system, described in further detail below after the description of the model parameters.

There are 27 input parameters in the model, shown in Table 2, that govern the flow of communication among the four agent classes in the ABM. The majority of the input parameters in the model have either uniform or triangular probability distributions, which means that the ABM is stochastic at its base and each model run is a unique realization chosen from the random probability distributions. The probability distributions for the parameters shown in Table 2 were estimated from the observed roadway project prioritization data. Experimental simulations of the intergovernmental decision-making process could be run by varying the probability distributions of these input parameters, as explained in the findings section below.

Figure 3 below shows the "state chart" for the agent class of transportation roadway projects. During the 2010 focus groups, one of the experienced participants described the VTrans decision heuristic for funding transportation projects as a "funneling approach" that is essentially represented for the project lifecycle of the agent class of projects in the ABM shown in Fig. 3. Every year, in practice, a large number of transportation infrastructure problems are identified by different agents in the governance network. In the ABM, we represent this as an exogenous parameter that determines the number of new projects added each year. This parameter enables us to model future exogenous shocks to the system that might lead to a relatively higher number of new projects periodically added to the system. VTrans keeps an updated list of these new projects and selects a subsample for undertaking feasibility studies (project engineering phase in Fig. 3). While in practice there are three phases of a transportation project—project engineering, right of way (ROW), and construction—we model this in the ABM in six states to capture the "waiting" time that leads to a chronic backlog of projects that are typically not funded due to the "funneling" of scarce federal and state funds when projects advance from phase to phase. The state "wait for fund of phase 1" shown in Fig. 3 thus represents the limbo in which the projects wait even before their

Table 2 Stochastic parameters and their default probability distributions used for calibrating the ABM to the Vermont context

Agent level	Parameter	Default value
Project		
1.	Project ID	Unique Project Identifier
2.	Duration of the construction phase (years)	Uniform (1, 5)
3.	Duration of right of way phase (years)	Uniform (1, 5)
4.	Duration of project engineering phase (years)	Uniform (1, 5)
5.	Cost of project engineering phase (dollars)	Uniform (100,000, 500,000)
6.	Cost of construction phase (dollars)	Uniform (1,000,000, 4,000,000)
7.	Cost of right of way phase (dollars)	Uniform (100,000, 400,000)
8.	RPC criterion of economic vitality (scale 1–10)	Triangular (7, 9, 10)
9.	RPC criterion of safety and security (scale 1–10)	Triangular (6, 8, 10)
10.	RPC criterion of accessibility, mobility, and connectivity (scale 1–10)	Triangular (6, 8, 10)
11.	RPC criterion of environment, energy, and quality of life(scale 1–10)	Triangular (3, 6, 9)
12.	RPC criterion of preservation of existing system (scale 1–10)	Triangular (2, 5, 8)
13.	RPC criterion of efficient system management (scale 1–10)	Triangular (5, 7, 9)
14.	RPC criterion of TIP Status (scale 1–10)	Triangular (3, 7, 10)
15.	V-TRANS criterion of highway system (scale 1–100)	Triangular (25, 50, 75)
16.	V-TRANS criterion of cost per vehicle mile (scale 1–100)	Triangular (25, 55, 85)
17.	V-TRANS criterion of project momentum (scale 1–100)	Triangular (5, 35, 65)
Town		
18.	Town ID	Unique Town Identifier
Regional planning commission (RC)		
19.	Regional commission ID	Unique Regional Commission Identifier
20.	Town distribution in RPC	Triangular (30, 60, 80)
State agency (SA)		
21.	Percentage of projects to be funded each year	0.1 (10 %)
22.	RPC distribution in the state	10
23.	Weight on regional priority	0.2
24.	Weight on highway system	0.4
25.	Weight on cost per vehicle mile	0.2
26.	Weight on project momentum	0.2
27.	New projects added each year	30

feasibility studies (in the project engineering state) are conducted. The decision nodes between waiting states and the three phases shown in Fig. 3 are modeled in the ABM as a classical project queue process: if a project is not funded in a given period, it is re-submitted in the next period, while the funded projects move on to the next phase, starting with project engineering, then moving to ROW and finally construction.

If a roadway project is prioritized in any of the three project phases, it is implemented in the model time according to stochastic project duration parameters for each phase as shown in Table 2. In addition, Table 2 shows the stochastic cost parameters for each of the three phases that are estimated from the STIP database. Structurally, the project class state chart shown in Fig. 3 thus captures the delays and the formation of project queues that are empirically observed in the VTrans STIP databases. The delays and queues across projects can be manipulated by varying the "duration" parameters in Table 2 under the project class. The state chart of the project agent class drives the dynamics of decision making shown in the overall ABM structure of Fig. 2.

