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Chaos Theory and Its Implications for Social Science Research

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Based on theoretical and mathematical principles of chaos theory, we argue that the customary social science goals of "prediction" and "control" of systems behavior are sometimes, if not usually, unobtainable. Specifically, chaos theory shows how it is possible for nearly identical entities embedded in identical environments to exhibit radically different behaviors, even when the underlying systems are extremely simple and completely deterministic. Furthermore, chaos theory arguments are general enough to apply to any type of entity, including individuals, groups, and organizations, and therefore they are relevant to a large domain of social science problems. As a result, this paper concludes with six familiar claims about the study of social phenomena for which chaos theory provides new theoretical arguments.

KEY WORDS: chaos theory; dynamic social systems.

> The only way to know how a complex system will behave after you modify it is to modify it and see how it behaves.
>
> *George Box*

INTRODUCTION

For decades, social scientists have searched for ways to predict social behavior. For a number of reasons, the precision of these predictions is often discouragingly low. In this paper we argue that some social behavior is hard to predict because it is, in a sense, unpredictable and the underlying social systems are inherently chaotic. This means that there exist social entities such as individuals, groups, organizations, or institutions, with virtually identical initial internal states, embedded in virtually identical environ-

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ments, which can exhibit totally different behaviors *even though* their behavior is governed by the exact same set of rules or "laws." This use of the word "chaos" denotes something quite distinct from other causes of error in empirical studies, such as randomness, exogenous variables, and measurement error. Additionally, as used here, "chaos" does not imply antisocial or psychopathic meanings of the word (e.g., Bender, 1973; Kalogerakis, 1973; Masserman, 1984; Zimbardo, 1969). Nor are we concerned with systems with a stochastic component, either in reality or in a model. In short, we believe that some social systems are characterized by "chaotic" behavior which precludes the possibility of predicting the future behavior of that system, and that researchers should learn how to begin identifying such situations.

While the scientific study of chaos is relatively new to the social sciences, the examination of chaotic systems in the physical and biological sciences has made rapid, significant progress during the last decade (Holden, 1986; Gleick, 1987; Mandelbrot, 1983). Interestingly, certain characteristics of these well-known chaotic systems are similar to the characteristics of social systems, suggesting that many social systems are chaotic (which we try to demonstrate in this paper). Once given the chaos in social systems, we then discuss the significant, and perhaps unsettling, implications of chaos theory for social science research.

The clearest examples of chaotic systems are mathematical models (such as the now famous Mandelbrot Set) which have very simple, completely specified, deterministic descriptions; yet, they exhibit wildly unpredictable behavior. In nature, many examples of what appear to be chaotic systems exist, and a new set of mathematical tools for describing and analyzing them has emerged (see Gleick, 1987, for a technically accurate, popular survey of chaos in non-social systems). We say they "appear to be chaotic" because these systems (such as cloud formations or fluid turbulence) exhibit wildly unpredictable behavior, and because our best understanding of them comes from mathematical models which are mathematically chaotic.

Indeed, there is considerable scientific interest in whether such physical systems can actually be chaotic (Lorenz, 1984). For example, even if one knows the exact components of air pressure and momentum, temperature, and humidity of every section within a cloud and its surrounding atmosphere, it is still impossible to predict how the cloud will behave specifically in the next few instants. Similarly, in an example from ecology, population size sometimes approaches an equilibrium point, but often jumps wildly and unpredictably from year to year, perhaps because population growth is chaotic by nature (Li, 1975; May, 1974). In this case, it is interesting to note that even simple mathematical models of population growth, such as $x_{t+1} = rx_t(1-x_t)$, are chaotic for some values of r.

Other examples of systems that seem to exhibit chaos are static in electrical transmissions (Berger & Mandelbrot, 1963; Mandelbrot, 1983), turbulence in air and fluid flows (Miles, 1989; Ruelle, 1971, 1980, 1983), stellar configurations (Wisdom, 1983, 1985), and human physiological patterns such as brainwaves (Arun, 1986; Goldberger et al., 1985; Mackay & Glass, 1977). In some of these phenomena, they may first appear random and chaotic, yet they can exhibit periods of quite stable behavior. In other systems, they may appear initially stable and then change suddenly and discontinuously to another state. Whether or not these phenomena initially appear chaotic and whether or not they actually are chaotic, the critical point is that our best understanding of these phenomena comes from mathematical models which are chaotic. That is, the models themselves behave in wildly unpredictable ways.

Typically, models that exhibit chaos are represented by iterated polynomials, for example, the population growth model mentioned above. Moreover, even if the theoretical models for some specific social science problem are not usually characterized by such polynomials, polynomials can still be used to approximate nearly any function. In short, they can be used in the study of a very large class of physical and social systems which might appear chaotic.

CHAOS IN SOCIAL SYSTEMS

In mathematics, physics, meteorology, ecology, and similar nonsocial science fields, the existence of chaotic systems is now fairly well established (Gleick, 1987). Evidence for chaotic behavior in the domain of social science began emerging in the late 1980s (Leifer, 1989; Kelsey, 1988; Loye & Eisler, 1987; Babüroglu, 1988) and has continued to the present (Medio, 1991; Nijkamp & Reggiani, 1991; Rosser, 1990). We believe that there are at least two useful indicators of chaos in social systems. For one, chaos is indicated by highly iterative, recursive, or dynamic structures that change over time. Systems or descriptions of systems that fit this mold will often exhibit chaotic behavior over some part of their domain. A second indicator of chaos is highly discontinuous behavior in the system, such as sudden shifts in organizational policy, downsizing, product discontinuations, voluntary employee turnover, etc. Interestingly, there are strong similarities between the mathematical models that produce chaotic behavior in biology and physics, and some of the models already used in the study of social behavior (e.g., Andersen & Sturis, 1988). At the abstract level, chaotic systems seem to share three important properties:

- The system being modeled is characterized by a state vector z_t at time t; what social scientists might call a cross-sectional or synchronic profile.
- The system is embedded in an environment characterized by another state vector u_t.
- The state of the system at time $t+1$ is a function of the system state z_t and the environment state u_t at time t.

We can profitably use a pictorial notation due to Pickover (1988) in Fig. 1. Figure 1 shows that the next state z_{t+1} depends on the current state and the environment, and the squiggle reminds us that the transformation may be nonlinear.

Loye and Eisler (1987, p. 58) suggest that the word "chaos" itself, because of its many negative senses in common parlance, might obstruct a clear understanding of the nature of chaotic systems. They suggest calling them *transformation systems* to emphasize that chaos often appears in systems that dynamically transform themselves from one moment to the next, subject to internal and environmental constraints. Also, instead of saying that a system is chaotic if its state z_t fluctuates wildly or unexpectedly, a less loaded word that can be used is "discontinuous" (in the chaos literature, the word "fractal" is sometimes used).

