

# 1 Theoretical Ecology for the Anthropocene

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## <sup>6</sup> Abstract

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## Chapter 2

### Simulation Models in Ecology

*M.D. Catchen, S.M. Flaxman*

*The electron is a theory we use; it is so useful in understanding the way nature works that we can almost call it real.*

*Richard P. Feynman*

\_\_The limits of language means the limits of my world.\*

Ludwig Wittgenstein (1922)\_\_

*Things are similar: this makes science possible. Things are different: this makes science necessary.*

Levins & Lewontin (1985)

## 2.1 Abstract

this is where the abstract goes

## 2.2 Introduction

### 2.2.1 What is science?

Science is fundamentally a theory of epistemology—a way of knowing. Within scientific epistemology, knowledge takes the form of theories—explanations of the natural world.

In practice, explanations of the natural world must be embodied in language. One consequence of this is that there is a limitation on what we can understand scientifically (or in any other sense)—that which we can represent in language ??? (For an example of the limitations of language, try to define to yourself what ‘knowledge’ means).

For example, if we wish to understand the properties of gravity, we are limited by the differences in what we can describe in different languages. Consider the following three theories:

$T_1$  : bodies with mass accelerate toward one another

$$T_2 : F_G = \frac{Gm_1m_2}{r^2}$$

$$T_3 : R_{\mu\nu} - \frac{1}{2}Rg_{\mu\nu} - \Lambda g_{\mu\nu} = \frac{8\pi G}{c^4}T_{\mu\nu}$$

All of them describe the same phenomena, and are, at least in some sense, correct (more on this in the next section). At some point we reach a point whereby we switch the notation from English to mathematics to make the communication easier.

I argue that the spectrum here the precision of the definitions we use.

What unites scientific theories across languages is that they all use constructed definitions. This is a necessary byproduct of being embodied in language. For example, for  $T_1$  to convey information, one must first understand what is meant by ‘bodies’, ‘mass’, ‘force’, etc.

The limitations of what a language can represent, then, places a limit on what we can any given scientific theory can describe. In practice, the language of scientific theories can be split into: (conceptual, qualitative, English), (quantitative, math). Different languages have different costs and benefits when describing theories.

For a theory to be valid, it must be capable of being disproven through observation. For

81 a theory to be disproven through observation, it must make predictions that may or may  
82 not agree with observed reality.

83 So, a valid scientific theory must make predictions that can be observed, and therefore  
84 must account for some measurable state of the universe.

85 They also take input and output, must make a prediction.

86 Different languages differ in the precision of the predictions they can make.

87 Validation of a model: more parameters means more difficult to \*disprove.\*

88 Ratio between information described by the model and predictive capacity

## 89 2.2.2 What makes a theory correct?

90 *To know how to distinguish between true and false, one must have an adequate idea of*  
91 *true and false.* Baruch Spinoza, *Ethics*

92 All three theories are, in a sense, correct<sup>1</sup>.

93 Why do we mean when we say a theory is accurate? Notice that as our model increases  
94 in its predictive accuracy, it engages with more constructs. Not an act of discovery, but  
95 an act of creation. Is the Ricci tensor  $g_{\mu\nu}$  real? It is a construct related to measurable  
96 quantities.

## 97 2.2.3 What is a model?

98 Today, a lot is meant by the word ‘model’.

99 The role of a theory in scientific epistemology is now what is often referred to as a ‘model’.

100 Theories must be embodied in language. The limitations of the language you use to de-

101 scribe a theory places limitations on what you can describe (Wittgenstein). For example,  
102 Verbal explanation gravity vs Newton vs. General Relativity? Are all three right? Is  
103 rightness just predictive accuracy down to a degree of error?

104 1

105 Theory / model as interchangeable words

106 For a theory to be scientific, must make predictions. Like a function: maps some input  
107 conditions to a predicted output.

108 Much easier to describe the mechanism of interactions than to describe the dynamics that  
109 unfold from them. use computers to sample that.

