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1 **Toward a Pluralistic Conception of Resilience**

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Abstract

The concept of resilience occupies an increasingly prominent position within contemporary efforts to confront many of modernity's most pressing challenges, including global environmental change, famine, infrastructure, poverty, and terrorism, to name but a few. Received views of resilience span a broad conceptual and theoretical terrain, with a diverse range of application domains and settings. In this paper, we identify several foundational tenets — dealing primarily with intent/intentionality and uncertainty — that are seen to underlie a number of recent accounts of resilience, and we explore the implications of these tenets for ongoing attempts to articulate the rudiments of an overarching resilience paradigm. Firstly, we explore the complementary nature of risk and resilience, looking, initially, at the role that linearity assumptions play in numerous resilience frameworks found in the literature. We then explore the limitations of these assumptions for efforts directed at modeling risk and resilience in complex domains. These discussions are then used to motivate a pluralistic conception of resilience, drawing inspiration and content from a broad range of sources and empirical domains, including information, network, and decision theories. Secondly, we sketch the rudiments of a framework for *engineered* resilience, the primary focus of which is the exploration of the fundamental challenges that system *design* and system *performance* pose for resilience managers. The conception of engineered resilience set forth here also considers how challenges concerning *time* and *predictability* should factor explicitly into the formal schemes that are used to represent and model resilience. Finally, we conclude with a summary of our findings, and we provide a brief sketch of possible future research directions.

You must be the change you want
to see in the world.

Mahatma Gandhi

48

1 Introduction

Our modern preoccupation with resilience arises out of a basic human need to endure. In recent years, a host of scholars and practitioners — such as Levin (1999); Folke (2006); Levin and Lubchenco (2008); Carpenter et al. (2012); Linkov et al. (2014); Troell et al. (2014); Ganin et al. (2016); Goel et al. (2018); Linkov et al. (2018); Massaro et al. (2018); Rocha et al. (2018); Scheffer et al. (2018), Linkov and Trump (2019), and van Strien et al. (2019) — have sought to outline the conceptual rudiments of an emerging “resilience paradigm”. Constructive efforts such as these — directed, as they are, at integration, synthesis, and (in some instances) prescription — represent reasoned attempts to assimilate and make use of what has become an increasingly disparate array of conceptual schemes, methodologies, and worldviews. By their very nature, these “paradigm-building” efforts are replete with choices — choices (and, indeed, meta-choices) that shape the definition and scope of the emerging paradigm, and that influence, ultimately, its applicability and usefulness to human and ecological affairs. An exploration of the burgeoning literature that surrounds the topic of resilience reveals a congealing set of foundational tenets that conceptually ground many contemporary accounts of resilience. For our purposes here, we single out three tenets that are seen to underly an increasing number of received views of resilience:

T1 Utilitarian Orientation. Within the theoretical landscape of many contemporary accounts of resilience, the need or quest for resilience is typically construed as a desirable or sought-after *end-in-itself*. Such a mindset — decidedly *utilitarian* in its orientation — is in contrast to conceptualizations that look, for example, to contextualize the notion of resilience by situating it within larger theories or accounts of collective action, self-organization and emergence, and human intentionality.

T2 Monolithic Approaches to Reasoning About Uncertainty. Most formal accounts of resilience utilize the language of probability to reason about uncertainty, making use of a diverse range of probabilistic representations and methodologies. While understandable, given the numerous successes that probabilistic methods have enjoyed (across a diverse range of disciplines and problem domains) in recent decades, the monolithic status that probability theory enjoys within the resilience literature ultimately

78 comes at the cost of a constrained vision of how uncertainty, in all its guises, might
79 best be managed in a diverse range of resilience-related settings and contexts.¹

80

81 **T3 Circumscribed Accounts of Human Cognition and Intentionality.** Most con-
82 temporary accounts of resilience pay lip service to the idea that human beings often
83 exhibit cognitive biases that impose limits or constraints on their ability to reason coher-
84 ently under uncertainty, even in relatively simple choice situations (e.g., simple gambles,
85 etc.). While the recognition of such biases is certainly relevant to the study of resilience,
86 a myopic focus on the *limitations* of human cognition has the effect of rapidly shifting
87 the focus away from *cognition*, broadly construed, towards, for instance, formal decision
88 aides capable of minimizing the potentially deleterious effect of these biases on deci-
89 sion quality. In so doing, however, what often ends up being excluded from numerous
90 contemporary accounts of resilience is the explicit consideration of matters pertaining
91 to *experimentation/observation*, *perception*, and *representation*, together with nuanced
92 treatments of *human intentionality*.

93 In what follows, we look to explore how tenets T1, T2, and T3 are currently being con-
94 strued and pursued within important strands of the resilience literature. Central to our
95 objectives is the desire to offer a constructive critique of important aspects of how these con-
96 struals and directions are currently shaping the research agendas and questions that underlie
97 numerous ongoing scientific research programs that address the topic of resilience. In this
98 regard, we shall argue that these tenets exert an influence that is — both individually and
99 collectively — overly constrained in its purview, and that ultimately limits the usefulness of
100 the resilience-related conceptual schemes and methodologies that emerge from these efforts.

101 From the outset, we note that many of the problems that we discuss here arise, in the
102 first instance, from a failure to acknowledge that resilience is a concept whose theoretical
103 bases lie not with just one “paradigm” or *weltanschauung*, but rather a plurality of concep-
104 tual schemes and viewpoints. This expansive viewpoint enables us to capture the complex
105 interplay of natural/physical phenomena, as well as important aspects of human behavior
106 and intervention, using a diverse panoply of descriptive, explanatory, and predictive tools.
107 Figures 1 and 2 highlight the generality and methods of this viewpoint, seen through a set of
108 conceptual lenses that are anchored in information, network, and decision theories. Figure 1

¹It is worth noting that numerous contemporary accounts of resilience often hover near this conceptual terrain when they probe the nature of uncertainty itself — with a number of commentators arguing, for example, that there exist fundamental limitations in our ability to make predictively informative assertions about large-scale socio-biological and technical systems. These limitations are often taken to have important implications for any well-motivated theory or conception of resilience; in this regard, later in our discussion, we offer some perspectives on the topic of *predictability* and its relevance to our evolving conceptions of resilience.

109 shows how human decisions give rise to emergent scale-free networks; Figure 2 depicts the
110 variables and probabilistic patterns that allow us to formally characterize complex systems,
111 dependent on desired performance and systems' drivers. By pursuing this path, we look to
112 broaden the field of vision that is brought to resilience-related challenges and concerns, in
113 ways that ultimately enable a *pluralistic* conception of resilience to emerge.

114 The discussion that follows is divided into three parts. In the first part, we explore the
115 complementary nature of risk and resilience. We begin this discussion by considering, first, the
116 role that linearity plays in many prevailing accounts of risk and resilience. This discussion
117 is then used to motivate a more general discussion concerning the challenges entailed in
118 modeling risk and resilience, in a broad range of empirical settings and contexts. We close
119 this section with an outline of the conceptual rudiments of a pluralistic approach to reasoning
120 about resilience. In the second part, we sketch the rudiments of a theory or conception of
121 *engineered* resilience. We begin this portion of our discussion by confronting the conceptual
122 and practical limitations of tenets T1 and T3. Specifically, we explore aspects of an idea that
123 is seen to underlie many contemporary debates surrounding the notion of resilience, namely,
124 that system *design* — and, by implication, optimal system *performance* (Figures 2 and 3
125 show probabilistic and time-dependent patterns of systems' performance) — is achieved *via*
126 resilience only. As part of this discussion, we go some distance towards countering this view
127 by exploring resilience frameworks and application domains where optimal system design is
128 seen to require (i) an awareness and understanding of complex *stakeholder preferences* and
129 *value trade-offs*; (ii) a multifaceted understanding of outcomes and consequences; and (iii) a
130 holistic understanding of what it means to optimize overall system performance. As part
131 of this discussion, we explore how *time* factors into our broadened conception of resilience,
132 and we take up matters pertaining to *criticality* and *predictability* in our characterization
133 and evaluation of complex systems. Throughout our discussion, we endeavor to cast a wide
134 field of vision — both conceptually and methodologically — and we provide illustrations
135 drawn from a diverse range of domains and empirical settings. In addition, we explore recent
136 theoretical and computational advancements in the study of resilience for socio-biological
137 and technological systems, from the perspective of complex systems science (see, e.g., Bialek
138 et al. (2001), Prokopenko et al. (2008), Marsili et al. (2013), Helbing et al. (2015), and Bar-
139 Yam (2016)). Furthermore, we seek to broaden the typically encountered thematic focus on
140 infrastructure, by also including alternative views drawn from studies of environmentally-
141 dependent, multiscale socio-biological systems. Finally, we conclude with a summary of our
142 findings and a brief discussion of possible future research directions.

143 2 Risk and Resilience in Complement

144 The Latin word *resilio* means to “rebound” or to “spring back” — and, indeed, our ordinary-
145 language usage of the word “resilience” is consistent with this etymology. In contrast, risk
146 is typically defined as the likelihood that a stressor affects a given system, considering that
147 system’s vulnerabilities, as well as its dynamics in space and time (Kéfi et al., 2013; Kefi
148 et al., 2014). Accordingly, resilience can be viewed as the observed or predicted response of
149 a system to one or more definable risks. In this way, risk and resilience are easily seen as
150 complementary notions, with a conceptual interplay that is, at once, both common-sensical and
151 capable of yielding important insights about complex systems, especially at systemic levels of
152 aggregation (Helbing et al., 2015).² In this section, we explore aspects of the complementary
153 nature of risk and resilience, beginning with an exploration of how our assumptions concerning
154 linearity play into our descriptions and representations of resilience. These considerations
155 then lead us to a more general discussion of the challenges associated with modeling risk
156 and resilience. We close this section with a tentative outline of the rudiments of a pluralistic
157 conception of resilience.

