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Emergent Properties of Scale in Global Environmental Modeling – Are There Any?

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ABSTRACT

This essay argues that much of the concern over issues of scale in the modeling of complex human-environment systems – of which integrated assessment models are a special case – tends to be preoccupied with bottom-up aggregation and top-down disaggregation. Deep analysis of the underlying explanation of scale is missing. One of the intriguing propositions of complex systems theory is the emergence of new structures at a high level of scale that are difficult if not impossible to predict from constituent parts. Emergent properties are not the mysterious creation of ''new material'' in the system, but rather the placement of the components of the system into their logical contexts (scales) so that the observer/modeler can see structures arise from them for the first time. The stochastic interaction among low-level elements that gives rise to emergent properties may be part of a larger process of self-organization in hierarchical systems. Self-organization and attendant emergent properties constrain low-level elements through a network of downwardly propagating positive feedbacks. Those feedbacks not only tend to hold the system in a temporary stable state, but they also render it vulnerable to radical reorganization by rapid external forcing. The vulnerability of the USA agricultural production system to climate change is given as an example of how a self-organizing, hierarchical system paradoxically may become susceptible to large external shocks as a result of the emergence of high-level structures that seek to protect its low-level components from short-term variability. Simulations of changes in Honduran maize production in the aftermath of Hurricane Mitch using the CLUE land use model demonstrate the influence of multi-scale complexity on the resilience of land use after disturbance. Finally, it is argued that improved understanding of emergent properties of scale may give fundamental insight into the conditions of surprise.

Keywords: scale, integrated assessment, emergent properties, climate change, adaptation.

1. SCALES IN CLIMATE CHANGE IMPACT ASSESSMENT

The quest for new scientific knowledge cannot escape certain dualities such as cause-effect, model-subject, and observer-object [1]. These dualities condition how we learn, what we learn, how we express the results and what we do with them afterward. They are the human constructs that are used to distinguish order from disorder. Scale[1] is a construct that permits the observer to locate self relative to a set of objects distributed in space, time and magnitude. It explains nothing in and of itself, but its perspective facilitates the discovery of pattern and process [2, 3]. To examine issues of scale in the epistemology of system behavior is to stray away from reductionism and toward the understanding of the relations between the components of a system and the system as a whole. The goal of this essay is to reflect on whether the concept of emergent properties of scale – real or imagined – is a useful construct to guide the development of models of global human-environment systems that consist of regional components and sub-components.

While their scale dimensions most uniquely characterize problems of global environmental change, very little deep analysis of the meaning of scale has been applied to the resolution (usually by modeling) of those problems [4]. Scale surfaces mostly as a practical modeling problem of scaling up from the very small to the very large or scaling down from the very large to the very small [5]. Scaling up and scaling down raises another duality of global environmental change research captured in the two modeling paradigms – ''bottom-up'' and ''top-down'' – that dominate the field of integrated assessment modeling (IAM),

[1]We use Gibson et al.'s [2] taxonomy of scale-related terms for this paper. *Scale* refers to the spatial or temporal dimensions used to measure phenomena. *Extent* is the size of the spatial or temporal dimension of a scale. *Resolution* is the precision of measurement of objects of a scale. *Levels* are the units of analysis located at the same position on a scale.

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especially as pertains to the simulation of biophysical and related human response to climate change [6]. The reference point for both paradigms is spatial and temporal scale.

A bottom-up approach is typified by process-level simulation of biophysical response to a change in climate variables across a range of "representative" modeling sites. The results are then passed to an integrative model (usually economic) of the region or globe that contains those sites in order to deliver a quantity that has policy relevance (e.g., Rosenberg [7], Parry et al. [8, 9], Rosenzweig and Parry [10]).

A top-down approach is typified by the development of reduced-form relations between climate, biophysical, and socioeconomic variables that are estimated (often econometrically) from data pooled at regional levels in order to estimate global impact directly [11–14]. Also included in this class are Ricardian (or "ergodic" according to Schneider et al. [15]) economic modeling approaches that statistically relate climate variables to land rents in cross-section (i.e., across regions at one point in time) in order to estimate national impact and adaptation [16, 17].

Both paradigms incorporate the results of large-scale general circulation model (GCM) experiments of climate change in order to simulate impacts. Mismatches in scale resolution between systems being modeled – illustrated best between GCM results with a resolution of hundreds of kilometers and their recipient site-specific process models with resolutions of a few meters – call into question the reliability of the simulated impacts [18].

Bottom-up approaches are conducive to the construction of regional profiles of climate change impacts from detailed process studies; important climate effects are often portrayed mechanistically and adaptive response can be tested in controlled sensitivity experiments [19]. Top-down approaches, particularly global IAMs, permit the global change problem to be represented as a tightly coupled biophysical and social system with explicit linkages and feedbacks among components. Very little is exogenous. Their use of statistical aggregates in the modeling of system components allows estimation of whole system adaptation rather than an *ad hoc* sampling of adaptive strategies as in the case of bottom-up approaches.

Scale-related criticisms apply to both paradigms. Bottom-up approaches are criticized for the crudeness by which site-specific model results are aggregated to derive regional estimates [5, 19]. Linearity among scales is often presumed in the aggregation of site model results. Assumptions of linearity imposed by the averaging of nonlinear relations across multiple sites in space may result in substantial aggregation error illustrated as in Figure 1. Accordingly, the greater the non-linearity is, the greater the aggregation error. Top-down approaches are criticized for their generality and the loss of regional detail that may obscure important

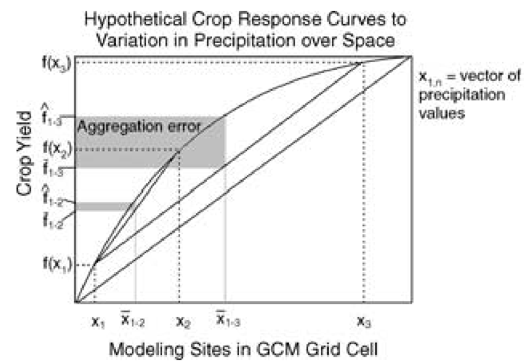

Fig. 1. Hypothetical aggregation error by up-scaling non-linear relations between crop yield and precipitation (Source: Easterling [19]).

distributional features of climate change impacts. Application of the results of top-down modeling indiscriminately to constituent regions risks the ecological fallacy [5].

We assert that scale-related problems associated with either approach are much more fundamental than those described above; such are merely symptomatic of a deeper failure to account for the inherent complexity of the entire system being modeled. We assume, for purposes of discussion, that most human-environment systems (defined below) that are of interest to global environmental change researchers are complex. That is, total system behavior cannot reliably be predicted by linear combinations of the system's (microscopic) sub-components [20]. Moreover, behavior in system sub-components may be constrained or controlled by larger (macroscopic) components. By extension, the difficulty of whole system predictability from below and the potential existence of control structures from above indicate emergent properties *a priori*. Such properties may arise by collective physical or biological processes, or by collective institutional thought. Moreover, they may be important levers to the understanding and manipulation of system behavior.