APPLICATION OF CHAOS THEORY TO SOCIAL SYSTEMS

Many social systems studied by social scientists can be characterized as transformation systems, and, in many cases, these systems show evidence of highly discontinuous behavior (Andersen & Sturis, 1988; Babüroglu, 1988; Kelsey, 1988; Leifer, 1989). However, many researchers are as yet unaccustomed to looking at topics from this point of view. It is important,

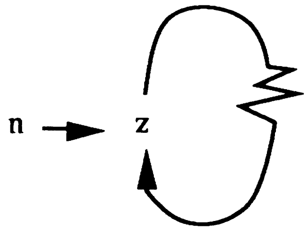

Fig. 1. A simple chaotic system.

however, that researchers watch for these characteristics in systems they study, since failure to do so can lead them to allocate resources to low payoff activities (i.e., insignificant results). There have been some suggestions of what specific topics might be most amenable to chaos theory.

First, there are systems which can be characterized as transformation systems, though they do not show evidence of highly discontinuous behavior. Loye and Eisler (1987) suggest such issues as solidarity, conformity, charisma, anomie, and norm formation are transformation systems which may have latent chaos within apparent stability. It is also easy to characterize much of the social network literature, especially the work on dynamic networks, as these types of transformation systems (Bernard & Killworth, 1979; Burt, 1975; Holland & Leinhardt, 1977; Hunter, 1975; Wigand, 1979).

Second, other potential examples of transformational phenomena which are inherently discontinuous or contain elements of unexpected change could be management succession (March & March, 1977), environmental change (Emery & Trist, 1965; Miles, 1989), organizational decline (Cameron, Kim, & Whetton, 1987), crisis behavior (Carley, 1986), negotiation processes (Fisher & Ury, 1981), decision making (Cohen, March, & Olsen, 1972; Masuch & LaPotin, 1989), work role transitions (Black, 1988; Nicholson, 1984), or organizational change (March, 1981; Wilkins & Dyer, 1988).

Since chaos theory can be potentially relevant to such a wide variety of topics, our discussion of its application is intentionally kept very general in this paper. Once readers gain an understanding of how chaos theory could apply to social science problems through our analysis, we would suggest that they examine their own research topics from the transformation systems point of view; look for areas of discontinuous, unexpected, or unpredictable change, and thus, apply our general statements about chaotic behavior to their specific areas of expertise.

THE NATURE OF CHAOS

It is important to remember that even systems that are extremely simple, completely described, and totally deterministic can exhibit chaotic behavior, and if simple systems can be chaotic, then complex systems will likely be even more so. Even a system as simple as the one diagrammed in Fig. 1 can be chaotic. All that is needed is to fill in some detail about how the new state is related to the old state. An important mathematical equation which produces chaotic outcomes is:

$$z_{t+1} = z_t^2 - \mathrm{u}, \qquad t = 0, \ldots, \infty \tag{1}$$

where z and u are complex numbers, and $z_0 = (0, 0)$. It is sometimes convenient to use a different notation that doesn't require complex numbers, such as

$$\left.\begin{aligned} x_{t+1} &= x_t^2 - y_t^2 - u_x \\ y_{t+1} &= 2x_t y_t - u_y \end{aligned}\right\} \quad t = 0, \ldots, \infty \tag{2}$$

where in this notation the state vector z_t has two components x_t and y_t, and likewise the environment state vector $u = (u_x, u_y)$. While the environment u could be a function of time, as are x and y, let it be constant $u_t = u$. Using complex numbers, it can be shown that Eqs. (1) and (2) are equivalent.

Equations (1) or (2), which underlie *Mandelbrot's Set* (Mandelbrot, 1983), the set of all pairs (u_x, u_y) for which x_t and y_t do not diverge to infinity, provide an example of a chaotic system, in this case a purely mathematical one. Equation (2) is simple and deterministic, yet unpredictable in the following sense. In general, there is no known way to predict whether x_t and y_t will diverge or not, given a specific (u_x, u_y). For some initial values of u, for example $u = (2, 2)$, x_t and y_t grow without bound as t increases, while for others, for example $u = (1/2, 1/2)$, they do not (see Appendix for details).

In itself, convergence or divergence is not remarkable. It is our inability to predict convergence or divergence that is remarkable. This discussion is cleaner in the notation of Eq. (1). Suppose that for two similar initial values u_1 and u_2 it is observed that z_{1t} and z_{2t} both converge to finite L. (By z_{it} we mean the value that z_t converges to as $t \rightarrow \infty$ when $u = u_i$.) What value for z_{3t} might be expected for an initial $u_3 = (u_1 + u_2)/2$ exactly halfway between u_1 and u_2? In a well-behaved world, one might bet that z_{3t} will also converge to L, or at least a value close to it. In the world created by Eq. (1), however, you would frequently lose this bet. For Eq. (1), there are an infinite number of cases where arbitrarily close u_1 and u_2 are separated by a u_3 that exhibits the opposite behavior, when z_{1t} and z_{2t} converge to L, z_{3t} diverges to infinity.

It is this "fractal" discontinuity that causes all the fuss. For a substantial portion of the values of the u_i, extremely close neighbors behave in opposite manners. Knowing how a large number of similar u_i behave is not sufficient for knowing how another, similar u_j will behave. In fact, increasing sample size to predict how u_j will behave is not even relevant in a chaotic domain.

Is chaotic behavior in this mathematical system any reason to be concerned about the possibility of chaos in the study of social systems? Let us suggest an analogy. Consider a topic like commitment. Suppose that (x_t, y_t) are two measurements of an individual actor's commitment, and $(u_x,$

u_y) represents the environment the actor encounters. Perhaps x is the actor's behavioral commitment, and y is attitudinal commitment, while u_x and u_y represent two forms of support for the actor, such as co-worker relationships and formal reward systems.

Next, and this is the fanciful part only useful for this example, suppose that an actor's new state, $z_t = (x_t, y_t)$, his or her behavior and attitude at time t, is accurately described by Eqs. (1) or (2).

Now suppose that person 1 and person 2 have similar co-worker relationships and formal reward systems in their environments u_1 and u_2, each start with the same behavioral and attitudinal commitments, (0, 0), and after prolonged exposure to their environments, each converges to the exact same commitment profile. That is, $z_1 = z_2$.

Now consider person 3, who also starts at (0, 0), and whose environment is very similar to u_1 and u_2. In fact, it is exactly halfway between them: Since persons 1, 2, and 3 all start with the same behavior and attitude, and their environments are nearly identical, it is surprising (i.e., unpredicted) when z_3 converges to a value completely different from z_1 and z_2. Of course, one poor prediction would not surprise any social scientist. The problem is that even in a study with a large number of actors, there can be a very large number of cases where arbitrarily similar actors can display radically different behaviors. Moreover, this dynamic can occur in social systems which may appear quite stable on the surface.