The six hundred town agents in the ABM contain the environment of the projects and keep track of the transportation projects during each of their six states described above. The ten RPC agents keep track of their town agents, as well as rank the transportation projects that are submitted to them every year based upon their multiple criteria expected value functions (shown in Table 1). The parameters for the seven RPC criteria are derived from the observed probability distributions derived from CCMPO data. The RPC agents rank the roadway projects and send them to the state agent. Under the baseline scenario (Scenario 1), the state agent assigns 20 % weight to the regional priority. So a project that is ranked number 1 by an RPC is assigned 20 points by the state agent, a project ranked number 2 is assigned 18 points, and so on until a project that is assigned a rank of 10 or lower is given 0 points by the state agent. Further, the state agent calculates its expected value for each submitted project according to its default criteria (40 % highway system, 20 % cost per vehicle mile, and 20 % to the project momentum) and ranks the projects by assigning rank number 1 to the project with the highest expected value, 2 to the next highest and so forth. The VTrans agent calculates

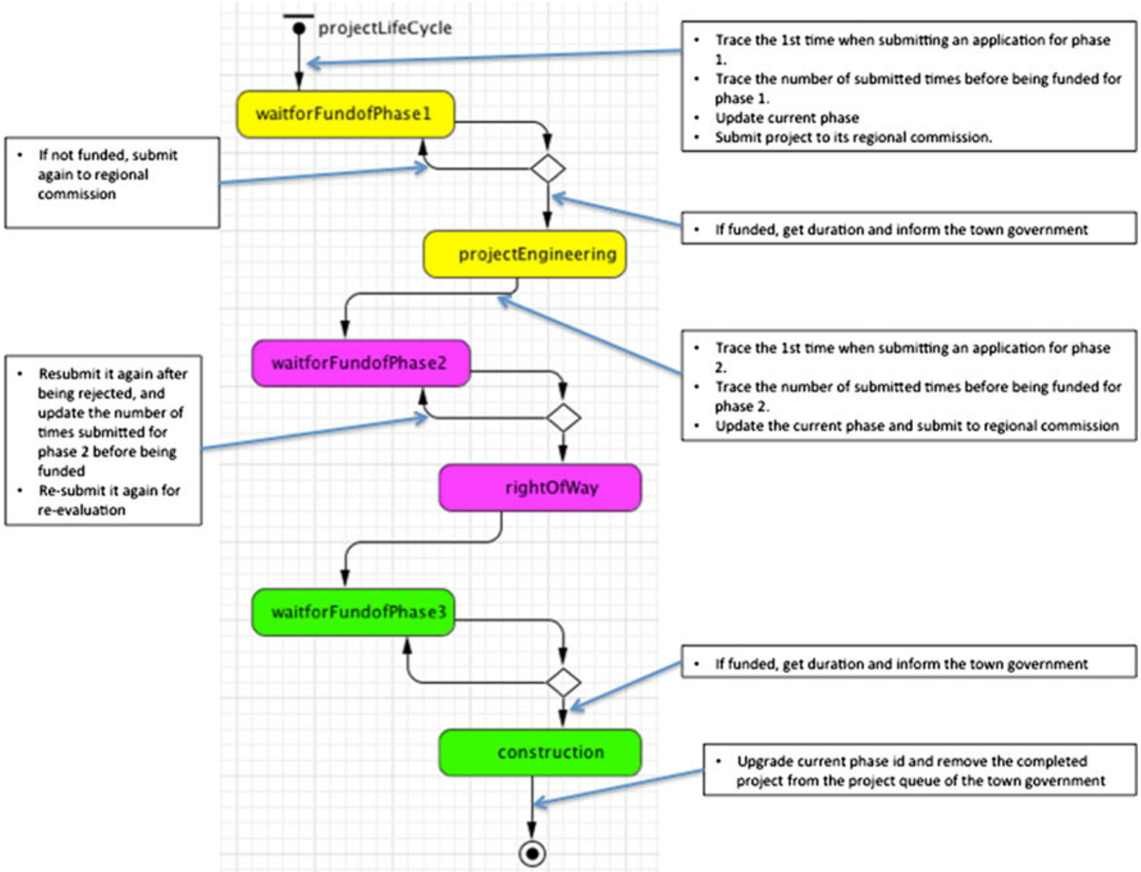


Fig. 3 Project life cycle state chart for the agent class of the projects (pseudo-code is shown in the boxes for the key transitions between the six life cycle states)

the total cost of the ranked projects and selects top-ranked projects for which funding is available in a given year. The rest of the projects are rejected for that cycle. The rejected projects are sent back to RPCs and local towns for evaluation in the next time period. New projects are added (through a user-defined parameter) every year that are evaluated along with the projects that were rejected in the previous cycle. Table 3 shows the pseudo-code for the JAVA function that implements this project ranking process in the ABM.

The ABM calculates the annualized flow of financial resources from the state government to regional and town jurisdictions. The flow of resources is contingent upon the project prioritization undertaken by the intergovernmental network of regional and state agents. Approval of projects for different regions on annualized basis and their associated costs were used to calibrate the computer simulation model against the observed data for Vermont. The findings from the experimental simulations presented in this paper, however, are generated from the model that is calibrated to reflect the institutional design structure of intergovernmental decision making in the state of Vermont. The users (e.g., policy makers, managers, and other stakeholders) can run baseline and alternative institutional design scenarios by defining the parameters for different scenario runs.

4 Findings from experimental simulations of alternative institutional designs

First, we present experimental simulations for six scenario runs for the parametric values as shown in Table 4 below. When used as a decision support system, this ABM can generate and run scenarios for stakeholder-defined parametric values. We chose the following six scenarios to represent major stakeholder values and concerns that were voiced in the focus groups. Scenario 1 (S1) shows a baseline scenario, whereby regional agents' rankings on transport projects are only given 20 % points, while the weight on highway system, cost per vehicle mile, and project momentum is defined at 40, 20, and 20 %, respectively. This baseline scenario assumes that 30 new roadway projects are added statewide every year and that federal government only makes funding available for projects ranked in the top 10 %. All the other input parameters shown in Table 2 are retained on their default values for all six scenario runs. In Scenario 2 (S2), an alternative intergovernmental institutional design scenario, all the parametric values of the baseline scenario are retained, except we increase the weight on regional commission priority from 20 to 50 % and reduce the weight on VTrans asset system management generated highway criterion from 40 to 10 %. In other words, *the baseline Scenario 1 gives relatively more weight to state level policy and planning considerations and less weight to regional-level considerations, while the alternative Scenario 2 gives relatively more weight to regional-level planning considerations than state level.* Scenario 2 is thus called the "regionalization" scenario. In Scenario 3 (S3), all the values of the baseline