In the remainder of this paper, we develop the argument that complex human-environment systems are hierarchical. We then review the concept of emergence within the context of scale and suggest a theoretical basis for emergent properties of scale based on observed self-organizing traits of hierarchical complex systems. Two applications of our theoretical reasoning are presented. First, we discuss the role of scale emergence of institutional structures that may increase the vulnerability of the U.S. agricultural system to climate change. Second, we describe the process of agroecosystem reorganization in the aftermath of Hurricane Mitch in Honduras as an example of the dissolution of vulnerable emergent structures as the result of a large external forcing. Finally, we argue that proper representation of scale-related emergence in models of complex, hierarchically structured human-environment systems may improve the capability of such models to anticipate surprises in store from global environmental change.[2]

2. HUMAN-ENVIRONMENT SYSTEMS AS COMPLEX AND HIERARCHICAL

The concept of human-environment systems is referenced extensively in this paper which warrants a brief explanation of its meaning. At a high-level of abstraction, there is no physical separation of ecosystems from socioeconomic systems. Both contain dissipative structures in a stable state far from thermodynamic equilibrium [22]. They are both open systems that require steady energy and material gradients. In the case of ecosystems, the energy source is the sun. In the case of socioeconomic systems, energy sources range from wood and fossil fuels, to the kinetic energy of falling water, to the heat of fission and several technologies that are just over the horizon. Both systems consume energy-laden, low-entropy materials for self-maintenance and the production (or reproduction) of new material forms. They also excrete or exhale high-entropy heat and material. Both are self-regulating by different mechanisms – ecosystems by natural feedbacks (abiotic controls) and socioeconomic systems by human institutions (markets, cultural norms and other social institutions). Material and energy exchange so freely between ecosystems and economic systems as to make boundaries between them indistinguishable except by convention (for example, the boundary between the market and non-market shown in Fig. 2). Hence, ecosystems provide services in the form of renewable natural resources (e.g., food, fiber, and esthetics) to economic systems. The point here is that the same laws that govern ecosystem dynamics operate as constraints[3] on socioeconomic systems – the result is similarities of spatial organization between the two, as shall be argued below. It is neither useful nor productive to reduce ecosystems and economic systems into independent parts in models of global environmental change processes, which, fortunately, is well ordained in both the bottom-up and top-down modeling paradigms. Hereafter, the term human-environment system is used to infer spatio-temporal assemblages of ecosystems, and their abiotic controls (climate mostly), and socio-economic systems that derive benefit from ecosystems.

It has been suggested that the components of ecosystems and economic systems are structured hierarchically in space and time [23–27]. A hierarchy is a partially ordered set of objects ranked according to asymmetric relations among themselves [28]. Descriptors useful in distinguishing levels of a hierarchy include, for example, larger/smaller than, faster/slower than, to embed/to be embedded in, and to control/to be subject to control. In ecosystems, the behavior of lower levels in the hierarchy (e.g., individual organisms) is explained by biological mechanisms such as photosynthesis, respiration, and assimilation [29]. At higher levels, abiotic processes such as climate variability and biogeochemical cycling impose constraints on lower level biological mechanisms. In economic systems, the lower levels of

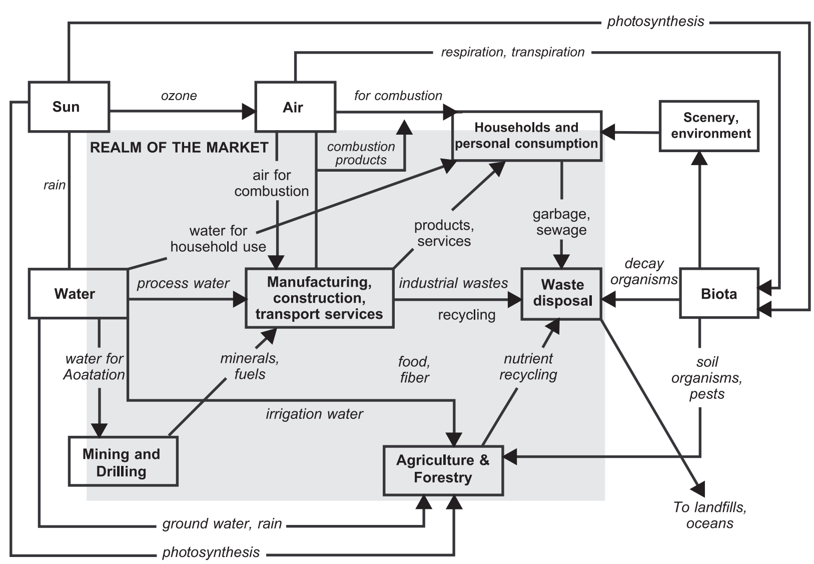

Fig. 2. The Human-Environment System (Source: after Ayres [22]).

[2]Our arguments are developed standing shamelessly on the shoulders of pioneers in systems analysis – especially the work of Priogogine, Weinberg and Boulding – and, more recently, in systems ecology – especially the work of Levin, Holling and Clark. We were greatly influenced by a thoughtful review of emergent properties by Wiegleb and Bröring [21].

[3]We do not mean to argue that economic behavior is "determined" by thermodynamic laws in the same sense as ecosystem behavior, but rather that thermodynamic laws impose challenges to human ingenuity that force adaptive change.

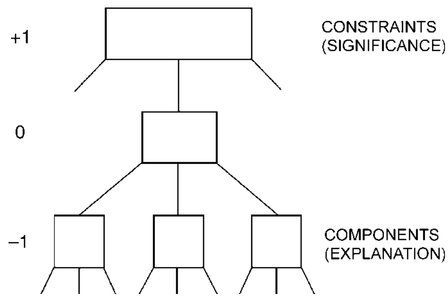

Fig. 3. Levels of a Hierarchy (Source: after O'Neill [24]).

the hierarchy are understood best in terms of rapidly changing production functions of individual firms. The higher levels impose constraints on individual firms in the form of slower moving nationally and internationally extensive features such as rates of inflation, prices, and national income [2].

Hierarchy theory evolved out of general systems thinking to explain the muli-tiered structure of certain types of production systems. The theory, in simplified terms, posits that the most useful way to deal with problems of global change in a multi-scaled complex system is to understand how the elements of the system behave at a single time-space level of scale [24]. That level (Fig. 3, Level 0) will itself be a component of a higher level (Level +1). Level +1 dynamics are generally slower moving and greater in extent than Level 0; they form boundary conditions that serve to constrain the behavior of Level 0. Level 0 may then be divided into constituent components at the next lower level (Level −1). Processes operating at Level −1 are generally faster moving and lesser in spatial extent than Level 0; they provide the mechanisms that regulate Level 0 behavior. They are represented as state variables (dynamic driving forces) in models of Level 0 [24]. Thus, the goal of hierarchy theory is to understand the behavior of complex systems by structuring models to capture dynamics at the next lower and higher scales of resolution. It provides a framework for testing for the property of emergence discussed in the several sections below.

