

A REVIEW AND ASSESSMENT OF NETWORK CONCEPTS AND THEIR
APPLICATIONS IN GEOGRAPHY AND RELATED DISCIPLINES

by

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ABSTRACT

Networks are a structure common to many disciplines. Research on networks has taken different forms in domains such as graph theory, sociology, vascular networks, small-world networks, geomorphology, ecology, evolution and engineering. Networks may be modeled as non-spatial networks (unvalued graphs), which contain only topological information, or as spatial networks (valued graphs), which contain both topological and distance or location information. Geographers study spatial networks whether the networks occupy absolute or relative space. All networks have topology and connectivity. Many networks are thought to have emergent, systems properties of flow, feedback, hierarchy, growth/reduction, indirect effects and robustness to error. As such, networks are a useful conceptual tool for modeling phenomena in and across many diverse fields.

INTRODUCTION

Networks are found in most all disciplines. In engineering networks are used to model electrical circuits. In anatomy the circulatory system is described as a network. Molecular biology considers metabolic networks. Artificial intelligence employs neural networks. Computer science has various computer

networks. City planning has road networks, water networks and electric grids. Geology has faults and fissures that create networks. Ecology has food webs. Mathematics has graph theory and branching processes. Geomorphology has stream and ridge networks. Anthropology and sociology have social networks. Economists have financial networks. Evolution has phylogenetic trees. Communications has communication networks. Even in our everyday language we may speak of family trees, “networking” or terrorist networks.

This paper explores networks in a variety of disciplines, suggests several ways of classifying networks by their different characteristics, and attempts to elucidate general properties common to all networks or classes of networks as described earlier.

The first section reviews network terminology. The second section briefly reviews the study of networks in seven different fields. These are illustrated in Figure 1. The third section classifies networks and shows how the treatment of networks in any of these subject areas often considers spatial properties—whether absolute or relative—of the networks. Thus, patterns and processes modeled as spatial networks concern geographers. Finally, the paper speculates on properties common to networks.

NETWORK COMPONENTS AND TERMINOLOGY

Various terminology has been used to describe the components of networks. This section aims to describe network elements, illustrate where network

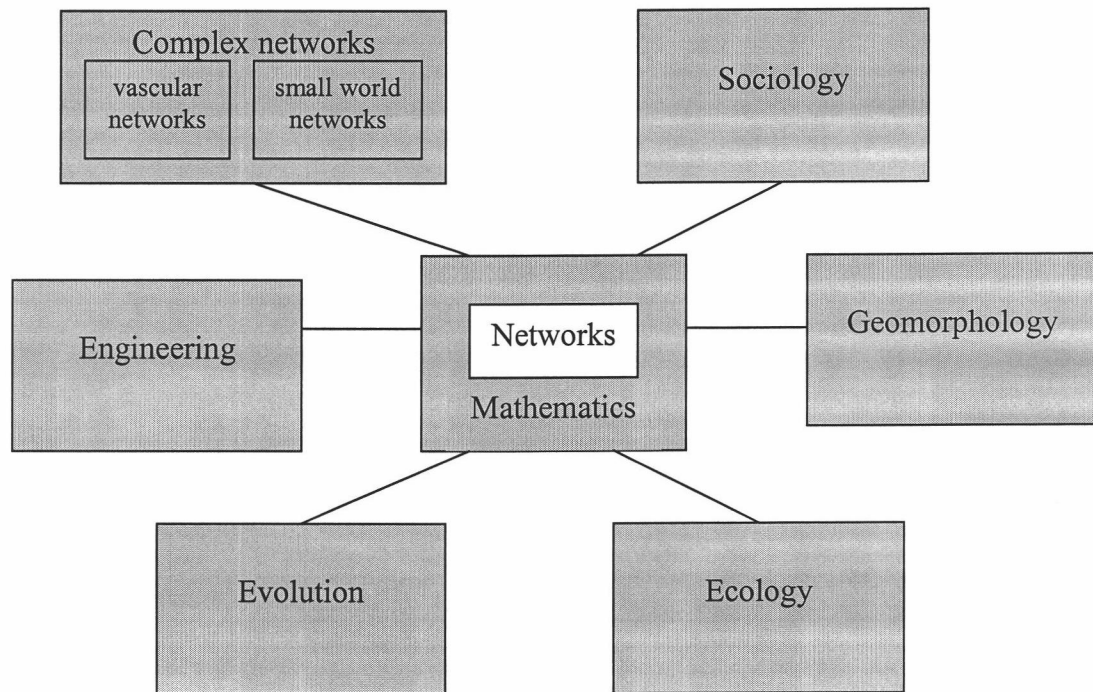


Figure 1. Network study and analysis in various subject domains reviewed in this paper.

components have been defined in the literature and show where terminology may or may not be equivalent.

Networks are structures that have two basic components: nodes and the links between these nodes. Or, stated another way, networks have two basic components: edges and vertices where the edges meet. The former language of nodes is generally used in the literature surrounding social network analysis, food web network analysis and utility networks. It underscores the fact that the nodes are often separate entities that have various relationships to each other as defined by the links. The latter terminology of edges and vertices comes from graph theory (Busacker and Saaty 1965). Here the emphasis is usually on the edges, with the vertices occurring because edges intersect. This terminology may fit well with

actor	arc
compartment	bond
component	branch
conductor	channel
constituent	connection
element	curve
fork	edge
hub	link
intersection	(line) segment
junction	one-cell (matrix)
knot	path(way)
node	(relational) tie
point	route
vertex	side
zero-cell (matrix)	spoke

Table 1. Elements of networks: Terminology

networks such as streams, where tributaries enter a main channel at *vertices* rather than *nodes*. However, much of this terminology is used interchangeably and there is very little consistency across the various fields of network study or even within a field. Most authors use several different terms in the same article to express *node* or *link*. A list of synonymous terms is found in Table 1.

The food web literature tends to use terms like *compartment* to show that nodes may gain, lose, and store energy or nutrients (Christian and Ulanowicz 2002, Ulanowicz 1999, Kay et al. 1989, Field et al. 1989, Mikulecky 1991). The small-world network literature tends to use the term *path* or *pathway* (Watts and Strogatz 1998, Jeong et al. 2000, Wagner and Fell 2000, Strogatz 2001). In a geographic information system (GIS), *arc* is often used (Chou 1997, Ch. 2). Social network analysis uses *actors* and *ties* (Wasserman and Faust 1994). Subject-specific terms are also used: neurons and synapses in neurology, for example (Feuvre et al. 1999).

Beyond the basics of nodes/vertices and links/edges, there are some more specialized terms used to describe network components. Geomorphologists often distinguish between internal and external links of a stream network (Shreve 1967, Abrahams 1984, Ichoku and Chorowicz 1994), and a particular node representing the most downstream point of a stream channel may be called an *outlet* or *root* (Karlinger and Troutman 1989). *Down node* and *up node* have been used to signify nodes in directional flow networks like streams (Ichoku and Chorowicz 1994). Sometimes, as in utility network analyses, certain nodes are defined as sources or sinks/terminals of matter, energy or information (Frank and Frisch 1970, Zeiler 1999, Ichoku and Chorowicz 1994). Finally, while it may not be part of the network per se, a *site* may be defined as an area or point serviced by a distribution network, such as a cell in a circulatory system (Banavar et al. 1999) or the area drained by a stream segment (Swanson and Jones 2002).

Some terms have been developed to describe elements larger than a single node or link but smaller than the entire network. The Web has been described as having a *core*, *upstream*, *downstream* and *tendrils* regions (Kleinberg and Lawrence 2001). In social network analysis, a pair of actors and the possible tie between them is a *dyad*; localized clusters may be called *cliques* or *relations* (Wasserman and Faust 1994, Collins and Chow 1998). In utility and communication networks, a set of links that connect one group of nodes to all remaining nodes may be called a *cut* (Frank and Frisch 1970). *Branches* of woody plants are units of study in plant ecology and physiology (Sprugel et al. 1991).

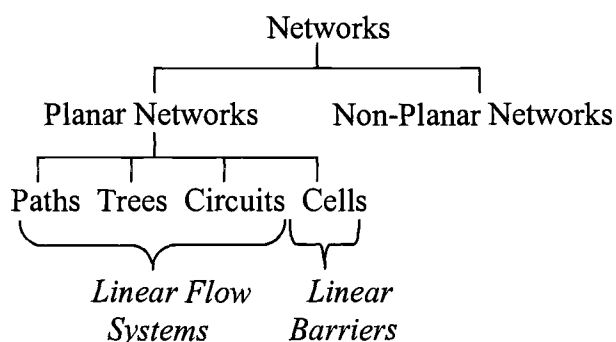


Figure 2. Topological classification of networks.
(Adapted from Table 15.1 in Haggett 1967.)

Various authors may assign nuances of meaning to the basic network terms. For example, Chou (1997, Ch. 7) distinguishes between nodes and vertices in GIS network analysis: nodes are at the

start and ends of line segments and carry information about the topology of the network, while vertices simply delineate the segment. Jeong et al. (2000) define a *hub* as a highly connected node. Wagner and Fell (2000) define a pathway as a *sequence* of adjacent vertices. This is called a *walk* by others (Karliringer and Troutman 1989). Kay et al. (1989) define an *arc* as a directed edge. However, none of these definitions are standard across the entire range of network literature.

The basic terms can be combined to make a standard classification of networks (e.g., Figure 2). A *path* is a sequence of links and nodes in which each node has no more than two links. A *circuit* is a path in which the first and last nodes coincide. A *tree*, or branching network, is a network that contains no circuits. *Cells* make up areal networks of polygons. These are all planar networks since they can be drawn in a plane so that the edges intersect only at their endpoints (Busacker and Saaty 1965). In addition to the networks shown in Haggett's (1967) diagram, networks may contain *loops* if both endpoints of one edge are the same vertex (Carré 1979).

