Evaluating the Sustainability of an Ecological System Based on Evolutionary Multi-agent Simulations

Kazuhiro Minami, Roberto Legaspi, Member, IEEE, Tomoya Tanjo, Hiroshi Maruyama, and Yoshiki Yamagata

Abstract—Resilience to a disruptive change in the ecological system is an essential property that makes our society sustainable. There seems to be a consensus among many researchers in various disciplines that diversity and adaptability are two of the key features of resilient systems to be able to persist in, recover from, or even reorganize as a response to, time of crises. However, it has yet to be unambiguously shown how these features stand together, complementary or otherwise, in providing resilience to an ecological system that involves the flow of energy between those that convert and supply it and those that consume. In this paper, we present an evolutionary multi-agent system for evaluating the effectiveness of these features and show several insights drawn from our preliminary results.

Index Terms—Multi-agent systems, resilience, sociotechnical systems, sustainable development.

I. INTRODUCTION

Written in one of Barry Commoner’s influential legacies – his book entitled The Closing Circle [4], are his four laws of ecology, one of which is that our ecology is a system that consists of multiple parts and each part is connected to everything else, hence, what affects one can eventually affect all – the disruption or flourishing of one species will have the consequential effect on other species. This argument remains to be raised in the scientific chambers where the sustainability of our ecological system, or ecosystem, has continuously been challenged and defended. Furthermore, humanity’s influence, which was once held as exogenous has become anthropogenic [29], and unfortunately, has been evidenced as increasingly disruptive to the natural course of our ecosystem (e.g., [28][6]). Commoner is one of those who first argued against the shortage of our energy sources and the threats that beleaguer our ecosystem and worked towards its sustainability.

In the context of ecological sustainability, researchers have long been looking through the resilience lens [13] [12] [10] [11] [3][33]. Because the term resilience has been increasingly used in various disciplines and application domains, there is no explicit unified concept by which it can be referred to, and to elucidate all theories that embed it and conceptual frameworks that embody it will require volumes of written work [19]. Hence, we can instead broadly define resilience as the ability of a system to withstand perturbations and enable generalized recovery once the system fails [20]. If sustainability is about preserving some function or means that we as human beings consider as valuable to our existence and flourishing, and if it is inevitable that we face an event that perturbs or even catastrophically destroys what we aim to preserve, then “sustainability over time requires resilience at each time” [19].

Resilience thinking, which was once contained within the bounds of natural systems, has been extended with a wider scope of concepts applicable to seemingly all sorts of systems (e.g., in [14] [15] [21][34][33]). Resilience has been used to describe general features – the literature also calls this categorization strategies, principles, conditions, or capacities – of a system that allows it to be perturbed before it changes configuration or shifts regime, adapts or transforms [19]. While the resilience literature has been faithful to indicate these features that make a system resilient (e.g., in [3][20]), to our knowledge, we still need to unambiguously demonstrate how these features stand together as complementary while being cognizant of the trade-offs present in their co-existence. Our goal in this paper is to make a first step towards clarifying the nature and dynamics of these resilience features.

We particularly study two of the key features, namely, diversity and adaptability. It has been found that ecosystems that are species-rich (i.e., have species diversity [17][24][26], possess different kinds of processes (i.e., have functional diversity [26][5]), or have similar functions but have higher susceptibility to threats or to changes (i.e., have response diversity [7]), can efficiently exploit the resources they need and effectively preserve their functions even if some of their components are damaged [7]. Secondly, because systems with adaptive capability generate novel ways of operations or systemic associations, they can persist in, or recover from, crises [19]. We study how these two features stand together in providing resilience to an ecosystem involving the flow of energy between those that convert and supply it and those that consume.

To analyze quantitatively the relationships between resilience features, we employ multi-agent simulations that model basic population-resource dynamics of an ecosystem. A
multi-agent system typically consists of autonomous agents whose individual behaviors depend on their goals, the other agents’ states, and the interactions between them. We find an agent-based modeling approach appealing since multi-agent simulations running many individual-centric agents allow us to understand important systemic behaviors of an ecosystem. Also, this approach strikes a compromise between the highly formal yet abstract mathematical models and the description-rich yet plausibly ambiguous reasoning based on intuition, hence achieving plausibly good degree of flexibility and realism [32].