3. EMERGENCE: REAL OR IMAGINED?

One of the more controversial concepts that came to prominence in the general systems theorizing of the 1960s was the notion of emergent properties. The essence of emergent properties is captured best in the psychologist Wundt's famous quote: "the whole is greater than the sum of its parts." Emergence literally is the process of coming into being. It suggests that the interaction of pattern and process at a smaller, faster scale produces a fundamentally new organization at a larger, slower scale [30]. It is described in several sciences including physics, chemistry, atmospheric sciences, economics, psychology and political science, but as a property of scale it receives special attention in ecosystem ecology [29, 31] where it is accepted, often uncritically, as an organizing principle of ecosystem form and function.

The notion of emergent properties of scale is important for a number of reasons. For one, some ecologists argue that emergent properties may serve as useful indicator variables for monitoring the stability and integrity of ecosystems in the face of rapid external forcing [25]. Management policies that manipulate emergent properties manipulate whole ecosystem behavior instead of fractions thereof. The same applies to human components of human-environment systems *a priori*. For two, the inclusion of emergent properties in modeling may reduce model uncertainty, which improves the anticipation of surprise (discussed below).

There has been a long-standing debate in the systems analysis literature over the existence of emergent properties. Wiegleb and Bröring [21] classify the two poles in this debate as *denial of emergence* and *ontological emergence*. In the former, *denial of emergence*, there is no emergence. To recognize emergent properties is to concede defeat in one's attempt to understand and model a system. The extreme version of this position is that everything in science is explained by the theory of quarks. Einstein, in his investigation of Brownian motion, asserted that we could predict the state of a system were we to know enough about the state of every molecule in the system – but he says in a footnote, "Dear reader, do not believe that you can do that." We believe it is misleading to think that we might "correctly" model global scale biophysical and human response to climate change by simply aggregating fine-scale mechanistic explanation properly. It is similarly misleading to think that the reduction of all modeling to the finest level possible gives purely mechanical and, thus, reliable explanation.

Levin [29] points out that at very fine spatial and temporal scales, stochastic phenomena or deterministically driven chaos make systems unpredictable, hence the replacement of classical mechanics by quantum mechanics at the smallest scales. Similarly, at the scale of individual human agents, behavior is not deterministic but rather stochastic. Were complex human-environment systems only to be understood in purely deterministic terms then a strong interpretation of Prigogine's [32] analogy that we are all merely actors in the pages of a cosmic history book already written would apply. There is no wiggle-room for emergence in this view and we reject it out of hand from further consideration in this essay.

At the latter pole – *ontological emergence* – the notion of emergence takes on a metaphysical dimension. Ontological differences between objects, literally differences between existence and nonexistence, are used to define the endpoints of emergence. *To emerge is to come into being*. Practically speaking, debates over ontological emergence focused on the precise conditions under which inanimate objects become animate ones. *Vitalism*, historically argued to be the almost magical or teleological emergence of life from the assemblage of cellular parts, was the object of much attention in biological sciences prior to the 20th century. Fundamental advances in cell biology have all but eradicated vitalism as a meaningful construct. It is now recognizable only in the psychology literature where concepts of ''soul'' and ''self'' remain irreducible [21]. Lovelock's [33] Gaia Hypothesis of a ''secretly'' self-regulating biosphere may be the quintessential example of ontological emergence on a grand scale: intriguing by circumstantial evidence but demanding of scientific blind faith to hold together. The concept of ontological emergence seems to have moved beyond all the scientific disciplines, save psychology and political science. It is now essentially a debate about ethics and human agency.

Between the two poles of denial of emergence and ontological emergence lies the view of *epistemological emergence*. Epistemological emergence takes several forms according to Wiegleb and Bröring [21] but the most relevant form to this discussion is *hierarchical* (synchronous) *emergence* and its special cases of *scale* and *model emergence*. This form accepts the validity of emergence in principle but does not demand an explanation of ontological differences.

3.1. Hierarchical Emergence

Hierarchical emergence is based on the presumption that the system of interest is structured hierarchically in time-space as per the above discussion. It can be thought of as the appearance of properties at a high-level of scale that is not derivable from the behavior of constituent (low-level of scale) components *a priori* [23]. Hierarchical emergence is the result of stochastic lower level interactions (elaborated below). It is high-level order emerging from low-level apparent disorder. Low-level disorder is more apparent than real because of interacting elements too complex and numerous to be practical to model deterministically.

Emergent properties as such may constrain low-level interactions while themselves being buffered from the random upward pulses of change from lower levels of scale as long as the whole system remains in a steady state. Long-term commodity price trends in a market economy illustrate the point. They strongly regulate producer and consumer behavior while being largely unaffected in the long-term by short-term fluctuations in supply and demand. However, systems theory suggests that large upwelling singularities or bifurcations may disrupt these relations between levels of scale [25]. An example of such a singularity in an economic system is the tendency for the sudden appearance of a radical new technological innovation to reorder relations of production so as to disrupt the downward propagation of price signals [27]. We will return to this point below.

Wiegleb and Bröring [21] note that shifts in scale by the observer/modeler may produce more than averages or constants. These shifts may make homogeneity out of heterogeneity and *vice versa*. They may bring order out of seeming disorder simply by magnifying or de-magnifying the resolution and extent of the data. This is *scale* emergence. In Levin's [29] example of the unpredictable nature of fine-scale stochasticity in a system, an increase in level of scale may collect enough objects in the system to regularize their behavior to the point that statistical generalizations are possible.

A related and somewhat obscure problem in geography and landscape ecology research is the ''modifiable areal unit problem (MAUP)'' [34, 35]. A shift in the sizes or shapes of the geographic units used to assemble data for modeling can in and of itself create homogeneity out of heterogeneity and vice versa.

In principle, the MAUP is demonstrated most effectively with gridded data. We tested for the existence of the MAUP with a gridded data set used to simulate climate variability effects on crop yields in the southeastern USA. The EPIC process crop model was run with 36 years of observed climate and $2 \times CO_2$ climate change (the climate changes were supplied by the CSIRO general circulation model described in Mearns [36]), management and environmental data allocated to a regular grid network consisting of 288 0.5° grid boxes imposed on the southeastern USA (Fig. 4). A series of maize yield simulations was performed at different levels of spatial aggregation of the input data. Two different aggregation strategies were used which simply altered the shapes of the aggregation units. One strategy aggregated all units in square clusters illustrated in Figure 4(a–e). The other strategy aggregated all units in linear clusters illustrated in Figure 5(a–e). For both the square clustering strategy and the

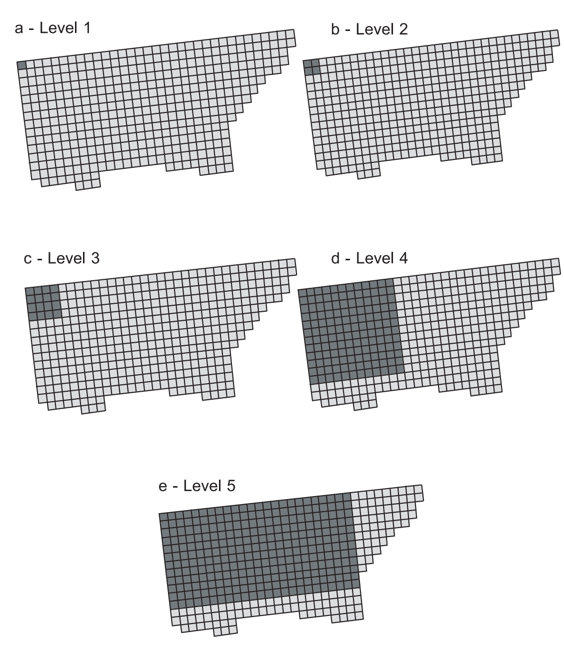

Fig. 4. Cluster (square) aggregation method.