158 2.1 On the Uses (and Abuses) of Linearity

159 Linearity is to science as, perhaps, concrete is to civil engineering and construction. Often
160 invoked as a convenient fiction, linearity assumptions are typically used to render systems
161 that are otherwise in-amenable to decomposition and analysis (due to, say, inherent system
162 complexities and/or attendant uncertainties), amenable to first-order approximation and eval-
163 uation. While oftentimes a sensible starting point in the analysis of complex systems, the
164 invocation of linearity assumptions can sometimes obfuscate and oversimplify, to the point
165 where erroneous (in some instances, even potentially dangerous) prescriptions can emerge,
166 requiring careful interpretation and bracketing. For our purpose here, we adopt the most
167 general definition of complex systems: systems whose cause-effect dynamics is highly non-
168 linear and non deterministic. Such systems are, of course, less trivial and predictable than
169 simple systems. Figure 4 illustrates the differences between linear and a non-linear systems,
170 where components’ interactions is a minor and predominant factor in systems’ response, re-
171 spectively. In the former and latter cases, a risk and resilience approach is suitable. Figure

²We construe risk and resilience in a manner that looks to eschew any kind of value- or norm-based hierarchy. In contrast, claims by researchers such as Linkov et al. (2014) that “resilience management goes beyond risk management” seem misplaced, in that they can be taken to imply a presumed hierarchy, with resilience somehow occupying a higher level of “importance”, enjoying a primacy that appears grounded in the belief that in designing and managing complex systems, the desire or quest for resilience is somehow “most essential” or “more fundamental” than other goals, objectives, and desired end-states. In truth, there are no *a priori* reasons to suppose that such views are supportable on theoretical grounds; their prescriptive relevance derives purely from a value-laden understanding of human meaning and purpose in specific contexts and situations.

172 5 shows how complex systems can be categorized into dynamical classes, based on how sys-
173 tems' components interact with each other and perform independently for achieving systems'
174 functions. The quantification of the functioning of complex systems is always dependent on
175 available data; therefore, any assessment should always consider the dependence of function
176 on the amount of information used that can reconstruct systems' networks (see, e.g., Servadio
177 and Convertino (2018) and Li and Convertino (2019)).

178 A common difficulty with many of the resilience frameworks that researchers have sketched
179 in recent years is the inherent linearity, in time and in space, of the examples that are often
180 cited in this work. In many instances, resilience is interpreted or seen as a single risk-response
181 function. For example, Linkov et al. (2014), and more recently Linkov et al. (2018), present
182 case studies that are grounded in decidedly linear characterizations of potential system states.
183 This simplistic view, while perhaps a useful starting point in such discussions, is in contrast
184 to more frequently encountered (certainly in the types of real-world systems they cite as
185 examples) non-linear system dynamics, where multiple drivers and events are considered over
186 extended time horizons. Only in the simplest cases can resilience be assessed or measured by
187 looking at just one instantaneous factor or event and its effects. An example of spatial non-
188 linearity is provided in Figure 7, where the community interdependence network (inferred
189 by the model developed in Servadio and Convertino (2018)) is applied to epidemiological
190 time series of Leptospirosis in Sri Lanka (Convertino et al., 2019). This example shows how
191 space and time are, indeed, connected and non-linear scale-free time series, representative
192 of epidemic critical states (depicted in the top plot), correspond to scale-free transmission
193 networks; vice versa endemic states are related to seasonal time series and exponential random
194 networks. This example typifies a line of reasoning that highlights the fact that resilience
195 cannot be assumed as a linear function as assumed by analytic frameworks and models that
196 claim to deploy the "science of resilience" in practical applications (see Linkov and Trump
197 (2019)). Moreover, resilience should not be evaluated solely in terms of "speed of recovery" to
198 some previous system state, before the influence of any stressor(s); instead, resilience should
199 also be evaluated in terms of the magnitude of effects, together with the full range of possible
200 state transitions via probability distribution functions, *including transitions toward "better"*
201 *or perhaps preferred system states* (see Figure 3). This probabilistic mapping of systems'
202 dynamics allow us to create the system potential landscape (Figure 8) that describes and
203 represents all likely systems' states, dependent on data-inferred dynamics and stakeholders'
204 mental models (including model choice(s) and preferences).

205 Experience teaches us that low risks can actually give rise to major impacts on systems

206 — an increasingly common occurrence in a non-linear world.³ The ubiquitous “cup and
207 ball” diagram is typically used to depict “system energy potential” (or potential landscape)
208 based on known risk factors (Figure 2), where stable states are characterized by low energy
209 (maximum entropy) and the low probability of a system change toward states with highly
210 likely changes (Perz et al., 2013).⁴

211 More generally, we recognize that resilience should be assessed in a manner that considers
212 *all* factors — to the degree possible — that significantly affect system performance, recog-
213 nizing that the response of a system facing one identified stressor is also dependent on the
214 resilience built for other stressors (perhaps in the past, or at the current state). This is the
215 reason why, in resilience-focused design, the baseline assessment of complex systems (existing
216 or planned) starts from known features and risks; these elements constitute systems’ known
217 history — such as previous diseases, species abundance trajectories, infrastructure failure
218 records, and the like.

219 For these reasons, consideration of non-linearities should factor prominently in any well-
220 motivated theory or conception of resilience in complex systems. An important non-linear
221 example not often considered in the literature concerns systems that are subjected to high
222 levels of *systemic risk*.⁵ Systemic risk differs from traditional definitions of risk in the follow-
223 ing ways: (i) the system is considered as a whole, in its entirety, across space and time; (ii) all
224 (objective-dependent) interconnections of the system are considered with other systems; and
225 (iii) the whole system landscape risk is considered, including multiple stressors and uncer-
226 tainty. Systemic risk therefore considers the full structural and functional networks, with
227 their uncertainty, determining frequency and intensity of system response.

228 Within the context of this systemic purview, the depth of the system response curve
229 (the traditional “cup and ball” diagram (Scheffer et al., 2001; Holling and Gunderson, 2002;
230 Scheffer et al., 2012; Perz et al., 2013) is not — contrary to what is sometimes asserted in
231 the literature — necessarily a measure of system resilience, but rather a measure of system
232 response to a particular risk. In many real-world contexts, to the extent that the potential
233 states of a given system are changing or evolving over time, the system response curve
234 should be construed in dynamical terms, accounting for changes in relevant portions of the

³An important early example of this line of reasoning is found in Charles Perrow’s seminal book, *Normal Accidents*.

⁴In mechanical systems, for example, an engineered product is evaluated for resilience by testing it under the same cyclical conditions, observing the systems’ responses over the time horizon for which the product’s functions need to be guaranteed. Such tests have obvious analogues within the realms of complex socio-ecological systems

⁵Systemic risk (Beale et al., 2011; Haldane and May, 2011; Helbing, 2013) can be defined as the likelihood of an outcome (typically adverse/undesired), evaluated by taking into account local vulnerability and systems’ interdependencies in space and time. Assessment of systemic risk typically entails considering multiple risks that are capable of affecting the magnitude of aggregate outcomes (such as multiple diseases, group behavioral dynamics, flooding, etc.) for a specified time horizon. More generally, *performance* can be evaluated considering systemic risk and attendant costs.

235 systemic risk landscape, as well as the ability for agents (e.g., affected populations) to learn
236 and adapt (where and when possible). In this way, resilience is, perhaps, more akin to a
237 “trajectory” (Figure 3) — thereby better represented by slopes of response and recovery,
238 depth of the system response curve, and post-shock values for system function over time
239 horizons deemed important or relevant for intervention and control. In truth, response curves
240 and system potential landscapes are partial elements of what system-level resilience is. We
241 now consider how the evolution of system performance should, in probabilistic terms, be the
242 risk-independent pattern to consider when evaluating systemic resilience.

243 **2.2 Models of Risk and Resilience**

244 The nature of the relationships that can be said to exist between “models” and “reality” is, of
245 course, a topic that has preoccupied philosophers and scientists, alike, for centuries. A review
246 of the salient themes that emerge from this body of thought is well beyond our scope here —
247 suffice it to say that we accept that the nature of the relationship between *any* model and
248 the “reality” it seeks to describe or represent is necessarily tenuous. To the extent that this
249 characterization is accurate, it is surprising to note that numerous contemporary accounts of
250 resilience seem to somehow lose sight of this point. This idea is most prevalent within certain
251 ideological camps (e.g., computational scientists), and it typically finds expression in a line
252 of thought that supposes that if a model is capable of generating highly accurate *predictions*,
253 then the embedded processes represent (or at least reflect) the “true” predicted processes.
254 Munoz-Carpena et al. 2013, for example, promulgate the view that “more information is
255 better”. This principle has its origins in the classical reductionist belief that the successive
256 accumulation of knowledge leads to closer and closer approximations of reality. A vast array of
257 empirical insights, derived from a range of scientific disciplines, teach us, however, that more
258 information can lead to more uncertainty. Accordingly, managing *information value* (Feistel
259 and Ebeling, 2016) is an important prerequisite to effective problem solving and decision-
260 making within the realm of complex systems. Furthermore, consideration of trade-offs that
261 exist between sensitivity, uncertainty, and complexity of information is a common problem
262 within existing decision-making paradigms, where perfect information is seldom available to
263 decision-makers.

264 A wide range of stochastic decision-making models have been proposed in the literature
265 that focus on modeling complex systems under uncertainty (Shalizi and Crutchfield, 2001;
266 Marsili et al., 2013; Helbing et al., 2015). This strand within the literature of work teaches
267 us many things — for example, that any model is an *information machine* (Marsili et al.,
268 2013; Quax et al., 2016), with its own variability, uncertainty, and complexity. In order to

269 analyze risk and resilience, the key is to have models that are capable of optimizing the
270 important trade-offs that exist between these features (which often exhibit non-linearity). In
271 such contexts, non-linearities can arise any number of ways. For example, the magnitude of a
272 system’s performance (gathered from data, or as an output of models) may be uninformative
273 about the magnitude of a given hazard and its risk in such instances; it is important to
274 also consider the significance of small changes in input factors that can potentially have
275 dramatic influences on performance. For instance, small, gradual changes in input factors
276 that accumulate over time and space can bring about cascading changes in interconnected
277 system performance metrics (e.g., numerous population outcomes that are related to one
278 single cause). This “butterfly effect” (as it is often described in the chaos theory literature —
279 see, e.g., Crutchfield (2012)) is the potential for a ripple in one part of a system’s “world” to
280 be amplified and subsequently lead to major disturbances in another part of the system (due
281 to the increased connectivity of system parts and multiple, interconnected systems) is another
282 symptom of non-linearity. This type of phenomenon is, of course, commonplace within many
283 biological systems, where, for instance, numerous biomarkers are highly interconnected and
284 even small changes may be extremely meaningful for overall system performance in the long-
285 term (see, e.g., Convertino et al. (2018)). At a much larger scale, consider the case of many
286 interdependent infectious diseases that are related to the same environmental and social
287 causes, leading to co-occurrent disease transmission (see, e.g., Convertino et al. (2014)).