## 110 2.2.4 Types of Models

111 Simulation models for dealing with complex systems

112 Types of models:

- 113 • data-models:
- 114 • process-based
- 115 • naive toy models
- 116 • ibm, etc. we got those parameters you asked for boss
- 117 • stupid classic stats stuff
- 118 • algorithmic models:
- 119 • predictive, but with no way of assessing mechanism. overfitting

120 Simulation models as a way of testing mechanism, computational power now available

## 2.2.5 Why Simulate?

Stochasticity is ubiquitous in ecological processes.

The tools we have to handle analytic probability limits the complexity of what we can consider.

Simulation allows us to describe the distribution of complex stochastic processes that cannot be easily explored with analytical tools.

Use computers to simulate to test mechanism, forecast, etc. Cite simulation as use

Approximate Bayesian Computation, intractable likelihood

high variance in predictions in ecology, complex mechanisms, stochasticity. tools of math makes it harder to validate predictions. no theory describes everything perfectly. even newton's gravity becomes intractable w/ 3 body prob.

Karl Popper, demarcation and falsifiable. Observation is not without theory. This collides with ecology. The model is always there, fish in water.

Most theories of model selection revolve around information theoretic criteria Cartesian reductionism and emergent phenomena Habitat loss and fragmentation are the primary causes of anthropogenic extinctions, and pose significant threats to biodiversity and ecosystem health around the globe (Haddad et al. 2015, Rands et. al 2010, Fahrig 2003). As a result, the literature surrounding habitat fragmentation is vast and spans a wide variety of subfields, and a wide-variety of definitions are used to describe fragmentation. "Habitat fragmentation" is often used as a catchall to refer to one or more of increasing patch-isolation, the loss of habitable matrix, and/or reductions in landscape connectivity. Fahrig (2003) defines fragmentation per se as purely the separation/isolation of a fixed amount of habitat. In no small part due to ambiguous (and sometimes conflicting) definitions, a wide variety of conceptual approaches have been used to study fragmentation and

its effects, ranging from focusing on the loss of patch area, the effects of landscape heterogeneity, disruption of interactions between species, edge-effects, and patch connectivity (Fischer and Lindenmayer 2007).

Broadly speaking, the conceptual models of habitat fragmentation have their roots in one of two subfields: island biogeography and metapopulation ecology (Collinge 2009). The Theory of Island Biogeography (TIBG), introduced by MacArthur and Wilson (1967), was conceptualized for terrestrial communities on oceanic islands, but it quickly was applied elsewhere under the assumption that many human-altered landscapes are well-approximated by an island structure—isolated regions of homogeneous landscape separated by inhabitable matrix (Haila 2002). The core ideas of TIBG relate island sizes and distances from one another to species richness. These ideas thus led to focus on both the amount of habitat available, and the dispersal structure of the islands. Many of the theoretical studies in the 1980s and 1990s focused explicitly on the relationship between habitable area and species persistence, such as percolation theory, and extinction debt. Haila (2002) critiques these assumptions and suggests re-conceptualizing fragmentation as a type of “human-induced environmental degradation”.

The second main subfield, the metapopulation framework, was introduced by Levins (1969), who modeled a system of infinitely many populations, each with a uniform probability of colonization or local extinction each generation. Metapopulation theory was more formally applied to fragmented landscapes by Hanski and Ovaskainen, who refined the Levins model to a finite number of populations with spatially-explicit locations, each with a unique probability of colonization arising from the metapopulation’s spatial structure. Models of this form are called Incidence-Function Models (IFMs) (Hanski 1994; Hanski and Ovaskainen 2000). IFMs have seen extensive use in conservation (cite some papers that have used IFM). Both the Levins model and IFMs are occupancy models: each patch/population is either occupied or unoccupied, and the persistence of the system lies in the balance of colonization by dispersal and local extinctions. Because the focal point of metapopulation theory is the dispersal capacity, the components of frag-



mentation that deal with patch size and edge configuration are largely ignored. The metapopulation system is thought of as a network of pointlike populations in space—they don't occupy any area and the key dynamics emerge as a product of their spatial configuration. However, the features of patch structure that metapopulation models tend to ignore can be captured by other means. For example, heterogeneity in patch sizes can correspond to different probabilities of local extinction. Other landscape dynamics can be captured using source-sink metapopulations (cite some source/sink, Gilpin).