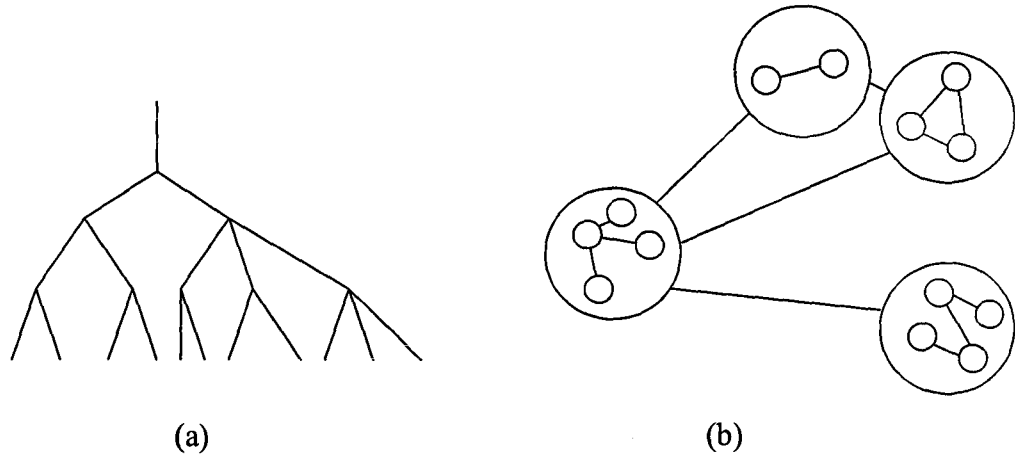


Figure 3. Two types of hierarchical networks: Branching hierarchy (a) and nested hierarchy (b).

Networks may be hierarchical in structure. Two types of hierarchical networks are possible (Figure 3): branching hierarchy and nested hierarchy. Many types of networks may be modeled as branching hierarchical networks; they include stream systems, evolutionary phylogenies, plant root systems, organizational flowcharts, and viscous fingering of fluids (see Fleury et al. 2001). In contrast, food webs and transportation systems are often modeled as nested hierarchical networks. For instance, Mainguenaud (1995) designed a data model to manage several levels of abstraction of road networks in an object-oriented GIS using a nested hierarchical network structure. Other researchers interested in food webs have relied on a hierarchical network approach also (e.g., Burns et al. 1991, Ulanowicz 1990).

SELECTED NETWORK LITERATURE

The following section reviews network study in a variety of fields—from mathematics and sociology to geomorphology and evolution.

Graph theory

Graph theory is the mathematical treatment of networks. Its beginnings are traced to the Swiss mathematician L. Euler (1707-1783) who took on the famous problem of finding a path that crosses the seven bridges of Königsberg, Prussia, once and only once. He proved it impossible (Biggs et al. 1976). Euler's solution starts with a reference to the mathematician G. W. Leibniz who noted two branches of geometry, one concerned with *magnitudes* ("which has always received the greatest attention") and another ("almost unknown") concerned with *position*. This geometry of position later came to be known as *topology* and is closely aligned with the study of networks. At the time, Euler knew of no applications or methods for this study of position but recognized that the Königsberg bridge problem, while seemingly geometrically construed, did not involve any measurement of distance and so appeared to be concerned with position only (Biggs et al. 1976).

Euler reduced the bridge problem first to a simplified diagram and then to a series of letter symbols representing each of the four land areas and seven bridges. In doing so he created what mathematicians today call a graph. A graph is made up of a finite set of vertices (in Euler's case, the four land areas), a finite set of edges

(the seven bridges), and a rule (the *incidence mapping*) for delineating which edges are connected with which vertices (Biggs et al. 1976, Busacker and Saaty 1965).

The mathematician J. J. Sylvester first used the word graph in its graph theory sense in 1878 in reference to the then recent convention of using letters and lines to represent molecules in “chemical graphic notation.” Today the term *graph* is used interchangeably with *network*, although, according to Busacker and Saaty (1965), *network* may imply that quantitative attributes have been ascribed to a graph. This may also be called a *valued graph*.

Graph theory defines a terminology to describe both local and global properties of a graph (Busacker and Saaty 1965, Carré 1979, Biggs et al. 1976, Wasserman and Faust 1994). These include *directed graph*, a graph in which an edge from vertex *a* to vertex *b* is distinguishable from an edge from vertex *b* to vertex *a*; *path*, a sequence of edges in which no edges or vertices are repeated; *circuit* (or *cycle* for directed graphs), a path of at least three vertices where all vertices are distinct except for the first and last vertices, which coincide; *degree* (also called *valence*), the number of edges a vertex has; and *connectivity*, a property of a graph if every vertex in the graph is joined by at least one path (Busacker and Saaty 1965).

All graphs may be represented geometrically. For some graphs, this is a geometric illustration of actual physical connection; for other graphs, it is a mere convenience and has no spatial counterpart in reality. Figure 4 shows two ways of representing the same graph: a geometric graph and a logical graph.

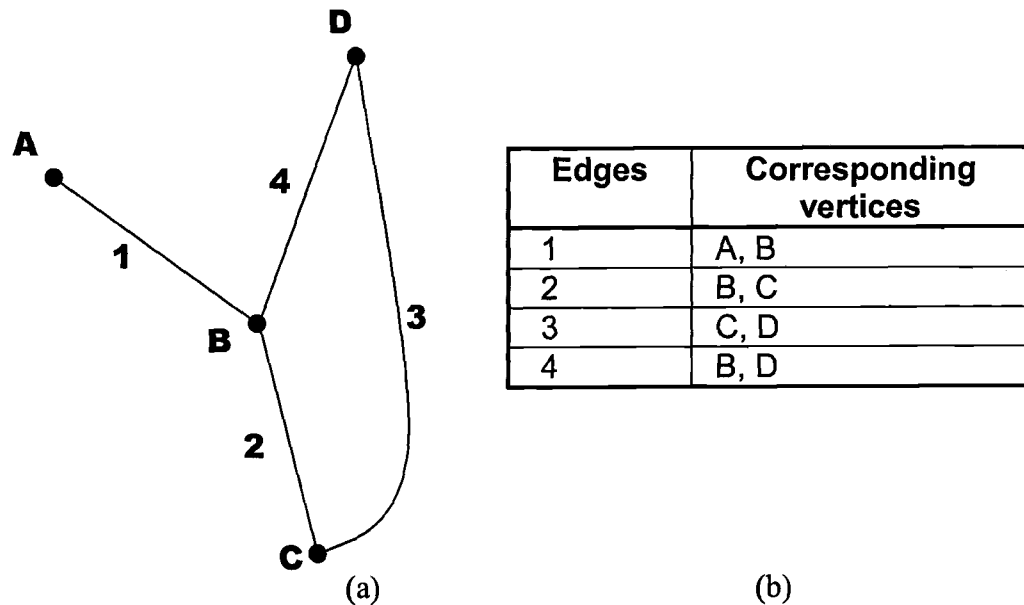


Figure 4. Geometric graph (a) and its logical graph (b). (Adapted from Figure 1-1 in Busacker and Saaty 1965.)

As will be seen later in the paper, graph theory is used in a wide range of applications, from economics to games to engineering, to solve problems like critical path analysis, connectivity, “coloration” problems and flow problems (Carré 1979).

The field of random graph theory has grown out of graph theory. Erdős and Rényi (1960) studied the growth of graphs (networks) as edges are added at random and, based on a given function of the dependence of the number of edges on the number of vertices, established the likelihood of a certain graph topology and properties such as graph diameter. They discovered that there is a threshold for many properties of graphs such that, given the dependency of the number of edges on the number of vertices, either almost every graph has a particular property or it does not: a so-called 0 – 1 law (Bollobás 1985). Until more recently, random

graphs and completely regular graphs, or lattices, were the two main graph types on which to base models of real-world networks (see section on “Small world networks”).

Social network analysis

Social network analysis refers to the study of society through the analysis of relationships among individuals or groups (Wasserman and Faust 1994). The precursor to social network analysis, the “sociogram” (Moreno and Jennings 1938) was a diagram showing relationships as links between points representing people. This idea was expanded upon, especially by the use of matrices and graph theory, to become the quantitative model and methodology of social network analysis. Social entities such as individuals, groups, organizations or nations form the nodes of the network; the relationships (such as kinship, money transfer, friendship, communication, etc.) between these so-called “actors” are the links, or ties, between the nodes. Social network analysis assumes that relationships in social behavior and institutions are critical to understanding society, and assumes that social entities (the actors) are interdependent. *Structure* refers to the pattern the network takes on; it impacts both the functioning of individual actors and the network as a whole. Social network analysis allows for the existence of properties that are characteristic of the entire network or to two or more actors while not being characteristic of any one actor. As should be evident, social network analysis was developed in part as an alternative to individualistic, reductionist, deterministic

approaches to sociology. This approach has been taken up by those in other fields, as will be seen in the next section and the section on trophic interactions (see McMahon et al. 2001).

Complex networks and scaling

Some of the most interesting work on networks has been stimulated by the search for understanding the quarter power law in biological systems and, concurrently, describing complex networks as systems using “small-world” models.