288 **2.3 System Dynamics and Resilience**

289 Proper characterization and evaluation of system response is central to any well-motivated
290 approach to resilience. Adding, then, to our observations above concerning non-linearities,
291 it is important to recognize that risk is not solely proportional to the depth of the system
292 response curve, as this reflects a system’s outcome as a function of *ex post* interdependent
293 hazards whose intensity may or may not be well predicted *ex ante*.⁶ This observation is
294 important, because unexpected events — and possibly other unknown factors — can hardly
295 be anticipated with perfect foresight, despite our best efforts to eliminate risks and to include
296 all salient factors. Instances where risk is seen to be proportional to the depth of the system
297 response curve typically arise when the system response curve is constructed using historical
298 data, focusing on correlations with one single hazard. The level that is reached by the system
299 after recovery, and the system’s ability to withstand or rebound faster after an identical shock
300 at future times, is but one of several crucial elements that should be evaluated when assessing
301 resilience and system criticality. More generally, we must seek to characterize and evaluate

⁶This point is often overlooked in the literature — see, e.g., Linkov et al. (2014).

302 overall system performance, over extended time horizons, considering all (again, to the degree
303 possible/practical) potential system states.

304 Our commentary above suggests that the task of arriving at credible estimates of resilience
305 requires a plurality of viewpoints and perspectives which are, in turn, capable of informing the
306 development of requisite schemes and frameworks that are able to confront the complexity
307 that the world presents to us, in a diverse range of settings and contexts. For its part,
308 complexity science provides a number of useful starting points for the kind of expansive
309 vision that we prescribe here:

310 • **Systemicity.** Consistent with our earlier discussion, the resilience of a complex sys-
311 tem is not just the response of that system to one well-identified hazard, but rather,
312 the response of that system to multiple connected hazards, plus any intrinsic ability of
313 that system to increase fitness. In situations where one hazard is identified, resilience
314 is a non-linear function of risk, where risk is not solely proportional to the magnitude
315 of the attendant hazards, but also considers its probabilities and vulnerability func-
316 tions (including exposure factors), convoluted to some uncontrollable noise. Equivalent
317 stressors can potentially give rise to a very different response; only a normalization of
318 system functionalities can make systems comparable in terms of resilience.⁷

319 • **Spatio-Temporal Non-Linearity.** In looking to formally characterize resilience, his-
320 tory often matters, i.e., resilience is typically history-dependent. More specifically,
321 resilience is dependent non-linearly on the present, the past, and future sensed risks.
322 Indeed, oftentimes, the larger the realized risk, the larger the resilience of the system —
323 “the more we fall the more we learn”. System performance achieved after a disturbance
324 (e.g., the slope of, and area under, the system’s functionality curve, and post-stress
325 performance) can change non-linearly; thus, the very same combination of risk factors
326 can lead to different resilience levels, and vice-versa. Small risks typically accumu-
327 late critically and generate systemic effects after cascading events on spatio-temporal
328 connections of complex systems. Notwithstanding this non-linearity, the higher the
329 controlled ability of a system to change to multiple varying states (desirably around
330 optimal states), dependent on environmental fluctuations, the higher the resilience.

331 • **Subjectivity.** Resilience is not solely proportional to one functional or structural cri-

⁷Consider, for instance, the case of a hurricane of the same intensity level hitting two nearby but very different locations; or a psychological stress affecting two individuals linked by family ties, but nurtured in very different environments. A wealth of social science theory and empirical case study teaches us that socio-environmental context exerts a tremendous influence in the response of communities and individuals to the same stressors. The detailed characterization of heterogeneities is therefore fundamental for predicting complex systems, and for comparing them after their normalization, dependent on the key heterogeneities leading to different outcomes.

332 teria (e.g., complementary damage, speed of recovery, etc.), but also to a stakeholder-
333 weighted multi-criteria function that captures desired system performance, stakeholder
334 preferences on performance drivers, and the quality of information related to perfor-
335 mance and disturbances. Quality of information, as much as other “intangible” criteria,
336 constitute the “subjective” components of resilience, beyond its strictly “objective” fea-
337 tures. In this way, so-called “cup and ball” diagrams that are commonly found in the
338 literature only reflect the *structural* components of resilience — and thereby omit crit-
339 ical features of many real-world systems.

340 **3 Steps Toward a Formal Conception of Engineered Re-** 341 **silience**

342 **3.1 Initial Steps, Towards a Plurality of Possible Destinations**

343 Coming out of the discussion above, what we now seek is the beginnings of a conceptual
344 outline for an enriched vision of resilience, where *human intentionality* is seen to play a
345 central, defining role. In what follows, we explore aspects of what it means to, in effect,
346 *engineer* resilience. In so doing, we draw inspiration and insights from a range of disciplines,
347 including complexity science, information theory, network and decision-theoretic sciences,
348 together with an appreciation for what it means to apply these concepts in a diverse range of
349 settings and contexts. Ultimately, we seek a conception of, and approach to, resilience that
350 is capable of serving a host of purposes, including:

- 351 • Helping life (at any scale of biological organization) to flourish sustainably on Earth;
- 352 • Protecting and providing thoughtful/purposeful stewardship of the Earth’s atmosphere
353 and ecosystems;
- 354 • The health and protection of people and property; and,
- 355 • The ability to sustain infrastructure that is essential to the proper functioning of our
356 increasingly technological society and its socio-economic systems.

357 All of these interconnected purposes, which reflect a “safe operating space for humanity”
358 (Rockström et al., 2009), are (and indeed must be) centered on a pluralistic conception of
359 resilience that encompasses both *self-organization* and *intentionality* of social actors and
360 complex systems. Pursuing such expansive ends requires that, independent of the size of
361 the complex system considered, the interconnections of a given system with all others must

362 be taken into account (to the extent that knowledge and resources allow). Increasingly,
363 such concerns are intertwined with more general societal desires or quests for sustainability;
364 we argue that any model of sustainability must consider forms of resilience that aim for
365 consistently improving desired ecosystem services versus risk-based approaches that focus on
366 maintaining current levels of desired services.

367 At its essence, a model is a representation of how a system is “seen” and described.
368 The sensitivity of a system’s features is defined by the so-called ST-scale that determines the
369 spatial and temporal lens of analysis. In a broader sense, cognition, ST-scale, and entropy are
370 the “how, where/when, and how much” that a system is analyzed. At the bottom of Figure 2,
371 the left plot is a single risk-dependent performance profile (deterministic), the middle plot is
372 a probabilistic performance profile, dependent on one single system’s driver, and the plot on
373 the right is a risk-independent probability distribution of performance.

374 The conceptual relevance and practical utility of our resilience framework is borne out in a
375 diverse range of empirical settings and contexts. It is instructive to consider examples drawn
376 from both natural and engineered systems. In the context of socio-environmental systems,
377 considering data and numerical simulations of Hurricane Katrina (2005) and Hurricane Sandy
378 (2012), the (ex post) resilience of New Orleans and NYC can be evaluated by considering
379 (i) the urban and natural ecosystem’s ability to respond early; (ii) the damage in terms of
380 structure and function; and (iii) the speed of recovery (Bonanno et al., 2007; Shultz et al.,
381 2007; Pietrzak et al., 2014; Valverde and Convertino, 2019). Interestingly, the same basic
382 concepts and approach finds application, for instance, in the study of infectious diseases,
383 with high and low frequencies of occurrence, in cases of foodborne and Ebola outbreaks,
384 respectively.

385 In the case of repetitive events, it is reasonable to expect that populations are capable
386 of learning, over time, how to be more resilient to equivalent (or at least “similar”) events.
387 In this vein, an interesting example is the state of Florida, which, in light of its recurring
388 tropical cyclone season, has put in place an efficient surveillance system for rapid response
389 and recovery. Along similar lines, other examples include flood control infrastructure and
390 runoff monitoring, which work effectively to reduce extreme runoff events. Within the realm
391 of public health, examples include the surveillance, hygiene, and sanitation infrastructure
392 put in place in developed and developing countries that are affected by waterborne diseases,
393 such as cholera (e.g., Bangladesh and Haiti are instructive examples of populations that have
394 built effective response mechanisms). Also worthy of note, in terms of system function, are
395 the networks of epidemiological surveillance of infectious diseases worldwide — e.g., FOOD-
396 NORS for foodborne outbreaks in the USA, and ProMED-HealthMap for infectious diseases

397 at the global scale. As part of their design, these systems seek continual improvement, and
398 have demonstrated an ability to minimize the incidence of massive outbreaks. All these
399 examples show how realized risks were necessary elements to building resilience over time;
400 moreover, they show that a purely ideological “risk-free” resilience approach does not exist.

401 Of course, learning systems such as those referenced above need to be maintained and
402 updated on a regular basis, taking into consideration natural and anthropogenic variability
403 (e.g., climate extremes, agricultural intensification, urbanization, and related factors). These
404 examples illustrate that active surveillance of system structure and function (e.g., supply
405 chain integrity/reliability and foodborne infection cases) is crucial to building and maintain-
406 ing resilience, and to avoiding catastrophic events. Ultimately, it is history that teaches us
407 that both positive and negative events are necessary to build resilient systems.⁸

408 Within the context of a more traditional risk-based framework, the change from one micro-
409 state to another is typically associated with an alteration of system function, observable in
410 the increased variability of system components (color of node from white to red), and for
411 major transitions also in the variability of system structure (e.g., connectivity among nodes)
412 (Figure 3). Before any tipping point, the variance of system function is increasing while the
413 stable state corresponds to a low variance state (e.g., network with “white nodes”).

414 From an information-theoretic perspective, similar transitions have been observed in social
415 systems (Borge-Holthoefer et al., 2016), where approaching critical states (a manifestation
416 of critical dynamics) implies an increase of fluctuations in the information exchange at the
417 system scale, after accumulation of local fluctuations above a critical threshold. These fluc-
418 tuations are typically responding to time-point hazards and do not necessarily reflect the
419 system’s long-term performance. An intuitive example of this is the hyperactivity of certain
420 physiological biomarkers that an individual presents during intense exercise; fluctuations of
421 all sizes occur until a peak performance level is reached, and after they slow down to base-
422 line condition levels. These dynamics and fluctuations do not reveal anything about the
423 long-term — for instance, the lifetime performance of the individual considered. Traditional
424 risk analysis has been mostly focused on these time-point single hazard-dependent events,
425 rather than having a long-term view that is more in line with resilience paradigms that are
426 focused on guaranteeing a positive resilient trajectory, with increasing systems’ performance,
427 independent of any preconceived risk.

428 Exploring these matters more broadly, we note that resilience is an innate property of any
429 living system, arising from the evolutionary pressures of survival, and giving rise, over the

⁸Interestingly, this is an idea that is reflected, in a negative way, by the current “exposomics” and epige-
netics theories of disease generation in populations, where a multiplicity of factors contribute to the health
of an individual (J Patel and K Manrai, 2015).