Although each agent is autonomous regarding its own objectives, decisions, and actions, it is still part of a whole system that demands it to interact with the other agents and also with the environment. In this sense, the ecosystem whose components are interconnected fits well as application domain of our evolutionary multi-agent system. The way we adapt here the term “evolutionary” is to refer to a modification of an agent’s characteristic for it to adapt to a changing environment.

We repeat multi-agent environment simulations, exploring a wide range of system parameters, and analyze the dynamics of system properties relevant to the resilience of an ecosystem. Our objective is to evaluate the effectiveness of diversity and adaptability to improve the resilience of an agent population in a changing environment that poses constraints to its ability to access its essential resources and thus threatens its survival.

The rest of the paper is organized as follows. Section II elucidates that the degree of flexibility and realism in our multi-agent simulations depends on basic concepts and simple models concerning the dynamics of an ecosystem. Section III covers the parameters explored in our simulation framework, and reports our simulation results with our analyses concerning the dynamics of the resilience features. We clarify our contributions in Section IV while discussing previous research related to our work. We finally conclude and suggest possible future directions in Section V.

II. MULTI-AGENT ECOSYSTEM SIMULATIONS

This section elucidates in detail our multi-agent simulation framework with a simple ecosystem, which is parameterized by the degree of diversity and adaptability in an agent population. We apply simple ecosystem modeling to our simulations to study the dynamics of interacting components in an ecosystem. The simplicity of our models allows us to focus on analyzing the relationships among resilience properties of the ecosystem.

A. Basic Concept of our Ecosystem Model

An ecosystem is formed by complex sets of symbiotic relationships among species and their environment. Scientists have approximated the number of species that inhabit the earth to be about 1.5 million¹. Commonly, when people talk about biodiversity, they are pertaining to the number of different species. Species facilitate the transfer and distribution of energy. They can be categorized in terms of the means by which they obtain energy either as a producer or a consumer.

¹ http://global.britannica.com/media/full/95049

The former produces its energy by itself. For example, plants can produce their energy from the sun by photosynthesis. Consumers, on the other hand, obtain their energy directly from producers or other consumers, which could be primary, secondary or tertiary ones in the energy pyramid. Species also interact with their surroundings, which at times may require them to adapt to certain changes. Their adapting to the changed environment can come with a cost. For example, cold-blooded species adapt to rise in temperature by residing in the shade or by not actively searching for food. This adaptation yields to the loss of energy, which they otherwise would have normally obtained.

Species exist in populations, or stocks. The North Atlantic species cod, for example, consists of several stocks, including the Canadian-Newfoundlandic, the Icelandic and the Arcto-Norwegian cod [9]. The characteristic of each stock is distinct, which may be genetic, a result of varied surroundings, or both. The change in stock size depends on several factors, including its intrinsic growth or regeneration, recruitment, natural mortality, and as a result of harvesting (and eventual consumption) by other species [9].

Since it is not possible for us to exhaustively incorporate all complexities involved in an ecosystem, we simplify our simulations by focusing on the above fundamental concepts and limiting our ecosystem model with the interactions shown in Fig. 1. There is a stock of species that is harvested as resource by some other species for daily consumption or use. This stock is replenished through its own regeneration. We can view this simply as a predator-prey or producer-consumer model. Secondly, the consumer population is characterized to be diverse, and can encounter certain constraints from their surroundings as a result of environmental change (e.g., climate change) or perturbation (e.g., natural hazard, exploitation), which consequently will require them to adapt. What is most important in our simulation is the second, i.e., how the diversity and adaptive capacity of the consumer species support their resilience to resource and environmental constraints.

![Fig. 1. Our simple ecosystem model adopted in our multi-agent simulation.](image)
having a well-fitted shell) and \( r_i \) is an amount of resource consumable or usable by the agent. A configuration \( c_i \) is a binary string of length \( L \), \( \{0,1\}^L \), where each bit in \( c_i \) tells whether the agent possesses a given characteristic. A resource \( r_i \) is a non-negative integer value. To explicitly refer to an agent \( a_i \) at time \( t \), we use a superscript for time \( t \) and denote it by \( <c_i^t, r_i^t> \).

