Landscape Ecology **16:** 33–39, 2001.

Research Article

The ecology of urban landscapes: modeling housing starts as a density-dependent colonization process

William F. Fagan[1,2,*], Eli Meir[1], Steven S. Carroll[2] and Jianguo Wu[1,4]
[1]*National Center for Ecological Analysis and Synthesis, 735 State Street Suite 300, Santa Barbara, CA 93101, USA;* [2]*Department of Biology, Arizona State University, Tempe, AZ 85287-1501, USA;* [3]*Department of Zoology University of Washington, Seattle, WA 98195-1800, USA;* [4]*Department of Life Sciences, Arizona State University – West, Phoenix, AZ 85069, USA; *(Corresponding author: Phone: 480-965-8263; Fax: 480-965-2519; E-mail : bfagan@asu.edu)*

Received 13 October 1999; Revised 11 May 2000; Accepted 28 March 2000

Key words: Density dependence, housing, multiple spatial scales, settling process, urbanization

Abstract

Data on permits for new housing starts are a key source of information on recent changes in the urban landscape of central Arizona, USA. Drawing primarily on the conceptual parallels between the process of urban expansion and the spatial spread of non-human species, we outline a nested series of 'colonization' models that could be used to study changes in urban landscapes through simulations of housing starts.Within our probabilistic colonization framework, the ecological principle of density-dependence (operating simultaneously on different spatial scales) governs the positioning of new housing units. These simple models afford a great diversity of possible spatial patterns, ranging from tight clustering of houses to urban sprawl to more subtle patterns such as aversion of housing developments from (and aggregation near) different kinds of landscape features. These models can be parameterized from a variety of types of governmental housing data. Ultimately, such a framework could be used to contrast development patterns among cities and identify pertinent operational scales and factors influencing processes associated with urbanization.

Introduction

Longstanding interest in the connections between human societies and ecological systems (e.g., Adams 1935, 1938; Lubchenco 1998; Collins subm. ms., Collins et al. in press) has been coupled recently with increased quantification of the extent and diversity of those connections (e.g., Vitousek et al. 1997; Cerveny and Balling 1998). Such research efforts and increased recognition of the need for better ecological understanding of the linkages between human-dominated and more 'natural' systems led the U.S. National Science Foundation to initiate in 1998 two Long Term Ecological Research projects focusing on urban systems, one emphasizing the Baltimore, Maryland, metropolitan area and the other the central Arizona-Phoenix region (the CAP LTER). Despite a long, but discontinuous, history of substantial human occupation (dating back roughly 1000 years to the Hohokam culture (Noble 1991; Redman 1992)), the landscape encompassed by the CAP LTER site is characterized by recent, rapid growth in population size and in the spatial extent of residential areas. Current estimates predict that Phoenix and its suburbs will grow by 80 new homes every *day* between now and 2025 (MAG 1999; Caputo 1999). Much of this urbanization is occurring on the outer fringes of the 750 km^2 metro area as patches of irrigated agricultural land and Sonoran desert habitat are replaced with residential developments and associated features (Gober et al. 1998).

Aspects of how cities grow and urban landscapes develop have long interested geographers, environmental planners, and social scientists (e.g., Chapin and Weiss 1968; Batty and Longley 1994). Indeed, the last decade has seen a tremendous increase in the applications of computer modeling and map-making to questions of urban growth. Perspectives afforded by fractal geometry have had a substantial impact (Batty and Longley 1994; Mesev et al. 1995), as have other approaches to modeling urban growth including neural network models linked to GIS platforms (Weisner and Cowen 1997) and heuristic optimization techniques (Densham 1991; Batty and Densham 1996).