430 long term, to an optimal pruning of coupled form and function (Bak, 2013; Banavar et al.,
431 2014). In this context, resilience is seen to depend on both the interconnected structure
432 and function of systems, where structure is determined by the physical interconnections of
433 system components, and function is the stakeholder-independent endogenous byproduct of
434 complex systems. For biological systems, a classical example is the brain, where structure is
435 determined by the dendritic assemblage of different neurons at the micro-scale, and where
436 function arises from the electrical activity among many neurons for supporting other system's
437 functions (e.g., brain dynamics at the meso- and macro-scale) (Damasio and Carvalho, 2013).
438 In this way, the brain is the central “system of systems” for human beings, responsible for
439 controlling all physical and functional processes.

440 In natural systems, the same duality of form and function is observed (West et al., 1997;
441 Banavar et al., 1999; Bak, 2013; Banavar et al., 2014; Tandler et al., 2015; Seoane and Solé,
442 2015; Koçillari et al., 2018). For instance, in river systems, structure is defined by the
443 river network, with optimal and ubiquitous features, whereas function is the water transport
444 mechanisms from a hydrological viewpoint, and so on and so forth, for geochemical and
445 ecological processes that become apparent by enlarging the purview of analysis. All of these
446 systems have embedded within them a natural capacity for building resilience over time,
447 considering both the capacity to withstand structure-forming shocks and the long-term drive
448 toward optimality (Hidalgo et al., 2016). Interestingly, for any individual, the human brain
449 is part of the “collective”, or part of the “aggregate societal brain”, at the population scale,
450 which is also determining (or at least influencing) the trajectories of natural and man-made
451 systems. In this sense, it is important to broaden the traditional field of vision that is brought
452 to such problems, to include consideration of the anthropogenic dynamics of resilience for
453 any system at the population scale (Diamond, 2005).

454 Our discussion thus far suggests that by enlarging the lens of analysis, it is possible to
455 observe coupled structures and functions simultaneously, but more importantly, to identify
456 the relevant information at any scale of analysis. In the case of river systems, for example, a
457 network of dams and locks is seen to provide services to human populations, including flood
458 control, hydroelectric energy, and transportation. As Linkov et al. (2014) and others have
459 suggested, all of these systems should be considered *in toto*, with complexity and network
460 theory providing useful analytic vehicles for exploring the structural and behavioral modalities
461 of such systems. For its part, complexity theory has much to teach us about resilience.
462 By simplifying the analysis of systems just enough to make possible the discernment of
463 important system drivers at different scales, complexity theory yields insights that are useful
464 for design and management purposes. From a decision-making perspective, it is useful to

465 recognize those situations where only a subset of drivers are important at the system-scale,
466 and where single component drivers are of second- or lower-order importance in relation to
467 the scale and objectives considered. This extraction of information can be accomplished using
468 global sensitivity and uncertainty analysis models that identify the important information
469 for the stated objectives. It is often the case that the emergence of systemic patterns arises
470 only from a subset of critical drivers, whose importance and interaction with other factors
471 is crucial to understanding the behavioral modalities and dynamics of the system. This
472 holistic understanding of complex systems can be achieved by exploring the whole system
473 landscape of potential states and their drivers, with emphasis on the dynamical trajectories
474 and stressors that lead to emergent patterns (Figures 3 and 7; the patterns depicted in
475 the latter figure illustrate the typical probability distribution function of infectious disease
476 cases, in the form of power-law and exponential distributions, corresponding to epidemics
477 and endemics, respectively).

478 **3.2 Time, Information, and Resilience**

479 At a foundational level, it is reasonable to suppose that *time* should factor prominently in
480 the theories and conceptual schemes that we devise to address resilience-related challenges
481 and concerns; in truth, however, this topic has been given scant attention in the literature.
482 Philosophers have, of course, long preoccupied themselves with the nature of the relationship
483 that human beings have with time. Though such discussions are somewhat removed from our
484 concerns here, an awareness and understanding of how humans *perceive*, *experience*, and *value*
485 time can meaningfully guide our efforts to broaden the conceptual terrain that contextualizes
486 and informs our understanding of resilience.

487 We begin this portion of our discussion by considering the situation where one or more
488 individuals (say, e.g., the “resilience managers” that Linkov et al. (2014) envision) are tasked
489 with creating and/or sustaining system-level resilience; such individuals must, as a matter of
490 necessity, come to understand that resilience must be viewed through the a complementary
491 set of lenses that partition time into various time horizons — ranging from the immediate
492 to the long-term. As an example, take society’s desire for *population resilience*, and the
493 events surrounding Hurricane Katrina in 2005 as a specific case in point. Some have argued
494 (Cutter et al., 2013; Tierney, 2014) — rightly so, we believe — that Hurricane Katrina was,
495 in fact, a *necessary event* for building resilience over time in that geographic region. The
496 probative portions of this argument require a general systems theory perspective, together
497 with a holistic view of collective action, taking into account all relevant factors affecting the
498 built vs. natural environment, together with an understanding of the attendant influence that

499 these factors and events have on political institutions and stakeholders' ability to effect change
500 directed at the development of effective flood protection systems. Similar arguments can be
501 made about Hurricane Sandy and the 9/11 terror attacks (Sarapas et al., 2011; Valverde and
502 Convertino, 2019). To be sure, arguments of this nature are inherently difficult, given that
503 we typically know more about the past than about the future — which in turn complicates
504 efforts to interweave causation and intervention in ways that give rise to desirable end-states
505 over time. This said, it is perhaps an inevitable feature of human existence and mankind's
506 (seemingly insatiable) desire for material progress that the discovery and elimination (or
507 minimization) of points of failure cannot occur without the occasional occurrence of negative
508 — sometimes even catastrophic — events. In this way, *failure constitutes an inalienable*
509 *element of resilience, understood vis-a-vis the arrow of time*; given this line of thought, it is
510 not surprising that much of the resilience management literature is grounded in theories of
511 adaptive management (Holling and Gunderson, 2002; Convertino et al., 2013), which mimics
512 the adaption, for biological systems, to fast and slow external changes.

513 Given these considerations, it is interesting to observe that many contemporary accounts
514 of resilience seem predicated on the idea that resilience is only an inherent, though perhaps
515 ultimately manageable, property of systems. Indeed, the notion of resilience as an “emergent”
516 property of systems (Kauffman, 1993; Jiménez et al., 2008; Anderson et al., 2013; Seoane and
517 Solé, 2015; Tandler et al., 2015; Lansing et al., 2017) is strangely absent from several recent
518 characterizations of the concept (see, e.g., Linkov and Trump (2019)). As we have already
519 noted in portions of our discussion above, biological science has much to teach us about
520 this kind of phenomena. Traversing the micro-to-macro cellular life and population scales
521 reveals instances where resilience is a continually evolving process, involving consideration
522 of the intertwined evolution of human and natural systems. Human history is, of course,
523 replete with examples of populations who have learnt, over time, how best to respond to
524 flooding, fires, crime, outbreaks of infectious and chronic diseases, war, and other large-
525 scale events (Diamond, 2005). There are aspects of this learning process that are overt and
526 intentional, and others that are less intentional, arising, sometimes, by accident or through
527 trail-and-error. Given the ever-expanding reach of data collection and analysis, combined
528 with burgeoning advances in artificial intelligence, computational science, sensor technologies,
529 and global system science, it is reasonable to suppose that the window of unpredictability
530 about past risks (i.e., “known knowns”) will be narrowed (though, of course, perhaps never
531 entirely closed), but new risks will emerge in relation to innovation and surprise. Almost
532 surely, the unexpected/unanticipated will still occur, and perhaps with even greater frequency
533 and/or severity (considering the dramatic changes the world is undergoing, e.g., climate

534 change, technological innovation, globalization, etc.). Such occurrences are likely to defy
535 expectations that are predicated on inferential mechanisms that presuppose stable historical
536 baselines, structural regularities, and the like. The tightly coupled nature of these systems,
537 together with the inherently “reflexive” nature of modern technological society (Beck, 2009),
538 almost ensure that mankind will underestimate risks. Even more broadly, hypothetically,
539 even our current resilient zeitgeist may be challenged, due to truly unexpected events that
540 force us to revise our current information and values, with dramatically different information,
541 in turn leading us to new conceptual (and computational) frames and modes of discourse and
542 analysis. The fundamental question that emerges from such possibilities is this: is there some
543 critical information that is always valid and upon which we can always build upon? This is
544 a line of questioning to which we now turn.

545 **3.3 Criticality, Predictability, and Resilience**

546 As discussed earlier, it is well understood that complexity theory provides a number of useful
547 analogies to physical systems that can significantly aid efforts to (i) improve theoretical and
548 computational models of these systems; (ii) understand system-level dependencies; and (iii)
549 guide the design and monitoring of complex systems by considering inner criticalities and
550 externalities. As instrumental as these models and frameworks are, there is a method-centric
551 tone that runs through significant portions of the resilience literature, much of it motivated
552 by a desire, on the one hand, to question the usefulness of traditional risk assessment tools
553 for assessing/measuring resilience, and a desire, on the other, to call for new “frameworks
554 and models enabling system-wide and network-wide resilience analysis” (Linkov et al., 2014).
555 Taken as a whole, these strands within the literature are not altogether successful in putting
556 across a coherent picture of resilience, for reasons which we now consider.

557 We begin by noting that the notion of “unpredictability” factors prominently in the nar-
558 ratives of both academic and non-academic commentators about resilience. Linkov et al.
559 (2014), for example, argue that “traditional risk assessment tools are limited in their use-
560 fulness for quantitative analyses of resilience”; at the same time, these same authors offer
561 prescriptions and illustrative case studies that seem distinctly rooted in traditional risk as-
562 sessment frameworks and models.

563 Our prevailing conceptions of risk require careful consideration to both sides of the tra-
564 ditional risk equation — an awareness/understanding of threats and hazards must in some
565 way be conjoined with ways to think and talk about consequential outcomes that play an
566 important role in the kinds of societies that we wish to inhabit.

567 It is not unreasonable to suppose that the gradual abandonment of the Gaussian view of

568 natural systems phenomena, combined with recently developed (and future) analytical and
569 computational tools capable of providing the mapping of systems' probabilistic landscape
570 (Figures 3 and 4) (i.e., systems' states and all trajectories considering all potential drivers
571 and their combinations) will, over time, increase the predictability of events that are currently
572 thought to be unpredictable.