Strogatz (2001) reviewed complex networks and delineated six reasons why networks are difficult to understand: (1) structural complexity, (2) network evolution, (3) connection diversity (i.e., links between vertices may have direction or be inhibitory or excitatory), (4) dynamical complexity (nodes may be nonlinear dynamical systems), (5) node diversity, and (6) meta-complications that arise from a combination of the former complexities. To study networks, different fields have masked certain complications while emphasizing others. Strogatz’s own field of nonlinear dynamics often looks at regular networks of dynamic nonlinear systems where, when nodes are driven by limit cycles, the network tends to synchronize. On the other hand, in static networks of complex architecture models exist for random graphs, small-world networks, scale-free networks and generalized random graphs (whose degree distribution does not have to follow only a Poisson distribution as with the classic random graph model). Strogatz (2001) speculates

that network architectures such as these may affect a network's ability to synchronize or resist error, but that more research is needed here since, "in the longer run, network thinking will become essential to all branches of science. . ." (275).

Scaling in vascular networks

The quarter power scaling law (also called the allometric scaling relationship) recognizes a relationship between organism body size and physiology. For example, larger organisms tend to have longer life spans and slower metabolism. If organism attributes such as life span or metabolic rate are plotted against organism body mass, the resulting relationship follows a quarter power law: for instance, life span is proportional to the $1/4$ power of body mass, metabolic rate is proportional to the $3/4$ power of body mass, duration of embryonic development is proportional to the $-1/4$ power of body mass, etc. (Williams 1997). Scientists have tried to decipher why these relationships scale by multiples of $1/4$ instead of $1/3$ as would be expected if the relationship was based solely on geometric constraints.

West, Brown and Enquist (1997) attempted an explanation of the quarter power law based on constraints caused by the circulatory system, a hierarchical (or branching) network. They showed that the quarter power scaling law could be derived from the physics of fluid flowing in the circulatory system.

Later, West, Brown and Enquist (1999) scrapped the fluid dynamics model for a simpler model based not on physics but on network geometry. Their reasoning follows that of Mandelbrot's fractal geometry (1982): the size and shape of an organism has both an external, conventional, Euclidean geometry where properties such as area, volume or mass scale by third powers and an internal, effective, fractal geometry where the hierarchical, volume-filling structure of the circulatory network creates an effective fourth dimension and properties such as blood volume and metabolic rate scale to the quarter powers. Key to the argument is the fact that capillary size is constant across species since basic network end units such as cells have a constant size regardless of organism size.

Banavar, Maritan and Rinaldo (1999) reviewed West and colleagues' work and, while they also used transportation networks with fixed transfer outlet sizes as the key to explaining allometric scaling, they came up with a simpler mechanism that is not confined to hierarchical networks. They concluded that the quarter power law is a feature of any optimally efficient network. Instead of minimizing energy dissipation as in West, Brown and Enquist (1999), Banavar et al. (1999) defined the most efficient network as that network where blood volume (or other transport substance, here denoted as V) is minimized. If T is the mean distance between transfer sites of a D -dimensional system, then V scales as $T^{(D+1)}$ and the metabolic rate (for a circulatory system) scales as $(\text{mass})^{D/(D+1)}$.

Both theories of allometric scaling have been applied to other domains. Smethurst and Williams (2001) looked at hospital waiting lists and argued that if

health care systems function as complex networks, they probably self-organize and thus operate at an efficient equilibrium. Because of the power laws inherent in many of these systems, complex systems have a large buffering capacity against change. “If it turns out that waiting lists in general conform to power laws, then this could explain why attempts to reduce them have only a temporary effect. A paradoxical feature of waiting lists that conform to a power law is that they represent the most efficient configuration for that organization” (Smethurst and Williams 2001, 653).

Allometric scaling laws at the level of the organism have been extended to the species, community and ecosystem levels (Enquist et al. 1998; Whittaker 1999; Enquist et al. 1999; Enquist and Niklas 2001; Enquist and Niklas 2002). The logic, as it has been applied to trees, is as follows. Since the metabolic rate of a plant scales as the $3/4$ power of the plant's mass, then the whole-plant resource uses should also scale as the $3/4$ power of the plant's mass. When the resource supply is constant, the maximal population density should be proportional to the $-3/4$ power of the average plant mass. (Traditional geometric models predict an exponent of $-2/3$.) Finally, since the rate of resource use per unit area is the product of population density and the rate of resource uses per individual, the total energy use (plant productivity) does not depend on body size.

If proved true, this work on allometric scaling is innovative for two main reasons. It provides an ecological law that appears to hold across various scales from the individual to the ecosystem. Also, this allometric law that governs even

macroecological features results from the network structure of the water and nutrient transport system of individual plants; Enquist and Niklas (2001) looked at vascular plant production and the use of space and energy resources and concluded that life-history differences in trees are constrained by allometric restrictions resulting from the fractal-like vascular transportation networks of individual organisms.

However, others such as Darveau et al. (2002) are critical of what they deem a single-cause explanation to the complex problem of allometric scaling. They argue that the quarter-power scaling exponent is the sum of multiple contributors to an organism's metabolism and control. They show that since there must be a difference in substrate use rate (such as oxygen) between basal and maximum metabolic rate, then under resting conditions organisms must have an excess of the substrate. This appears to invalidate the claims of Enquist and colleagues (1998, 1999, 2001, 2002) whose allometric model relies on substrate delivery limits imposed by the distribution system of the organism.

Small-world networks

Another branch of network research began with a paper by Watts and Strogatz (1998) on "small-world networks" and has been expanded to include a subset of small-world networks, "scale-free networks."

Models of complex network topology tend to assume one of two extremes: either a network has completely random connection topology or completely regular

connection topology (a “lattice”). The former, random graph theory, was developed by Erdős and Rényi (1960) but is rarely a good description of real complex networks which tend to lie somewhere between random graphs and regular lattices. Watts and Strogatz (1998) investigated this murky middle ground by simulating networks of varying degrees of topological randomness and looking at two network properties: characteristic path length, L , and the clustering coefficient, C . L is the average number of edges in the shortest path between two nodes while C is the average of the ratio of connected nearest neighbors to all nearest neighbors, or “cliquishness” of a typical subset of a network. L is a global network property and is also called network diameter. C is a local property. Regular networks (lattices) are highly clustered, and their diameter grows linearly with the addition of nodes. Random networks are poorly clustered and their diameter grows logarithmically with the addition of nodes.

What Watts and Strogatz (1998) found on the continuum between random graphs and regular lattices are “small-world networks” that are highly clustered like

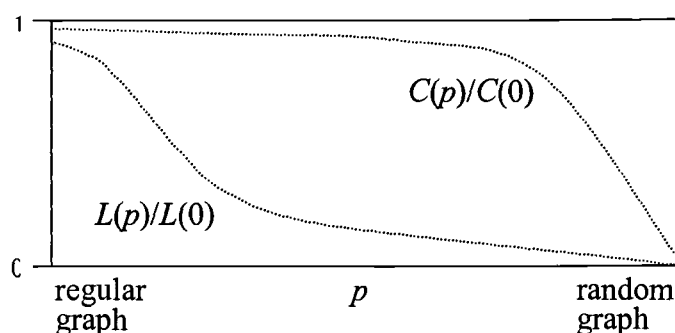


Figure 5. Normalized characteristic path length and clustering coefficient for a family of random graphs. (Adapted from Figure 2 in Watts and Strogatz 1998.)

regular lattices yet have small diameters like random graphs. As shown in Figure 5, as one goes from a regular network to a random one, the

characteristic path length L drops rapidly due to the addition of a few random long-range edges while C stays almost constant. This suggests that that transition from a regular network to a small-world network is barely discernible at the local level.

Watts and Strogatz (1998) looked at a nematode neural network, a power grid for the western United States and collaboration among film actors and found them all to be small-world networks. They also modeled the spread of disease through networks of varying topological randomness and concluded that, while all models of disease spreading “indicate that network structure influences the speed and extent of disease transmission, . . . our model illuminates the dynamics as an explicit function of structure, rather than for a few particular topologies, such as random graphs, stars and chains” (p. 442).

In the Erdős-Rényi random graph model and the Watts-Strogatz small-world model, the probability $P(k)$ that a node is highly connected to k other nodes decreases exponentially with connectivity (or degree), k , indicating that highly connected nodes are very rare. In fact, Barabási and Albert (1999) found that in many large networks, vertex connectivity actually follows a scale-free power-law distribution where—in agreement with small-world networks—highly connected nodes dominate connectivity. Barabási and Albert found the power-law distribution to be true for such networks as film actor collaborations, the Web, an electrical power grid and citations in scientific publications.

Such a high level of self-organization in diverse networks is caused by two features not present in former models: growth and preferential attachment—new

vertices tend to attach to highly connected vertices. Barabási and Albert (1999) found that if these two properties were removed from the model, the scale-free nature of the network was eliminated.

A paper by Albert, Jeong and Barabási (2000) expanded these ideas to illuminate properties of error tolerance and attack vulnerability in complex networks. The robustness of many systems to error or failure is often credited to system redundancy, but Albert et al. (2000) showed that this robustness is a property not of all redundant systems but of all scale-free networks. The scale-free property of networks following a power law vertex connectivity distribution yields an amazing tolerance to the removal of random vertices. However, when the most highly connected vertices of a scale-free network are “attacked,” its diameter increases rapidly. In contrast, random graphs are not tolerant of error, and the impact of deliberate attack is roughly the same as random failure. Albert and colleagues (2000) believe that this robustness of scale-free networks “is probably the basis of the error tolerance of many complex systems, ranging from cells to distributed communication systems” (p. 381).