However, despite such efforts, ongoing changes in urban landscapes have apparently not received widespread attention from ecologists (Collins et al. in press). To help bridge this gap, and incorporate ecological dynamics into human-dominated systems, we seek to present a complementary framework for modeling the urbanization process, a framework developed with attention to the fundamental ecological principle of density dependence. In particular, we view urban growth and expansion as an ecological colonization process in which individual colonists (houses) occupy available space and influence subsequent development. From this perspective, processes of urbanization are in many ways similar to the settling of marine larvae on hard substrates (Sutherland and Karlson 1977; Dean and Hurd 1980; Sutherland 1981), the growth of plant populations via seed dispersal and seedling recruitment (Fagerstrom 1997), or 'bath' models of insect pest redistribution in agricultural landscapes (Winterer et al. 1994; Banks and Ekbom 1999). In the sections that follow we suggest ways in which the ecological meanings of such terms as facilitation, inhibition, and interaction neighborhood that are typically associated with the colonization dynamics of non-human organisms might have a place in studies of changing urban landscapes.

Density dependence: a parallel between urbanization and 'natural' ecological processes

Maps of city growth show a great diversity of patterns (e.g., Batty and Longley 1994) including growth features that depend upon geographic constraints (e.g., river courses or mountain ridges), legal constraints such as urban growth boundaries (e.g., Ferguson 1997), and the relative economic value placed on different land parcels. Urban growth in different portions of the Phoenix metropolitan region appears influenced by some or all of these factors (e.g., Burns 1992; Gober et al. 1998). For example, the spatial distribution of permits for new housing starts exhibit a 'doughnut' shape that is characteristic of many US cities (Whyte 1968), indicating rapid expansion outward from a city core (Figure 1.). Such urban growth patterns offer an intriguing parallel to patterns emerging from studies of the spatial spread of species in the context of ecological invasion dynamics (e.g., Skellam 1951; Andow et al. 1990; Kot et al. 1996; Lewis 1997). Clearly housing units do not reproduce in the sense that a spreading species does, and as such, mathematical models of invasion dynamics that combine reproduction with dispersal to quantify spread rates are not directly applicable to the housing starts problem. However, taking reproduction out of the picture by assuming a limitless (or in other cases externally limited) supply of available colonists, but retaining density-dependence to govern the actual colonization process, affords a modeling framework that might be applicable to some cases of both urban expansion and species spread.

Because data on construction permits like those in Figure 1 are useful indicators of urban growth patterns (Halls et al. 1994) and because spatiotemporal data on new housing starts have been one of the key datasets available to CAP LTER scientists early on (Gober et al. 1998), we frame our model of urban growth in the context of residential expansion, calling our landscape units 'houses' for convenience, though they could easily be thought of as subdivisions as well.

We view urban expansion as a stepwise process involving the addition of new houses to an already built-up landscape. Ours is certainly not the first effort to adopt this 'adding-on' perspective toward understanding the spatial spread of cities, which occurs in various forms in both early probabilistic growth models (Chapin and Weiss 1968) and models involving diffusion-limited aggregation (Witten and Sander 1981, 1983; Batty and Longley 1994). However, the key connection we seek between ecological processes and urbanization (namely viewing urbanization as a multi-scale, density-dependent colonization process) is not explicit in earlier treatments of changing urban landscapes.

Such density dependence of house construction would likely operate on multiple scales simultaneously. For instance, the probability of a house being built might depend upon housing density at both a large scale (perhaps reflecting the availability of grocery stores or emergency services) and a small scale (reflecting the number of neighbors). Multiple neighborhoods likewise exist for many non-human species. For example, a plant's competitive neighborhood need