In short, this commitment analogy suggests at least two fundamental points: First, for some systems, knowing an entity's state, its environment, and the "laws" which govern the transformation of the state from one time to the next are not sufficient to guarantee that the long run behavior of the entity can be predicted. While z's behavior can be simulated in order to better understand it, it cannot be predicted in a chaotic system. Second, collecting more data points and knowing the behavior and environment of a larger number of extremely similar entities is not sufficient to predict the behavior of a new entity with the same profile in the same environment. Unfortunately, such is the nature of discontinuous, chaotic systems where statistical means, linear and nonlinear regressions, or structural equations are useless in one's attempt to understand chaos. However, graphical representations can help us better understand chaos where these traditional analytic tools fall short.

GRAPHICAL REPRESENTATIONS OF CHAOS

Much of the research performed on chaotic systems in the physical and biological sciences has benefitted from visual representations of chaotic behavior using high-powered computers with advanced graphics capabilities

(Gleick, 1987; MacDonald et al., 1985). In order to better understand chaos, it is useful to have a way to produce visual representations (derived from mathematical models) of chaotic behavior.

Remember that the set of u for which Eq. (1) does not diverge is known as Mandelbrot's Set, shown in Fig. 2. You can see that the boundary between the light and dark areas is irregular, and would not be well represented by a linear or nonlinear regression curve. (As an aside, the reader may be familiar with pictures of Mandelbrot's Set which are brilliantly colored. This is accomplished by coloring points in the set with one color, and coloring points not in the set with different colors, depending on how near the point is to the set. In our pictures, we take the less ornate but more accurate approach of coloring non-set points white.) The fine detail of Mandelbrot's Set is interesting in that it is "self-similar," meaning that closeup views of a small part of the boundary have the same characteristics as the entire boundary. The nested patterns resulting from the Mandelbrot Set resemble Russian doll sets in which each smaller doll is similar to the larger dolls. To see this infinite, self-similar patterning process, we magnify a region near the boundary between those u that diverge, and those that

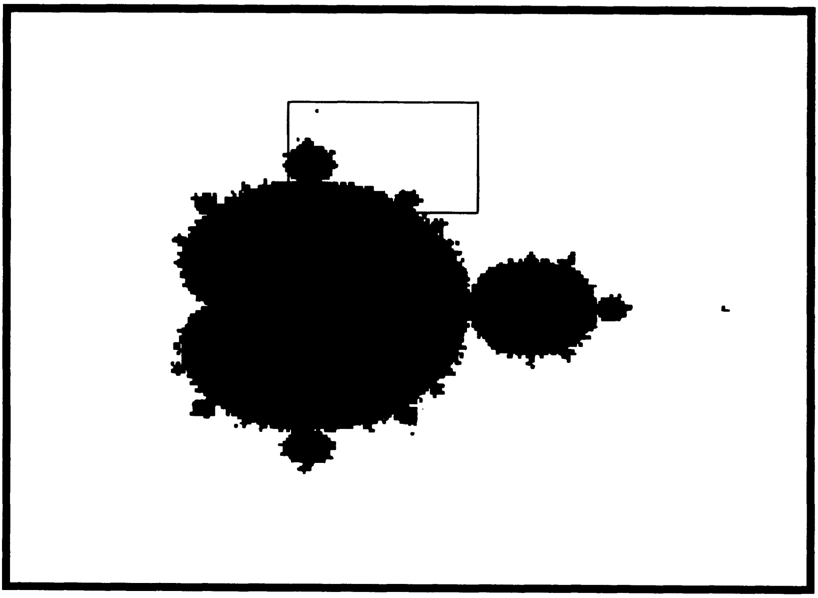

Fig. 2. A low resolution picture of Mandelbrot's Set. White areas represent u for which z_t diverges. The small rectangle shows the region magnified in the next figure. The resolution of this picture is limited by computer time and the printing device used to produce it.

do not, shown in Fig. 3. (Readers new to chaos studies are perhaps confused by what these pictures have to do with Eq. (1), and should read Appendix.)

As you can see, the magnified region reveals further, fine-grained complexity that the lower magnification disguised. This is an important characteristic of many chaotic systems. It suggests that the boundary between the set of points that behave one way and those that behave another way is not smooth. Rather, it is unpredictably discontinuous, regardless of the level of magnification that is used. This irregular, or "fractal," boundary is part of the unpredictable nature of Mandelbrot's Set. Near this boundary, points u_1 and u_2 (representing the environments of two entities in our analogy) neither of which are in Mandelbrot's Set might be separated by point u_3 which *is* in the set, and thus behaves very differently.

It seems self-evident that such discontinuous patterns of behavior are not amenable to traditional mathematical and conceptual tools intended for the analysis of phenomena in a continuous world. By this, we mean that analysis of variance and regression analysis do not seem to offer any useful understanding of Figs. 2 and 3 because these types of discontinuities are often hidden from quantitative analysis since cross-sectional research designs cannot recreate the complex boundary discontinuities with one

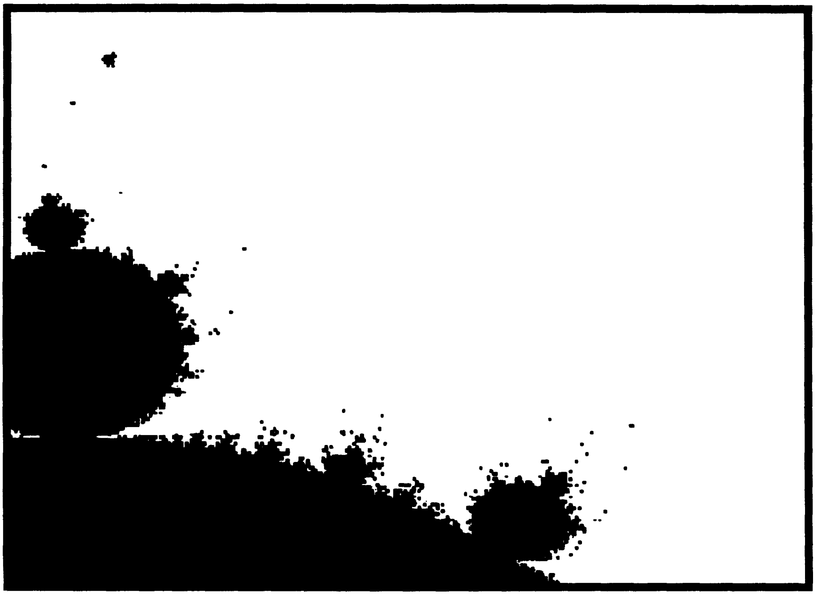

Fig. 3. A magnified region near the boundary between black and white in Fig. 2.

panel of data. Consequently, cross-sectional research on inherently chaotic phenomena may actually produce an illusion of certainty (i.e., prediction) for a social phenomenon with underlying unpredictability. Thus, one needs to utilize the appropriate level and type of analysis to reveal the discontinuities of chaotic phenomena. Before addressing this issue directly, we will attempt to link chaos theory concepts even more closely to social science contexts.