Amaral et al. (2000) conclude there are three classes of behavior for small-world networks. They claim that scale-free networks are only one type of small-world networks and suggest two additional classes of small-world networks: broad-scale (or truncated scale-free) networks and single-scale networks. The three classes of small-world networks are determined by varying constraints on preferential attachment in the form of vertex aging, cost of adding a link or limited

capacity of the vertex. Scale-free networks have a vertex connectivity distribution characterized by a power law. Broad-scale networks have a vertex connectivity distribution characterized by a power law up to a certain threshold point; that is, the most highly connected nodes are not scale-free. Single-scale networks have a vertex connectivity distribution characterized by an exponential or Gaussian tail. Amaral and colleagues (2000) investigated an electric-power grid, airport routes, movie actor collaborations, friendship networks, a nematode neural network and a lattice polymer chain and found them all to be single-scale networks with the exception of the actor network which is a broad-scale network. Unlike other studies (Barabási and Albert 1999, Jeong et al. 2000, Wagner and Fell 2000), Amaral et al.'s (2000) investigation of small-world networks did not yield any scale-free networks.

Watts and Strogatz (1998) suggest that small-world networks are probably widespread in the natural and human-made/technological world and several other authors have given examples as well.

Jeong et al. (2000) compared the metabolic networks of 43 organisms and found that in spite of differing metabolic components, pathways and sizes, all the networks show topological similarities of scale-free networks and have the same diameter. This last surprising feature appears to not be characteristic of non-biological scale-free networks. Jeong et al. (2000) propose that "the evolutionary selection of a robust and error-tolerant architecture may characterize all cellular networks, for which scale-free topology with a conserved network diameter appears

to provide an optimal structural organization” (p. 653). Wagner and Fell (2000) offered a similar report of a scale-free small-world network from their investigation of the metabolic network of *E. coli*.

Non-biological small-world networks have also been investigated. Kleinberg and Lawrence (2001) showed that despite the lack of an engineered architecture, the Web shows a high level of self-organization and that, as it is so decentralized, the Web’s scale-free network topology must arise from local behavior of preferential attachment.

An intriguing feature of some networks is their ability to be “navigated” using only local knowledge. Interest in this aspect of networks dates back to an experiment in the late 1960s where individuals throughout the U.S. were asked to mail letters to a target person in Boston by sending her or his letter to an acquaintance who in turn would forward the letter to one of their acquaintances. Of the letters that reached their final destination, the average number of times the letter was forwarded was around six (Travers and Milgram 1969). Kleinberg (2000) showed that it is possible to navigate a small-world network with only local information if the right level of clustering is present. Watts, Dodds and Newman (2002) called this navigation property of social networks *searchability*. Based on six underlying assumptions about social networks, they presented a model showing that individuals have two types of partial information—information on social distance and information on network paths—that together can successfully direct a

message through a social network even if the global network structure is unknown at the local level of the individual.

Geomorphology and landscape ecology

Stream channels and forest roads are examples of the main physical networks that have been studied in geomorphology and landscape ecology. Until more recently, the study of stream networks in geomorphology was dominated by the use of metrics such as bifurcation ratios, drainage density and link magnitude that described topological properties of the network (see Abrahams 1984). Channel growth and development was generally explained in terms of Shreve's (1967) random topology model: stream networks are topologically random in the absence of environmental controls, and stream link length and drainage area are independent, random variables (Abrahams 1984). In terms of stream ecology, the network structure of streams has rarely been taken into consideration; the current framework based on the River Continuum Concept (Vannote et al. 1980) does not take a network understanding of the stream system. Two new approaches are enlarging the network view of streams and other network features in the landscape.

Swanson and Jones (draft 2002) propose that a network perspective in landscape ecology has been neglected but has much to offer. Network structures such as forest roads and streams are prime examples of form following function. Because such networks transport flows of water, sediment, organisms, etc., they show network properties of connectivity, (homogeneous) distribution and service to

all areas of the landscape. Because of their transport function and high edge-to-area ratio, their importance and impact may not be evident merely from the small fraction of the landscape they occupy. Branching networks show unique capacities in the face of disturbance: a debris flow initiated in one tributary of a stream network may affect all areas of higher stream order downstream but leave smaller tributaries undisturbed as areas of refuge. Branching networks may also be more vulnerable to disturbance as when a landslide across a road cuts off transportation to an area. Swanson and Jones suggest that this interaction between networks and the areas they service in a landscape (or between networks and other networks, as in Wemple, Jones and Grant [1996]) may offer insight into understanding the scaling laws suggested by Levin (1992).

Rodríguez-Iturbe and Rinaldo (1997) expand on Mandelbrot's (1982) assertion that rivers are fractals since they exhibit similar pattern over a range of scales, many of their variables demonstrate the power law relationship (i.e., discharge to channel width or depth) characteristic of scale-free patterns and processes, and they are practically space-filling with a fractal dimension near two (Tarboton et al. 1988). They suggest an "optimal channel network" model based on fractals that takes into account the statistical chance of random topology models along with an added deterministic factor of "necessity": energy expenditure minimization. The efficiency of the network—minimization of energy loss both locally and globally along with homogeneous energy expenditure throughout the network—is used to explain the branching, fractal structure of stream channels.

Kirchner, Feng and Neal (2000) found that a catchment's release of chloride as measured in streamflow follows a fractal scaling pattern. Whereas catchment runoff followed rainfall levels with only a slight delay and attenuation of signal, chloride concentrations were strongly dampened and exhibited power-law scaling. This implies that flow through a catchment follows a power-law travel time distribution where the catchment has both a short-term response to and a long-term "memory" of input variation. Kirchner, Feng and Neal (2000) suggest their findings may be related to such factors as fractal scaling in soil pores, bedrock features and the flowpath to the stream. Supporting this conjecture, Haggerty et al. (in press) have shown that tracer transport through the hyporheic zone of a 2nd-order mountain stream follows a power law residence time distribution.

Ecology

An important question in ecology is how the structure of food webs and ecosystems affects system stability. Research done in the 1970s showed that complex ecosystems should be less stable or have weaker interspecific interactions than simple ecosystems (May 1973, Gardner and Ashby 1970). For example, food web species richness increases with decreasing food web connectance (Yodzis 1980, Pimm 1984). The idea that complexity destabilizes food webs was an enigma to ecologists who observed that existing natural systems tend to be complex (Polis 1998).

McCann, Hastings and Huxel (1998) showed that interaction strengths between food web components are key to resolving this apparent dichotomy. According to their model, weak links dampen oscillations between consumers and resources, which in turn lowers the chance of extinction.

Berlow (1999) suggested that weak links in food webs also are important for their contribution to system variability. Because both direct and indirect and positive and negative interactions occur in food webs, it is possible that effects that counterbalance each other are deemed “weak” and their importance underestimated by ecosystem researchers and managers.

More recently, Neutel, Heesterbeek and de Ruiter (2002) showed that real food webs are so arranged that the sum of interaction strengths of links in long trophic cycles (called *loops* by the authors) is lower than for cycles of the same length in randomized food webs. Long cycles have many relatively weak top-down (predator-prey) effects due to a decrease in biomass at higher trophic levels and predators feeding on more than one prey type. Since weak interactions are thought to contribute to food web stability, these findings help explain why food webs may be so complex but still preserve stability.

Other food web studies have focused on “network analysis.” Network analysis is “a branch of ecology that deals with applying mathematical methodologies to flow-storage models to identify holistic and emergent properties of ecosystem behavior” (Fath and Patten 1999, 177). It arose from Leontief’s input-output theory of economics, which, in turn, had been influenced by the study

of electrical circuits (Margalef 1991). So-called network analysis in ecology is both an analytical tool, mainly for studying trophic interactions and energy flow through ecosystems, and a way of conceptualizing ecosystems (Higashi and Burns 1991).

Network analysis in ecology has developed out of a concern that science is too intent on reduction and mechanism, and that a systems approach is needed to understand ecosystems (Higashi and Burns 1991, Patten 1991, Ulanowicz 1990). Ecosystems are viewed and modeled as networks in which individual organisms, species or other such groupings are considered nodes connected by links involving the exchange of nutrients or energy (Kay et al. 1989, Patten 1991). For instance, Asmus and McKellar (1989) performed a network analysis of a salt marsh food web using 19 compartments (edaphic algae, birds, sediment dissolved organic matter, etc.) and the amount of energy exchange from photosynthesis, respiration, emigration and immigration. They were able to determine, among other things, that the oyster reef portion of the salt marsh depended upon the water column for 69% of its energy and that most of the cycled flow depended on cycles of two path lengths.

Fath and Patten (1999) show that networks at lower levels of organization have properties of *structure* and *function* (process), and these regulate the *behavior* of the system expressed at a higher level of organization. Matrices are constructed using the known topology and energy or nutrient flow values of the food web network. An unvalued, directional matrix of the food web's topology is called the

structural information matrix, or adjacency matrix, and used in pathway analysis.

Four other valued matrices (showing flow between components, input into the system, output out of the system and storage in components) represent the food web's function. These matrices are the basis of flow analysis, storage analysis and utility analysis and are useful for determining such network behavior as retention time, turnover rates, cycling rates, indirect contributions and qualitative relationships like competition and mutualism.

In particular, the network functional analyses of flow and utility have been used to create four hypotheses central to network environ analysis (Fath and Patten 1999). From flow analysis (which identifies cycling rates and indirect contributions), come the emergent properties of *dominance of indirect effects*, *amplification* and *homogenization* while from utility analysis (which identifies qualitative relationships such as competition) comes the property of *synergism*. These are each looked at in turn.

Many food webs show a greater contribution from indirect effects than from direct effects (Fath and Patten 1999). Indirect effects are defined as flows between nodes that are not adjacent: in the network $A \rightarrow B \rightarrow C$, indirect flow is $A \rightarrow C$ while direct flow is $A \rightarrow B$ and $B \rightarrow C$. Because of the suspected dominance of indirect effects in food webs, the "whole set of network interactions is potentially more important in determining the system behavior than are the direct transactions" (Fath and Patten 1999, 177).