573 Ultimately, we are inclined to believe that there are good reasons to suppose that “un-
574 predictability” should not factor prominently in our willingness to accept the claim that
575 traditional risk analysis tools “are no longer sufficient to address the evolving nature of
576 risks in the modern world” (Linkov et al., 2014). In truth, we are inclined to believe that the
577 dilemma that unpredictability poses in any discussion of resilience is not either/or, nor should
578 it be seen to be conceptually or practically “fatal”. The sensibility of this viewpoint can be
579 argued a number of ways, including (i) the ability to render complex systems amenable to
580 parsimonious analysis by exploiting recurrent patterns arising from universal topological fea-
581 tures; (ii) the rareness of completely chaotic behavior versus critical dynamics;⁹ and (iii) the
582 oftentimes poorly-motivated quest for precision in analyzing extreme events. The latter point
583 is, unfortunately, a bias of modelers who look to maximize model predictive accuracy in ways
584 that are spurious (due, mainly, to the limitations of the data at hand) and that often fail to
585 heed the precision-oriented limitations that system errors impose within complex systems.
586 With sound models (conceptual, analytical, computational, and practical models), it is pos-
587 sible to scale-up small events to large events, along their power-law distributions, and to
588 thereby estimate the frequency and intensity of potentially catastrophic events. An example
589 where this approach has been applied successfully comes from the fields of hydrogeomor-
590 phology and hydroepidemiology, to predict large runoff and cholera events (Bertuzzo et al.,
591 2011; You et al., 2013; Convertino et al., 2014; Convertino and Liu, 2016). Zipf's law — a
592 special power law with an exponent close to unity — is ubiquitously observed in nature. The
593 inverse relation between rank and frequency of events implies the existence of a few frequent
594 extreme patterns and numerous rare patterns. The origin and function of Zipf's law has been
595 explored with respect to information processing in language and communication evolution,
596 as well as numerous applications within natural systems. Zipf's law has also been observed
597 in the activity patterns of real neural networks, though probing its functionality in the an-
598 imal brain is a formidable task; these empirical findings suggest an incredible connection
599 between optimal decision making and criticality that can be implementable in current intel-
600 ligent computer systems. In this regard, some authors have identified a critical layer where
601 the cluster size distribution of processed data obeys a reciprocal relationship between rank

⁹N.B. that even chaotic behavior displays stable attractors.

602 and frequency. Deep learning ensures balanced data grouping by extracting similarities and
603 differences between data. Furthermore, it verifies that data structure in the critical layer is
604 most informative to reliably generate patterns of training data. Therefore, the criticality can
605 explain the operational excellence of deep learning and provide a useful conceptual vehicle
606 for probing optimal network architectures.

607 Where such considerations lead us, then, is that while we may never reach complete
608 predictability for all of the events that currently (or may possibly) interest us, advancement
609 of global sensitivity and uncertainty analyses, supported by information theory, can leverage
610 “unpredictability” as a positive impetus for exploring all system states, and to find optimal
611 design alternatives. The same predictive models can also be used for surveillance purposes
612 (Convertino and Hedberg, 2014; Vilas et al., 2017) in order to rapidly detect early warning
613 signals for potentially catastrophic events that clearly determine critical transitions (Scheffer
614 et al., 2001, 2012).

615 **3.4 System Landscape, Management, and Resilience**

616 Our commentary above goes some distance towards suggesting that risk and resilience can,
617 in certain respects, be seen as two sides of the same coin. For the design and management of
618 complex engineering systems, risk factors can be identified as causal factors affecting resilience
619 via analyses of data and the assessment of systemic-level risk(s) (Sheffi et al., 2005; De Weck
620 et al., 2011; Helbing, 2013). Our ability to arrive at credible (and requisite) representations
621 of systemic landscapes is a vitally important prerequisite to any reasoned attempt to develop
622 sensible *prescriptive* theories and frameworks directed at the design and management of
623 complex engineering systems. It is this final topic to which we now turn.

624 We begin by noting that portfolio approaches suggested in the literature incorporate sys-
625 temic purviews of risk, and are capable of considering a multitude of scenarios for complex
626 systems (see, e.g., Valverde and Convertino (2019)). Such frameworks can aid decision-maker
627 efforts to identify the optimal design paths that support optimal form and function of systems
628 in terms of resilience. Portfolio-based approaches to systems management typically embody
629 dynamical models that reflect both the “blind watchmaker” dynamics of nature (criticality à
630 la Bak) and causal external triggers, geared towards identifying optimal solutions that take
631 into account the randomness and variability of system events. Portfolio approaches also con-
632 sider the structure of the system analyzed, and they are capable of learning from previous
633 events and outcomes; further, they enable decision-makers to make optimal decisions, based
634 on both system structure and function, by identifying optimal design and management alter-
635 natives, after evaluating the (often) combinatoric space of potential alternatives, constrained

636 by available budgets and resources. The scenarios considered are also unobserved scenarios
637 — in contrast to reductionist models that only reproduce observations — that are used to
638 explore a vast plurality of potential system outcomes for taking optimal decisions in the face
639 of what is considered possible.

640 An in-depth understanding of potential system states can be built by taking advantage
641 of uncertainty propagation methods on probabilistic computational models. For instance,
642 global sensitivity and uncertainty analyses (GSUA) are perturbation methods that propagate
643 uncertainty from system drivers to outcomes (e.g. performance); these are input and output
644 factors in a model designed to predict system dynamics. An idealized example is provided
645 in Figure 8, where two drivers — labelled F1 and F2 — can affect the whole system or
646 just one of its components (it is possible to consider the whole system, or just a portion of
647 it in the physical domain). More generally, it is important to recognize that global scale
648 factors and outcomes are much like systemic scale factors; however, global factors are not
649 necessarily created by systemic components (such as networks that connect communities),
650 whereas systemic outcomes are systemically distributed. In this way, systemic outcomes can
651 be global, but global outcomes are not necessarily systemic because they can be driven by
652 concomitant local factors.

653 In the context of contagion phenomena (such as infectious diseases, but other examples
654 include cyber-attacks, false information diffusion, and species invasion), outcomes are out-
655 breaks over a region (a system's component can be a geographical area, while the whole
656 system is the whole globe). F1 and F2 can be two different pathogenic drivers, such as Zika
657 and Dengue viruses (hazards). Systemic factors could include, e.g., transportation networks,
658 while local factors might include local weather factors that determine the environmental niche
659 of pathogens (these can be vulnerability features, such as rainfall and landscape wetness in-
660 dex). Global factors can, for instance, be similar vulnerability features that are homogenous
661 across all communities (e.g., lack of medical facilities). These common global factors can give
662 rise to equivalent epidemics without the need of systemic factors, such as long-range human
663 mobility networks. A good distinction between epidemics and pandemics is likely related to
664 the presence of systemic networks which are the predominant contagion spreading feature of
665 the latter.

666 Systemic performance is not necessarily associated to one single risk, but rather to multiple
667 risks; therefore, resilience is not the complementary function of one single risk function. In
668 Figure 8, state *A* is characterized by the dominance of one stressor that acts *locally* (e.g.,
669 due to local weather) and produces local outcomes (such as a local endemics). These local
670 outcomes are typically associated by a bimodal distribution that, for instance, corresponds

671 to seasonal dynamics. State B is characterized by the coexistence of two stressors at the
672 local and global scale. State C is characterized by the predominance of one single stressor
673 that is systemic. States B and C are typically associated with one mode in the probability
674 distribution function, because hazards are typically more rare, stronger, and systemic than for
675 state A that is occurring regularly with a much smaller recurrence time. State C is typically
676 associated with a critical dynamics that is characterized by a power-law distribution of system
677 stressors and outcomes.

678 Such considerations suggest that the focus of complex system design and management
679 — including “resilience management” — should be on reducing complexity to manageable
680 levels required to achieve articulated goals and objectives (Jones, 2014). This can be achieved
681 by improving traditional modeling methods, integrating these methods with real-time sen-
682 sors, finding optimal design rules by investigating analogous systems, and mining relevant
683 information from data. From this vantage point, the prescriptive import of the prevailing
684 resilience paradigms require an important conceptual coda. To be sure, risk managers should
685 seek to identify critical transitions, critical states, tipping points, and the like, wherever and
686 whenever possible; still, the fact remains that *much of this learning will occur in the wake of*
687 *accidents and catastrophes*. Rarely will “zero-event, zero-consequence” or even “early integra-
688 tion” approaches to resilient design be prudent or even feasible; in truth, in some instances,
689 such approaches may even be counter-productive (Park et al., 2013).

690 As with resilience, risk can be independent of any hazard because risk is a function
691 related to a definable set of relevant system outcomes (such as a structural failure, species
692 extinction, or disease outbreak), which can occur without any external factor occurring or a
693 clear failure of specific intrinsic factors. These risks, or decays in systems’ performance, are
694 related to systems’ self-organization. However, systems’ self-organization alone is not able to
695 entirely alleviate our persistent inability to predict completely the whole spectrum of systems’
696 outcomes. Hence, from this consideration it stems the need to include the “environmental
697 noise” in mathematical models, which allow us to have a better representation of the combined
698 self-organization–environment dynamics on complex systems. Therefore, risk and resilience
699 are both evaluative functions of a desired performance (e.g., a “systemic ecosystem service”);
700 both functions can be seen as the first derivative of the system’s performance function, and
701 their negative or positive sign determines their connotation of being risk or resilience. The
702 same models can be used to evaluate risks as well as resilience about criteria that can have a
703 positive or negative connotation, depending on how these criteria are viewed and managed.
704 The dynamics of these criteria (e.g., resources to manage) are dependent on both intrinsic
705 and extrinsic dynamics, and can be included into decision analytic frameworks and models

706 that aid efforts to manage systems' performance.

707 4 Conclusion

708 Our discussion above has sought to offer a constructive commentary concerning important
709 aspects of our evolving conceptions of, and approaches to, resilience. In so doing, we have
710 availed ourselves of a number of disparate views of resilience, each of which provides a purview
711 and lens through which to construe the syntax and semantics of different paradigmatic con-
712 ceptions of resilience. We now offer a closing commentary that looks to provide a tentative
713 outline of possible future research directions that takes the pluralistic conception of resilience
714 set forth here as its point of departure.

715 To this end, we begin by noting that if resilience is a desired or sought after property
716 of systems (i.e., of societies, cities, communities, etc), then, all things being equal, it seems
717 reasonable to suppose that “stakeholders” — broadly construable to include all forms of life
718 on this planet — will prefer to enjoy the benefits that resilience brings/provides sooner rather
719 than later. Just how such benefits are to be quantified and evaluated is a problem that poses
720 vexing challenges for system planners and risk managers. A partial list of such challenges
721 will include the complex preference structures that are endemic to these systems, as well as
722 the multifaceted nature of the potential benefits (arriving or realized over both short- and
723 longer-term time horizons). To be sure, it is far too easy to suppose that the challenges
724 that resilience poses for affected stakeholders are somehow surmountable by appealing to *one*
725 paradigm, or by subscribing to a “one-size-fits-all” mentality as to how such problems might
726 be thought through and addressed in practical terms. Our remarks here perhaps go some
727 distance towards making the case that there are, in fact, a plurality of “paradigms” that
728 are capable of informing our understanding of how such matters might best be framed and
729 approached.