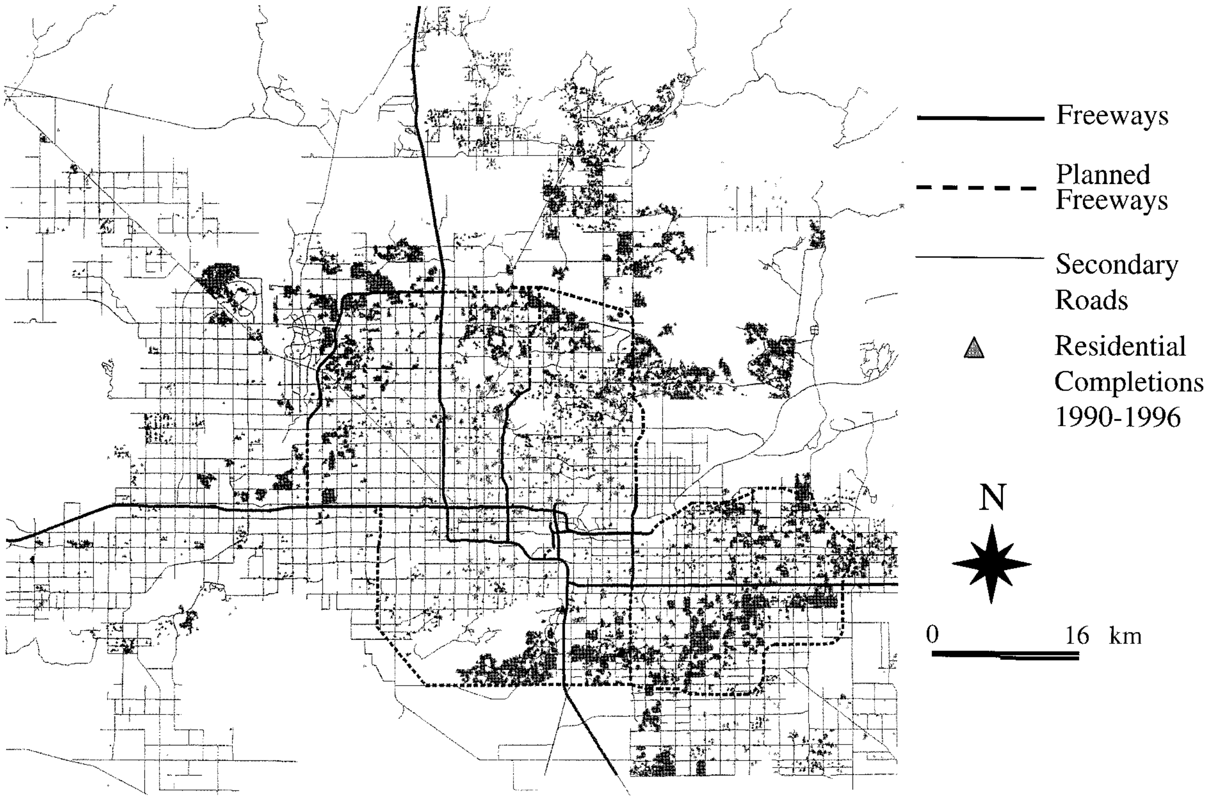

Figure 1. Spatial map of new housing starts in the Phoenix metropolitan area, cumulative over the years 1990–1997. Individual houses are represented by tiny triangles that, when present at high density, merge into the gray clusters on the map. Source: Maricopa Association of Governments (MAG 1999).

not be the same as its dispersal or pollination neighborhood (Holmes and Wilson 1998). Similarly, facilitative aspects of Allee effects (Allee 1951; Groom 1998) might enhance colonization or establishment of a species on one scale while intraspecific competition for resources inhibits it on another scale.

Clearly it would be interesting to understand what factors are contributing to the differential patterns of urban spread (and consequent replacement of native Sonoran desert or agricultural habitats) evident in different regions of the Phoenix metro area (Figure 1). To help develop a framework for understanding these and other ecological changes in the Phoenix area (and ultimately other urban landscapes as well), we propose a series of statistical models to quantify patterns of the spread of housing starts across an urban landscape. Each is a probabilistic model capable of generating a wide range of patterns, and the parameters governing such urban spread can be estimated from map data of past housing starts.