Network amplification is a result of network components getting back more than they put in (Fath and Patten 1999). This behavior is due to cycling in well-connected networks where the total flow through a node may be greater than the total input into the network.

Network homogenization is also the result of network cycling. Here, the hypothesis is that there is a tendency for flow to become equally distributed throughout the network, especially if the network is highly connected (Fath and Patten 1999).

Finally, the hypothesis of network synergism proposes that overall network relations are inherently more positive than is apparent from direct interactions alone (Fath and Patten 1999). By virtue of the network's organization, all involved living constituents reap positive benefits (Müller 1997, 145).

The existence of indirect effects in ecological networks raises the issue of causality. Ulanowicz (1990, 1997, 1999) recalls the four levels of cause defined by Aristotle—material, efficient, formal and final—and argues that they are intrinsically hierarchical in nature: they operate at different scales in the same system (Ulanowicz 1997, 13). He posits that modern science concerns itself only with material and efficient (or mechanistic) causes. At risk of being accused of—in his own words—misguided transcendentalism, Ulanowicz (1990, 1997, 1999) attempts to identify and quantify formal and final cause using network analysis as a model. He claims that the positive feedback inherent in any cyclic network is a formal cause of the network's growth and development. A quantitative measure of

this growth and development is *ascendency*, a measure of network size (flow activity) and organization (pathway articulation). System ascendency should increase as a system matures and decrease if a system becomes perturbed.

Ulanowicz (1991) claims it may also be possible to measure effects of final cause since formal cause (ascendency) at the network level may be final cause at a finer scale.

Network analysis in ecology has been applied almost exclusively to food webs. Examples of this can be found in Higashi and Burns (1991) and Wulff, Field and Mann (1989). However, there is promise that concepts of network analysis (at least in terms of the perspective rather than the tool) are being used in broader ecosystem contexts. Maurer (1999) has suggested some similar ideas for macroecology in his book *Untangling Ecological Complexity*.

Building on Salthe's (1985) ideas of hierarchy with upper- and lower-levels of causation, Maurer (1999, ch. 8) argues that ecology has been mainly concerned with lower-level processes while disregarding causation from larger spatial and temporal scales. For example, in computer simulations of the species-area relationship, he shows that a model incorporating upper-level causation in the form of geographic range structure (with the assumption that species do not have equal access to local sites) performs better than random models based on habitat heterogeneity and passive sampling.

Food web study invokes relative space in the form of "energy-space" or "nutrient-space" but tends to ignore absolute space—the fact that the food web

components must be in proximity of one another in order for the exchange of energy, information and nutrients. (The distinction between absolute and relative network space will be made in a later section.) Polis, Anderson and Holt (1997) suggest ways to form dynamic, “spatially subsidized” food webs from the integration of landscape ecology and food web ecology. They document the movement of detritus, prey and consumers in the landscape and propose that food web dynamics are heavily reliant on this movement, which is a function of a heterogeneous landscape. Thus, landscape variables such as habitat boundaries and patchiness—which themselves may be modeled as network systems—are important features of food web ecology.

Genetic networks

The evolutionary history of a group, or phylogeny, is often represented by a graphical summary, or phylogenetic diagram (Freeman and Herron 1998, ch. 10). The phylogeny is a best estimate that describes the pattern and sometimes the timing of branching events. If the phylogenetic diagram is rooted, the result is often called a *tree*. Rooted phylogenies “root” the tree to a common ancestor and reveal the order in which events occurred. Sometimes the length of the branches is proportional to time or the amount of genetic change (Freeman and Herron 1998). In contrast, unrooted phylogenies are sometimes referred to as *networks* (Gee 2000), and they do not attempt to account for the sequence of evolutionary events.

In this paper, we consider both phylogenetic trees and phylogenetic networks to be networks.

The crux of the problem in phylogenetics is deciding which tree (or network) best fits the data. Not only must there be a method for evaluating the best tree, but since there are so many possible trees for even small numbers of taxa (2,000,000 different branching patterns exist for a tree with 10 species, for example) there must also be a method for finding the best tree. The four basic methods available for estimating trees—distance-matrix, maximum parsimony, invariants and maximum likelihood—are reviewed by Swofford and Olsen (1990, ch. 11). In addition, more recently researchers have also been using a method called Bayesian inference, a probabilistic method that is similar to maximum likelihood methods but much faster for large data sets (Heulsenbeck et al. 2001, Murphy et al. 2001, Karol et al. 2001).

The process of “horizontal transfer” (sometimes called lateral transfer) occurs when genetic information moves from one lineage to another. It is deemed a rare occurrence in the history of life in which the regular transfer of genetic information occurs through inheritance. The best-known case of horizontal transfer is that of organelle DNA: chloroplasts and mitochondria, which have their own DNA, probably evolved from bacteria living symbiotically in early eukaryotic cells (Freeman and Herron 1998). New evidence from complete genomes of bacteria suggests that horizontal gene transfer among very early organisms may mean the

“trunk” of the tree of life is a cyclic network where branches may both split and merge (Pennisi 1998).

Rohlf and colleagues (1990) performed a simulation to determine how the topology of a phylogenetic tree influences the accuracy of the estimated phylogeny. They looked at both tree balance (also called *tree symmetry*) and tree “stemminess”, the average distinctness of the taxonomic subsets on a tree, for three models of evolution: phyletic, speciational and punctuational. Accuracy was determined using “consensus techniques” (Rohlf 1982, Colless 1980) to compare the proportion of datasets in common between the estimated tree and the known tree. Tree topology was found to have considerable effects on the accuracy of estimating phylogenetic trees. In general, trees with high stemminess are easier to estimate than trees with low stemminess, and tree balance also may improve the estimate’s accuracy.

Finally, it has been suggested that a network view of gene interactions is a better measure of biological complexity at the organism level than the number of genes in an organism’s genome or the number of interactions between genes (Szathmáry et al. 2001). Borrowing from graph theory and network studies in ecology, Szathmáry et al. (2001) propose applying network indices like clustering coefficients and node degree to gene-regulation networks to provide better measures of biological complexity.

Engineering of service networks, with a focus on GIS

A great deal of research in the fields of engineering, mathematics and computer science has applied graph theory to problems in the design and function of communication, utility, transportation, computer and operations networks. The journal *Networks*, for example, is dedicated to such applications.

Classic network design problems include the minimal spanning tree—finding the minimal length of arc needed to connect all nodes in a network—and the maximal covering tree—finding the network(s) that services the most nodes given a finite set of resources to construct or maintain the arcs (Hutson and ReVelle 1989). One example of this is the design of transmission corridors for power lines, pipelines or highways. Huber and Church (1985) discuss how the use of grids in computer modeling of transmission corridors may introduce representational error in the form of proximity, orientation and/or elongation error.

Other design problems involve the location of some facility on the network (ReVelle and Swain 1970). For these problems, the analysis may be based on some total distance (where distance may be metric or in terms of cost or time) for travel to the facility(s), a maximal service distance, or a maximal coverage for a given service distance and number of facilities (Church and ReVelle 1974). For instance, Murray and Church (1995) give an optimal solution approach for locating a waste disposal site given a discrete set of potential locations.

Another set of problems involves network flow. Here the objective is to find the shortest path through a network, the maximum flow possible, or the minimum cost of flow (Ahuja et al. 1993, ch. 1).

Finally, network analysis in transportation and utilities may also involve selecting node and link capabilities (as in diameter of pipes in a gas pipeline network) and analysis of the system vulnerability to error or attack (Frank and Frisch 1970).

The geographic information system (GIS) has become an important tool in the fields of transportation and utilities planning (e.g., Glasbrook 1994, Greene et al. 1999, Fiset and Cavayas 1997). Here, the main questions usually involve finding the shortest path through a network, optimizing facility location or finding which center serves a particular link (Lupien et al. 1987). In their key paper on GIS and networks, Lupien, Moreland and Dangermond (1987) state that GIS contributes to network analysis because its database management system enables the calculation of realistic flow constraints in a network. Research on network *design* in a GIS appears to be limited, although Greene and colleagues (1999) have applied GIS for network design in sewer systems with good results as have Taher and Labadie (1996) with water-distribution networks.

GIS-based networks also have been used to extract drainage channel networks from digital elevation models (DEMs) (e.g., Moore 1996, Colin et al. 2000, Yang et al. 2002, Verdin and Verdin 1999) and model economic networks (Benenson et al. 1998).

The current network model used by ESRI (Environmental Systems Research Institute) for ArcInfo v. 8 software is designed with transportation and utility networks in mind. The geodatabase consists of two synchronized networks: a geometric network that records a set of features, and a logical network that has no coordinate values and exists to store the network topology only (Zeiler 1999). ArcView has a Network Analyst extension and ARC/INFO has an ARC NETWORK package; both are designed to solve network problems such as shortest path, nearest facility or other transportation issues (ESRI White Paper 1998).

In one of the few papers to specifically treat network modeling in a GIS, Mainguenaud (1995) presents a Graph Data Model that combines graph theory with object-oriented models. This nested hierarchical model uses object orientation to overcome the problem of differences in data structure between entities represented as polygons (i.e., a town) and entities represented as networks (i.e., a railway or road grid). With object orientation, a polygon at one level of scale may be an abstraction of a local area network or a node of a greater network at another level of scale (i.e., a town may be an abstraction of a local road grid and/or may be a point feature on an interstate highway).