Table 3 Pseudo-code for the JAVA algorithmic function describing the ranking of the projects by the state agent in each annual cycle

1. Request regional commission agent to rank the projects in its jurisdiction and submit its final rankings to a "Regional Priority" database
2. Calculate final ranking score based on the multi-criteria decision rule for roadway projects that includes regional priority, project momentum, highway system, and cost per vehicle mile
3. Update final ranking score for each roadway project
4. Sort the projects from the highest to the lowest final ranking score
5. Acquire total amount of funding available from the federal agent
6. Select the top-ranked projects for funding conditional upon total funding made available by the federal agent
7. Update the state chart of the project agent based upon the following decision rule:

(i) if a project is funded, it moves to the next stage of project cycle (as shown in Fig. 3) in accordance with the stochastically generated duration time for each stage of the project cycle

(ii) if a project is not funded, it is rejected by the state agent and sent back to local towns and regional commissions for submission in the next funding cycle

8. Move to the next annual cycle

scenario are retained except that the weight on cost per vehicle mile is increased from 20 to 50 %, while the weight on highway system is reduced from 40 to 10 %. Scenario 3 is thus called the "cost-effective" scenario, a scenario in which the cost-effective projects are prioritized in the system. Scenario 4 (S4) is similar to the baseline scenario except the percentage of projects to be funded each year is tripled from 10 to 30 %, hence its name, the "funding flux" scenario. Scenario 5 (S5) represents a "sequestration" scenario, whereby the federal funding parameter is reduced from the 10 % default value to 5 %, while remaining parameters are similar to baseline scenario. Finally, Scenario 6 (S6) represents a so-called sequestration and shock scenario, which is similar to the sequestration scenario (S5) except that the number of new projects added due to exogenous shocks (e.g., climate change induced floods) is increased from 30 to 40 new projects each year in the model simulation horizon of 50 time periods. While the ABM can be potentially used to run the experimental simulations to reflect many other desirable multi-level institutional rule structures, here we focus on Scenarios 2–6 as illustrative examples of alternative intergovernmental institutional rule structures. All the results reported below in Figs. 4, 5, 6, 7 and 8 are averages of 1,000 realizations for each of the six scenarios. Further, all simulations are run on a fixed seed to enable reproducibility of the results reported here. Since the ABM is initialized with random parameters as shown in Table 2, 1,000 model runs for each scenario provide a robust set of findings.

Figure 4a shows the emergent patterns of funding allocation (US $ nominal) over a period of 50 years for Scenarios 1, 2, and 3. Broadly speaking, for the baseline scenario S1, the ABM reproduces the observed "basins of attraction" in terms of annualized funding allocations by modeling the existing intergovernmental institutional design structures. The "black swan" events are ignored at this stage of the model development. Figure 4b shows the emergent patterns of funding allocations (US $ nominal) from running Scenarios 4, 5, and 6. The funding flux

Table 4 Parametric values for six alternative scenarios

Parameters	Scenario 1 (baseline)	Scenario 2 (regionalization)	Scenario 3 (cost-effective)	Scenario 4 (funding flux)	Scenario 5 (sequestration)	Scenario 6 (sequestration and shocks)
Weight on regional priority	0.2	0.5	0.2	0.2	0.2	0.2
Weight on highway system	0.4	0.1	0.1	0.4	0.4	0.4
Weight on cost per vehicle mile	0.2	0.2	0.5	0.2	0.2	0.2
Weight on project momentum	0.2	0.2	0.2	0.2	0.2	0.2
Percentage of projects to be funded each year	0.1 (10 %)	0.1 (10 %)	0.1 (10 %)	0.3 (30 %)	0.05 (5 %)	0.05 (5 %)
Number of new projects added each year	30	30	30	30	30	40