Methods

Probabilistic perspectives on the spatial distribution of housing starts

To identify factors (like existing housing density) that influence the spread of new housing, we will model housing starts in a particular year using one of three models from the broad class of generalized linear models (Nelder and Wedderburn 1972; McCullagh and Nelder 1989; Agresti 1990). The choice of which model to select depends in part on the form of the data available (i.e., whether the data are obtained for each vacant lot in the study area or are collected as a summary measure per areal unit such as a square kilometer block).

The first approach views the urbanization process on a binary, lot-by-lot basis: in a given year a house is either built on a vacant lot or it is not. Parameterizing such a model requires data for each vacant lot in the study area. Specifically, we need to know for each of the n vacant lots that existed at the beginning of the year (i.e., all places where houses might potentially be built) whether or not a house was constructed on the lot sometime during the year. To determine if housing density, both in the immediate neighborhood and in a more extended neighborhood, affects the probability of a house being built, we use both local and regional density measures as predictor variables. One could easily add other predictor variables (e.g., distance to the nearest shopping center, or a measure of areal affluence) to the model to capture the effects of other salient factors influencing housing starts. When the process of urbanization is envisioned this way, one can use the Bernoulli model and its associated logit link function (η_i) where

$$\eta_i = \log\left(\frac{\pi}{1-\pi_i}\right) = \boldsymbol{x}_i'\boldsymbol{\beta} \tag{1}$$

to model

$$z_i = \begin{cases} 1 & \text{if a house was built at the } i\text{th location,} \\ 0 & \text{if no house was built at the } i\text{th location,} \end{cases} \tag{2}$$

where π_i is the probability that a new house is constructed at the ith location, $i = 1, \ldots, n$, $\boldsymbol{x}_i' = (1, x_{i1}, x_{i2}, \ldots, x_{ip})'$, x_{ij} is the jth predictor variable for the ith location, p is the number of predictor variables, n is the number of vacant lots at the beginning of the year, and $\boldsymbol{\beta}$ is the vector $(p+1)$ of parameters to be estimated.

A second approach to the problem is similar to the first, but models the proportion of developed lots per unit area (e.g., square kilometer) using predictor variables aggregated over each areal unit. This second approach is based on the binomial model and again uses the logit link function (see Equation (1)) to model the proportion

$$\left(\frac{y_i}{m_i}\right), \tag{3}$$

where y_i is the number of housing starts in the ith square kilometer and m_i is the number of potential building sites (i.e., vacant properties) in the ith square kilometer at the beginning of the year.

For a third approach, we model the number of housing starts per square kilometer; the predictor variables are again aggregated on a per square kilometer basis. The third approach is based on the Poisson model and uses the log link (η_i) where

$$\eta_i = \log(\mu_i) = \boldsymbol{x}_i'\boldsymbol{\beta} \tag{4}$$

to model y_i. The third model, thus, focuses on the number of housing starts per unit area without special reference to the number of vacant lots (data that might not exist in an accessible form). Consequently, analyses involving the Poisson model may provide less information than models that use more data.

The selection from among the three models depends on the type of data that are available to the researcher and on the determination of which response variable is most meaningful to a particular study. If data are available to fit the Bernoulli (lot by lot) model, the researcher can potentially fit all three models. However, if data are collected to fit either the second or third models (houses per unit area, with and without consideration of available lots, respectively), fitting data to the first model is impossible. Likewise, if data are collected to fit the third model, one cannot fit either of the first two models.

All three of the models can be fit (i.e., the components of the parameter vector β can be estimated) using standard generalized linear model fitting routines, for example, SAS PROC GENMOD (SAS 1995). When fitting the models, one should investigate the assumption that the observations are independent and if necessary modify the modeling routine to account for non-independence (Gotway and Stroup 1997).

Simulation of sample landscapes

To illustrate the sorts of housing start patterns that might result assuming that the above simple models approximate the housing start processes, we simulate the most general case (the Bernoulli process with the logit link) and generate figures showing a range of housing start patterns. We adopt this approach in the simulations that follow because it most closely matches the form of the real housing start data gathered for Figure 1.