SIMPLE META-MODELS OF SOCIAL BEHAVIOR

Instead of having (x_t, y_t) represent two measurements of a single individual, suppose that x represents marketing, and y represents production, and for each of these work units there is a measure of *effectiveness*. Marketing's effectiveness depends on its previous effectiveness, production's previous effectiveness, and marketing's environment u_x, and similarly for production. This is shown in diagrammatic form in Fig. 4.

It is easy to see how this type of diagram could show a complex pattern of interactions between any number of work units by adding more entities u, v, w, ..., each behaving within some environment u_u, u_v, u_w, ..., with arrows showing which entity affects others. The arrows have squiggles in them to denote nonlinear dependencies of each entity on some others. As before, suppose the environments u_x and u_y remain constant over time, and that the transformation of x and y from time t to $t + 1$ is stable. It is perhaps interesting to note that this diagramming technique, which is, of course, virtually identical to the kinds of diagrams that social scientists draw to represent patterns of social interaction (e.g., Sailer, 1978; Weick, 1979),

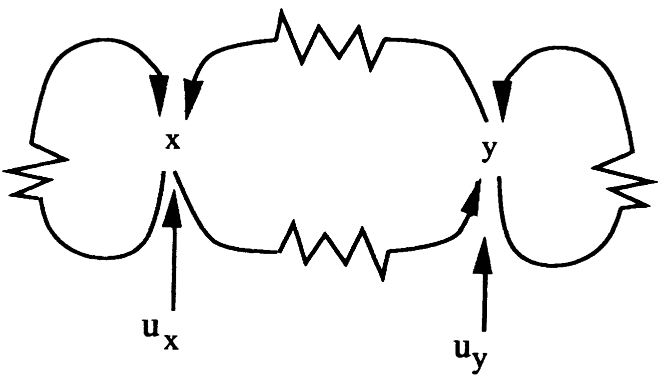

Fig. 4. A simple meta-model of social behavior.

was recently proposed by a computer scientist and mathematician (Pickover, 1988) as a general way to depict a large class of chaotic systems in natural and social domains.

How might such a system behave? Given a starting point for x, y, and the u, we can monitor x and y through time. They might diverge, the effectiveness of x and y careening wildly away from the norm and staying there (e.g., becoming disastrously ineffective). Or, they might reach some stable configuration, perhaps converging to some single pattern of effectiveness (e.g., consistently moderate in effectiveness) (called a "static attractor"). They could also alternate among a set of effectiveness values, for example moving consistently from high to medium (called a "dynamic attractor"). Or, they could alternate among an apparently infinite and unstructured, but bounded, set of effectiveness values (called a "chaotic" or "strange attractor"). This means that their effectiveness would change constantly and unpredictably within a bounded range.

To explain the form of relationship between x (marketing) and y (production), it would be necessary to determine the values of the parameters, or at least to find some satisfactory approximation. Practically speaking, this is asking a lot. No social science study has ever collected enough data through time to permit such models to be accurately determined, but it is possible in principle. At this point, we can only roughly estimate that such a study would require measurements at at least 1000 points in time for every entity to the system, and perhaps 100 such systems would need to be studied. Again, roughly estimating, this amounts to at least 200 megabytes of data. Even if a data set this large were collected, the dilemma of respondent reactivity may create validity threats.

Assuming the data were collected, an infinite number of simple deterministic, mathematic rules (the "laws" social scientists look for) might be used to characterize the relationship between x (marketing) and y (production). The class of all such models is infinite, however, even if we restrict them to subsets of simple quadratics. As an example, though, we have experimented with rules of the following form which describe a simple nonlinear system with an interaction term:

$$x_{k+1} = r_x{}^1 x_k^2 + r_y{}^1 y_k^2 + r_{xy}{}^1 x_k y_k - u_x$$

$$y_{k+1} = r_x{}^2 x_k^2 + r_y{}^2 y_k^2 + r_{xy}{}^2 x_k y_k - u_y \tag{3}$$

The rs are small, randomly chosen coefficients. We hit upon Eq. (3) by simple experimentation. We were looking for a pair of equations that could in some sense represent a large number of plausible models that might describe the transformation of states of two interacting entities through time (these could be individuals, groups, or organizations). Mathematically, Eq. (3) would offer a first cut approximation to many such models and it is unlikely that changing the form of Eq. (3) would have much substantial effect on the rest of what we say here. Also, since simple quadratics can be used to approximate many functions that might describe actual two-person social systems, it is plausible to say that for some values of the *r*s we would have models of those systems, but, of course, we can offer no such models here.

For this example, we selected the *r*s randomly and investigated the behavior of those systems. These random models are representative of the types of models that we might obtain by fitting Eq. (3) to data, so we call them *metamodels.* In our experiments, the metamodels often produce chaotic behavior. For example, Figs. 5 and 9 provide a visual representation of the hypothetical dynamics between marketing (x) and production (y) and illustrate some potential metamodels of these relationships. The figures also display the characteristic fractal or discontinuous patterns of areas of divergence (in white) which might represent conflictual relationships between departments and areas of nondivergence (in black) which might represent the continuation of cooperative relationships. Moreover, closeups of parts

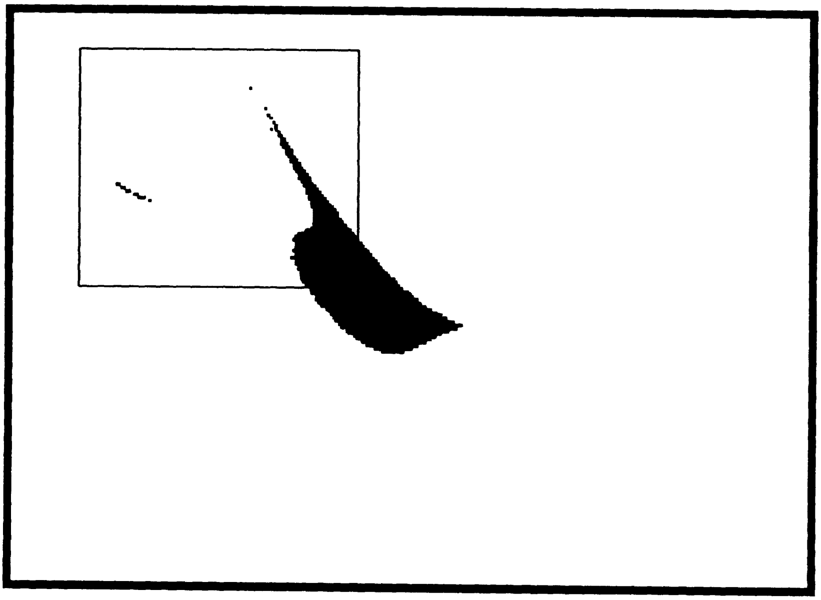

Fig. 5. System generated by Eq. (4), for u_x and u_y in the interval [-5, 5].

of the system in Figs. 6–9 show that what might appear predictable in Fig. 5, is in fact chaotic with an arbitrarily fine data structure.