We represent the constraints imposed by the environment in our agent model as a constraint \( C = \{c_1, c_2, \ldots, c_L\} \), where each member \( c_j \in C \) is also represented as \( \{0,1\}^L \). The constraint \( C \) is a set of agent configurations that fit well to the corresponding environment; that is, if an agent’s configuration \( c_j \) matches one of the members in \( C \), we say that the agent satisfies the constraint \( C \), which implies that the agent thrives in the environment.

We introduce next the notion of an agent’s fitness. An agent’s fitness represents the degree of fitness to the environment. While an agent’s configuration makes a binary decision whether the agent fits in a given environment, the agent’s fitness indicates the possibility of the agent’s satisfying the constraint in the near future. We compute an agent \( a_i (= <c_i, r_i>) \)’s fitness \( \eta_i \) as follows:

\[
\eta_i = 1 - ldist(c_i, C)
\]

where the function \( ldist(c_i, C) \) returns the distance from \( c_i \) to the nearest element in \( C \). This distance function can be computed using any distance metric. Our simple formula is as follows:

\[
ldist(c_i, C) = \arg\min_j \sum_{j=1}^{L} \frac{(c_{i,b} - c_{j,b})^2}{L}
\]

The logic here is that the higher the value of \( \eta_i \) is, the fitter the agent is to its environment.

While a configuration pertains to what enables an agent to achieve a specific goal, fitness refers to the viability of such ability. For example, unicellular organisms must have locomotion and movement faculties to be able to respond to their environments. An instance of this is the Euglena that has special receptors to detect light to feed itself. Another example would be warm-blooded animals who are able to hibernate, i.e., their body temperature drops, heart rate slows down, metabolic functions suspended, etc., for them to survive winter as this process allows them to conserve energy when food is scarce and migration is difficult. Cold-blooded animals like the turtles aestivate by burying themselves in mud for up to several weeks or months at a time. Another interesting case is that of the hermit crab who must use shells from other animals (e.g., snail shells) for protection against predation and drying out. Human beings, of course, make use of all cognitive, affective and physical faculties, and create tools and technologies, to obtain resources for energy.

Next is the resource stock. We compute the natural growth rate of a resource stock \( S \) using a logistic growth function, which can be considered as the simplest form of biological growth functions, but with the assumption that the environment is constrained, e.g., there are no migrations involved [2]:

\[
G(S) = rS\left(1 - \frac{S}{K}\right)
\]

where \( K \) is the carrying capacity, which pertains to the maximum possible size for \( S \). This means that as \( S=K \) further growth is no longer possible. Parameter \( r \) is the intrinsic growth or regeneration rate of \( S \). As \( r=0 \) implies that resource is non-renewable.

**C. Population-Resource Dynamics**

The agent population and resource change dynamically over time in relation to each other in our multi-agent simulations. Starting with the resource stock, it is diminished by the total amount of resource obtained by the entire agent population:

\[
S^{t+1} = S^t + rS^t - \sum_{i=1}^{N} r_i^t
\]

where \( S^t \) is the amount of resource stock at time \( t \) and \( r_i \) is an agent \( a_i \)’s resource at time \( t \). Each agent \( a_i \) acquires its resource as follows:

\[
r_i^{t+1} = r_i^t + \eta_i^t \beta
\]

where \( \beta \) is the maximum amount of resource that each agent can obtain at a time. We use the same coefficient \( \beta \) for every agent as a notion of a hypothetical fair resource share, i.e., each agent is entitled to the same amount of resource. Even though every agent \( a_i \) is supposed to get a fair share, the actual amount it gets, however, depends on how much it fits in the environment, which is indicated by the fitness factor \( \eta_i^t \) for each \( a_i \).

The amount of resource an agent \( a_i \) possesses determines not only its survival, but also influences its capacity to reproduce. If an agent has \( r_i > \theta \) where \( \theta \) is some threshold implies that agent \( a_i \) at time \( t \) is capable enough to bear an offspring and that agent \( a_i \) thus reproduce a new agent \( a' \). This means that the offspring agent \( a' \) inherits its parent \( a_i \)’s attributes as follows:

This reproduction process is similar to children inheriting aspects of their parent’s genetic traits and behavior patterns (e.g., cultural norms and beliefs). At the same time, the parent agent provides nourishment to its offspring by giving some portion of its life energy and resource for the offspring to survive. The constant \( rc \) represents the cost of giving birth

\[
a'^{t+1} = \arg\min_{c_i} \left( a_i^t, r_i^t = \frac{r_i^t + rc}{2} \right)
\]
(e.g., energy lost during birth, time resource required to rest, etc.). Conversely, if agent \( a_i \)'s resource is below zero (i.e., \( r_i < 0 \)), that means that the agent has no more capacity to survive, and, therefore, will die in the following time step. Each time an agent dies or a new one is created, the agent population is updated accordingly at the next time step. This implies that the agent population grows or shrinks dynamically over time.