We implement the simulations in an iterative process, in which an available lot is chosen at random and a house is built or not depending on the characteristics of the surrounding areas. We assume that a fixed number of housing permits are available per time step (year) and after building or not building a house, move randomly to another lot in the landscape until all permits are exhausted for that year. We use the inverse link function

$$\pi_i = \frac{e^{\boldsymbol{x}_i'\boldsymbol{\beta}}}{1 + e^{\boldsymbol{x}_i'\boldsymbol{\beta}}} \tag{5}$$

to determine the probability (π_i) of a house being built on a specific lot. If a random number drawn from a uniform (0,1) distribution was $\leq \pi_i$ we located a house on that lot. By varying the elements of the parameter vector ($\boldsymbol{\beta}$) we determine how the probability of a housing start depends upon the densities of existing houses or other predictor variables on the appropriate spatial scales.

To conduct our simulations, we used a simplified form of Equation (5) that focussed strictly on the influences of housing density as determinants of house construction, a parallel to ecological scenarios in which densities of conspecifics can have overriding influence on settlement patterns (Fagerstrom 1997). That is, we calculated the probability of a house being built as

$$\pi_i = \frac{e^{\beta_0+\beta_1 d_1+\beta_2 d_2}}{1+e^{\beta_0+\beta_1 d_1+\beta_2 d_2}}, \tag{6}$$

where d_1 and d_2 are the densities of houses on local and regional neighborhood scales, respectively. We chose the sizes of the local and regional scales and values for the coefficients β_0, β_1, and β_2 to illustrate the range of patterns that this model structure can generate. Specifically we aimed to recreate spread patterns typical of tight residential packing, urban sprawl, and aggregation/aversion phenomena. For the simulations, we used the ecological modeling software package Ecobeaker (Meir 1996, 1999). A rectangular grid (with wrap-around boundaries) was used to represent one slice through the urban landscape. Different neighborhood scales on this rectangular grid were represented by contiguous square blocks of housing lots (of different dimensions) centered on the lot in question. At the start of each simulation existing houses were restricted to one row of grid cells along one edge of the landscape.

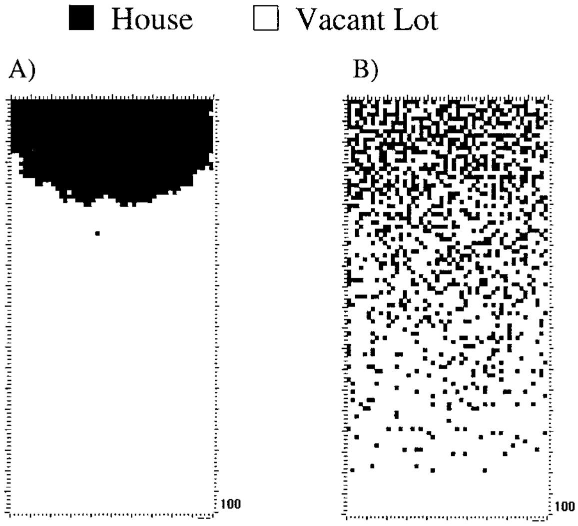

Figure 2. Output from an Ecobeaker simulation (Meir 1996, 1999) of new housing starts. In (A) 1000 tightly clustered houses are produced when the probability of settling is enhanced by a high density of houses on both local and regional neighborhoods. In (B) an equivalent number of houses sprawls across much more of the urban landscape grid when the probability of construction is decreased in areas with houses already built. In (A), the local scale is a 9 cell area centered on each potential housing site whereas the regional scale is a similarly centered 25 cell area. Referring to the parameters in Equation 6, for each panel, d_1 is the density of houses in the local neighborhood and d_2 is the density in the regional scale. In (A) $\beta_0 = -8$, $\beta_1 = 30$ and $\beta_2 = -3$. In (B) the local and regional neighborhoods are 1 and 441 cells in area, respectively, $\beta_0 = 5$, $\beta_1 = -30$ and $\beta_2 = 30$.