For the issues we are trying to illustrate through Figs. 5–9, the exact values of the r are unimportant, but are included for completeness. To begin, we view in Fig. 5 the set generated by the pair of equations

$$
\begin{aligned}
x_{k+1} &= -1.0x_k^2 + -0.998029y_k^2 + -1.833476x_k y_k - u_x \\
y_{k+1} &= -0.646715x_k^2 + -0.270796y_k^2 + -1.634678x_k y_k - u_y
\end{aligned}
\tag{4}
$$

In Fig. 6, we magnify the picture somewhat and can see that the boundary of the center blob is not smooth as it appeared to be in Fig. 5. In fact, the boundary is discontinuous, or chaotic. This underlying discontinuity is revealed even further as we zoom in progressively closer on the boundary of the center blob. Specifically, in the lower left corner of Fig. 8 is a small cuba-shaped cluster. After zooming in on it, Fig. 9 reveals a series of nested semi-spirals surrounded by further instances of diverging points in close proximity. Interestingly, these spirals could not have been predicted when first examining the boundary on the center blob in Fig. 5.

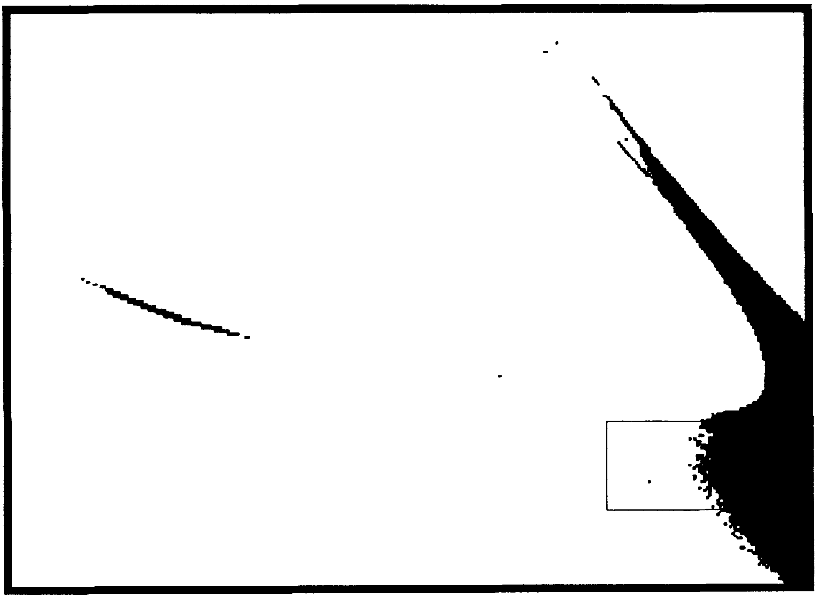

Fig. 6. Magnified view of system generated by Eq. (4).

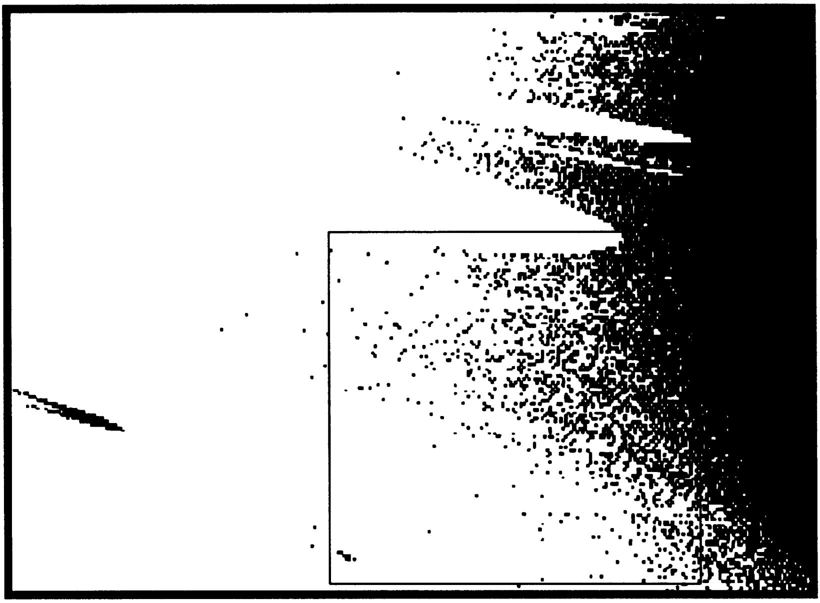

Fig. 7. Further magnification of Eq. (4). Take u_x from [−1.646875, −1.305469], and u_y from [.522, 1.157].

This brief tour of the fractal or discontinuous patterns of divergence and nondivergence (in white and black, respectively) illustrates graphically that very slight shifts in certain parameters can result in radically different patterns of behavior. In these figures, the inherent unpredictability of metamodel relationships between marketing and production departments was also illustrated. Moreover, attempting to fit traditional research designs and statistical analyses over the behavioral patterns revealed in Figs. 5–9 would have been dysfunctional and deceptive in terms of explaining the underlying data structure. Interestingly, the pattern of nested complexity shown in Figs. 5–9 is not unique to the system generated by Eq. (4). Nearly every set of randomly generated coefficients has produced a new pattern featuring the same highly discontinuous behavior shown in Figs. 5–9. The one illustrated is typical.

It is worth noting that class of equations represented by Eq. (3) includes Mandelbrot's generating equation when $r_{x1} = 1$, $r_{y1} = -1$, $r_{xy2} = 2$, with the other rs equal to zero. Let the complex numbers $z_k = (x_k, y_k)$ and $u = (u_x, u_y)$. This means that Mandelbrot's Set, perhaps the best-known member of the class of chaotic systems in mathematics, is a member of our class of metamodels of two-person social systems. Though perhaps far-