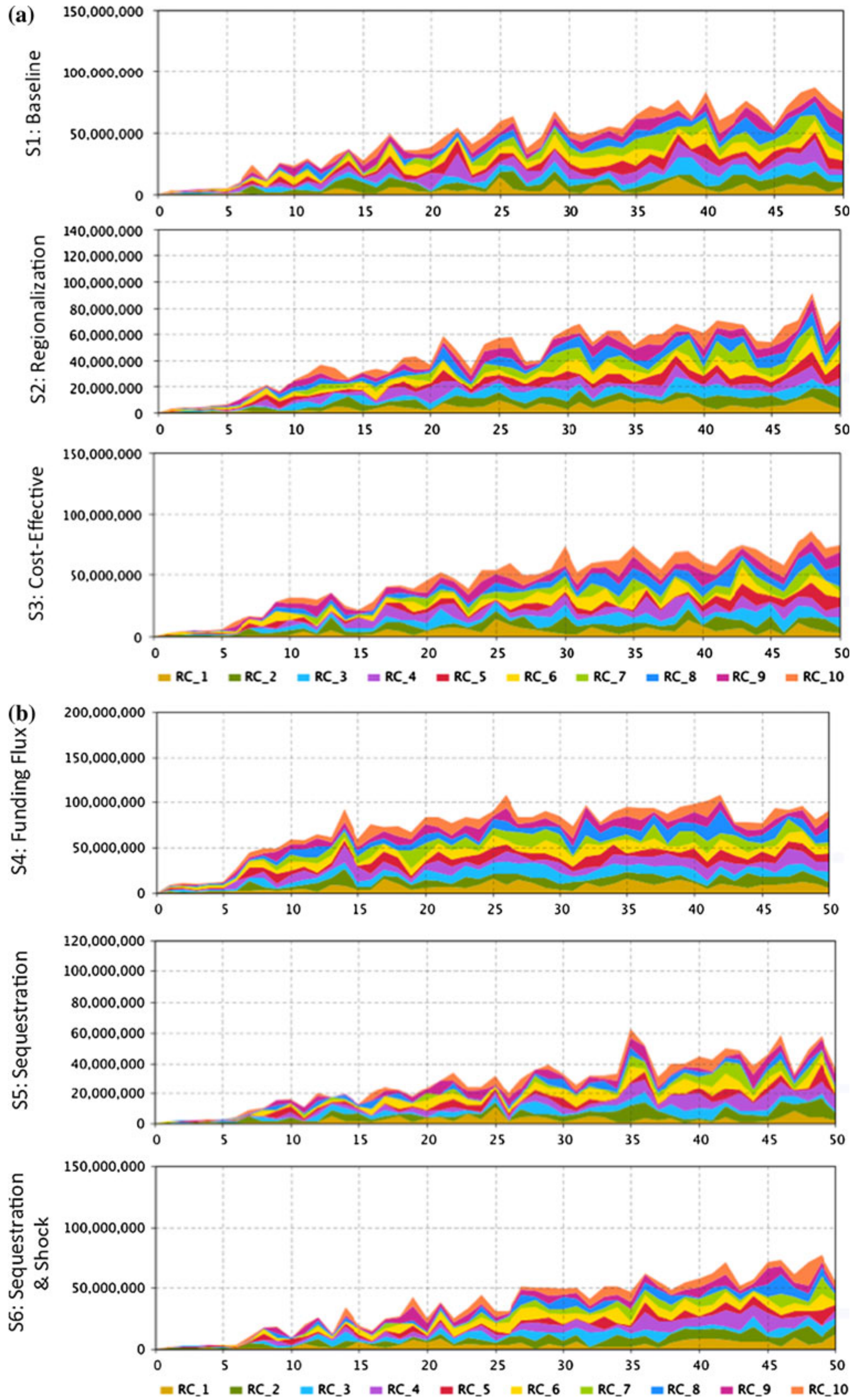


Fig. 4 The emergent patterns of funding allocation at the regional level for **a** Scenarios 1, 2, and 3. **b** Scenarios 4, 5, and 6

scenario S4 leads to a large influx of projects, as expected under ARRA-like black swan events, while the sequestration scenarios S5 and S6 show relatively smaller monetary flows in the system due to potential exogenous shocks. Despite these differences, all scenarios show that there are some RPCs that attract relatively large amount of funds,