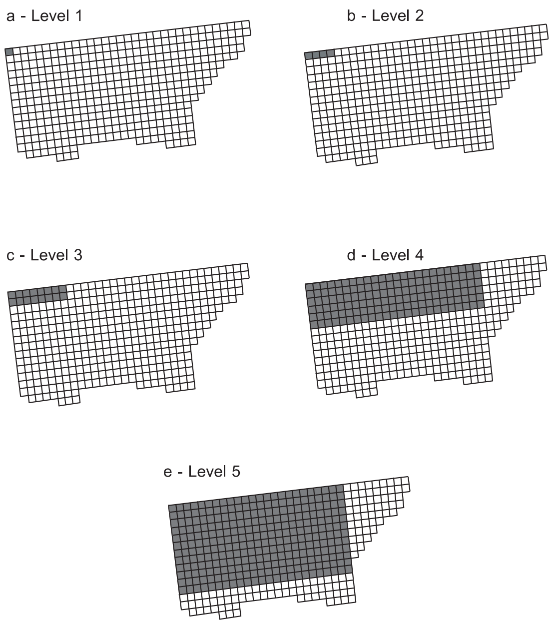

Fig. 5. Linear aggregation method.

linear clustering strategy, Level 1 was the finest resolution with independent model simulations for each of the 288 grid boxes. At Level 2, independent simulations were run for 72 2×2 aggregates for the square clustering and 72 1×4 aggregates for the linear clustering. At Level 3, there were 18 4×4 and 2×8 aggregates. At Level 4 there were 2 12×12 and 6×24 aggregates. At Level 5 both aggregation strategies (cluster and linear) produced 1 12×24 aggregate. Yields at each of the levels were averaged across the network to create one average yield per level for purposes of comparison (Table 1). The temporal coefficients of variation of modeled yields at each level were handled similarly. At each level of aggregation a Student's t-test was performed on the paired (linear vs. cluster) yields to determine whether there were statistically significant differences.

As can be seen in Table 1 the simple change in shape of the clustering of network components (grid cells) has minimal effects on mean yields at most levels although some of the differences were statistically significant in the climate change case. Level 5 yields show the greatest differences (both in the observed climate and climate change cases). At Level 5 the full effects of the different spatial paths the two aggregation strategies take with the input data are fully accumulated which probably explains the significance of the differences. We suggest, although do not test, that even these Level 5 yield differences would probably narrow in a Monte Carlo type design that considers several different aggregation strategies.

Although examples in the literature [34, 35] do show that the MAUP can indeed be a significant influence at the aggregate level, the resulting emergent features probably represent the failure to account for hierarchical structures in the system rather than a meaningful high-level property of the system [35]. For example, a gridded aggregation scheme that happens upon the exact pattern that maximizes differences in climate between clusters might be expected to show substantial accumulated yield differences with respect to any other aggregation pattern because of the great importance of climate in distinguishing large-scale differences in crop productivity. This may explain why some of the differences between yields in the above example were significant at one level of aggregation but not at other levels.

These simple explanations of scale-related emergence beg the question: Do they truly reveal underlying process or are they merely an aggregation sleight of hand with the data? This question raises an even more fundamental question that strikes at the heart of the meaning of epistemological emergence. Is an emergent property constituted of "new material" in the system or is it simply a relationship between the system and the Table 1 observer? To wit, is the "market" a tangible object that appears out of thin air or revelation that appears when the system is viewed in a certain space-time context?

The answer to this last question is that properties "emerge" for a particular observer because he or she could not or did not predict their appearance because of lack of data or understanding or both [37]. That same property may be perfectly predictable to another observer. We assert that properties emerge at different levels of scale due to imperfections in how the observer/modeler interprets the

Table 1. South-eastern USA simulated corn yield response to 1960–1995 observed climate and CSIRO climate change ($2 \times CO_2$) at different levels and shapes of units of aggregation: yields averaged over time and aggregation units.

Climate	Level 1 (288)		Level 2 (72)		Level 3 (18)		Level 4 (2)		Level 5 (1)	
	Cluster	Linear	Cluster	Linear	Cluster	Linear	Cluster	Linear	Cluster	Linear
Observed	6.29	6.29	6.28	6.23	6.00	6.15	5.69	5.38	5.77**	5.41**
CV	.077	.077	.077	.077	.056	.048	.049	.042	.044	.038
$2 \times CO_2$	6.19	6.19	6.00**	5.83**	5.78**	5.97**	5.65**	5.71**	5.84**	5.38**
CV	.080	.080	.079	.083	.069	.056	.052	.050	.048	.050

Note. ** = Statistically significant at 0.001 alpha level.
Values in parentheses are number of aggregation units at a given level.

scales at which various driving forces of a system operate. Emergent properties appear when different objects of a system are brought into a logical context [21].

Emergent properties may also appear by accounting more fully for system complexity [23] (Wilbanks, personal communication). For example, additional data may greatly alter the understanding of relations among components of a non-linear system. Hence, complexity can be scaled as well as space and time. Moreover, several studies of hierarchical complex systems reviewed in a recent National Research Council report [38] conclude that complexity may be best understood at those portions of the scale that traverse the transition from deterministic to stochastic understanding. This transition tends to occur at meso-scales (regional) rather than macro-scales. Such scales are a natural focal point for increased modeling effort.

It seems reasonable to conclude that emergent properties of scale are best articulated in terms of observer-system relations and not as ‘‘new material’’ in the system. The new material view casts us back into the muddled debate of ontological differences. Until fairly recently an underlying process-based justification of epistemological emergence, useful as guidance to the modeling of hierarchically structured human-environment systems, was lacking. Recent thinking about processes of self-organization and dissipative structures has been applied to hierarchy theory casting a new light on the framing of epistemological emergence.