Results and discussion

Urbanization in a featureless landscape

As a simple illustration of our approach, consider the disparate growth patterns of cities with and without strict regulations governing the pace and pattern of urbanization (e.g., contrast Portland, Oregon with Phoenix, Arizona [see Ferguson 1997 for a discussion of growth regulations]). In some cities growth regulations prohibit (or at least lessen the likelihood of) housing construction in remote portions of the urban area. In such cases, new construction is constrained to the immediate vicinity of already built-up areas until some threshold density is reached. By manipulating parameters governing the influences of housing density on local and regional scale neighborhoods (the coefficients β_1 and β_2 in Equation (6)) we produce patterns in which houses tend to be tightly clustered or widely spaced, capturing key features of both constrained growth and urban sprawl (Figure 2).

Urbanization influenced by landscape features

Consideration of density dependent processes alone can also reproduce other well known features of urban growth morphology. For example, housing density often increases in the vicinity of favored areas (e.g., parks) whereas density decreases in the neighborhoods surrounding disfavored areas (e.g., trash dumps). If one excludes sections of the urban landscape from housing construction (as would be true for a predefined park or trash dump), it is possible to replicate both the aggregation and avoidance type housing patterns depending on how the unbuildable lots are treated and what model parameters are used (Figure 3). For example, if unbuildable lots in a model landscape

Figure 3. Output from an Ecobeaker simulation of new housing starts showing the influences of landscape features on housing patterns. Treating disfavored features (e.g., trash dumps) as already built-up leads to an absence of houses in the immediate vicinity, whereas treating favored areas as empty of houses results in increased occupancy of nearby lots. Referring to the parameters in Equation (6), for each panel, d_1 is the density of houses on the local 9 cell neighborhood and d_2 is the density in the regional 49 cell neighborhood; $\beta_0 = -0.5$, $\beta_1 = -30$ and $\beta_2 = 20$.

are considered devoid of houses and the colonization probability is high when there are few houses within the local neighborhood of a potential house site, then lots immediately surrounding the unbuildable lots will feature a disproportionate concentration of houses (Figure 3). Likewise, if the unbuildable lots are treated as occupied and the colonization probability is low in high density areas, few houses will be built in lots near the unbuildable areas (Figure 3).

Conclusion

Simple models of urban landscape change that incorporate density dependence into a probabilistic colonization context can be used to generate a diversity of city growth patterns (Figures 2 and 3). Although we expect future research to extend these efforts (e.g., by modeling within a GIS framework featuring the irregularly sized lots that often typify urban areas), here we have not tried to parameterize versions of the models from data nor to use the model to forecast urban growth patterns. Indeed, the data necessary for such analyses are just now being compiled for the Phoenix metropolitan region by other CAP-LTER researchers (e.g., Gober et al. 1998). Instead, our goal has been to introduce the problem, with an emphasis on highlighting multi-scale density-dependence as one connection between the dynamics of human-dominated landscapes and 'natural' ecological processes. Drawing such parallels is an important first step because it suggests ways in which some of what we already know about ecology can be incorporated into studies of urbanizing areas.

Eventually it would be instructive to examine how ecological attributes, in addition to residential density, associated with cities of different growth forms (for example Portland, Oregon with its stringent growth limits (Ferguson 1997) or more mature cities like Baltimore, Maryland) influence these models of landscape change. Such investigations would provide insight into the kinds of factors (and their operational scales) that influence urban growth patterns. Such understanding is important because urbanization is increasingly rapid on the global scale. Indeed, by the year 2000, 50% of the world's population will live in cities (United Nations 1996). Similarly, the success of efforts to manage development of urban systems in ecologically responsible manners will likely hinge upon an awareness of the factors that influence the growth and spatial spread of cities. Recognizing and taking advantage of parallels between colonization dynamics (and other features) of 'natural' and human-dominated systems should facilitate ecological studies of urban systems.