ESRI products are generally based on the vector spatial model while other GIS software, such as IDRISI, is based on a raster spatial model. Husdal (2000) studied the ease of representing networks in both models and concluded that vector-based network models are not only the most intuitive, but are most suitable for analyzing precisely defined paths like roads or rivers, and networks where

attributes heavily influence the network. Raster-based network models are most suitable for situations involving finding a path across terrain that does not have already defined paths as is the case when extracting stream channels from DEMs.

NETWORKS AND GEOGRAPHY

The following section relates networks specifically to the study of geography by reviewing concepts such as topology, geometry, and relative and absolute space, and examining how these concepts apply to the study of networks in general, and especially in geography.

Some background information

Topology and geometry

Topology is a type of geometry in which order and contiguity are more important than Euclidean geometry properties of distance, orientation and straightness (Cole and King 1968). If a network or other figure is drawn on a piece of paper, those characteristics of the network that remain unchanged even if the paper is stretched, crumpled or bent are topological. The most important topologic property of networks is connectivity; adjacency and containment are other topological properties (Chou 1997). (Note: Connectivity in this sense should not be confused with connectivity as it is used in graph theory to define a network where all nodes are joined by at least one path.)

Relative versus absolute space

Abler, Adams and Gould (1971) make a distinction between absolute space—the traditional treatment of space by geographers—and relative space. “The number of dimensions we use and the way we measure distance along them determine the nature of any space we construct” (p. 73). Relative space involves things like time-space, cost-space and genetic distance. Absolute space involves real distances and locations on the face of the earth. An example of a transportation network in cost-space is found in Figure 6.

Conceptual models

All networks are abstractions of reality—models constructed to generalize patterns, processes and relationships of the real world. The network as a model may correspond to actual physical, material entities, or it may not (Figure 7). It is often helpful to visual these networks as graphical/diagrammatic representations,

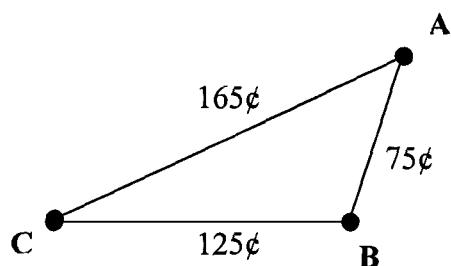


Figure 6. Network using cost-space: Cost of shipping one ton of goods between cities A, B and C. (Adapted from Figure 3-15 in Abler et al. 1971.)

either as a “mental map” or a virtual or real graphical representation (Figure 4a). Or, it may be helpful to represent a network as a table of nodes and links as in Figure 4b or as a matrix as in Table 2. Unvalued tables and

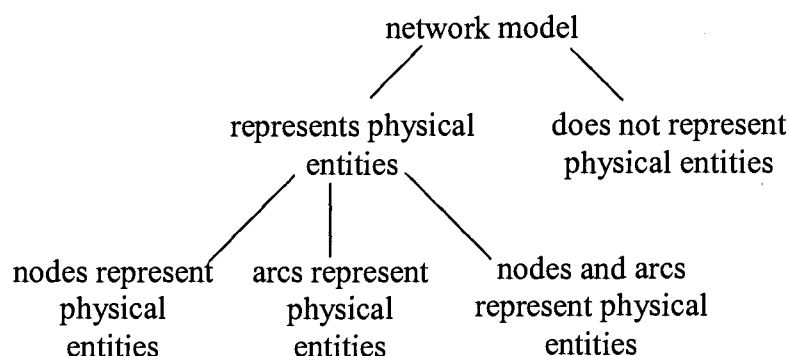
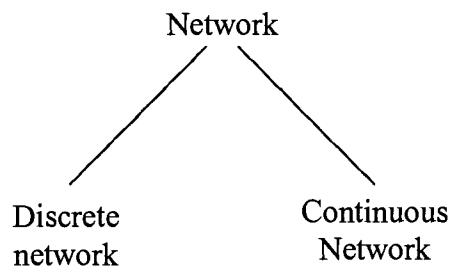


Figure 7. Networks that model physical entities versus networks that do not.

matrices such as these contain all the topological information in a network, but no location or distance information. A diagrammatic (*geometric*, according to Busacker and Saaty, 1965) representation of a network may contain location information as well as topologic information. A network (as an abstraction, table, matrix or graphical representation) consisting of only topologic information is sometimes referred to as a “graph” (Haggett and Chorley 1969).

Marital relation between Florentine families																
FAMILY																
Acciaiuoli	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Albizzi	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0
Barbadori	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0
Bischeri	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0
Castellani	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0
Ginori	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Guadagni	0	1	0	1	0	0	0	1	0	0	0	0	0	0	0	1
Lamberteschi	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Medici	1	1	1	0	0	0	0	0	0	0	0	0	1	1	0	1
Pazzi	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
Peruzzi	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0
Pucci	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ridolfi	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1
Salviati	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
Strozzi	0	0	0	1	1	0	0	0	0	0	1	0	1	0	0	0
Tornabuoni	0	0	0	0	0	0	1	0	1	0	0	0	1	0	0	0

Table 2. Matrix representation of a network. (From Table B.6 in Wasserman and Faust 1994.)



Continuous versus discrete

Some networks are continuous while others are discrete (Figure 8). Discrete

Figure 8. Discrete versus continuous networks.

networks are such that the

existence of edges depends on the existence of the edges' vertices: if a vertex is removed from the network, all of its edges cease to exist. This is the case, for example, in a food web: if a species is removed the species no longer functions as predator or prey and thus not only the species "node" is removed, but all the links incident to it. This need not be the case for continuous networks. A circulatory system is an example of a continuous network: if a vertex is removed, say, by a tourniquet, although network flow is restricted, the edges leading to and from the vertex still exist.

Non-spatial and spatial networks and geography

All networks have topology. Some networks also have a spatial component (Figure 9). These spatial networks may be founded in absolute space or in relative space according to the distinction made by Abler, Adams and Gould (1971).

Thus, non-spatial networks contain topological information but, at least at the local level, contain no spatial information, no shape, no distance. These networks have only topologic geometry. A matrix graph of the network would

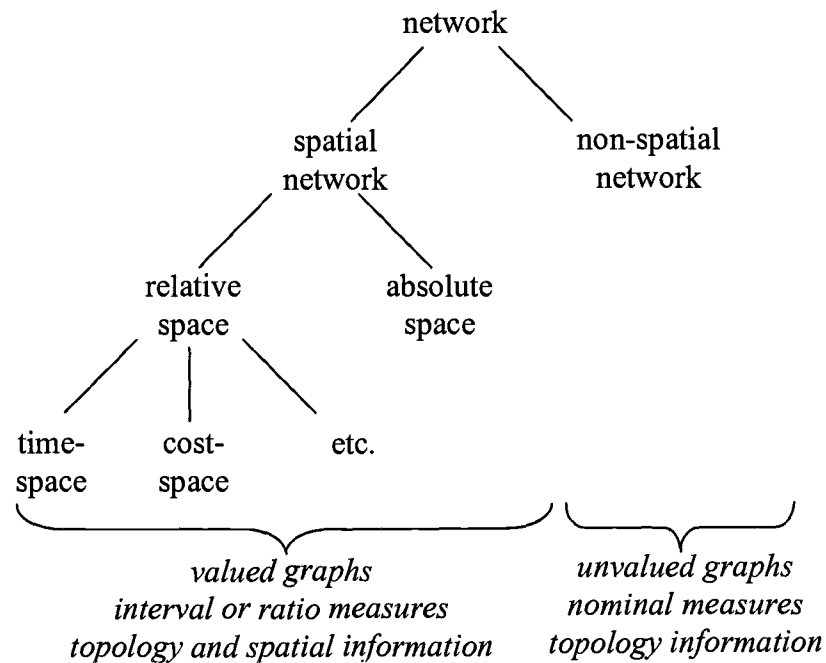


Figure 9. Spatial versus non-spatial networks.

consist only of ones and zeros, thus representing the binary nature of the network: either there is or there isn't a relationship between two nodes. Measurements are nominal. A matrix such as seen in Table 2 contains all the information of the network. Often the term *unvalued graph* (a graph with only nominal measurements) is used to describe a non-spatial network.

It may be of interest to include information about the location (relative or absolute) of the nodes in a network. In addition, it may be of interest to also include information about the length and shape of the arcs in the network. If either is specified, the network has spatial properties. Spatial networks, whether in absolute or relative space, are concerned with both the relationships and connectivity information given by the network topology *and* the distance (and

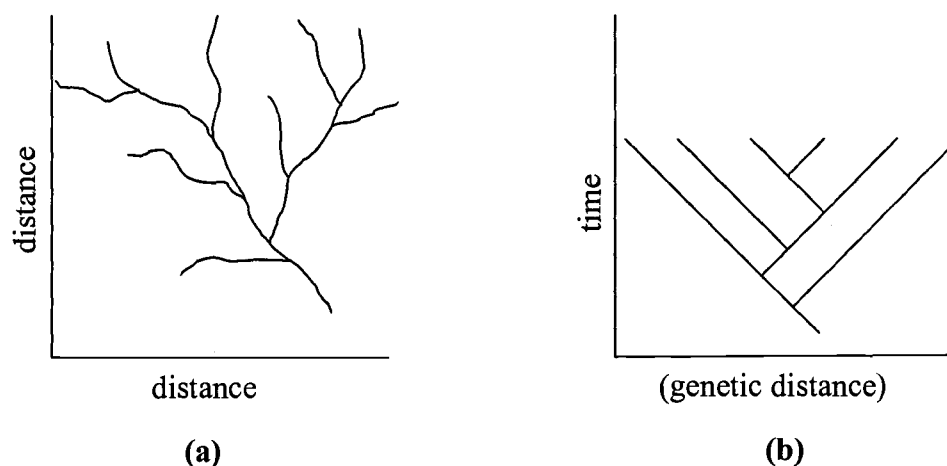


Figure 10. Two spatial networks: A stream network (a) and a phylogenetic tree (b).

sometimes shape and orientation) information given by the location of the nodes and/or the length of the arcs (length measured in absolute space or in time-space, etc.). A matrix graph of the network consists of numerical values representing the distances or lack thereof of links between nodes. The network also may be spatial by virtue of the nodes having location whether or not the arcs have distance. Measurements are interval or ratio. These networks have both topologic geometry and Euclidean (or Manhattan or Riemann, etc.) geometry.