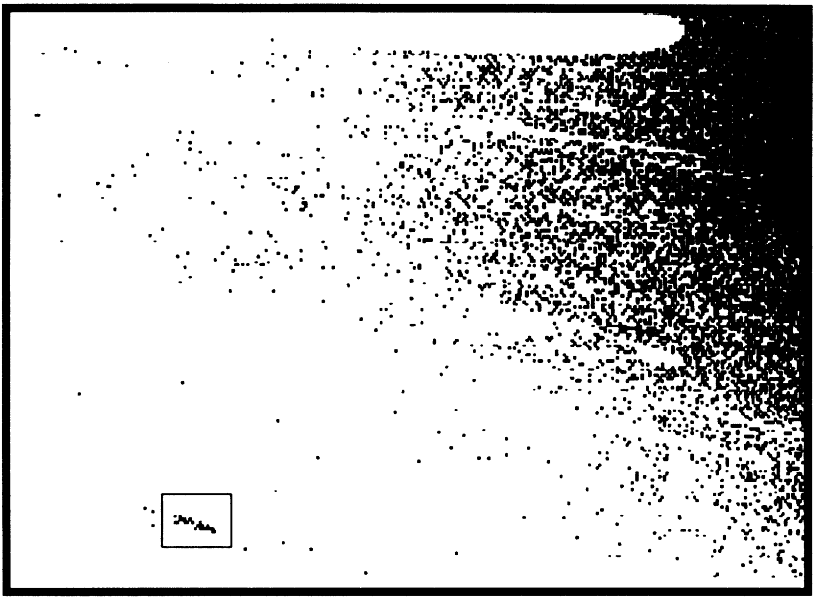

Fig. 8. Yet further magnification of the system generated by Eq. (4). u_x is in [−1.543386, −1.360947], and u_y is in [.525325, 0.930975].

fetched, it is possible to offer an interpretation of Eq. (2) in social terms. Suppose x and y measure two work groups' social cohesiveness. The transformation $x_{t+1} = x_t^2 - y_t^2 - u_x$ characterizes a work group which tends to remain stable $z = (0, 0)$ when x is just a bit more or less cohesive than y; the transformation $y_{t+1'} = 2x_ty_t - u_y$ characterizes a work group which tends toward cohesiveness whenever either x or y are cohesive, and so on. We realize that this is, in fact, armchair modeling; however, we insist that there are some very important lessons to be gained from the fact that these simple models produce such unusual patterns of behavior. One reason why these lessons are important is that chaos seems to be quite common in social contexts.

CHAOS IS COMMON

Early on in this research, we worried that even though chaotic models are theoretically interesting and seemed quite relevant to social systems, they might actually be rare or exotic. Moreover, it seemed that if mathematical chaos is rare, then by analogy chaos in social systems might be

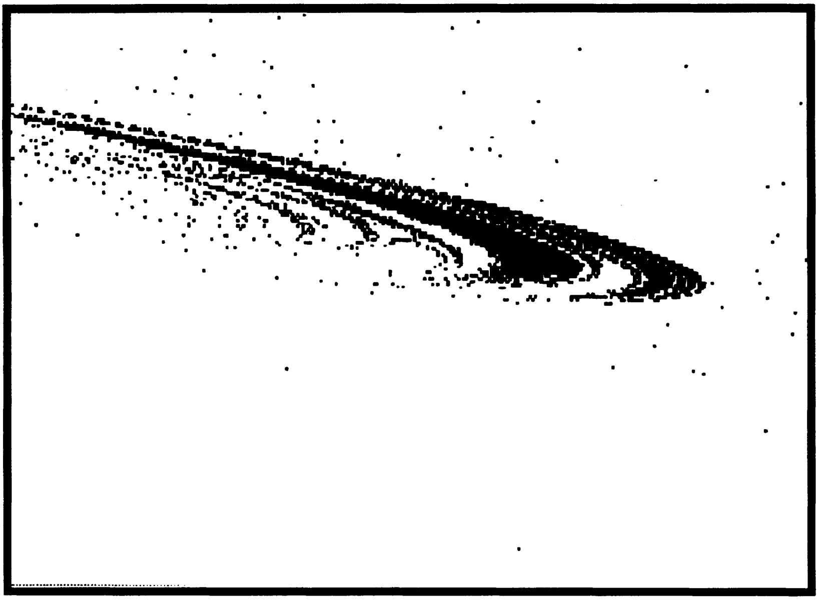

Fig. 9. The last magnified view of the system generated by Eq. (4), u_x in [−1.510319, −1.4943561], and u_y in [.539523, .586172].

equally rare. However, many different values for the *r*s in Eq. (3) have been tried, and so far all of them have exhibited chaotic behavior. Based on this analysis, we, like Mandelbrot (1983) and other social scientists (e.g., Andersen & Sturis, 1988), feel that chaotic systems are quite common in social contexts, and the only reason they are so rarely discussed is that they are so difficult to identify or work with.

IMPLICATIONS OF CHAOS THEORY FOR SOCIAL SCIENCE RESEARCH

Since chaos appears to be quite common in the social as well as physical environments, we have outlined several important implications of chaos theory for social science researchers to consider in their research designs and analytic approaches. These implications result from our fundamental argument that many social systems reflect the central components of chaos theory. In other words, they are iterative recursive systems that can exhibit discontinuous changes over time and as such, require a careful reassessment of traditional approaches to social science.

Implication 1. So long as social sciences continue to rely on cross-sectional studies, it is unlikely that they will discover and model the chaotic nature of social systems.

How do social scientists typically study systems that fit the model of chaos presented here? Suppose the equations like the ones we have been using and graphically illustrating (e.g., Figs. 5–9) actually describe some class of two-person social systems. Typical researchers might choose a number of systems "at random" and then measure the states x_i and y_i of the entities and environments u_x and u_y with as much precision as they can afford (which is usually not very much). After collecting the data, they would attempt to correlate the states and environments with some other measurements, compare subgroups, and so on and so forth.

Usually, social science measurements are cross-sectional or synchronic. It is widely recognized that more attention should be paid to change to more accurately assess human behavior (Cook & Campbell, 1979), but it is difficult to find affordable ways to do so. When longitudinal studies are possible and utilized, however, measurements can be repeated after some time δ, permitting correlations and comparisons of the data from time t and $t + \delta$. Suppose that δ is a long enough time that evidence for the divergence or nondivergence of x_t and y_t is easy to see. The researcher might then use statistical analyses to attempt to build a model that predicts similar outcomes for entities with similar initial states and environments.

To truly access a chaotic system, though, thousands of synchronic observations would be necessary, spaced out over a long enough time period that potential divergent behavior would have time to manifest itself. Furthermore, these data points would need to avoid the potential reactivity bias of respondents providing information about themselves or their workplace over so many points in time.

Implication 2. Poor analytical results (e.g., low R_2 values and lack of statistical significance) are to be expected when analyzing chaotic systems with standard statistical methods.

When entities with similar starting points and environments end up behaving differently, social scientists customarily conclude that they have omitted some important variables, that their measurement is too rough, or that the random or stochastic part of the problem has overwhelmed the patterned part. To improve the research, they try harder to eliminate these three problems in subsequent studies. Instead of trying harder, however, we suggest that social scientists should try something different. Trying to predict will fail if the systems are indeed chaotic. As we saw in the sets of equations and corresponding Figs. 5–9, if the relevant states are near the boundary between diverging and nondiverging parts of a chaotic system, the accuracy of such statistical models could be spuriously low. Even if hundreds of very similar entities all diverge, another hundred with nearly identical profiles might not, since the underlying causal laws themselves produce discontinuous behavior. More importantly, there is no way beforehand to predict who will diverge, and who will not, even in the unlikely case that no variables have been omitted, measurement has been perfect, and no stochastic error is present.