Acknowledgements

This paper resulted from the Urban Ecological Modeling Working Group at the National Center for Ecological Analysis and Synthesis (NCEAS), a center funded by the U.S. National Science Foundation (Grant #DEB 94-21535), the University of California at Santa Barbara, and the State of California, USA. We thank J. Collins, N. Grimm, P. Kareiva, and A. Kinzig for comments that helped frame the project.

References

Adams, C. C. 1935. The relation of general ecology to human ecology. Ecology 16: 316–335.

Adams, C. C. 1938. A note for social-minded ecologists and geographers. Ecology 19: 500–502.

Agresti, A. (1990) Categorical Data Analysis, John Wiley, New York, NY, USA.

Allee, W. C. 1951. The social life of animals. Beacon, Boston, MA, USA.

Andow, D., Kareiva, P., Levin, S. and Okubo, A. 1990. Spread of invading organisms. Landsc Ecol 4: 177–188.

Banks, J. E. and Ekbom, B. 1999. Modelling herbivore movement and colonization: pest management potential of intercropping and trap cropping. Agric Forest Entomol 1: 165–170.

Batty, M. and Longley, P. 1994. Fractal Cities. Academic Press, London, UK.

Batty, M. and Densham, P. J. 1996. Decision support, GIS, and urban planning.
http://www.geog.ucl.ac.uk./pdensham/s_t_paper.htm

Burns, E. K. 1992. Vance's Commuting Analysis: An Application in Tempe, Arizona. APCG Yearbook, pp. 77–96

Caputo, M. 1999. 'Regular citizens' will deal with valley boom: growth issues spread beyond technocrats. The Tribune. 50 (361): A1, A5. Thomson Newspapers, Inc. Tempe, AZ, USA.

Cerveny, R. S. and Balling, R. C. 1998. Weekly cycles of air pollutants, precipitation, and tropical cyclones in the coastal NW Atlantic region. Nature 394: 561–563.

Chapin, F. C. and Weiss, S. F. 1968. A probabilistic model for residential growth. Transport Res 2: 375–390.

Collins, J. P. Subm. ms. Struggling with ourselves: incorporating human societies into ecological theory. J History Biol, in review.

Collins, J. P., Kinzig, A., Grimm, N. B., Fagan, W. F., Hope, D., Wu, J. and Borer, E. T. In press. Urban Ecology: Cities afford a powerful model for developing and testing ecological theory that integrates humans. American Scientist.

Dean, T. A. and Hurd, L. E. 1980. Development in an estuarine fouling community: the influence of early colonists on later arrivals. Oecologia 46: 295–301

Densham, P. J. 1991. Spatial decision support systems. *In* Geographical Information Systems: Principles and Applications. Pp. 403–412 Edited by D. J. Maguire, M. F. Goodchild, and D. W. Rhind. Longman, London, UK.

Fagerstrom, T. 1997. Population dynamics in sessile organisms: some general results from three seemingly different theory-lineages. Oikos 80: 588–594.

Ferguson, T. W. 1997. Down with the burbs! Back to the city! Forbes 159: 142–4.

Gober, P, Burns, EK, Knowles-Yanez, K and James J. 1998. Rural to urban land conversion in metropolitan Phoenix. *In* Arizona Policy Choices. Pp. 40–45 Edited by J. S. Hall Morrison Institute for Public Policy, Arizona State University, Tempe, AZ.

Gotway, C. A. and Stroup, W. W. 1997 A generalized linear model approach to spatial data analysis and prediction. J Agric Biological Environ Stat 2: 157–178.

Groom, M. J. 1998. Allee effects limit population viability of an annual plant. Am Nat 151: 487–497.