D. Diversity and Adaptability

The diversity of the agent population is determined by the unique configurations present. To measure such diversity, we employ Simpson's diversity index [27] as follows (for other measures, e.g., of biodiversity, the reader may refer to [23]):

\[
D^t = \frac{1}{\sum_{i=1}^{Q^t} \left( \frac{n^t_{i}}{N^t} \right)^2}
\]

where \( Q^t \) is the number of unique qualities, therefore unique \( c \) configurations at time \( t \), in the population \( N^t \) and \( n^t_{i} \) is the number of agents with the same unique quality. We did not include at this time the existing distinctions associated with biodiversity as mentioned earlier in this paper, such as species, functional and response, since we currently focus on studying collective effects of diversity on system resilience. However, when we differentiate functional diversity and redundancy as our future work, we expect that the latter also becomes a key feature for system resilience. Such a differentiation might be achieved using a clustering algorithm that categorizes all existing configurations into multiple groups and then computes the degree of similarity among those groups, which could be possible indicators to detect redundancies (e.g., similar to [17]).

Since adaptability is the ability to generate new ways of operations in response to a dynamically changing environment, we represent this ability as the capability for an agent \( a_i \) to flip bits in its configuration \( c_i \) to move closer towards the constraint:

\[
\epsilon_i^t+1 = \text{flip bits}(c_i^t)
\]

where the function \( \text{flip bits} \) flips a given \( l \)-bits in \( c_i \). The value of \( l \) is indicative of the adaptation speed.

III. SIMULATION, RESULTS AND ANALYSES

A. Simulation Parameters

Table I enumerates the parameter values we used for our simulation. Our ecosystem model parameters pivot from one of the important sustainability indicators, specifically, the carrying capacity \( (K) \). In ecological terms, this is the maximum size of the population that can be supported indefinitely upon the available ecosystem resources and services without permanently eroding the productivity of that ecosystem [25]. Living within the limits of what an ecosystem can provide depends on three factors, namely, the population size of species \( (N) \), the amount of resource stock \( (S) \), and the per capita consumption, which in our case is \( \eta \times \beta \).

We start each simulation with a small agent population size that can grow or shrink depending on the dynamics involved in the simulation. Each agent is encoded as a 16-bit string and starts with 10 resources. At each iteration, each agent will need 200 resources to reproduce. We want to note here that we tested for several values for these agent-related parameters. The simple reason for us choosing the initial parameter values is because they allow our agent population not to grow exponentially so fast or become extinct so quickly. Furthermore, we also consider two types of an agent's adaptability, namely, random and intelligent. While the former simply requires flipping a certain number of randomly chosen bits, the latter flips a specified number of bits in \( c_i \) to move towards the least-distant component of the constraint \( C \). Lastly, we test for different diversity indices of the initial agent population. It is important to note that our agents are myopic, i.e., they lack the discernment or long-range perspective in thinking or planning across multiple time periods and instead focus on the current time step.