4. SELF-ORGANIZATION AS A DYNAMICAL THEORETICAL BASIS FOR SCALE-RELATED EMERGENCE

The development of a theoretical explanation for the existence of emergent properties of scale in human-environment systems requires the unraveling of the very meaning of complexity. Most simple systems consisting of a small number of elements can be understood structurally and modeled mechanistically (Fig. 6, Region I). They represent ‘‘organized simplicity.’’ Full description of a simple two-object system requires only four equations: one for each object to describe how the object behaves by itself (‘‘isolated’’ behavior equation), one to describe how the behavior of each object affects that of the other (‘‘interaction’’ equation) and one to consider how the system behaves absent the objects (‘‘field’’ equation). As the number of objects increases, there is only one field equation and one isolated equation per object. The number of interaction equations, however, increases by the ‘‘square law of computation’’ (2^n, where n is the number of objects). For example, 10 objects require $2^{10} = 1{,}024$ interaction equations. Complex human-environment systems consist of many times more than 10 objects.

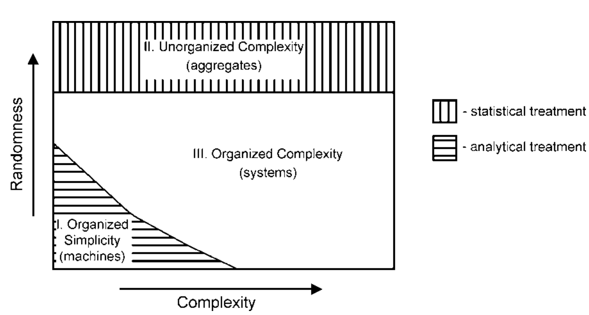

Fig. 6. Complexity versus randomness.

As noted above, human-environment systems are not purely deterministic at any level of scale. But it is possible to simulate generalized human behavior at small scales, using agent-based modeling and other stochastic approaches, as a simple stochastic system with a finite number of possible outcomes. This is analogous to simulating organized simplicity in Figure 6. However, as the number of agents increases with scale, the complexity of interactions rises. A model that tracks every agent’s interactions with every other agent, and with the environment, rapidly eludes comprehension and computation even with massively parallel processing. Yet, at the extreme of large numbers of agents at low levels of spatial and temporal scales, the interactions within the population are random and therefore predictable in a statistical sense by their aggregation to high levels of scale (Fig. 6, Region II). In such populations, the ‘‘law of large numbers’’ dictates that the probability that a property of any one object in the population will deviate significantly from the average value of that property across all N objects is $1/\sqrt{N}$. Hence, the larger the value of N, the more predictable the property becomes. According to Weinberg [37] such populations are complex but random (lacking structure) in their behavior such that they are regular enough to be studied statistically – they represent ‘‘unorganized complexity.’’

The problem with this typology is that most of the domain of human-environment systems lies between organized simplicity and unorganized complexity. It is the domain of ‘‘organized complexity’’ (Fig. 6, Region III). The understanding and modeling of land use change illustrates this problem. At low levels of scale, Turner and Meyer [39] posit that a wide range of social driving forces influence land use and land cover change, including economics, culture, location, politics, and environment. Change in the structure of familial inheritance of land may be as important as change in land rent in the determination of land use. Such features are embedded in highly reduced-form structures or totally absent in large-scale models of land use change.

At high-levels of scale, Turner and Meyer [39] argue that Ehrlich and Holdren’s [40] IPAT relation – defined as: Intensity of human impact on the environment (I) = Population (P) × Affluence (A) × Technology (T) – usefully explains large-scale patterns and trends of land use change. Elements of IPAT are easily identified in global IAMs such as the IMAGE 2.0 model [41] that simulates land use change as a function of change in agricultural demand, which is approximated by changes in population and per capita income. Turner and Meyer [39] imply, however, that the absence of low-level driving forces in most extant land use models results in potentially serious prediction errors at small scales.

Systems of land use change that cross several space-time scales lay between the structure and precision of organized simplicity and the lack of structure and large aggregates of unorganized complexity. Too complex for analytical solution and too structured and organized for pure statistical treatment, this is the domain of complex human-environment systems and the logical focal point of integrated assessment models. Weinberg [37] refers to these as ''medium number systems'' subject to the law that large fluctuations, irregularities, and discrepancies will occur more or less regularly. We assert equivalence between medium number systems and the meso-scale of human-environment systems. This is the (regional) scale at which the modeling of complexity is most tractable *a priori*.

The propensity for large fluctuations, irregularities and discrepancies is a necessary condition for self-organization, a feature of medium number systems that plays a central role in explaining the appearance of emergence in those systems. Buenstorf [27] describes self-organization as a dynamic process whereby structures and properties emerge at the system level out of intense interactions among system components. Normally self-organization is discussed in terms of physical systems. An example is the difficulty of upscale propagation of local governing equations of climate because extreme non-linearity is encountered in the aggregation process [42].

For a system to exhibit self-organizing tendencies, it must receive steady inputs of energy/and/or material (i.e., be far-from-thermodynamic equilibrium) and be subject to powerful positive and negative feedbacks across levels of scale that are spawned by non-linear relations among components. At low-levels in the system, the sum total behavior of components exhibits large random fluctuation [27]. Buenstorf [27] citing Prigogine and Stenger [43] argues that positive feedback is necessary to amplify random fluctuation at low-levels of a system. Change in price signals (positive feedback) prompted by technological innovations (random fluctuation) is often given as a prime example of such in economic systems. The amplification of low-level random fluctuation results in the self-selection of high-level properties that constrain low-level behavior. This is a necessary condition for the emergence of high-level structure out of low-level randomness (stochasticity). Prigogine and Stengers [43] argue that negative feedbacks serve as system checks that help maintain the system structure. Furthermore, Holling [44] argues that self-organized hierarchical systems that are in a steady state are highly vulnerable to complete reorganization when subjected to strong external forcings (e.g., climate change).

From the practical standpoint of policy-motivated modeling, the failure to match temporal and spatial scales of human activities with those of nature has been an abiding problem in the science of climate and society interactions [4, 44]. This failure stems in part from the misinterpretation of modelers at the whole system level of the meaning of self-organizing pulses of upwelling change from finer scales in the system and the emergent structures that these pulses create. The challenge in applying concepts of self-organization to socioeconomic components embedded in human-environment systems is the identification of positive and negative feedbacks that give rise to emergent properties at high-levels of scale in a spatial hierarchy.

4.1. An Application to the Problem of the Vulnerability of the USA Agricultural Production System to Climate Change

The co-evolution of national agricultural production systems with global climate change illustrates the problem of mismatches of scale. The expansion of global agricultural capacity apace with the expansion of demand is one of the great success stories of the 20th century. So successful have the combined outputs of national production systems been that real costs of production worldwide have declined causing real food prices to decline in turn for more than a generation [45]. This trend likely will continue into the first few decades of the 21st century.