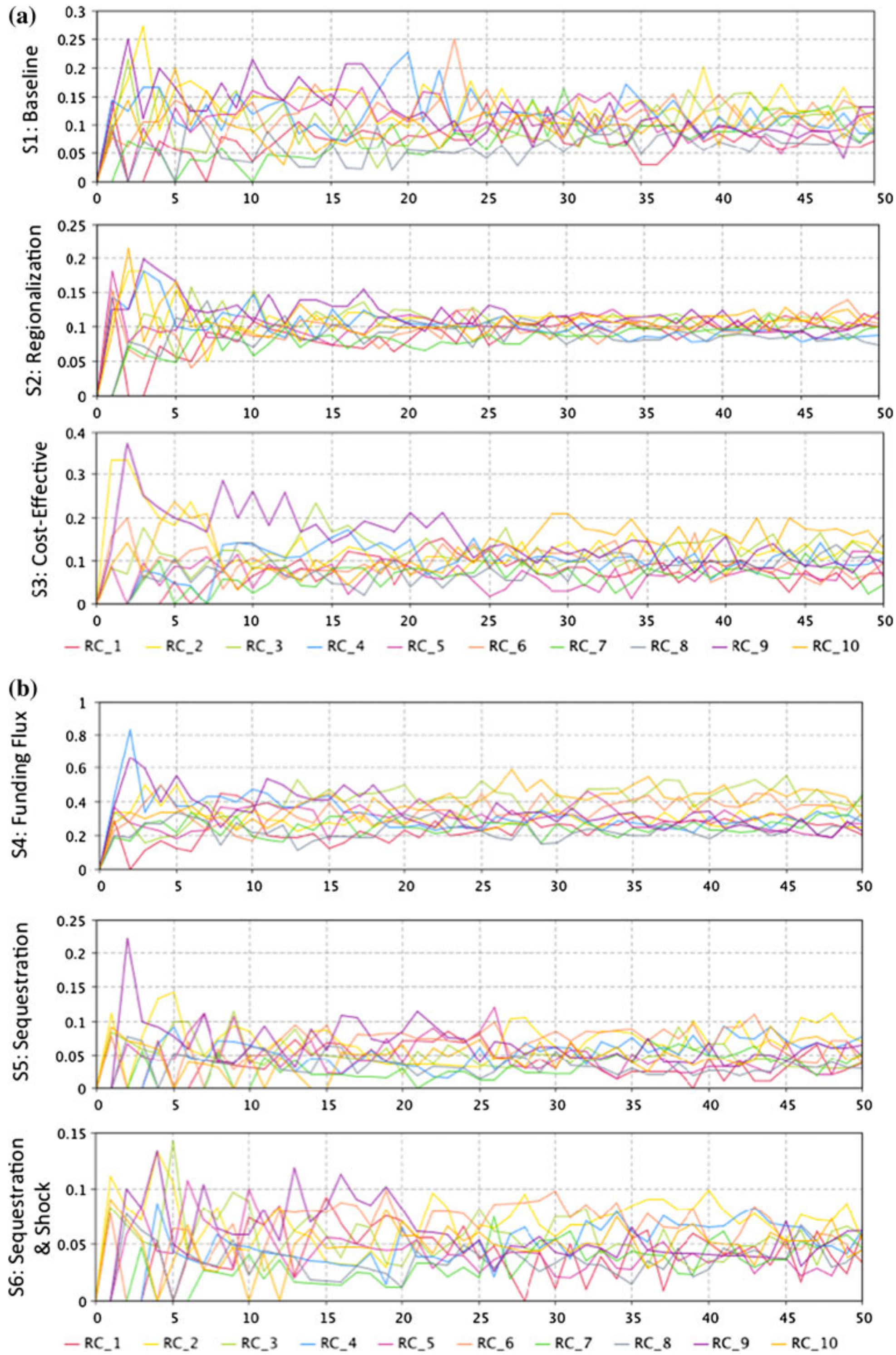
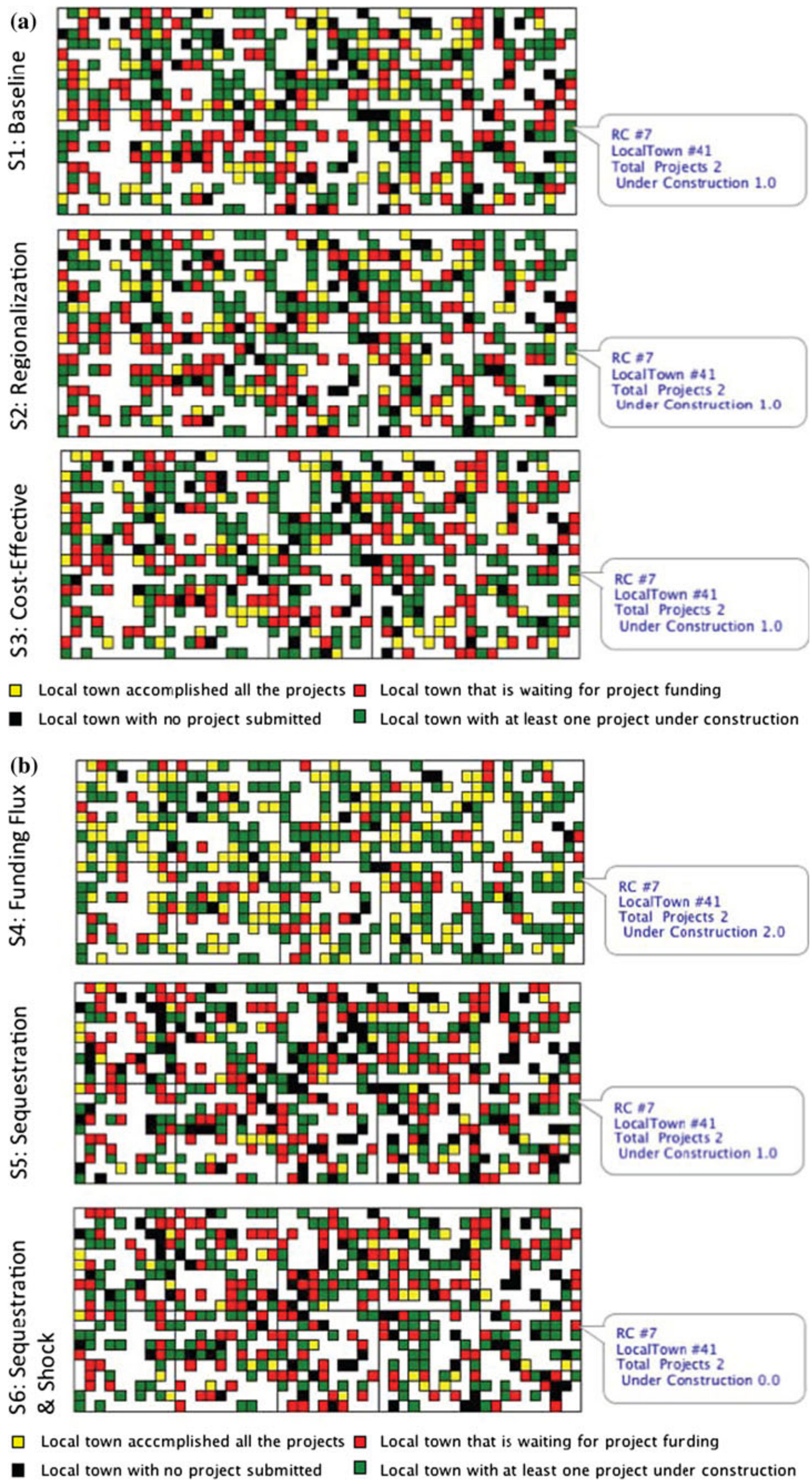


Fig. 5 Emergent patterns of project success rate at the regional level for **a** Scenarios 1, 2, and 3. **b** Scenarios 4, 5, and 6

i.e., the basins of funding attraction are reproduced in almost all six scenarios. There are, however, subtle differences between the scenarios that we present below.