Halls, J. N., Cowen, D. J. and Jensen, J. R. 1994. Predictive spatio-temporal modeling in GIS. Proc Sixth Int Symp Spatial Data Handling 1: 431–448.

Holmes, E. E. and Wilson, H. B. 1998. Running from trouble: long-distance dispersal and the competitive coexistence of inferior species. Am Nat 151: 578–587.

Kot, M., Lewis, M. A. and van den Driessche, P. 1996. Dispersal data and the spread of invading organisms. Ecology 77: 2027–2042.

Lewis, M. A. 1997. Variability, patchiness, and jump dispersal in the spread of an invading population. *In* Spatial Ecology: the Role of Space in Population Dynamics and Interspecific Interactions. Edited by D. Tilman and P. Kareiva. Princeton University Press, Princeton, NJ, USA.

Lubchenco, J. 1998. Entering the century of the environment: a new social contract for science. Science 279: 491–497.

MAG (Maricopa Association of Governments). 1999. Population Growth Projections. Phoenix, AZ, USA.

Meir, E. 1996. Ecobeaker 1.0 An Ecological Simulation Program. Sinauer Associates, Sunderland, MA, USA.

Meir, E. 1999. Ecobeaker 2.0 An Ecological Simulation Program. Beakerware, Ithaca, NY, USA.

McCullagh, P. and Nelder, J. A. (1989) Generalized Linear Models. Second Edition. Chapman and Hall, New York, NY, USA.

Mesev, T. V. and Longley, P. A. 1995. Morphology from imagery: detecting and measuring the density of urban land use. Environ Planning A27: 759–780.

Nelder, J. A. and Wedderburn, R. W. M. 1972 Generalized linear models. J Roy Stat Soc A135: 370–384.

Noble, D. G., ed. 1991. The Hohokam: Ancient People of the Desert. School of American Research Press, Santa Fe, NM, USA.

Redman, C. L. 1992. The impact of food production: short term strategies and long-term consequences. *In* Human Impact on the Environment. pp. 35–49 Edited by J. Jacobsen and J. Firor, eds. Westview Press, Boulder, CO, USA.

SAS. 1995. SAS/STAT user's guide. Version 6.12. SAS Institute, Cary, NC, USA.

Skellam, J. G. 1951. Random dispersal in theoretical populations. Biometrika. 38: 196–218.

Sutherland, J. P. 1981. The fouling community at Beaufort, North Carolina: a study in stability. Am Nat 118: 499–479.

Sutherland, J. P. and Karlson, R. H. 1977. Development and stability of the fouling community at Beaufort, North Carolina. Ecol Monog 47: 425–446.

United Nations (United Nations Centre-for-Human-Settlements-Habitat). 1996. An Urbanizing World: Global Report on Human Settlements, 1996. Oxford University Press, Oxford, UK.

Vitousek, P. M., Mooney, H. A., Lubchenco, J. and Melillo, J. M. 1997. Human domination of Earth's ecosystems. Science 277: 494–499.

Weisner, C. and Cowen, D. J. 1997. Modeling urban dynamics with artificial neural networks and GIS. *In* ACSM/ASPRS Annual Convention and Exposition Techical Papers: Auto-Carto 13. pp. 66–75.

Whyte, W. H. 1968. The Last Landscape. Doubleday, New York, NY, USA.

Winterer, J., Klepetka, B., Banks, J., and Kareiva, P. 1994. Strategies for minimizing the vulnerability of rice to pest epidemics. *In* Rice Pest Science and Managemant. pp. 53–69. Edited by P. S. Teng, K. L. Heong and K. Moody. Selected papers from the International Rice Research Conference. International Rice Research Institute, Manila, Philippines.

Witten, T. A. and Sander, L. M. 1981. Diffusion-limited aggregation: a kinetic critical phenomenon. Phys Rev Lett 47: 1400–1403.

Witten, T. A. and Sander, L. M. 1983. Diffusion-limited aggregation. Phys Rev B 27: 5686–5697.