We have neither shown nor have we attempted to argue that the chaotic part of social behavior always dominates the nonchaotic part. The question is not simply whether or not chaos exists, but the degree to which chaos occurs and the degree to which such chaos is relevant to particular research questions. Even chaotic systems can exhibit nonchaotic behavior over much of their domain.

Consider the situations depicted in Fig. 10, where the x and y dimensions represent two variables of interest in some study, the white area represents combinations for which the systems under study diverge, and the shaded area represents combinations which do not diverge, with a fractally chaotic boundary. The four numbered rectangles represent particular research projects. Just as an anthropologist might be interested in pygmies while a basketball coach is interested in giants, it is possible that not all studies of a chaotic system will be interested in those values for which chaos occurs. It is easy to imagine a research project where all of the individuals under study are well within the subset that doesn't diverge (study 1), for example workers in a profitable firm in a slow changing industry. Another study might fall well within the subset that diverges (study 2), perhaps the CEO has absconded with the funds, causing the workers to diverge away from equilibrial behavior, and thus the fractal boundary is not germane to those studies. If the profiles of the subjects of the investigation are all far away from the domain of nondivergence (white areas), or conversely, if the profiles are all tightly clumped deep within the domain of nondivergence (black areas), then the chaos inherent in the system is relatively unimportant.

In the divergent case (study 2) an important issue, though, is the rate of divergence. Using the commitment example again, the rate at which individuals lose their commitment is important, especially when the commitment profiles can influence important outcomes such as turnover and performance. In the nondivergent case (study 1), the interesting questions are about the range of states exhibited by various types of individuals and how frequently they change. It would be useful, for example, to know what range of values commitment can take, and how long the various types of commitment last.

In study 3, the domain of interest is large, and thus divergent over the most part. In many ways, study 3 would be similar to study 2. The

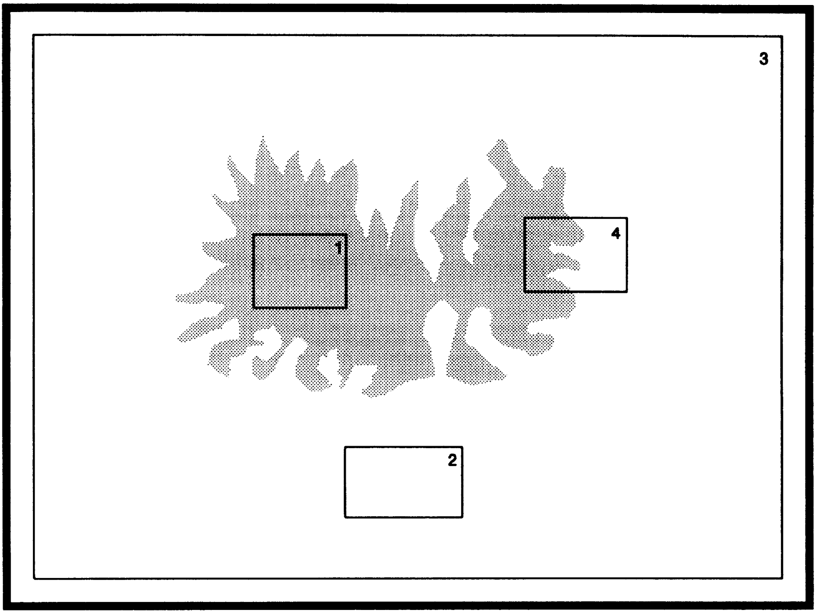

Fig. 10. Four hypothetical studies of a chaotic system.

difference is that for a small part of the domain, the entities behave in a substantially different way. Using typical statistical methods, we would expect the results of study 3 to be somewhat weaker (e.g., lower R_2) than study 2 if some of the cases under study happen to fall in the shaded area. As a result, whatever model is fit to the "divergers" would fail for the "nondivergers," and *vice versa.* Divergers and nondivergers are essentially from different populations, so any attempt to fit a single model will perform poorly due to the underlying differences in sample composition.

In study 4, it is clear that some individuals fall on either side of the boundary of a fractal set and chaos will dominate any other pattern. Near the boundary, it is impossible to predict which individuals will diverge, and which will not, because of the intrinsic unpredictability. From our perspective, the most significant research problems depend on whether the profiles of entities place them near the boundary between divergence and nondivergence. Observation of individual cases near this boundary reveals that some diverge and some do not; however, further examination of the system will only reveal finer details of chaotic behavior when examining the boundary cases because of the "fractal" nature of the boundary. We emphasize that doing social science better, that is, better measurement, larger samples, better statistical methods, and better theories, will never improve the accuracy of prediction in situations like study 4. In fact, it may even make things worse. Crude techniques will likely miss the fine chaotic structure generated by the process, while accurate longitudinal measurement would permit distinguishing among diverging and nondiverging individuals only after, and not before, they had diverged or not diverged.

Implication 3. Use simulation techniques to study chaotic or complex social systems, but do not expect to be able to mimic any specific actual systems.

If better methods and research can actually result in less precise predictions of behavior, what should social scientists do? First, it seems clear that researchers must determine whether their particular research problem fits the chaotic profile. In other words, if the problem under examination is characterized by a transformation system, with (1) entity states, (2) external environments, and (3) nonlinear iterations (i.e., current states dependent upon previous states), the system will likely exhibit some degrees of chaos over some of the domain. In this situation, the researcher must determine whether the particular problem lies well within either the divergent and nondivergent parts of the system (both of which are nonchaotic) or near the border (which is inherently chaotic).

If the core problem lies near the border between the divergent and nondivergent domains of the system, then predictive research approaches are doomed to fail since such phenomena are discontinuous, and the only way to know how the actual phenomenon will behave is to watch it behave as we did earlier in Figs. 5–9. Unfortunately, sufficient observations could, by themselves, have a dramatic reactive effect on the system (Nunnally, 1978).

There are approaches to explanation and understanding suited to the study of chaotic systems, however. One way to increase our understanding of chaos in the social world is to build a sufficiently detailed simulation, and then analyze its behavior. A good example of this is the gradual resurgence of interest in simulation of decision making and work behavior in organizations (Padgett, 1980; Carley, 1986; Masuch & LaPotin, 1989). For nonsocial phenomena, where chaos has already been accepted as a frequent state of affairs, researchers have become accustomed to building simulation models which behave like the phenomenon under study, yet have little expectation that they can actually build a predictive model of a specific, empirical instance of the phenomenon (see Gleick, 1987 for a review of these simulations).

Implication 4. Statistical technology will remain useful, but will play a different role in the analysis of chaotic systems.