As for the dynamically changing environment, our simulation creates a new constraint at time \( t \) by adding or removing a specified number of its components from time \( t-1 \). This is analogous to a gradual change in the environment. Furthermore, we simulate the scenario where shocks or perturbations are randomly introduced in the environment by totally changing the constraint \( C \), i.e., by replacing all of its components with new randomly selected configurations.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ecosystem Model</strong></td>
<td></td>
</tr>
<tr>
<td>Carrying capacity ((K))</td>
<td>2,000,000</td>
</tr>
<tr>
<td>Regeneration rate ((r))</td>
<td>1</td>
</tr>
<tr>
<td>Initial stock ((S^0))</td>
<td>(K)</td>
</tr>
<tr>
<td><strong>Agent</strong></td>
<td></td>
</tr>
<tr>
<td>Initial population ((N^0=K*small_const))</td>
<td>100</td>
</tr>
<tr>
<td>Initial resource of an agent ((r_i^0))</td>
<td>10</td>
</tr>
<tr>
<td>Resource required to reproduce ((\theta))</td>
<td>200</td>
</tr>
<tr>
<td>Bit length ((L))</td>
<td>16</td>
</tr>
<tr>
<td><strong>Adaptation</strong></td>
<td></td>
</tr>
<tr>
<td>Adaptation strategy</td>
<td>{random, intelligent}</td>
</tr>
<tr>
<td>Adaptation speed</td>
<td>1</td>
</tr>
<tr>
<td><strong>Diversity</strong></td>
<td></td>
</tr>
<tr>
<td>Diversity index</td>
<td>{1, 10, 50, 100}</td>
</tr>
<tr>
<td><strong>Constraint</strong></td>
<td></td>
</tr>
<tr>
<td>Initial constraint size</td>
<td>{13, 26}</td>
</tr>
<tr>
<td>Constraint change</td>
<td>{gradual, abrupt}</td>
</tr>
</tbody>
</table>
Fig. 2. The various result graphs are representative of the trends in our simulations. For every set of simulation conditions, we record the values of the agent population \( N \), stock size \( S \), and average per agent resource harvest/consumption \( \eta \times \beta \). Figs. 2-a to 2-c show the different Case-1 scenario results, while Figs. 2-d and 2-e demonstrate trends in Case-2 scenarios.

(a) Case-1 scenario; gradual change of constraint (three components at each iteration); intelligent adaptation; maximum number of iterations is \( 10^4 \)

(b) Similar to the conditions in (a), where the only difference is that abrupt changes to the constraint were introduced at random intervals during simulation

(c) Similar to the conditions in (a), but with random agent adaptive capacity

(d) Case-2 scenario; with more frequent abrupt changes in the constraint; random agent adaptive capacity; maximum duration of simulation is \( 2.5 \times 10^3 \)

(e) Similar to (d) in conditions but with the agents intelligently adapting to abrupt changes in the constraint
B. Simulation Results and Analyses

We compile all our result graphs in Fig. 2. The purpose why we lump all together the graphs in one figure is for the reader to immediately and conveniently see the over-all picture and what our results suggest. As we mention in Section II, since existence within the limits of the ecosystem services depends on the population size \( N \), resource stock size \( S \), and per capita consumption, given as \( \eta \beta \), we present our results along these three parameters. The horizontal axis of each graph represents the number of iterations (or time steps) in our simulation. Each graph shows the behavior of the agent population with corresponding initial diversity indices \( D = \{1, 10, 50, 100\} \). We aim to check the effect and outcome of starting with a diversity-poor or diversity-rich population. During the course of the simulation, the diversity index is re-computed as per (1).

As can be seen in all the graphs, our simulations end with the agent population becoming extinct due to one of two reasons, as follows:

- **Case-1**: The agent population did not obtain enough resource, which consequently hindered it from populating. This is shown in Figs. 2-a to 2-c.
- **Case-2**: The agent population was able to acquire enough resources to populate over time until the point when the increase in population became exponential. At that point, the carrying capacity could no longer sustain the fast increasing population and the stock size eventually depleted to zero. This is shown in Figs. 2-d and 2-e.

In the early stages of our simulation design, we were trying several parameter values to see if there were cases where the simulation would not end in this extreme case; instead the population size showing, for example, a bell curve and sustaining itself. However, due to the random characteristic of major variables, e.g., constraint and agent configuration changes, it became difficult to really control the simulation, so instead, we just let the patterns to emerge. Needless to say, however, our results are still relevant and meaningful as they provide real-world implications. For example, in a human societal sense, Case-1 scenario is analogous to populations in a poor settlement where resources are scarce or in situations where the population is hindered from reproducing, either naturally or due to situational constraints (e.g., financial, unemployment, discrimination, etc.). Case-1 can also be representative of ecological species that became extinct due to environmental constraints, natural hazards, or human exploitation. Case-2, on the other hand, is representative of the case where human society, for example, continues to exploit the natural resource while ignoring the negative effect of significant population increase. This is also analogous to a predator species invading, dominating and eventually consuming the entire prey species in one location.