730 As we have observed in the numerous examples cited in our presentation above, each
731 problem domain — be it infrastructure, public health, technology, and a host of others —
732 presents its own unique set of challenges and objectives. In this light, discussions about
733 resilience “paradigms” are best grounded in carefully posed questions that are capable of
734 forming the basis of research agendas that confront the problems and limitations of prevailing
735 theories and methodologies. To illustrate, we close our discussion by suggesting four lines of
736 research that hold the promise of expanding upon the pluralistic conception of resilience that
737 we have outlined here:

- 738 • Computationally efficient models for better characterizing the stochastic structural and

739 behavioral modalities of resilience in complex systems (e.g., identifying structural and
740 functional scale-invariant factors responsible for emerging stable patterns, and factors
741 that maintain or increase resilience, avoiding undesired critical transitions);

742 • Sensing and monitoring technologies, with emphasis on characterizing uncertainty, igno-
743 rance, and surprise (e.g., development of models capable of exploring how quick-shocks
744 and pre-cursor events can lead to transitions of interest, given their relevance to low
745 probability/high consequence outcomes);

746 • Improved methods for identifying and visualizing system drivers, especially in systems
747 with complex dependencies and interactions;

748 • Analytic frameworks that combine theories of resilience with theories of intentionality
749 and collective action.

750 Many of the research topics outlined above have a broadly construable *participatory* ele-
751 ment, with the overarching goal of achieving a type of resilience that is arrived at by minimiz-
752 ing the frequency and magnitude of undesired system effects, via instruments oriented towards
753 anticipation, sensing/monitoring, learning, and adaptation. Other research trajectories are,
754 of course, possible, and entirely consistent with the spirit that underlies the pluralistic con-
755 ception of resilience that we have sketched here. Ultimately, we must strive to confront the
756 essential tension that arises out of our need to view resilience, on the one hand, as an intrinsic
757 quality of all life forms on Earth and, on the other, as one of a number of viable instrumental
758 means to a plurality of possible trajectories and desired outcomes for humankind.

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963 **Figure Captions**

964 **Figure 1. Holistic Conception of Collective Phenomena Leading to Scale-Free**
965 **Resilient Networks.** Individuals self-organize around collective decisions that result in
966 emerging patterns. These patterns, such as patterns of human mobility (the middle plot rep-
967 resents average scale-free mobility fluxes in NYC from and to Manhattan using the shortest
968 path tree from any location to another), are the by-product of (bottom-line) local interactions
969 among individuals constrained on a mobility infrastructure (i.e., multiple sets of transporta-
970 tion networks), typically designed by structured, top-down decisions. Top-down decisions
971 are planned via decision-analytic models (bottom of the figure, for instance) that can inte-
972 grate stakeholder needs and preferences, and network features. The spontaneous criticality
973 of living systems enhanced by critical decision-making can sustain optimal complex system
974 performance and resilience trajectories. As is the case for natural networks, the local search
975 for local minimum energy expenditure under global constraints and objective(s), leads to
976 optimal scale-free networks.

977

978 **Figure 2. General Conception of Pluralistic Resilience for Complex Systems.**
979 (A) Complexity, sensitivity, and uncertainty morphospace for complex systems. These fea-
980 tures of complex systems can be related to systems' cognition, spatio-temporal scale, and
981 entropy that defines the information of any system (e.g., data) or models (as "information
982 machines") representing the real systems. (B) Different conceptions of resilience proposed in
983 the literature: single event system's response curve and performance-driver system's land-
984 scape in the left and middle plots. The right plot shows our conception of resilience, where
985 the pdf of system's state is evaluated in different time periods; the transition between pdfs
986 toward desired system's performance reflects system's resilience. The same temporal consid-
987 eration, i.e., how the system responds to stressors, can be made for the other two resilience
988 views, but fails to consider the long-term trajectory, the whole spectrum of stressors, intrinsic
989 system's drivers including stakeholders' preferences, and surprises.

990

991 **Figure 3. Long-term Trajectories of System's Performance.** The change from
992 one system (average) performance state to another typically involves a long-time span, which
993 is different from the short-term response to stressors that may show a high degree of non-
994 linearity (e.g., small stressors can cause large effects). The change from one single stressor
995 state to another is typically associated with an alteration of system function (or, more holis-
996 tically, performance), observable in the increased variance of system components (depicted
997 as change of node color, from white to red), before the change occurs. For major transitions,

998 this change is also observable in the high variance of system structure (e.g., connectivity
999 among nodes). A “resilient” stable state generally corresponds to a low variance critical
1000 dynamics (e.g., network with “white nodes”), but mutable in case of necessity. The black
1001 trajectory shows a resilient system that increases system performance over time, versus a
1002 resistant system that recovers from point stressors, but does not increase the performance
1003 over time (green trajectory), and a anti-resilience system (orange trajectory) that does de-
1004 crease system’s performance over time. The pdf of system’s performance (Fig. 2) for the
1005 black trajectory has the highest, most positive, and least uncertain performance.

1006

1007 **Figure 4. Network-Based Dynamical System Classification.** Undirected or weakly
1008 directed networks (left), where one node is dependent on many independent nodes, is typical
1009 for linear systems. A highly direct network (right), where any node is dependent on many
1010 interdependent nodes, is typical for non-linear systems. The former can be the case of a river
1011 network, while the latter can be a biological network such as the microbiome. A risk and
1012 resilience approach is the best approach for the linear and the non-linear system. Node 1 can
1013 be thought of as the performance function to predict.

1014

1015 **Figure 5. Characterization of System Dynamics via Global Sensitivity and**
1016 **Uncertainty Analyses.** Global Sensitivity and Uncertainty Analyses (GSUA) plot (left)
1017 characterizes complex systems according to their dynamics with respect to a predicted per-
1018 formance (e.g., node 1 in the networks depicted in Fig. 4). Red nodes (i.e., model/system
1019 factors) represent a system with critical dynamics, while blue and green nodes represent a
1020 system with a linear (deterministic) and non-linear (chaotic) dynamic, respectively. Critical
1021 systems are systems characterized by scale-free dynamics that ensure high resilience. pdfs
1022 and time series on the right of the GSUA plot show the typical dynamics for different systems.

1023

1024 **Figure 6. Information Selection of Resilient Systems.** Scaling analysis of total
1025 information as a function of the information threshold. When a system transitions from one
1026 phase to another, it loses or gains symmetry. In this context there is an ideal scale-invariant
1027 region for which the total information (i.e., the *uncertainty*) that a system can gain about a
1028 system’s dynamics is the same. However, for low values of the information threshold (defining
1029 the *sensitivity* of the system) more redundancy of information exists. This can lead to a loss
1030 of information or to a higher risk of predicting risk without accuracy, due to the inclusion of
1031 irrelevant nodes. The maximum value of the information entropy has the highest utility for
1032 a decision-maker in terms of system’s predictability. *Complexity* is related to network com-

1033 plexity determined by the diverse set of functional network properties. Lowest complexity
1034 and highest sensitivity are typically associated with each other, due to the lack of redundant
1035 nodes.

1036

1037 **Figure 7. Epidemiological Epitome of Complex System Dynamics.** Spatial net-
1038 work topology (of a functional nature, considering the interdependence of cases) is important
1039 in determining the dynamics of complex systems, and also in determining areas with high
1040 risk and in defining systems' resilience. In epidemiology, high risk areas are associated with
1041 persistent, large outbreaks. The persistent "bouncing-back" dynamics of these critical areas
1042 has nothing to do with the ability of the population to respond to outbreaks, but rather, is
1043 related to the intrinsic dynamics of the disease. Criticality is, in such cases, an undesired
1044 property. Resilient communities are more likely those that sustain low levels of the disease,
1045 such as the community highlighted in green. These communities tend to be more isolated,
1046 but their undesired critical performance is avoided by the isolation versus at-risk communities
1047 that are hubs of scale-free networks (e.g., the purple community). The blue network defined
1048 on the map is the *optimal transmission network*, which is the directed scale-free network
1049 (toward the capital community Colombo, depicted as the black node on the map), assessed
1050 by using the maximum transfer entropy algorithm of Servadio and Convertino (2018) on the
1051 epidemiological patterns of Leptospirosis in Sri Lanka.

1052

1053 **Figure 8. Potential System Landscape.** The system landscape represents all po-
1054 tential states of the system (and trajectories from one state to another) that are identified
1055 by system's performance pdf, as a function of a multicriteria driver function (stressors, vul-
1056 nerability, and exposure functions, derivable using traditional risk analysis methods). Stable
1057 resilient states are characterized by small total energy dissipation, minimum entropy, and
1058 low probability of system's transitions toward unstable states. These resilient states have
1059 also high free energy, which allows them to change state in case of need. The whole system
1060 landscape can be mapped via uncertainty methods, such as information-theoretic GSUA that
1061 identifies all potential system states (e.g., A, B, and C among all others) and the correspond-
1062 ing pdfs defining the likelihood of events to occur at different scales (e.g., for the whole system
1063 and for subcomponents).