The consensus position is that the USA agricultural production system will be resilient in the face of climate change [46]. This is partly justified by historical experience of industrialized agricultural production in dealing successfully with challenges that are analogous to those posed by climate change – such as the historical success in stoking production to meet the challenge of feeding a growing and increasingly wealthy global population with surpluses to spare [47]. This position is backed by many global modeling studies (summarized in Adams et al. [48]). But is the system as resilient as we might think? A rough sketch of the vulnerability of the USA agricultural production system to climate change from a hierarchical systems perspective might suggest otherwise.

Virtually any agricultural production system is an example of a complex human-environment system with scale-related emergent properties, but industrialized production systems even more so. It embeds a dissipative structure far-from-thermodynamic equilibrium in that large throughputs of low entropy energy (solar radiation and fossil fuel) and material (nutrients, seed, pesticides), plus labor, are required for maintenance and production. The system is hierarchical in scale with individual farm enterprises that manage agroecosystems at the lowest levels of scale, a portfolio of agribusinesses and a network of regional and national institutions (e.g., cooperative research and extension, commodity crop boards) that nurture and constrain at

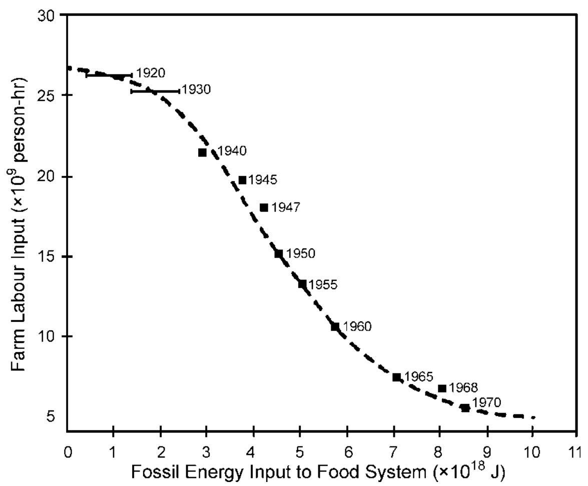

Fig. 7. Substitution of energy for labor in American agriculture in the 20th century.

the next level, and national and international markets that stabilize the system from their perch at the highest levels of scale.

The origins of the hierarchical structure of the contemporary USA agricultural production system are many but much can be traced back to a remarkable series of technological innovations that span over a century. Complexity has risen. Many of those innovations centered on the use of energy in production. Historically, anywhere in the world that the value of labor has risen relative to other production inputs, the substitution of relatively cheaper energy inputs for relatively more expensive labor has taken place [49]. Figure 7 shows the substitution of energy for labor inputs in USA agriculture in the 20th century. This substitution was enabled by technological innovations leading to labor saving mechanization. More recently in developed countries technical innovations have led to a second energy revolution in agricultural production. For the past two decades production has followed a trajectory of decreasing energy intensity measured by the proportion of energy input per unit output where output is either a unit of mass (yields or total production) or total value of production. Interestingly, these two energy-related trends are analogous to the same transformations that take place as ecosystems self-organize into a stable state.

Although normally evaluated by its large-scale effects on production, the drive for technological innovation is inescapably a localized process. Hayami and Ruttan [50] posit that technological innovation in agriculture is induced endogenously. According to Hayami and Ruttan's ‘‘induced innovation hypothesis’’ [50], as factor scarcity arises, increasing factor prices signal it. As those price increases persist, strong signals are conveyed to the agricultural research establishment to develop new technologies to substitute for more costly old ones in order to hold down costs of production.

Because regional variations in resource endowments lead to regional differences in farmers' comparative advantage, the pattern of induced innovation will be likewise regionally distributed [50]. Farmers at one location have quite different sets of technological needs than those at another location. The development of successful hybrid corn varieties illustrates the point. In the USA, each state land grant (agricultural) university has its own state corn breeder. The process of corn hybridization represents the ‘‘invention of a method of inventing’’ varieties adapted to each growing region [50]. That is, the successful development and diffusion of commercial hybrid corn varieties has been accomplished by the evolution of a complex research, development, distribution and educational system. This system has depended on close cooperation among public sector research and extension agencies, a series of public, semipublic and cooperative seed-producing organizations and private sector research and marketing agencies. The research that produces these innovations is conducted through a series of local and regional institutions such as agricultural universities and their research and extension stations and the various regional institutions of the Consultative Group on International Agricultural Research. Even the agricultural research efforts of the private sector are largely regionally distributed.

As long as producer and factor prices do not exceed critical thresholds, only the steady stream of continual fine-tuning adjustments aimed at adapting cropping systems to challenges in their local production environments (i.e., spatial and temporal variability in pests, climate, soils) takes place. Occasionally, however, one particular technical innovation rises above the others in importance and may create a bifurcation in output amounts of sufficient magnitude as to prompt the emergence of new institutional structures which downwardly-regulate lower levels usually through government programs and prices [51]. The application of nitrogen fertilizers to corn and eventually to a wide range of row crops begun shortly after World War II in the USA, coupled with the hybridization of corn (described above), brought about a remarkable global upsurge in yields and production. From the whole system perspective, a major innovation such as this appears to be a fluctuation welling up randomly from many regions as the innovation rapidly diffuses to the farms comprising the low-level components of the spatial hierarchy.

Collectively, these random fluctuations of induced technological innovation and the bifurcations of output they produce give rise to emergent, self-regulating (feedback) mechanisms at higher levels in the spatial hierarchy. In this sense the system is nonlinear. As noted above, one such self-regulating mechanism is price. But price is well represented in most agricultural impact assessment models and is sufficiently obvious as not to be very interesting here.

Another, perhaps less obvious, self-regulating mechanism is the collective goals of society that find expression in national agricultural policies. In the USA, the dominant goal of agricultural production policy is the stabilization of interannual agricultural output [47]. It is reasonable to conjecture that such a goal of stabilization emerged as a national scale policy out of concern over increases in the variability of crop yields that necessarily accompany technologically-driven increases in mean crop yields. A plethora of government programs carry out the goal of stabilization of agricultural output. It includes, for example, commodity crop insurance programs, the Conservation Reserve Program and numerous tax exemptions accorded uniquely to farmers.

These programs represent strong positive feedbacks to local production. They encourage farmers to take on more climate risk than otherwise [52]. One program aimed at stabilization but that may, in the long run, increase the vulnerability of the USA agricultural system to climate change is that of government-guaranteed crop prices [53]. These price support programs stipulate that farmers must establish an average yield of a specific crop on a base acreage over a specified period of time (usually five years) in order to qualify for payments. While such a program encourages stability in the types of crops planted and lowers risk to farmers, it is a strong disincentive to flexible changes in the mix of crop species being planted by participating farmers. The net effect of such "safety net" programs is to encourage the expansion of high-revenue crops – often the most sensitive to climate variation – into climatically marginal areas for those crops and, as such, help dictate the spatial pattern of cropping systems.