More importantly, however, is that even if our simulations end with the extinction of the agent population, this does not all sideline or deter us from achieving the objective of our study. In fact, it allows us to immediately obtain the answer to our fundamental question, i.e., *what is the impact of resilience features and are they complementary?*

We shall now look into the simulation results and provide our analyses, starting with the outcomes in Fig. 2a where the situation involves intelligent adaptations by the agents and gradual changes are imposed on the constraint. To implement a gradual constraint change, the simulation program randomly adds or removes three constraints per time step. We find in the figures that the extinction of the diversity-poor population (with \( D=1 \)) is faster than the others. The life duration of the most diverse population (with \( D=100 \)), on the other hand, is longer than the rest (it lasted for \( 10^5 \) iterations). Furthermore, as evidenced by the graph for “ \( \eta \) (average) \times \beta \)”, the diversity-rich populations are more effective in obtaining their resource, which implies that they are more fit to the constraint and maintain higher \( \eta \) values.

Fig. 2b shows the results when the simulation program introduces random and abrupt shocks by completely changing the constraint components. It can be seen here that, as compared to the results in Fig. 2a, the agent populations became extinct faster, with the most diversity-rich population lasting for only \( 2.5 \times 10^3 \) iterations. We note here that we held the same horizontal axis length in Figs. 2a and 2b to compare their agent populations’ life durations. This suggests that the occurrence of severe shocks can shorten the lifespan of a generation. Another interesting aspect we want to note is that by closely inspecting the graph in Fig. 2b(N), we can see points in time where the populations experience major shocks and their sizes go down abruptly, and the populations of higher initial diversity “recovered” more after the shocks and eventually last longer. We highlight this aspect below in Fig. 3.

![Agent Population (N)](image)

**Fig. 3.** After the occurrence of major shocks, the populations with higher initial diversity indices were able to sustain themselves more after the shocks.

Fig. 2c represents the last major aspect we want to point at this time. The simulation scenario was the same as that of Fig. 2a, except that the adaptive capability of the agents is made random. It can be seen that all four kinds of populations became extinct faster, with abrupt decrease in populations right at the beginning, as compared to the ones in Fig. 2a. This means that since their adaptability is random, there was no adaptability to satisfy the constraint. What is more interesting for us, however, is that it is not necessarily the most diverse...
population \((D=100)\) that lasts the longest, nor was it the one which had the highest fit in a random-adaptive condition. As we recall, this seemed to occur most of the time, if not always, as we tried some more simulations with the same condition. An implication of this is that even if the population was more diverse, without being more adaptive to the constraint, the population is still likely to degenerate more. This and the previous two results may suggest that diversity and intelligent adaptive capacity when complementing each other can help a system become more resilient.

We can hold the same analyses and insights above as we observe closely the results in Figures 2d and 2e, which are representative of Case-2, but with one particular insight added. Here, we immediately tested for the condition where abrupt shocks were introduced more often. In these two graphs, we hold the horizontal axis length equal to see the difference in terms of the populations’ life span. To immediately see this difference, we put up first the results where adaptation was made random, in Fig. 2d, followed by the results with intelligent adaptation strategies. We immediately see that as the agents became more adaptive and fit to the environment, the more resources they obtain, and the faster their population size increases. The result, of course, is that the stock size was also quick to deplete. Our additional insight, therefore, is that if a system becomes highly adaptive, satisfying more each time existing constraints while consuming its available resources without being cognizant of their depletion rate, that system will eventually collapse.

IV. RELATED WORKS

There is no doubt that the breadth and depth of the literature of ecological resilience research is significant given that ecology is one of the first sciences where sustainability and resilience thinking was infused [4][13]. It is also the case that agent-based modeling [8][16][1], as well as system dynamics modeling [30], have been employed to help test various hypotheses in ecological resilience research. Our focus, however, is to study the evolutionary ecology of artificial artifacts. Specifically, we investigate the desirable global properties of an ecological system that makes it resilient to a dynamically changing, as opposed to static environments. Furthermore, it is also our aim to study complementary relationships between, and possible trade-offs among, key resilience properties. Finally, we chose a multi-agent system as a testbed for our study to scale across other domains since many complex systems in various domains have been implemented as a set of autonomous self-organized entities [22].