The field of landscape genetics shows progress toward unification of these two large bodies of theory through the use of network models. In part due to the increasing affordability of high-throughput sequencing technology, the field of landscape genetics, introduced by (Manel et al. 2003), has sought to synthesize population genetic models with an understanding of landscape features using large-scale genomic data. The application of spatial networks has seen extensive application in this domain as well. Isolation-by-resistance (McRae 2006), useful in developing theory for real landscapes, habitat quality is not a 0/1. How do we think about resistance to gene flow? Resistance surfaces (Spear et al. 2010) are raster approach. Populations or individuals are modeled as points in space, each cell of the raster is assigned a resistance value, etc. etc. Using a network is a convenient abstraction for the location of a population. We lose some details about the variance of the environment within the environment, but that is the reality of modeling.

The task of modeling is to build a world. Science doesn't discover, science creates.

Cartesian reductionism and dialectical approaches to ecological worldbuilding

## 194 Chapter 3

# 195 Critical Transitions in Landscape Connectivity

196 *M.D. Catchen, S.M. Flaxman*

197 *Philosophers have hitherto only interpreted the world in various ways; the point is to*  
198 *change it.* Karl Marx, *Theses on Feuerbach* (1845)

## 199 3.1 Abstract

200 this is where the abstract goes

## 3.2 Introduction

Ecological processes occur in both space and time. The way in which ecological processes emerge across spatiotemporal scale is central to the fundamental questions of ecology and evolutionary biology. For example, the understanding the interaction between spatial distributions of both species and environmental factors is at the heart of biogeography. The spatial distribution of genes is fundamental to the study of speciation. Further, human activity has, in a (geologically speaking) relatively short period of time, rapidly altered the face of the planet Earth. This drastic change in the structure of Earth's terrain has had overwhelmingly negative effects on the planet's biodiversity, and understanding the consequences of landscape change is fundamental to conservation.

Historically, the effect of land-use change on biodiversity has been studied under the banner of 'habitat fragmentation'. Much debate occurred regarding what precisely is meant by this term—however what remains clear is that habitat loss is one of the leading drivers of biodiversity loss globally (cite).

Landscape connectivity is fundamental to many questions. Practically, land use management and landscape 'design' are major methods for conserving biodiversity in face of climate change and continued human development

What needs to be done?

What did I do, and why does it address what needs to be done?

## 3.3 Methods

### 3.3.1 Ecological Dynamics on Spatial Graphs

Ecological data, especially data about biotic processes, is often pointlike—a measurement taken of some ecological process associated with a spatial coordinate.

Spatial graphs are often used to model a system of habitat patches.

Here we model a system of populations, represented as nodes in a spatial graph, with edges representing dispersal between populations. We consider then consider a measurement of an ecological process at each site  $f(x_i)$ , which maps spatial locations to measurement values  $f : \mathbb{R} \rightarrow \mathbb{R}$ .

In this paper, we consider the measurement in question to be the size of the population at that point.

Here we propose modeling landscape connectivity as a combination of two different factors: the probability than any individual migrates during its lifetime,  $P(m)$ , and the conditional distribution of where an individual migrates to given where they started, often called the dispersal kernel. For example, if we denote the probability that an individual born in  $X_i$  reproduces in  $X_j$  as  $P(X_j|X_i)$ , we can define the dispersal matrix as

$$\Phi_{ij} = \begin{cases} P(X_j|X_i) P(m) & \text{if } i \neq j \\ 1 - P(m) & \text{if } i = j \end{cases}$$

Here  $\Phi_{ij}$  represents the probability that any individual born in  $i$  reproduces in  $j$ .

We then can consider modeling the dispersal kernel,  $P(X_j|X_i)$ , using a variety of methods. This is in

Empirically, resistance surfaces are a good way to model this. Theoretically, various functional forms representing isolation-by-distance have been used. (See next section).