Figure 5a, b shows the success rate of project funding (modeled between 0 and 100 %) over the 50-year simulation horizon. The RPC success rate is measured in the ABM through estimating the average percentage of total projects funded per RPC per year for 1,000 simulations. There are two noticeable patterns in Fig. 5a, b. First of all, the RPC success rate varies, expectedly, around the "dummy" federal funding parameter. The baseline scenario S1 shows a success rate of 10 ± 5 %. The regionalization scenario S2 and

Fig. 6 The shifting basins of attraction at the town/city level under **a** Scenarios 1, 2, and 3, **b** Scenarios 4, 5, and 6. The results show the funding outcomes at the end of a 50-year simulation horizon. Towns/cities are organized in a grid of 10 RPCs



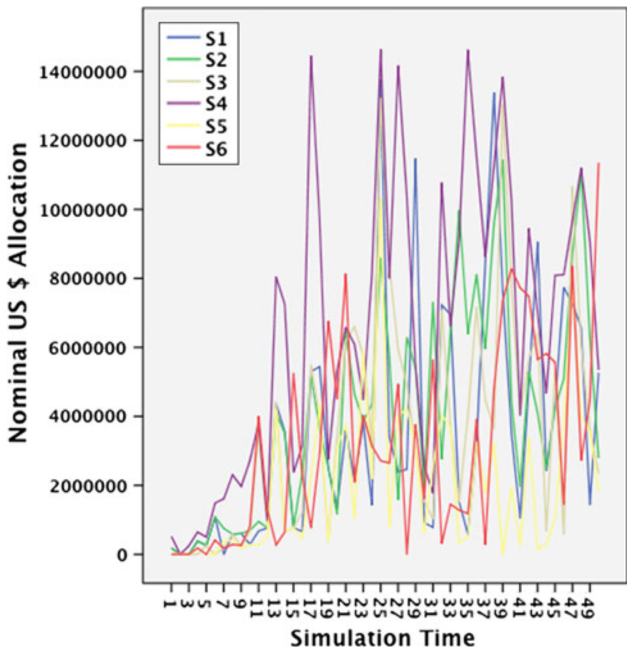


Fig. 7 Simulated US$ allocation for RPC # 1 under all six scenarios

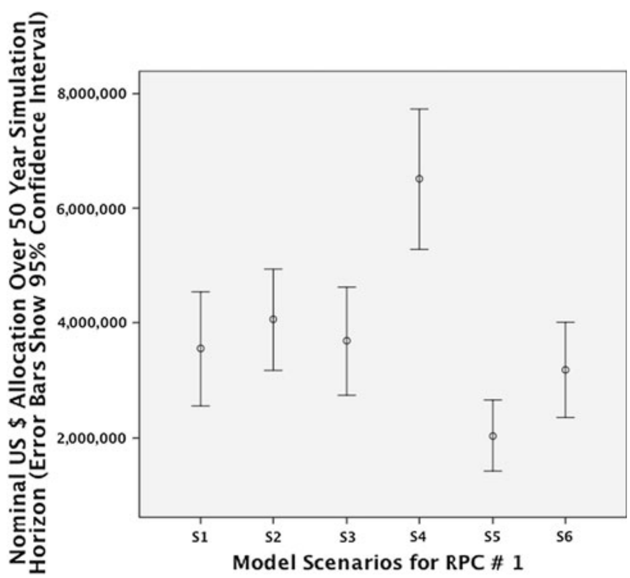


Fig. 8 Statistical comparison of aggregated simulated US$ allocation for RPC # 1 under all six scenarios

the cost-effective scenario S3 also retain similar success rate averages around 10 %. In contrast, the success rate for the funding flux scenario S4 is between 20 and 40 %, while the sequestration scenarios S5 and S6 show diminished average success rate of 5 % with varying variability for different scenarios. This first pattern shows the fidelity of the ABM to the exogenous parameter of funding availability. It is, however, the second pattern that is truly emergent and generated from the internal structure of the ABM. This second pattern concerns the variability in the success rate across the six scenarios. Noticeably, the emergent pattern in Scenario 2 (Fig. 5a) shows a reduced variability across the percentage of funded projects for RPCs over time, which implies that the basins of attraction are weakened under the regionalized institutional design scenario (S2). This reduction in variability is obvious from comparing success rates across all scenarios shown in Fig. 5a, b. Interestingly, the cost-effective scenario S3 shows a strong pattern for multiple basins of attraction. Theoretically, these emergent patterns of attractors under alternative institutional designs provide interesting insights: a decentralized approach in intergovernmental decision making, i.e., more weight on regional priorities as shown in regionalization scenario S2, leads to a more "equitable" pattern of funding allocations and project financing. On the other hand, counter-intuitively, higher weight on choosing more "cost-effective" projects, as in Scenario 3, generates and sustains less equitable and stronger funding attractors. The differences in the funding outcomes between Scenarios 2 and 3 demonstrate potential equity and efficiency trade-offs in the policy outcomes.

Turning our attention toward exogenous shocks, a higher influx of funding in the system, as in Scenario 4, merely raises the funding levels but does not necessarily change the basins of attraction patterns compared with the baseline scenario. Sequestration scenario S5 and sequestration and shock scenario S6 result in increased variability in the success rates compared to other scenarios, thus implying that more competitive funding situations could lead to more pronounced winners and losers in terms of attracting federal and state funding for transportation projects.