"Good" models of social systems are those that produce representations of social behavior which are in some way indistinguishable from actual organizational patterns. If and when this occurs, we suggest that researchers have obtained a reasonably good understanding of the phenomenon. This is not the same as being able to predict the outcome of any particular event. Even after characterizing the actual event as precisely as possible, being off by only a smidgen (e.g., only 10^{-10}) on some key parameter could completely invalidate the outcome of the simulation as a predictor in a chaotic social system. For example, in Figs. 5–9 we showed that slight parameter changes revealed significantly different outcomes from figure to figure.

This is not to say that the current arsenal of quantitative techniques is useless. While such methods are normally used for prediction, in the examination of chaotic social systems, these techniques can still help us understand behavior. In fact, the "data" collected about a simulation will probably be very "good" data. In many respects, traditional quantitative methods will work much better in the study of simulated organizations than they do for real organizations (see Masuch & LaPotin, 1989 for a good example of such a simulation).

Implication 5. Qualitative methods will increase in importance when studying potentially chaotic social systems.

In cases where it is preferred to study actual social behavior, along with quantitative research methods, qualitative approaches to understanding chaotic social systems may prove beneficial. This is in part a function of the complex nature of chaotic phenomena. In order to understand chaos, it must be examined in its dynamic, unpredictable setting, as it occurs. This is why high-powered computer-graphical representations of systems have become so important in fields where the importance of chaos has been recognized. The idea is to put a tremendous amount of data into a form where the human perceptual system can make sense of it.

Quantitative techniques, for the most part, presuppose a static snapshot of the organization in the form of data. To capture the chaotic nature of a transformation system, a massive amount of quantitative data is required, more than most researchers can afford to collect. On the other hand, interviews and observation can provide pertinent information for understanding the negotiated, changing nature of chaotic social systems. However, qualitative methods can be characterized as emphasizing validity at the expense of reliability (Kirk & Miller, 1986). They can be just as scientific and objective as nonqualitative studies, but by their nature they are flexible and can quickly adapt to changing conditions in the field. In a sense, the questions and responses in an interview or the events one chooses to look at during observation are a large number of very small experiments, "designed" on the fly. While qualitative studies might incur problems of intersubjectivity and low reliability, they can have the advantage of efficiently producing a large amount of valid data which is necessary to understand how a chaotic social system might behave.

Implication 6. Social science must develop a definition of "understanding" when analyzing chaotic systems.

An ongoing debate between quantitative and qualitative researchers has often centered upon the desirability of prediction vs. understanding as the primary goal of research. In the case of extremely chaotic social systems, however, the debate is over. The only attainable scientific goal is understanding when researching a chaotic domain. However, it is sometimes hard for scientific writing which does not claim to be able to tell the future to find an appropriate publication outlet. Essentially, in studies where prediction and control are possible (i.e., not in the chaotic domain), publications are a reasonable result. Yet, descriptive research may be the only achievable goal for studies of chaotic systems, and this research goal may be in direct contrast to the implicit or explicit assumptions of some publication outlet editors or reviewers. As a result, studying potentially chaotic phenomena may well be a critical task for the social science community to engage in, but it may be one with initially lower rewards than traditional predictive and control research.

SUMMARY

Fundamentally, we have argued that chaotic systems which clearly exist in the physical world are probably quite common in the social domain. In the past, as social scientists we have been generally unaware of chaotic phenomena which are discontinuous, unpredictable, and yet governed by a set of laws. Moreover, the bulk of social science research from our perspective has studied social phenomena as if they were continuous and nonchaotic with cross-sectional research designs. This approach reflects in part the idealized goal of prediction and control (inculcated in most graduate programs), our natural tendency to use research methods we already know, and the typically prohibitive costs of collecting longitudinal data.

Given our arguments that many social phenomena are inherently chaotic and thus unpredictable, the research goal of understanding is the only viable objective when studying chaotic social phenomena. In short, systems exhibiting chaotic behaviors can only be understood, whereas, nonchaotic systems can be understood, predicted, and perhaps controlled. As a result, it is fundamental that we assess carefully the nature of our research problems and ascertain whether they potentially fit a chaotic profile. In addition, we hope that readers will take chaos theory frameworks and apply them to a wider range of research problems at either a theoretical or philosophical level in order to assess the potentially chaotic nature of social phenomena and develop better methods for modelling such phenomena. By so doing, we are convinced that social science will understand in much more depth and breadth the chaos which indeed exists in the social systems that surround us.

APPENDIX: DISPLAYING CHAOTIC SYSTEMS

To display Mandelbrot's Set, or any other chaotic systems, we make use of the fact that pairs of numbers (or a complex number) can be equated with points in the usual Cartesian coordinate system. Here we work through two examples:

First, consider the point $u = (2, 2)$. Starting with $z_0 = 0 + 0_i$ or $(x, y) = (0, 0)$, and converting u to its complex number equivalent, $u \rightarrow 2 + 2_i$, compute $z_1 = z_0^2 - u = -2-2_i$ using Eq.(1) or x_1 and y_1 using Eq. (2). Here is what happens if we repeat this iterative process a few times:

t	*z*
0	0 + 0i
1	−2 − 2i
2	−2 + 6i
3	−34 − 26i
4	478 + 1766i
5	−2890274 + 1688194i
.	.
.	.
.	.
∞	∞

and before long, z_t has careened off to very large values. To convert this table to Eq. (3) notation, equate x with z's real part, e.g., 478, and y to the imaginary part, e.g., 1766.

Since $u = (2, 2)$ causes z_t to diverge to ∞, we color the point (2, 2) white — it is not in Mandelbrot's Set.

Again, this time for $u = (1/2, 1/2)$.

t	z
0	0 + 0i
1	−.5 − .5i
2	−.5 + .5i
3	−.25 −.5i
4	−.6875 −.25i
.	.
.	.
.	.
56	−.5107613 − .1956228i

57	−.2773912 − .3001669i
58	−.5131543 − .3334727i
.	.
.	.
.	.
159	−.5107613 − .1956228i
160	−.3990690 − .2486151i
161	−.4025534 − .3015708i
.	.
.	.
.	.
199	−.4195819 − .2639228i
200	−.3936062 − .2785256i
201	−.4226506 − .2807412i
.	.
.	.
.	.

After 200 iterations, z_t still hasn't diverged, nor will it. Therefore, $u = (1/2, 1/2)$ is in Mandelbrot's Set, and we color it black. There is a notable approximation implicit here. To truly test a point, an infinite number of iterations is required. For purposes of putting a picture of Mandelbrot's Set, or any other chaotic system in this paper, we assume that a large number of iterations is equivalent to an infinite number.

In any case, this is how any point in the plane can be tested. It either belongs to Mandelbrot's Set, or doesn't. For other systems, such as Eq. (4), the same process is used.

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