Now we move to considering the dynamics an ecological process/measurement taken at each site,  $f(x_i)$ . We can now represent the dynamics of this system using a reaction-diffusion model,

hey fartbag you have to explain why matrix notation works  $\dot{x}_i = (1-m)x_i + m \sum_{j \neq i} \Phi_{ji} x_j$

$$\frac{d\vec{x}}{dt} = g(\Phi^T \vec{x})$$

Here,  $g(x)$  is a function that represents the hypothesized mechanism that represents how the ecological measurement evolves locally. For example, in the next section we will consider the stochastic logistic model,

$$g(x) = \lambda x(k - x) + \sigma dW$$

However,  $g(x)$  can represent any ecological process of interest, for example if the state space of  $x$  is allelic frequencies,  $g(x)$  could describe genetic drift, or if  $x$  represents community compositions across space,  $g(x)$  could describe competition between species as a function of environmental conditions. Coevolutionary states across space, mosaic, etc.

### 3.3.2 Transitions in the Synchrony of Metapopulation Dynamics

Here, we apply the above SGD framework to answer the question: when do transitions from the system behaving as one unified system to many independent systems occur?

One can intuitively assess the boundary conditions of this problem: if the probability that any individual migrates  $P(m) = 0$ , the system is not one but instead a collection

of independent systems. However, if  $P(m) = 1$ , the spatial structure ceases to carry much meaning and the system is one unified system. Where in the space of landscape connectivity, as represented by  $\Phi$ , does a system of metapopulation dynamics shift from being several independent populations to one single population?

### 3.3.2.1 Population Dynamics

We model population dynamics within each local population  $X_i$  using the stochastic logistic model. The dynamics of the number of individuals in population  $i$  are described by the stochastic differential equation

$$dN_i = K_i \lambda_i (K_i - N_i) dt + \sigma dW$$

For the sake of reducing parameter space, we consider all populations as having the same  $\lambda_i$  and  $K_i$ , however, future work could include exploring the source-sink dynamics in this system by varying intrinsic growth rates and carrying capacities across populations.

### 3.3.2.2 Measuring Synchrony

We must first determine what we mean when we say that a metapopulation is a single, unified system versus many independent systems. In the context of population dynamics, we consider the total sum of the count of individuals across all sites as  $N(t)$

$$N(t) = \sum_i N_i(t)$$

If the dynamics of two systems are independent, then we would expect weak correlation between  $\Delta = N(t+1) - N(t)$  and  $\Delta_i = N_i(t+1) - N_i(t)$ . However, if the system is truly ‘one’, then we would expect  $\Delta$  and  $\Delta_i$  to be the same. The crosscorrelation between two vectors  $\vec{X}$  and  $\vec{Y}$  is given by

$$R_{XY} = \begin{bmatrix} E[X_1Y_1] & E[X_1Y_2] & \dots \\ E[X_2Y_1] & E[X_2Y_2] & \dots \\ \vdots & \vdots & \ddots \end{bmatrix}$$

279 Luckily, there is already a variety of tools used to measure correlations between time-  
280 series. Crosscorrelation function, lags, etc.

### 281 3.3.3 Numerical Simulations

282 Optimizing a landscape numerically

283 How do you maximize synchrony based on limited amount of possible change dispersal  
284 potential space?

285 evenness of eigenvalue centrality compared to numerical computation over whole space

## 286 3.4 Results

287 In figure one we can see

## 288 3.5 Discussion

289 landscape connectivity is a function of scale.

## 290 3.6 References

291 *It is thus not to be wondered at, that among philosophers who attempt to explain things in*  
292 *nature merely by the images formed of them, so many controversies should have arisen.*

293 Spinoza, Ethics, Prop. 40: Note 1

294 *To know how to distinguish between true and false, one must have an adequate idea of*  
295 *true and false.*

296 Spinoza, Prop. 42: proof

297 \_Concepts do not wait for us ready-made, like celestial bodies...They must be invented,  
298 fabricated, or rather created, and would be nothing without the signature of those who  
299 create them\_.

300 Gilles Deleuze, What is Philosophy?



## References

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