It is often most convenient to represent stream channels, utilities, vascular systems and transportation systems as spatial networks in absolute space. As such, graphical representations of these networks have absolute distance (as feet or kilometers, for example) as each dimension (Figure 10a). The network in the figure is two-dimensional, but it is easy to imagine extending this idea to a third spatial dimension for three-dimensional networks.

On the other hand, in a two-dimensional graphical representation of an evolutionary phylogeny, time (often relative time) is the one dimension and evolutionary distance may be the second dimension (Figure 10b). Such networks contain time-space information as well as topological information. These temporal networks exist *over* time. The nodes are not all in existence at once. The arcs are temporal in the sense that they connect the nodes through time. Inherent in these networks is a chronology. Without this chronology the network ceases to exist. These networks tend to be branching, or tree, networks.

More than one network model is possible for a process or pattern from the real world. A network of airline routes between cities is taken as an example. A non-spatial, topological model is shown in Figure 11a and 11b. A spatial model using absolute space is shown in Figure 11c and 11d. A spatial model using cost-space is shown in Figure 11e and 11f. Other models for the same airline network are possible.

Interesting to note is that non-spatial networks may have spatial aspects at the global level. At the global level, the network has properties like diameter and walk or circuit lengths and distances. These are not measured in absolute space nor in time- or cost-space but in “network space”: how many steps are needed to get from one node to another along the network. Furthermore, the network may, at the global level, take on characteristics of shape: clustering has been identified in some social networks (Wasserman and Faust 1994) and tendrils and core regions identified in the Web (Kleinberg and Lawrence 2001), for example. How and why

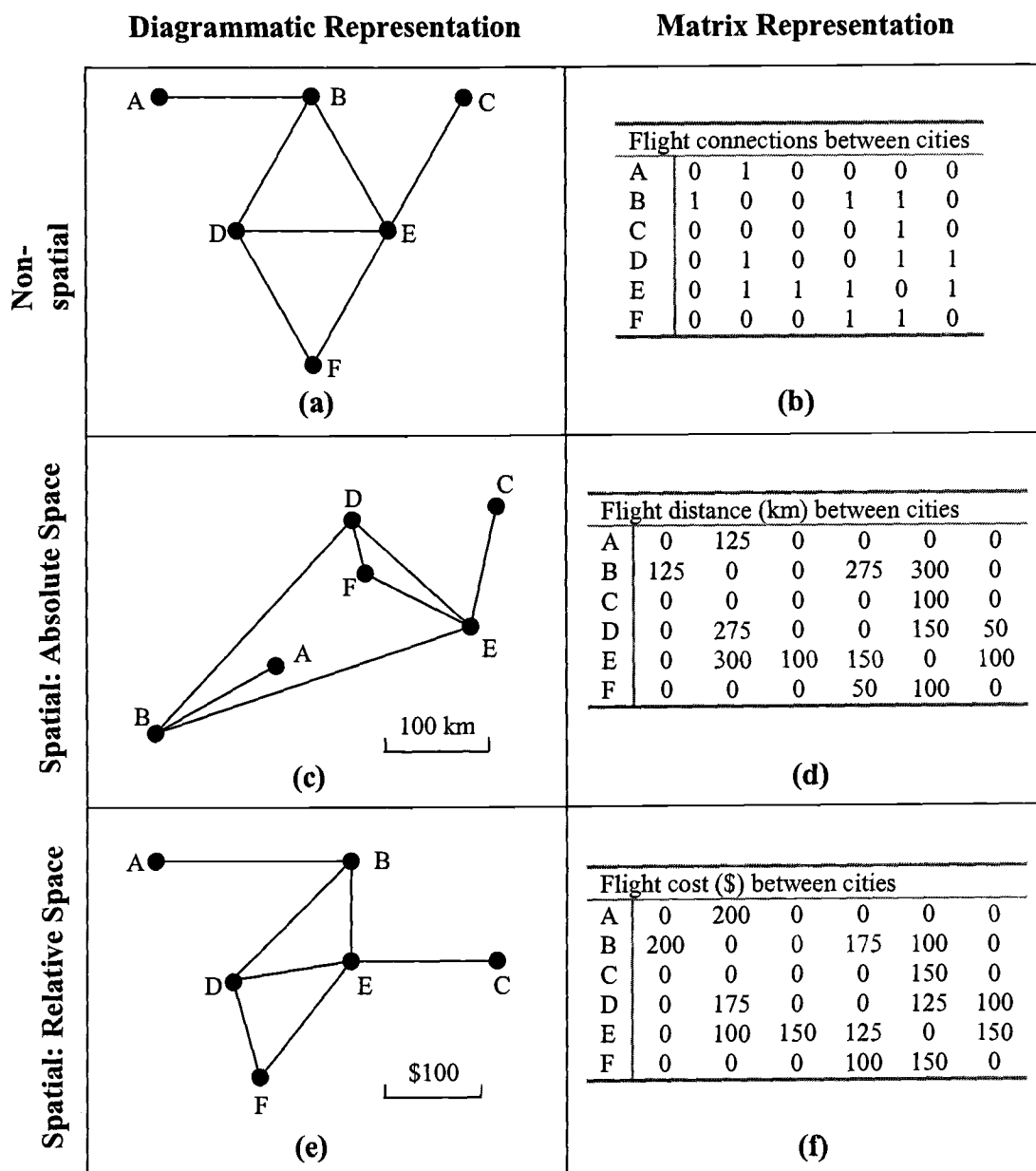


Figure 11. Several different ways of modeling an airline route with networks.

these emergent spatial properties arise out of non-spatial information is an interesting phenomenon deserving of more study.

Using the network as a vehicle, this categorization may help give cohesiveness to the often amorphous field of geography. Geographers have interest

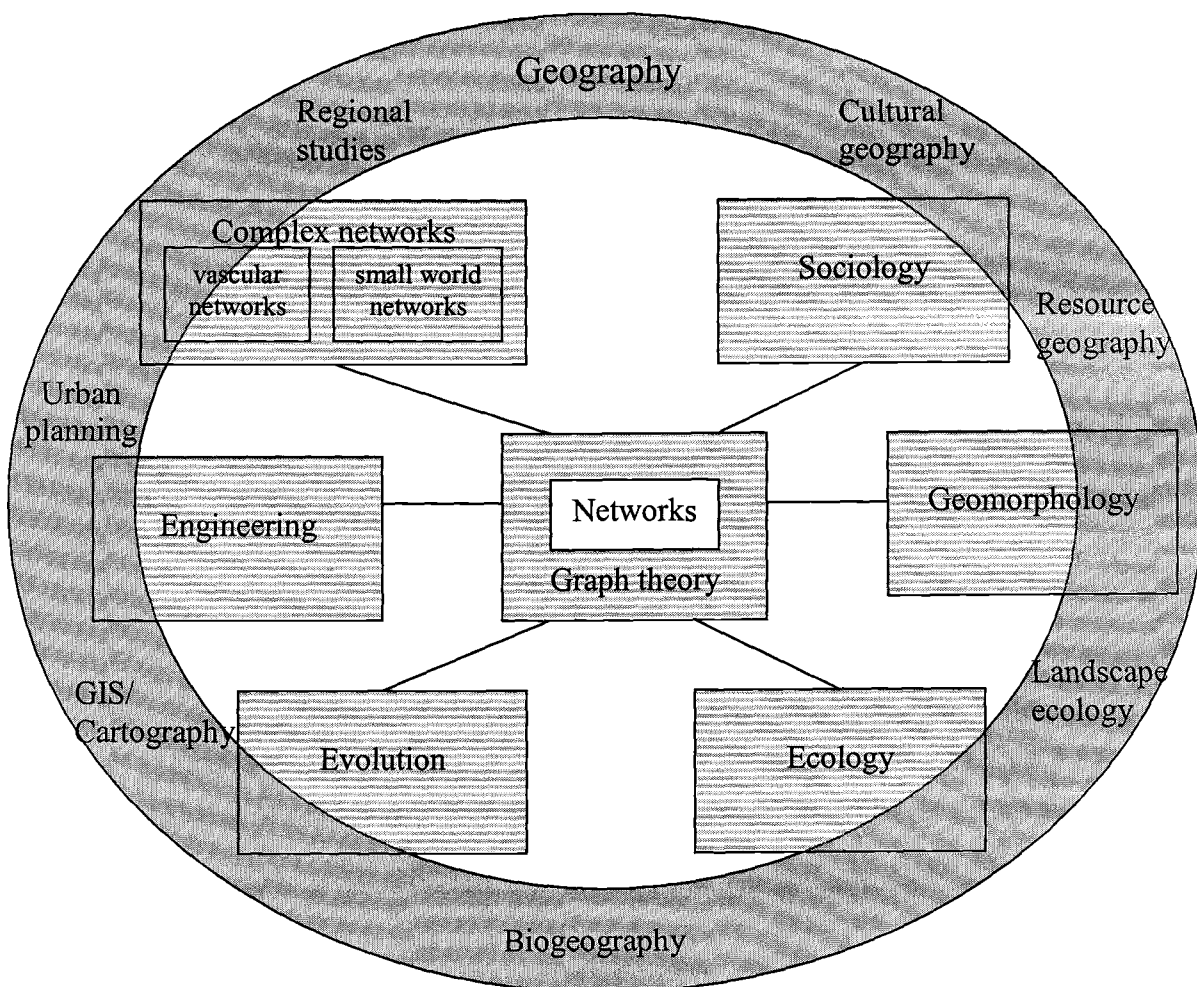


Figure 12. The study of geography as the study of networks.

in studying spatial networks whether these networks are conceived of as occupying absolute or relative space (Figure 12). Physical geographers may study networks in absolute space such as streams. Urban planners may study geography in terms of the time it takes to travel along a city's road network. Economic geographers may study networks in cost-space. Cultural geographers may study networks in social-space. Biogeographers may study networks in genetic-space, and so on.