As climate changes and society absorbs the losses of farmers who continue to grow increasingly climate-inappropriate crops, the system actually becomes less stable or more vulnerable to major malfunction. At some point the climate changes will accumulate to where stabilization programs make no sense to society at large, resulting in abandonment and system-wide reorganization. In an ecosystems context, Holling [44] calls this a process of "creative-destruction" that accompanies his view of "nature evolving" (as opposed to "nature as equilibrium"). The same concept seems roughly to apply to the co-evolving climate and agricultural production systems.

What lessons for modeling can be drawn from this example? First and foremost, if appearances can be deceiving they will be when a complex human-environment system is poorly specified in a model. The probability of deception is directly related to the degree to which the system is nonlinear. If the system being modeled is hierarchically structured then principles of hierarchy theory should be applied. There is no one "correct scale" for the study of a hierarchical human-environment system and the choice of modeling scale in integrated assessment modeling has too often been an arbitrary one. O'Neill's [24] recommendation that models of spatially hierarchical systems should include state variables from one level of scale below the level of interest and constraining variables from one level above should be followed. That is, models should be parameterized over long enough time scales to capture the evolution of self-organizing structures that span spatial scales. Fine resolution (low-levels of scale), fast time-step state variables that capture stochastic processes such as the sudden (but predictable) appearance of innovation should be combined with coarse resolution (high-levels of scale) slow time-step variables that capture total system features such as markets and national and international production and trade policies. This type of modeling approach is likely to reveal the emergent structures of scale that feedback to constrain and stabilize low-level component dynamics. The incorporation of such modeling structures in integrated assessment modeling should allow the increased realism of estimates of whole system vulnerability to external shocks such as climate change to be achieved.

4.2. Emergent Properties, Vulnerability and Resilience of Land Use Systems with Environmental Forcing: The Case of Hurricane Mitch and Honduran Agriculture

Complex system theories as developed for the ecosystem might apply to the land-use system (see Loucks [54], Conway [55], and Fresco [56]). The validity of the assumptions on the constancy of the land-use system can be illustrated by drawing from the work of Holling [57, 58]. He proposed using two properties to describe the system's reaction to a disturbance, resilience and stability. A system is stable, when after a temporal disturbance, it can return to the previous equilibrium, whereas resilience refers to the ability to absorb changes of state variables, and still persist after a disturbance.

Figure 8 illustrates the concept of resilience [57]. Over time, connectedness builds as patterns of land use are locked in by the emergence of large-scale controls such as prices, infrastructure and government policy. The system becomes

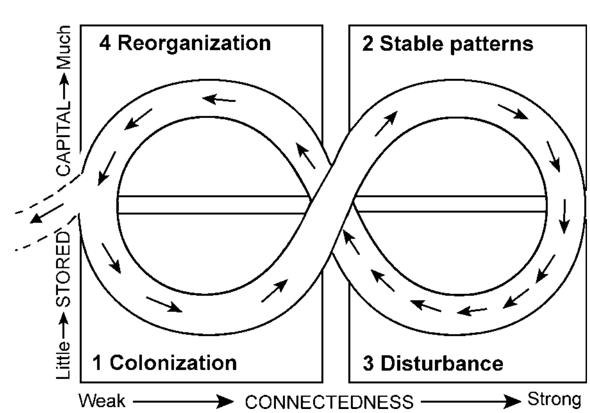

Fig. 8. Four land-use system functions and the flow of events between them (Source: redrawn from Kok and Winograd [64] and adapted from Holling [57: fig. 23, p481]).

brittle and vulnerable to external forcing as in the case of an extreme climate event. When a hurricane strikes, stable land-use patterns will rapidly be changed, during the short disturbance phase. Stored capital is lost but the system's complexity remains guided partly by persistent large-scale properties that emerged in the previous equilibrium phase such as price mechanisms and government programs (disaster relief). Loss of connectedness (complexity) describes the reorganization phase that is initialized afterwards. Subsequently, the system returns to its former equilibrium, although key variables will certainly have changed, and a new (re)colonization phase will start, which will result in stable land-use patterns while capital and connectedness build up. Those patterns are not equal to the starting position; i.e., the land-use system is unstable, but driven by the same set of variables, and thus resilient.

The properties of the land-use system and their relationship with ecosystem theories can be illustrated with results obtained from the application of a land-use change model called the CLUE modeling framework to Honduras, simulating effects of hurricane Mitch.

4.2.1. *The CLUE Modeling Framework*

The CLUE (Conversion of Land Use and its Effects) modeling framework [59–61] is best described a dynamic, multi-scale land-use change model, that explores the spatially explicit effects of future land use changes, using scenarios. At the highest aggregation level (usually a country), yearly demand is calculated, based among others on expected changes in population, income, diet composition and export/import developments. Changes in demand are subsequently allocated in a two-step top-down procedure with an intermediate 'optimal' resolution, based on statistical parameters. The finest resolution is a rectangular grid, sized between 150×150 m and 15×15 km. Relationships between land-use types and a large set of potential land-use determinants are quantified using multiple regression techniques.

4.2.2. *Mitch Scenario*

Within days after hurricane Mitch struck Central America on October 26th, 1998, the first images became available on the path of the hurricane, total rainfall, damaged roads and bridges etc. [62, 63], together with information on production losses of e.g., banana plantations (Internet, various sources). The speed with which data became available provided the opportunity to apply the CLUE modeling framework to Honduras and project the long-term impact of the hurricane. A detailed description of the assumptions of the scenario is given by Kok and Winograd [64]. Main assumptions include: the heavy rainfall that accompanies the hurricane temporarily excludes areas from production; a large number bridges and roads are destroyed; import and export are reduced; economic growth is depressed. The assumed lower income results in a lower demand for beef and thus agricultural area; export and import reductions have the same effect.

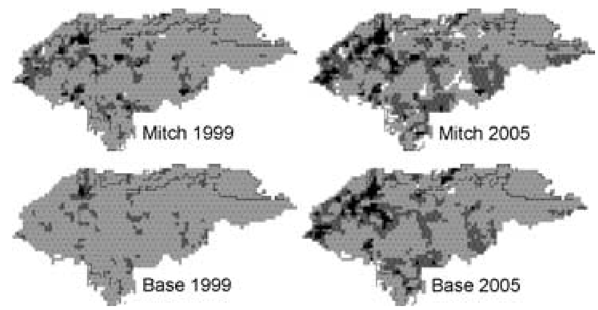

Fig. 9. Short-term and long-term effects of hurricane Mitch on cover percentage of maize in Honduras. Depicted are modeled changes in cover between 1993 and 1999, one year after the hurricane (left), and between 1993 and 2005 (right), for the Base scenario (bottom) and Mitch scenario (top). Changes are classified in decreasing cover (white), increasing cover (dark gray and black), and no change (medium gray). Lines indicate the flooded area. Each grid cell is 7.5×7.5 km (Source: redrawn from Kok and Winograd [64]).

In Figure 9, the short-term and long-term effects of hurricane Mitch on land-use patterns in Honduras are illustrated with hot-spots for maize. One year after the hurricane, land-use changes are clearly more dynamic in the hurricane scenario as compared to the Base scenario. The maize area has increased significantly in extent outside the area that was flooded, while land-use patterns in the base scenario are far more stable. Seven years later, however, effects of the hurricane have diminished. Although dynamics in the Mitch scenario are somewhat higher, the overall patterns of both scenarios are similar.