From the scenario runs shown in Figs. 4a, b, 5a, b, we can draw a few conclusions about how this system works. First, if the percentage of weight given to regional considerations is raised under an alternative institutional design structure, it will result in a "phase change" and switch the basins of attraction in terms of allocating federal and state transportation funds. An emphasis on increasing the weight on a "cost-effective" scenario does not necessarily result in this phase change. Second, in the context of a larger transportation policy debate about the 3Cs between state, regional, and local governments, we find that a shift in the relative power from the state to the regional governments could trigger a more equitable distribution of funding across regions. This observation will likely be of great interest to stakeholders. Some interests, such as towns or regions who feel that they have not received their "fair share" of federal transportation dollars, may use these results to argue for changes to the intergovernmental system. However, the beneficiaries of the current baseline system might resist such changes in the intergovernmental institutional designs. The relevant decision makers and policy makers could use this ABM as a decision support system to redesign the intergovernmental decision-making rules, resulting in a desirable trade-off among equitable and cost-effective allocation of federal and state tax dollars. The effect of these multi-level institutional design changes at the town level is even more pronounced than the RPC level, as shown in Fig. 6a, b.

Even one small change in the institutional design structure results in highly significant changes in terms of the local towns whose projects get funded (shown in yellow and green), versus local towns who either keep waiting for their projects to be funded (shown in red) or who do not even submit a project in the 50-year simulation horizon (shown in black) in Fig. 6a, b. This contrast is more pronounced in Fig. 6b, which compares funding flux scenario S4 with sequestration scenarios S5 and S6. The funding flux scenario S4 displays mostly green and yellow towns, while the sequestration scenarios S5 and S6 display more red towns. Further, if we track an example town (shown in Fig. 6b as Town #41 in RPC # 7), we find that both of its projects get funded under the funding flux scenario S4, one of its two projects gets funded under the sequestration scenario S5 and neither project gets funded under the sequestration and shock scenario S6.

At the RPC level, the differences among the six scenarios can be discerned by comparing the funding level for the same RPC under different scenarios, as shown in Figs. 7 and 8. As a demonstration example, we chose RPC # 1 in the model. Figure 7 shows a large inter-annual variability in funding for RPC #1 over the 50-year time horizon under the six scenarios. Figure 8 shows a statistical summary (mean and 95 % confidence interval around the mean) for aggregate RPC #1 simulated allocation under the six scenarios. Findings in Fig. 8 come close to representing alternate stable states (basins of attraction) of funding allocations for RPC #1 under different (n-1 dimensional state space) scenarios. Clearly, sequestration scenarios S4 and S5 result in significantly less funding allocation over the 50-year period for RPC #1 compared with the funding flux scenario S4. The regionalization scenario is slightly better than the baseline scenario but not statistically significant. Similar results are found for other nine RPCs, but there are slightly different attractor patterns in each case.

5 Discussion and conclusion

All models are abstractions of reality. It is the function and purpose of computer simulation model design to broadly define the boundaries of a dynamic policy and governance system that is abstracted from a systematic set of observations of complex reality. The main purpose of designing the ABM presented in this paper was to simulate the operational decision-making dynamics of project prioritization processes among multi-level government agencies. We intentionally excluded five other project classes and just focused on roadways. While this simplification allowed us to focus on modeling the institutional rules across different levels of government, the competing dynamics that occur in terms of allocation of funding across different project classes (i.e., between bridges and roadway, and/or bike/pedestrian, and park and rides) have been ignored in setting up the system boundaries. Similarly, social boundaries have been scaled up to represent governmental organizations as agents, while in practice networks of individual and group social actors also comprise the governance networks.

In this paper, we introduced pattern-oriented agent-based modeling as a complex system-based policy analytical tool to compare alternative institutional designs of intergovernmental decision-making processes for the allocation of transportation funds and to ascertain their respective effects on the emergence of basins of funding attraction. We have presented a calibrated agent-based model (ABM) of the transportation governance network in the state of Vermont for roadway construction. This ABM enables simulation of the dynamics of transportation project prioritization processes under alternative inter-governmental institutional rule structures and exogenous shocks. In particular, this ABM enables decision makers to visualize the impacts of alternative inter-governmental institutional rules on the emergent patterns of financial investment flows from federal to state, regional, and local scale governments. The results from experimental simulations suggest that the current institutional configuration between state- and regional-level governments generates basins of attraction in supporting the development of transportation infrastructure projects. These basins of attraction privilege a small subset of towns/cities and regions, while other towns/cities and regions struggle to fund their transportation projects. We find that these struggles could become even more pronounced under funding sequestration and exogenous shock scenarios. Further, an emphasis on assigning more weight to "cost-effective" projects might not necessarily change the current basins of attraction; however, higher weight on regional priorities could generate more equitable allocation of resources across regions. This study represents a very tangible way to employ the computational modeling of complex governance networks to the study of pressing public policy and economic challenges.

There are many possible ways, both vertically and horizontally, to extend and generalize the ABM presented in this study. Within the current transport policy domain, the ABM could be made spatially explicit by adding GIS layers. Further, the ABM could be extended to all six transport project classes. Explicit rules of federal programs, such as the Surface Transportation Program, Interstate Maintenance Program and others, could be incorporated in an upward expansion of the model. Similarly, in a downward expansion of the model, the complex dynamics that occur in local towns and their planning commissions/boards could be explicitly captured. Further, even at a finer grain, the outcomes of the funded projects could be ascertained by coupling integrated land use transportation models such as UrbanSim with the governance network simulation model presented in this paper.