Secondly, our simulation system consists of multiple agents, wherein each agent can be viewed as a digital organism [31]. As such, we can provide these agents with the notion of adaptation and self-replication simply by manipulating their configurations (which we implemented here as bit-strings). It is the case, however, that while other research focus on the mechanisms for deriving complex organismic features in evolutionary processes (e.g., [18]), our aim is to model and investigate the resilience features of evolutionary agents in a dynamic environment.

From our previous investigation [22], we applied in this paper a more realistic scenario by incorporating a basic ecosystem model in our multi-agent simulation.

V. CONCLUSION AND FUTURE WORK

We conducted various multi-agent simulations with a basic ecosystem model while changing system parameters to obtain detailed measurements of the resilience features of dynamic agent populations. The two specific resilience features that we observed here are diversity and adaptability. The results of our simulations are not primarily aimed to answer issues in ecological system, albeit we used an ecosystem model to guide our simulations towards a more realistic scenario, nor to study the processes involved in the evolution of digital organisms, but to report what may be existing relationships among key resilience features.

Our results suggest that an agent population that is both diverse and adaptive to changing environmental constraints are more resilient at the wake of major shocks. This implies that even though an agent population is diversity-rich, with the absence of an adaptive capacity, that population can still lend itself vulnerable to perturbations. This also implies that an agent population with lesser diversity is more likely to have less adaptive capacity compared to diversity-rich populations.

We hope that the observations gained from our multi-agent simulations motivate the community to look further into the implications of those results and help further other researchers to learn design principles for building resilient systems.

VI. REFERENCES


[10] C. Folke, S. Carpenter, B. Walker, M. Scheffer, T. Elmqvist, L. Gunderson, and C. Holling, “Regime shifts, resilience, and biodiversity...

VII. BIOGRAPHIES

Kazuhiro Minami is a research associate professor at The Institute of Statistical Mathematics in Japan. He has been working on security and privacy in pervasive computing particularly focusing on secure information sharing among mutually untrusted parties. He is currently working on new software engineering disciplines for developing resilient ICT systems, which could recover from disastrous situations in a flexible and graceful way. After finishing a Ph.D degree, he spent several years as a lecturer and a postdoctoral researcher at University of Illinois, and then took a position of an associate professor at National Institute of Informatics until March 2012.

Roberto Legaspi (M’2011, F’4) was born in Manila, Philippines. He obtained his PhD degree from the Graduate School of Information Science and Technology, Osaka University, Japan. He is currently a research associate professor at the Research Organization of Information and Systems, Transdisciplinary Research Integration Center and is working within the auspices of The Institute of Statistical Mathematics. For more than a decade, he has been addressing compelling issues in the area of human behavior computing for human-centric intelligent system interactions. His current research involves looking into various system resilience theories, frameworks and applications through the lens of behavior computing.

Tomoya Tanjo is a technical assistant at The Institute of Statistical Mathematics in Japan. He obtained his PhD degree in 2012 from the Graduate School of Engineering, Kobe University in Japan. From 2012 to March 2013, he was a project researcher at the National Institute of Informatics. He has been working on artificial intelligence, especially constraint programming, Boolean satisfiability, and answer set programming. He is currently working on representing and developing resilient systems by using these frameworks.

Hiroshi Maruyama was born in Yokohama, Japan in 1958. He graduated from The Graduate School of Science and Engineering, Tokyo Institute of Technology in 1983. He joined IBM Research, Tokyo Research Laboratory and worked on various computer science fields such as logic programming, natural language processing, machine translation, hand-writing recognition, XML, Web services, and security. From 2006 to 2009, he served as the director of IBM Tokyo Research Laboratory. In 2011, he joined The Institute of Statistical Mathematics where he is engaged in researches on services science and systems resilience.

Yoshiki Yamagata graduated from the University of Tokyo (PhD in System Science). Since 1991, he works at the National Institute for Environmental Studies (NIES, Tsukuba). Currently, he is studying about the climate risk management as Principal Researcher of Center for Global Environmental Research (CGER). He is also affiliated with IIASA (Vienna) and Institute of Statistical Mathematics (ISM, Tokyo). His recent research topics include: Land use scenarios, resilient urban planning and Spatial network analysis. He has lecture series at the University of Tokyo, University of Tsukuba and Hokkaido University. Internationally, he has contributed as Lead Author of IPCC, Steering Committee of “Global Carbon Project” and Editor of “Applied Energy”, etc..