The important lesson of this example is the powerful influence of large-scale controls (national demand for agricultural land) on small-scale land use features (area planted to maize) during the reorganization of those features after external forcing (Hurricane Mitch). Although the specific patterns of land use are changed by the hurricane, the small-scale complexity embedded in relations between regional resource endowments and farming ingenuity and steered by aggregate national forces of demand for agricultural outputs recreate a landscape whose functions are similar to pre-disturbance conditions but are now better adapted to environmental conditions (maize is farther from flood-prone areas).

5. ARE ISSUES OF SCALE AND SURPRISE CONNECTED?

Kates and Clark [65], summarizing the work of Holling [66], state that surprises occur when perceived reality departs sharply from expectations, when causes turn out to be different than was originally thought. Models often inform our expectations of the future. However, it is doubtful that even the best modeling strategies will accurately and precisely forecast surprise. To do so would require making tractable the ability to decrease *fundamental uncertainty* defined as a situation so novel that no current model of any kind applies [67]. But it is possible to decrease *model uncertainty* defined as the surprise that arises when model outcomes fail to predict actual events because of the way the observer/modeler connected the model's variables together [67].

Kates and Clark [65] point out a number of techniques that are useful in anticipating surprise. They include historical retrodiction (learning from experience with past unexpected events), contrary assumptions (sensitivity analysis of assumptions underlying projections), asking experts their opinions, and imaging (an unlikely event is imagined requiring a plausible scenario to justify it to be constructed). Kates and Clark [65] also suggest models of system dynamics to anticipate surprise but no mention is made of the issue of scale in their essay.

It would appear from the discussion in previous sections that there is, in fact, a strong connection between emergent properties of scale and surprise. Emergence is equated with surprise the first time it is discovered in the process of contemplating the additional complexity of a system. Afterward it may be demonstrated that the observer need not have been surprised at all once the system is better understood which, quoting Weinberg [37], "is a small consolation if the emergent property was an explosion." Hence, some aspects of surprise may arise purely from our modeling mistakes. When things go wrong in a model, when linearity is assumed of a non-linear system, for example, society is ripe for surprise. Mark Twain satirizes this point in *Life on the Mississippi* [68]:

> "In the space of one hundred and seventy-six years the lower Mississippi has shortened itself two hundred and forty two miles. That is an average of a trifle over one mile and a third per year. Therefore, any calm person, who is not blind or idiotic, can see that . . . seven hundred and forty-two years from now the Lower Mississippi will be only a mile and three quarters long. . . There is something fascinating about science. One gets such wholesome returns of conjecture out of such a trifling investment of fact."

The application of the principles of hierarchy theory and self-organization to modeling could improve our understanding and prediction of the conditions that produce surprise. In short, it could predict the potential for surprise. Surprise detected in a model provides the opportunity not to be surprised in practice.

It is particularly important that model structures be developed to relate small-scale stochastic processes to the dynamics of larger scale system features since those are the features that provide stabilizing feedbacks to the small-scale. Holling's [44] hypothesis of encroaching system "brittleness" stemming from prolonged stabilizing feedbacks should be tested. Brittleness preconditions surprise.

In the case of agricultural vulnerability to climate change, the potential seeds of surprise may be in the localized nature of endogenous technical change and how large-scale institutions emerge to stabilize the fruits of small-scale technical change. Stability in this case is gauged by the long-run dependability of yields of the highest paying (and most climate-sensitive) crops. As noted above, enforced stability breeds brittleness possibly setting up an unanticipated "climate surprise" that would even surprise the Intergovernmental Panel on Climate Change, which rates the probability that the global agricultural production system would be seriously hampered by climate change as medium to low. The foregoing is, of course, is pure conjecture not having done the necessary modeling, but it certainly is not implausible.

6. CONCLUSION

A reasonable concluding question to ask is: To what extent have notions of scale emergence penetrated integrated assessment modeling of human-environment systems? In our view the answer is very little and superficial. A recent study by Darwin [17] illustrates the point. He noted major differences in the results of his model of the response of the global agriculture system to climate change depending on whether the model was run with the regions of the world disaggregated or with the regions aggregated to the global level. He clearly demonstrated the importance of scale resolution in IAMs and opened concern over what the underlying causes of the scale differences that he encountered were. This concern raises a serious question about the providence of projecting the model's results onto the dynamic, hierarchically structured real world. This question applies to all of the IAMs that do not embed hierarchical structure.

The ultimate worth of IAMs is the value of their predictions as usable knowledge to decision makers across a range of levels of spatial scale. IAMs must provide information to decision makers on levels of scale that concern them [17]. Cash and Moser [69] reiterate this point. Highly aggregated predictions of climate change impacts are little more than idle curiosities to local and regional decision makers.

From the foregoing discussion we conclude that the problems of IAMs may extend well beyond the simple problem of matching the scale of aggregation of results with the scale of the decision. We assert that the typical structure of current IAMs, whether bottom-up or top-down, does not anticipate emergent properties of scale. Having the ability to detect emergent properties is fundamentally necessary to the revelation of surprise and the further improvement of modeling. Most global IAMs are specified to represent structure and process at the highest level of the human-environment system hierarchy. Communication between levels of scale is primarily top-down (e.g., the determination of local land use change by change in global agricultural demand) with very few examples of process information being conveyed from lower levels to the top. In the few examples of IAMs that are bottom-up (e.g., Parry et al. [9], Rosenzweig and Parry [10]), pulses of information from low-levels to top levels are deterministic and feedbacks from the top levels (prices) are not explicitly coupled to low-level behavior.

Root and Schneider's [6] proposed ''strategic cyclical scaling paradigm'' (iterative scaling up and scaling down of models of different scales of a system) is praiseworthy as a start in bringing individually modeled components of the human-environment hierarchy together and testing for the existence of emergent properties. Techniques being developed to integrate variables simultaneously across levels of scale, such as multi-level modeling [70] accomplish the goal of strategic cycling scaling in a single model. Multi-levelmodeling potentially provides novel insight into the evolution of explicit small-scale process into regional patterns and then into large-scale emergent properties.

The scope of integrated assessment modeling has grown enormously over the past half decade. It now embraces efforts ranging widely from modeling individual agent behavior at a small scale to modeling material, energy and economic exchanges through the biosphere and economy at a global scale. The arguments of this paper extend to all forms of integrated assessment modeling of problems embedded in systems that necessarily traverse more than one level of spatial and/or temporal scale.

Finally, the time is at hand to take seriously the arguments of ecologists and systems theorists that not only does scale matter but that dealing with issues of scale explicitly is a fundamental requirement for modeling real world complexity. Absent a multi-scale structure, there is the strong possibility that IAMs are themselves doomed to be a source of surprise.

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