The ABM presented in this study can be coupled in the future with integrated land use, transportation, and environmental simulation models to test system-wide effects of alternative institutional designs on the differential emergence of transportation infrastructures and networks across the urban to rural gradients. Further, inter-modal competitive dynamics can also be added to simulate the trade-offs encountered in funding different classes of transportation projects. A true test of the generalizability of this ABM will be its calibration to another state in the USA, an effort that is currently undergoing. For extending the model to other states or countries, the probability distributions of the ABM parameters would need to be empirically estimated for calibrating ABM to that particular geographical scope. Recent advances in network analysis and data mining approaches can also potentially be coupled with agent-based modeling to simulate real-world intergovernmental policy arenas. In the future, the ABMs could be adapted to model the impact of simultaneous black swan events as exogenous shocks in the policy systems. Such policy modeling developments could permit direct testing and refinement of multiple institutional design frameworks such as IAD, MSF, and ACF across different public policy arenas.

Acknowledgments We gratefully acknowledge funding from the United States Department of Transportation via the University of Vermont Transportation Research Center and National Science Foundation EPS-1101317. Authors bear complete responsibility for all the data and information provided in this article.

References

Agranoff R, McGuire M (2003) Inside the matrix: integrating the paradigms of intergovernmental and network management. Int J Public Adm 26:1401–1422

Batty M (2007) Cities and complexity: understanding cities with cellular automata, agent-based models, and fractals. The MIT Press, Cambridge, MA

Baumgartner FR, Jones BD (2002) Policy dynamics. University of Chicago Press, Chicago, IL

Grimm V, Revilla E, Berger U, Jeltsch F, Mooij WM, Railsback SF et al (2005) Pattern-oriented modeling of agent-based complex systems: lessons from ecology. Science 310:987–991

Henson SM, Costantino RF, Desharnais RA, Cushing JM, Dennis B (2002) Basins of attraction: population dynamics with two stable 4-cycles. Oikos 98:17–24

Holling CS (1973) Resilience and stability of ecological systems. Annu Rev Ecol Syst 4:1–23

Ingram P, Robinson J, Busch ML (2005) The intergovernmental network of world trade: IGO connectedness, governance, and embeddedness. Am J Sociol 111:824–858

Intermodal Surface Transportation Efficiency Act of 1991, Pub. L. No. 102–240, 105 Stat 1914

Janssen MA, Ostrom E (2006) Empirically based, agent-based models. Ecol Soc 11(2): 37. http://www.ecologyandsociety.org/vol11/iss2/art37/

Jones C, Hesterly WS, Borgatti SP (1997) A general theory of network governance: exchange conditions and social mechanisms. Acad Manag Rev 22:911–945

Kauffman S, Peterson C, Samuelsson B, Troein C (2004) Genetic networks with canalyzing Boolean rules are always stable. PNAS 101:17102–17107

Kickert WJM, Klijn EH, Koppenjan JFM (1997) Managing complex networks: strategies for the public sector. Sage, London

Kingdon JW (1984) In agendas, alternatives, and public policies. Little, Brown and Company, Boston

Klijn EH (1996) Analyzing and managing policy processes in complex networks. Adm Soc 28:90–119

Koliba C, Meek J, Zia A (2010) Governance networks in public administration and public policy. CRC Press, Boca Raton, FL

Krugman P (1994) Complex landscapes in economic geography. Am Econ Rev 84:412–416

Marsh D, Rhodes RAW (1992) Policy networks in British government. Clarendon Press, Oxford

Milward HB, Provan KG (1998) Measuring network structure. Public Adm 76:387–407

Neary JP (1978) Dynamic stability and the theory of factor-market distortions. Am Econ Rev 68:671–682

Ostrom E (2005) Understanding institutional diversity. Princeton University Press, Princeton, NJ

O'Toole LJ (1997) Treating networks seriously: practical and research-based agendas in public administration. Public Adm Rev 57:45–52

Page F, Wooders M (2009) Strategic basins of attraction, the path dominance core, and network formation games. Games Econ Beh 66:462–487

Rhodes RA (1997) Understanding governance: policy networks, governance, reflexivity and accountability. Open University Press, Maidenhead

Sabatier P, Jenkins-Smith H (1993) Policy change and learning: an advocacy coalition approach. Westview Press, Boulder, CO

Scheffer M, Carpenter S, Foley JA, Folke C, Walker B (2001) Catastrophic shifts in ecosystems. Nature 413:591–596

Taleb NN (2010) The Black Swan: the impact of the highly improbable fragility. Random House, New York, NY

Vandermeer J, Granzow de la Cerda I, Perfecto I, Boucher D, Ruiz J, Kaufmann A (2004) Multiple basins of attraction in a tropical forest: evidence for nonequilibrium community structure. Ecology 85:575–579

Walker B, Holling CS, Carpenter SR, Kinzig A (2004) Resilience, adaptability and transformability in social-ecological systems. Ecol Soc 9:5. http://www.ecologyandsociety.org/vol9/iss2/art5

Wuensche A (1999) Classifying cellular automata automatically: finding gliders, filtering, and relating space-time patterns, attractor basins, and the Z parameter. Complexity 4:47–66

Zia A, Koliba C (2011) Accountable climate governance: dilemmas of performance management across complex governance networks. J Comp Policy Anal Res Pract 13:479–497