NETWORK PROPERTIES INFLUENCING SYSTEM BEHAVIOR

Are there properties common to all networks? The following paragraphs are speculations on properties characteristic of all networks, or of certain classes of networks as defined in the previous sections. All the properties of networks mentioned below—connectivity, flow, emergent properties, hierarchy, robustness, growth and reduction, feedback and indirect effects—are *system* properties. They are not properties of isolated edges or nodes, but global properties of the network. Much of this paper has concentrated on networks as structure but now the emphasis will be on networks as system.

By definition, all networks have the property of connectivity. At times the emphasis is on how point features like people in social circles or substrates in metabolic pathways or pages on the World Wide Web are connected to each other. At other times the emphasis is on how the connections themselves are arranged: how tributaries form stream networks and how traffic flows through cities. In either case, a key reason for the use of a network model for the pattern or process is to show connectivity. Much of the information contained in a network model—the topology—concerns connectivity. For many networks—possibly for all networks where both edges and vertices are physical entities—connectivity is important to preserve flow be it the flow of material, energy or information.

All networks consisting of at least two connected nodes have both local and global properties. These global properties are emergent properties that occur at coarser scales and are not necessarily characteristic of any single node or link or

even of the additive properties of any group of nodes or links. Examples of this are readily found in social network analysis and food web network analysis.

Many networks are hierarchical, either as branching hierarchical networks or as nested hierarchical networks. Many hierarchical networks have fractal properties and as such are self-similar, exhibit scale-free properties like power-law connectivity distributions, and display emergent properties. Hierarchy plays an important role in many ideas of scale and is investigated in the study of vascular networks, sociology, geomorphology, ecology and GIS representation.

There is much interest in network tolerance to disturbance and network robustness to error and attack. It has been shown that some network configurations are more tolerant of disturbance than others. Error tolerance is a generic property of communication networks because of their scale-free connectivity distributions (Albert et al. 2000). The effect of disturbance such as landslides and debris flows on an ecosystem is influenced by the structure of networks like stream channels and ridge systems (Swanson and Jones 2002). Autonomy of branches in woody plants may limit the damage of a local injury to the entire plant (Sprugel et al. 1991).

Most all networks are capable of growth and/or reduction. The small-world network literature has addressed the issue of network growth to some extent (Albert et al. 2000, Jeong et al. 2000, Watts and Strogatz 1998). However, these studies are usually limited to discrete networks where nodes are added and each additional node either does or does not have a connection to the other nodes. Network reduction in these networks has only been studied in light of disturbance events

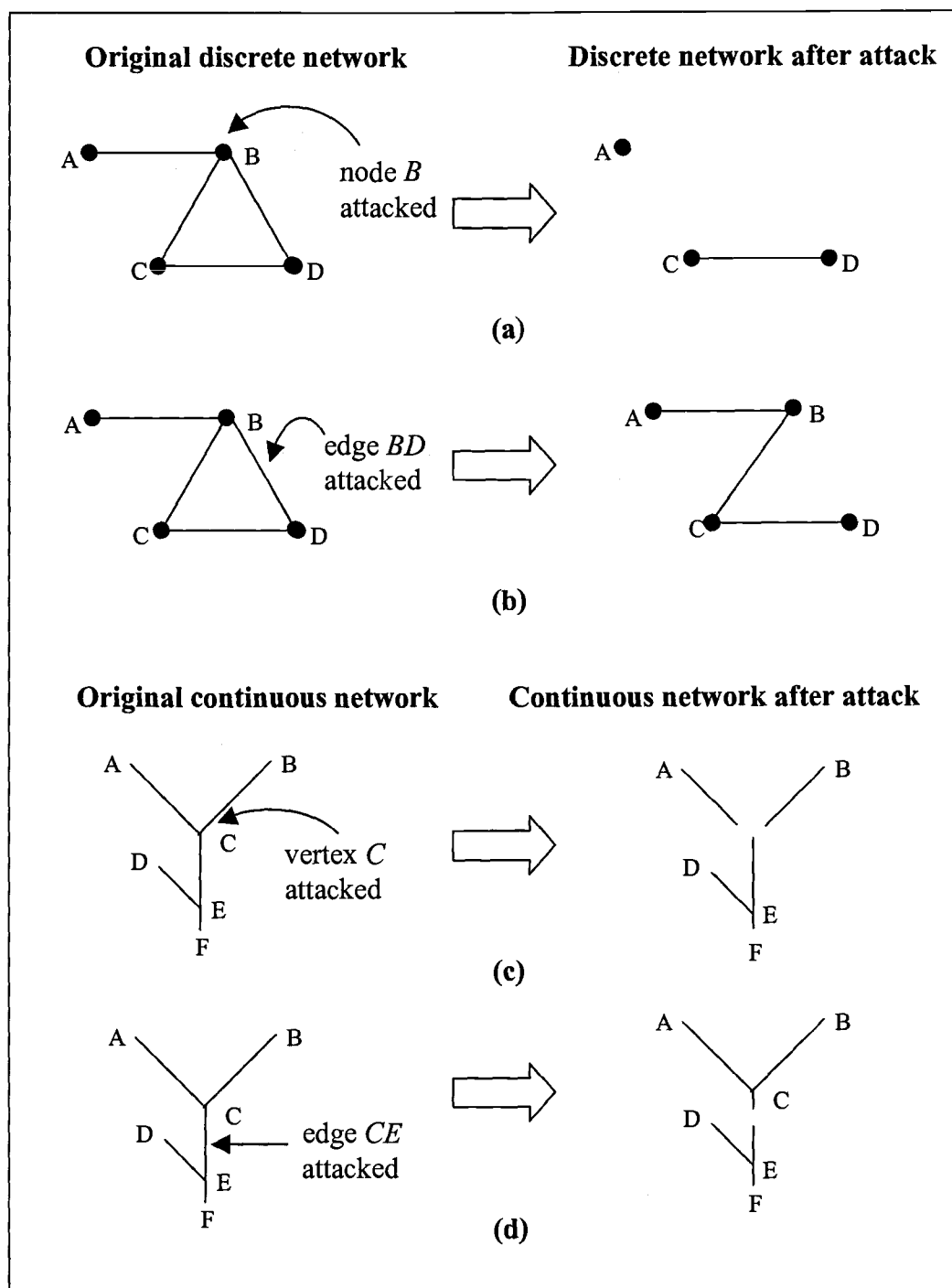


Figure 13. Possible responses of discrete (a,b) and continuous (c,d) networks to attack.
 where a large network is ultimately reduced to several or many smaller networks.
 In these cases, disturbance in the form of attack to a node destroys not only the

node but also all links to it (Figure 13a). In the case of a disturbance to the link, the entire link is destroyed and the nodes that were its endpoints are reduced by one degree (Figure 13b).

Little is known about the dynamics of continuous networks of the sort where growth and reduction make take either of two forms: 1) new nodes may appear or disappear as just seen, and 2) edges may lengthen or shorten *without* the addition of a node. Stream networks are examples of this latter type. A reduction in a network like a stream system does not necessarily mean the creation of several smaller networks from the original network; instead, the network may be more inclined to “shrink” by the removal and/or shortening of external edges. A disturbance may remove a vertex, in which case the edges connected to this vertex might still exist as external edges (Figure 13c). Or, a disturbance may attack an edge (Figure 13d), in which case, unlike the previous example in the paragraph above where the entire edge is destroyed, two edges may be created. If this is the case, then at what point along the edge the network is attacked makes a difference.

Cyclic networks are often credited with the capacity for feedback. This is certainly an emphasis in the food web literature and also in the biochemical network literature. Several authors have investigated the role of positive feedback in food web networks on both the behavior and organization of the ecosystem (Ulanowicz 1990, Deangelis and Post 1991). Barkai and Leibler (2000) have created a model to show that biochemical networks are adaptive because the

network acts as a feedback system responding to system activity rather than system parameters such as enzyme concentration.

Finally, networks as systems exhibit indirect effects as well as direct effects and networks as structures allow for the possible quantification of these indirect effects. Research in food web ecology suggests that indirect effects are more important than direct effects and thus a network approach to the study of food webs is essential (Ulanowicz 1997).

CONCLUSION

It is often convenient to model systems as networks. This can be seen from the use of networks in fields as diverse as mathematics, sociology, geomorphology, physics, engineering, ecology and evolution. Intriguing results from the study of networks in these disciplines suggest that 1) networks can be classified based on structural characteristics such as connectivity distributions or information characteristics such as spatial information, and that 2) many types of networks have common properties of connectivity, feedback, indirect causality, hierarchy, growth, self-organization and tolerance to error.

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