1064

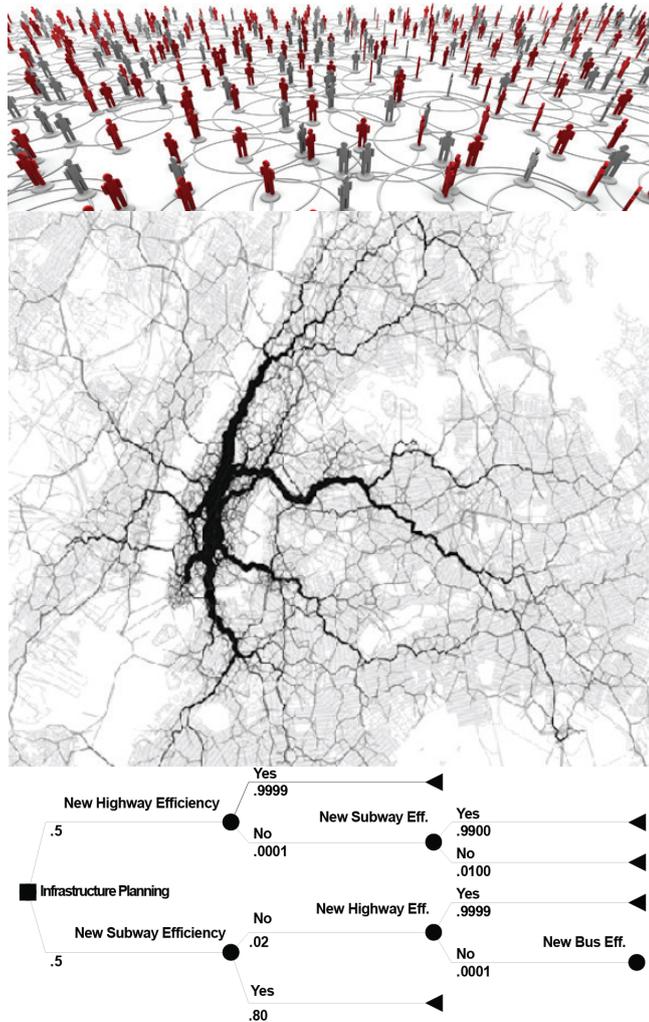


Figure 1:

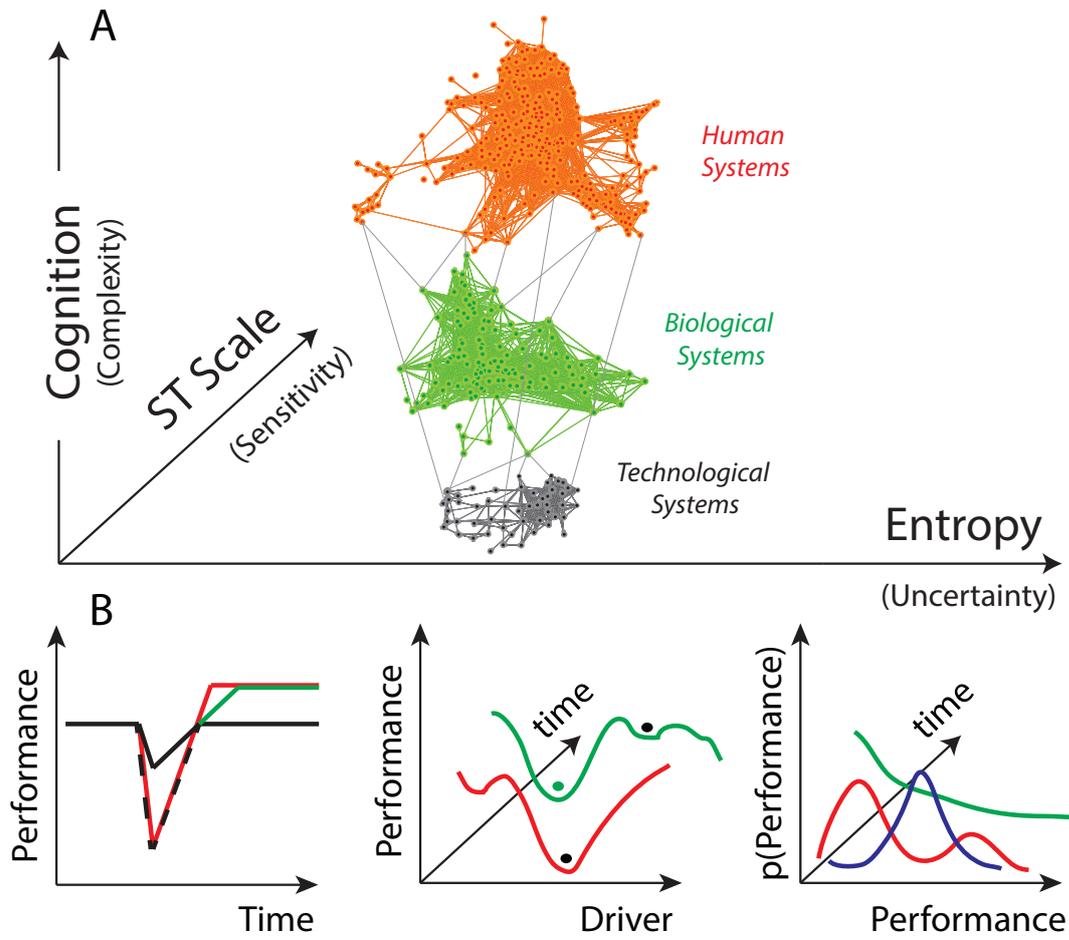
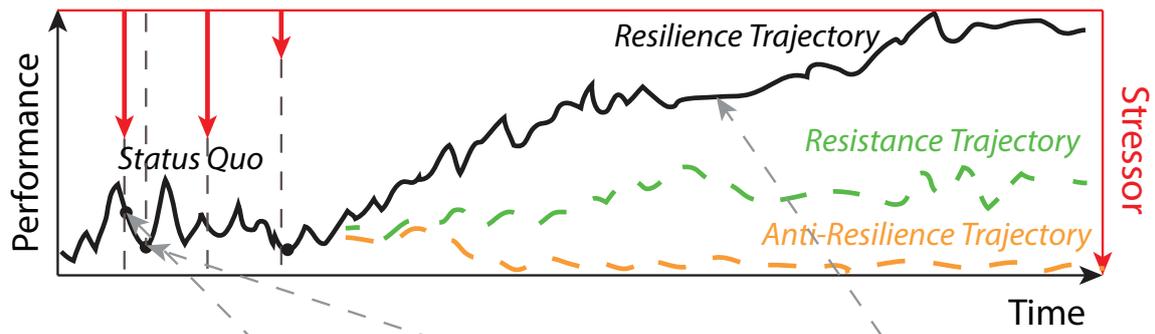


Figure 2:



Variability

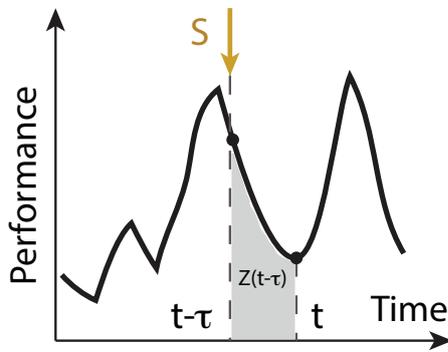
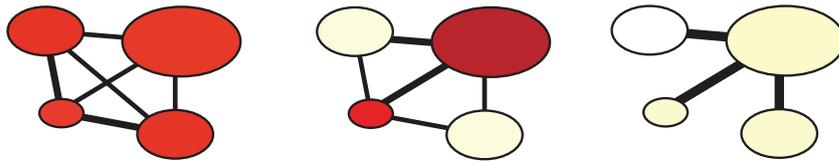
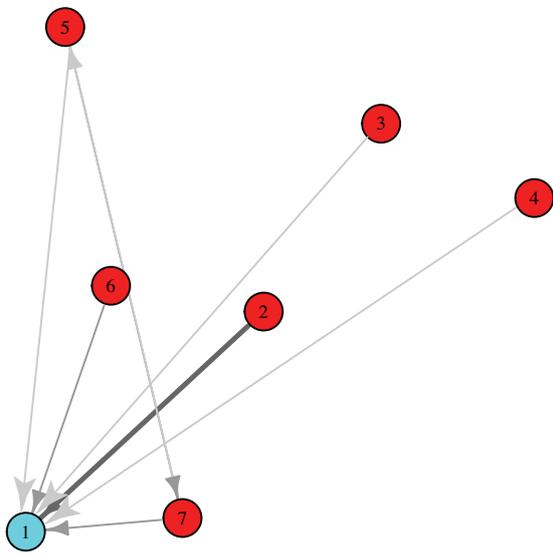


Figure 3:

Risk Approach (Linear System)



Resilience Approach (Non-Linear System)

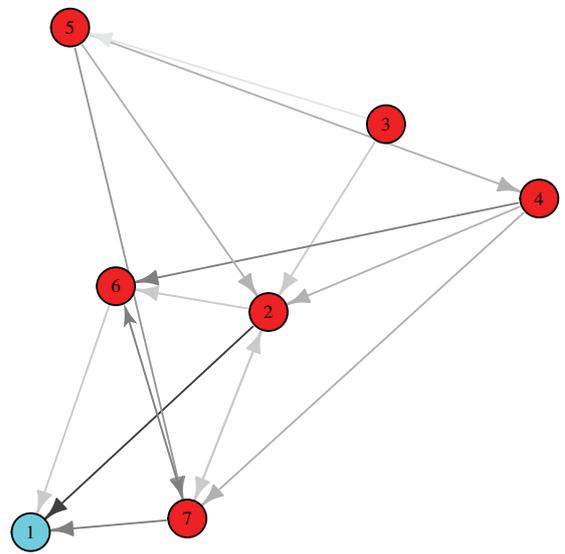


Figure 4:

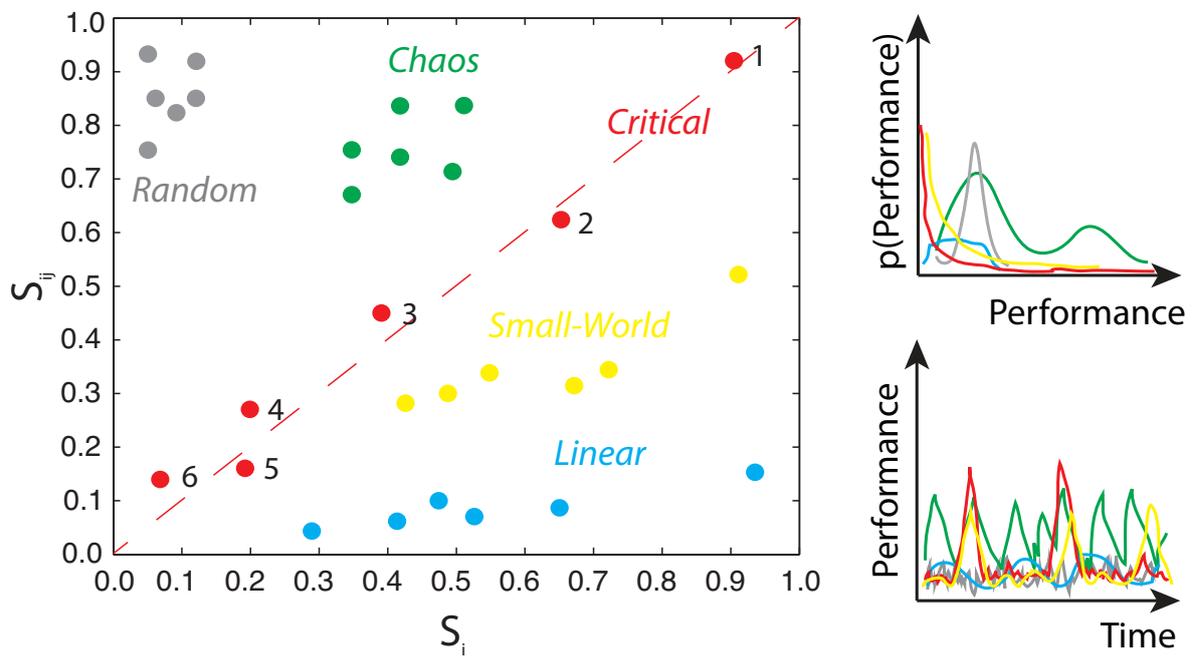


Figure 5:

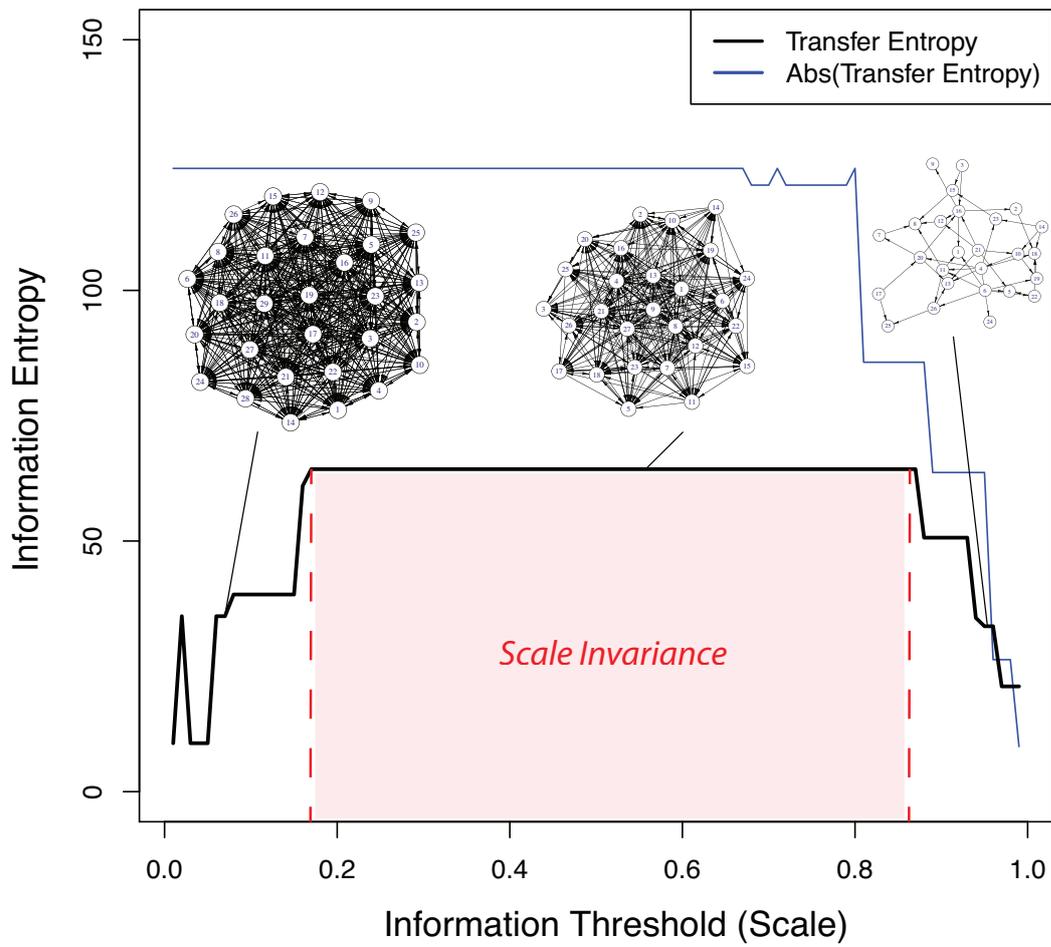


Figure 6:

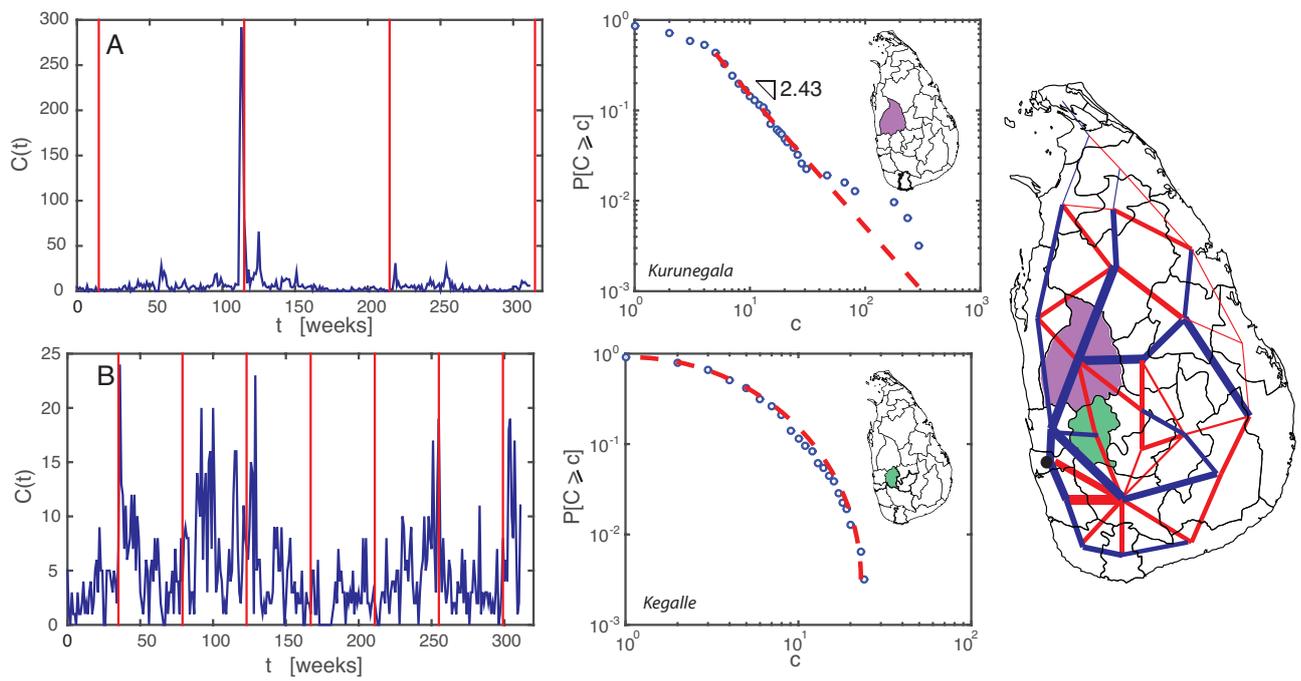


Figure 7:

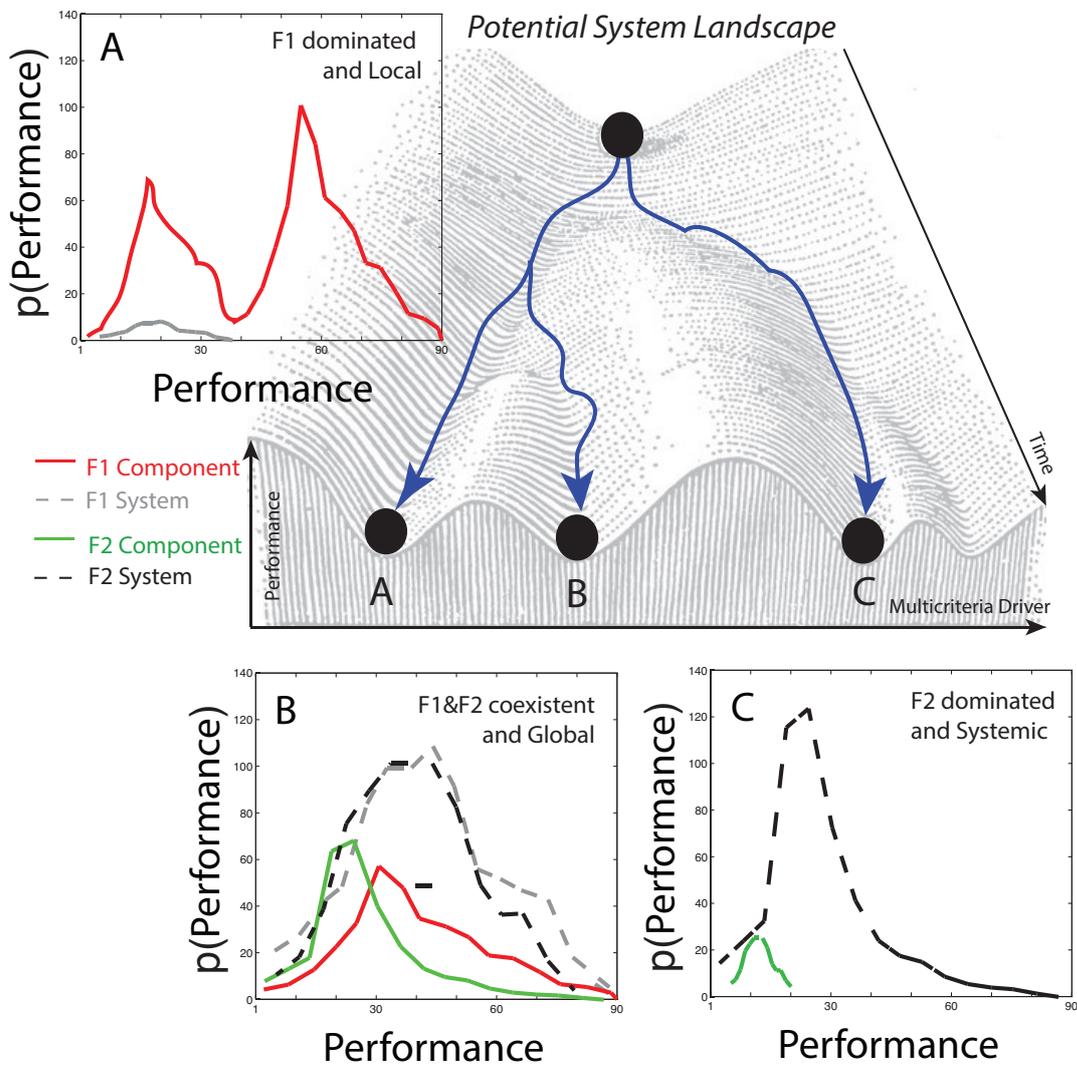


Figure 8: