



Computational Science Technical Note **CSTN-015**

## A Zoology of Emergent Patterns in a Predator-Prey Simulation Model

K. A. Hawick and H. A. James and C. J. Scogings

2006

We describe the characteristics and behaviour of emergent patterns we have found in a simple predator-prey simulation model. We have extensively simulated a “flatland” populated with microscopically detailed individual animals. Animals’ behaviours are rule-based and follow a predator-prey schema based on a small number of adjustable parameters. We have searched the model parameter space and found regimes of rich emergent behaviour and have devised various observation techniques and quantifiable measurements to characterise the growth behaviour of the emergent spatial patterns. We report on a taxonomical classification of the emergent patterns or “macroscopic life-forms” found in our model and a preliminary analysis of the transformations between different collective patterns.

Keywords: emergent pattern; predator-prey model development; agent-based modelling

### BiBTeX reference:

```
@INPROCEEDINGS{CSTN-015,
  author = {K. A. Hawick and H. A. James and C. J. Scogings},
  title = {A Zoology of Emergent Patterns in a Predator-Prey Simulation Model},
  booktitle = {Proceedings of the Sixth IASTED International Conference on Modelling,
    Simulation, and Optimization},
  year = {2006},
  editor = {H. Nyongesa},
  pages = {84--89},
  address = {Gaborone, Botswana},
  month = {September},
  keywords = {emergent pattern; predator-prey model development; agent-based modelling}
}
```

This is a early preprint of a Technical Note that may have been published elsewhere. Please cite using the information provided. Comments or queries to:

Prof Ken Hawick, Computer Science, Massey University, Albany, North Shore 102-904, Auckland, New Zealand.  
Complete List available at: <http://www.massey.ac.nz/~kahawick/cstn>

# A Zoology of Emergent Patterns in a Predator-Prey Simulation Model

K.A. Hawick, H.A. James and C.J. Scogings  
Institute of Information & Mathematical Sciences  
Massey University – Albany  
North Shore 102-904, Auckland, New Zealand  
email: {k.a.hawick, h.a.james, c.scogings}@massey.ac.nz

11 April 2006

## ABSTRACT

We describe the characteristics and behaviour of emergent patterns we have found in a simple predator-prey simulation model. We have extensively simulated a “flatland” populated with microscopically detailed individual animals. Animals’ behaviours are rule-based and follow a predator-prey schema based on a small number of adjustable parameters. We have searched the model parameter space and found regimes of rich emergent behaviour and have devised various observation techniques and quantifiable measurements to characterise the growth behaviour of the emergent spatial patterns. We report on a taxonomical classification of the emergent patterns or “macroscopic life-forms” found in our model and a preliminary analysis of the transformations between different collective patterns.

## KEY WORDS

emergent pattern; predator-prey model development; agent-based modelling.

## 1 Introduction

Artificial-life simulation models aim at exploring the complex behaviour that can emerge [2] on a system-wide scale in response to microscopic or localised decisions made by constituent agents [1, 10, 14]. In [7] we reported on some of the emergent spatial patterns we had discovered in our predator-prey based artificial-life model. Our model is based on prescribed microscopic rules for individual animat agents [3, 12] co-existing in

a simulated “flatland.” We developed a number of techniques for semi-automatically identifying these patterns using cluster methods and various recognition heuristics. In this present paper we describe a classification scheme or “zoology” of these emergent patterns and note some of the emergent behaviours of these animat aggregates. We describe some of the multi-scale effects observed in our model and present a preliminary formulation of aggregate transformation rules.

In section 2 we outline the essential features of our core model. We report our main results for this paper in section 3 in the form of observations and a detailed description of the “zoology” of emergent spatial patterns or macroscopic life-forms that occur in our simulation model. In section 4 we report on typical probabilities of occurrence for the emergent patterns, and in section 5 we describe an analysis of the probabilities of transmutation between different patterns. Finally in section 6 we conjecture how these methods might be of interest for analysing other spatially-oriented simulation models.

## 2 The Predator-Prey Model

Our experimental model is essentially a predator-prey model in which the prey (rabbits) are assumed to have access to unlimited food supplies but where the predators (foxes) will starve to death unless they consume rabbits. Animats also have a finite life span and will die of old age, unless eaten first in the case of rabbits.

The behaviour of each animat is governed by a set of

simple rules. At this stage of development the rules are fixed for each species of animat and thus all foxes have identical rules and similarly for all rabbits. Examples of rules are “move away” if a fox is adjacent, for rabbits, and “move towards a rabbit if hungry” for foxes. Both species include rules for breeding with adjacent animats of the same species.

When two animats breed successfully a new animat is created. The success of breeding depends on a number of factors such as the number of animats of the same species in the local area (overcrowding) and in the case of foxes the number of rabbits in the area (available food). A key efficiency feature of the simulation that enables us to study the large system and long time regimes described in this present paper is to determine what animats are nearby, as inputs to the animats behaviour [15].

The animat rules are arranged in an order of priority. Thus if the conditions for rule 1 are met then rule 1 will be executed and the rest of the rules will be ignored. If the conditions for rule 1 are not met then the conditions for rule 2 are checked and so on. Thus every animat will always execute exactly one rule at each time step of the model. We have presented a detailed description of the rule combinations elsewhere [7].

The animats are free to move on what is effectively an infinite plain without bounds. In practice our simulation runs are limited by the number of animats we can hold in memory rather than the physical extent of the simulated “flatland.” Animats can also be co-located with other animats. New animats “born” as a result of breeding are initially placed in the same location as one of their parents. However the animat rules ensure that successful animats will always seek the company of others, either to breed with the same species or in the case of foxes to obtain food in the form of rabbits.

This built-in “seeking out of other animats” leads to the emergence of spatial clusters of animats. These clusters of microscopic animats can be observed as macroscopic organisms in their own right. The observed organisms display a surprising richness of spatially interesting structures.

### 3 A Zoology of Aggregate Patterns

Following a great deal of observation of simulation model runs and attempts at classification, we identified four major categories of aggregate pattern or “macroscopic organism” that emerge from our model. We categorise them under the following headings:

**Waves** - generally thin wavefronts of animats that ap-

pear to move in a coordinated way.

**Blobs** - dense clumps of animats - particularly “rabbits”

**Spiral Curves** - delicate rotating structures of animats

**Transitional Clusters** - hybrids that can easily become any of the other forms

Each of these patterns has a number of particular properties which we discuss in detail below as well as noting some sub-species or sub-categories of “waves” and “blobs.”

We typically initialise model runs with a random or simple regular block of animats. The model shows remarkable robustness and insensitivity to the precise initial conditions. The patterns we describe below emerge with no need for any particular seeding or choice of initial conditions.

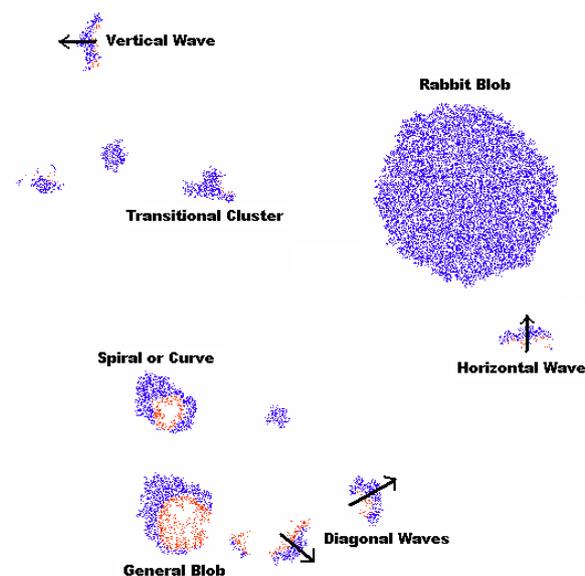


Figure 1: The “Zoo” of typical emergent patterns in our model. Features have been automatically classified as shown.

Figure 1 shows a number of typical emergent patterns that commonly occur in the model and which we discuss below. This “zoo” shows features that have been automatically classified using the heuristic and recognition algorithms that we describe elsewhere [7]. “Rabbits” are shown as dark (blue) pixels and “foxes” as

light(red). As the figure indicates, a large rabbit blob has developed because of the absence of foxes in its immediate vicinity. the “horizontal wave” is moving upwards (as shown) and will almost certainly collide with the rabbit blob if the simulation evolves further. This could lead to an effect similar to that of the general blob (also shown in the figure) which is the remnants of a smaller rabbit blob that has previously been partially consumed.

The transitional cluster shown in the figure is in the process of becoming a diagonal or horizontal wave and is the last vestige of yet another rabbit blob that has been almost entirely consumed.

The spiral/curve shown in this figure illustrates the problem of accurately classifying features and will likely evolve into another a more easily classifiable feature in the future.

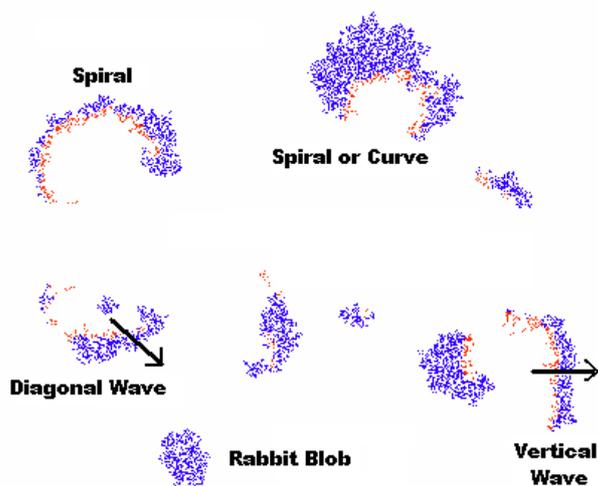


Figure 2: A typical spiral pattern of animats.

Figure 2 shows a more clearly recognisable **spiral** as will have evolved because of the unique interactions between rabbits and foxes in our model. Spirals are the most sophisticated spatial structure that occur in our model. They are highly sensitive to particular interacting battlefronts of the animat species but perhaps surprisingly spirals frequently do occur. We have described some of the parameters and circumstances that lead to spirals elsewhere [4]. Spiral patterns are not uncommon in nature [16] but it is still unobvious how to precisely parameterise them or indeed how they will emerge in a particular model run. In this sense they are a truly

emergent feature.

Automatic classification is performed by dividing each cluster into quarters (based on the centre of the cluster) and counting the animats present in each quarter. The ratio of numbers in the various quarters defines the classification type of spatial cluster. The exact heuristics we employ are described elsewhere [7]. We now discuss each of the classification types.

### 3.1 Waves

Four types of wave-fronts have been identified. These are diagonal waves, horizontal waves, vertical waves and what we term “thin diagonal” waves. Diagonal waves are defined as those clusters where one quarter contains less than 10% of the total number of animats in the cluster. Thin diagonal waves are defined as those clusters where two or more quarters contain less than 10% of the total number of animats in the cluster. Horizontal and vertical waves are not defined by checking quarters. Instead the spread of animats from the centre is calculated to see if a definite horizontal or vertical rectangular bounding-box emerges. This is unlike the diagonal wave where the bounding box is much closer to a square.

Wave-fronts usually form after the collapse of a blob or spiral. The predators (foxes) spread out into a line to maximise their chance of finding prey (rabbits) and the rabbits become spread out in a corresponding line as they flee from the foxes. Thus two semi-parallel lines of animats merge into a cluster and travel in a wave across the area of interest. Wave-fronts often dissipate when encountering another cluster and the wave effect is then broken up.

Thin diagonal waves do not occur very often compared to the other types of wave and were included as a separate type simply because they were easy to identify. Thin waves can grow to become normal waves but can also dissipate very rapidly.

### 3.2 Blobs

A “blob” is what we term a spatial cluster in which the animals are tightly packed and will often appear visually as a filled compact circle of animats. The blobs are classified by the density of the animats within them and will override other classifications such as spirals, curves or wave fronts. There are two types of blob. These are pure rabbit blobs and general blobs.

Rabbit blobs contain **only** rabbits and can become very large very quickly. If rabbits find themselves in

an area with no foxes present they will stay close to other rabbits and breed<sup>1</sup>. This rapidly leads to a huge circular rabbit blob often containing tens of thousands of rabbits. If foxes (often in a wave) approach close enough to a rabbit blob they will rapidly eat their way into it causing it to collapse and reform into a spiral or curve and thence into a travelling wave.

The likelihood of a rabbit blob forming is directly linked to the rabbit birth rate parameter. The higher the birth rate the more likely that rabbit blobs will occur when the model is run.

A general blob contains both rabbits and foxes. While it can be classified as a general blob it is perhaps really a transitional cluster which will evolve into a travelling wave or curve as rabbits are consumed and the animats spread out.

A blob containing only foxes will almost never occur as foxes are always searching for rabbits. Although they will move towards other foxes for breeding purposes, a cluster containing only foxes would rapidly dissipate as foxes moved away in search of food.

### 3.3 Spiral Curves

Spirals and curves are the most fascinating clusters to emerge from the predator prey model. A spiral will form from a wave front when the rabbit line (which is leading the front) overlaps the pursuing line of foxes. The rabbits on the extreme end of the line stop moving as there are no foxes in their immediate vicinity. However the rabbits and the foxes in the centre of the line continue moving forward. This forms a small trail of rabbits at one (or both) ends of the front. These rabbits start breeding and the trailing line of rabbits thickens and attracts the attention of foxes at the end of the fox line that turn towards this new source of prey. Thus a spiral forms with foxes on the inside and rabbits on the outside. If the original overlap of rabbits occurs at both ends of the line a double spiral will form. Spirals can also form as a rabbit blob collapses after foxes eat into it.

Although spirals have been the most interesting form to emerge from the model they are also the hardest cluster to classify, hence the title spirals and/or curves. A spiral is defined as a cluster where one quarter contains more than 28% of the total animats and the other three quarters all contain more than 18% of the total animats. Spirals often change shape quite rapidly and this can lead to the classification of the cluster being continually switched from spiral to transitional and back again. A

<sup>1</sup>Which is why we nickname this animat species as “rabbits”

spiral can also become a general blob if the density of the animats increases within it.

### 3.4 Transitional Clusters

These clusters are typically noisy and hardest to classify but maybe important as a mechanism for one aggregate pattern to change into a significantly different one.

Any cluster which can not be classified in any other way is deemed to be a transitional cluster. As with any automated process a line has to be drawn and many transitional clusters appear visually to be spirals, curves or diagonal wave fronts. As a spiral or diagonal wave move they can cross over the classification threshold and produce a sequence of spirals (or diagonal waves) intermixed with transitional clusters.

## 4 Probabilities of Emergence

Although a great deal can be learned about the typical patterns formed in our model from study of animated sequences, we desire a more quantitative way of comparing different simulation runs. In particular we are interested in the relative abundance of occurrence of the spatial patterns we have described. The bulk behaviour of the model is relatively straightforward to study, and we can record temporal profiles of the different species of animat populations.

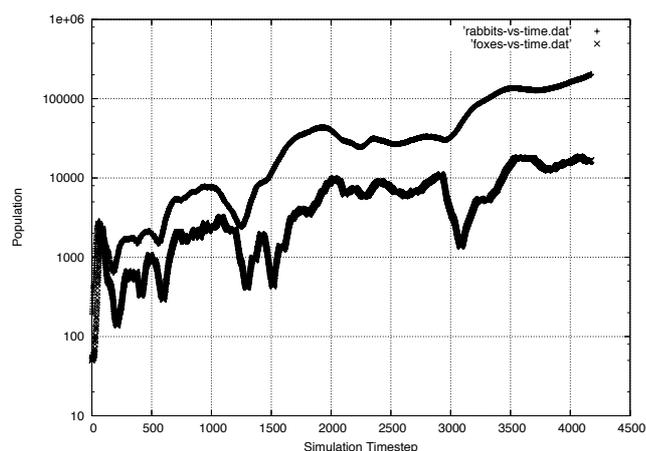


Figure 3: Animat population plotted on log-linear scale, showing slow growth envelope with periodic boom-bust growth of rabbits, lagged by a corresponding boom-bust for foxes.

Figure 3 shows a typical population profile for rabbit and fox animats in our model. The general form is one of a slow growth envelope as animats expand to explore their space, with periodically oscillating boom-bust cycles of growth for prey, lagged by corresponding cycles for predators. This oscillatory bulk behaviour is expected from the usual analysis of predator-prey scenarios using Lotka-Volterra equations [11, 17] for instance. However, the spatial mix of emergent patterns is not so simple. The slow growth envelope is due to our model supporting open boundaries. This is attractive as it is unaffected rigid wall spatial boundary effects and is therefore less dominated by the usual overcrowding phenomena that is seen in a study of the closed form Lotka-Volterra partial differential equations. The spatially emergent structure of blobs, spirals and so forth in fact is closely linked to the more complex oscillatory sub-structure seen in figure 3. Since the population is spatially distributed rabbits can breed unchecked if they happen to do so in a region of space in which they are unmolested by foxes. Likewise foxes can become locally extinct if there are not rabbits available for food. This can cause interesting swings in the global population. Unlike the simpler Lotka-Volterra case however, the global populations can recover from local disasters or extreme population densities such as the large rabbit blob that forms around time-step 2000 or the near fox extinction that occurs near step 1300.

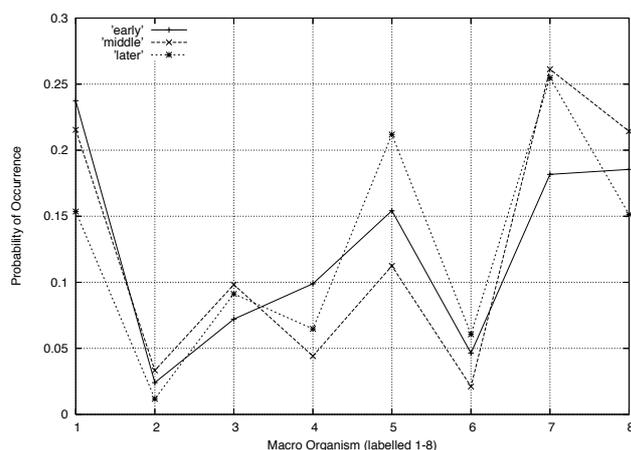


Figure 4:

The data shown in table 1 and plotted in figure 4 shows the average relative probability of occurrence of each of the macroscopic spatial patterns in the model. Three sets of data are presented for early, middle and

later stages of a typical model run. Of note is the considerably different relative probabilities of each species and the surprising continued relative abundance of spirals that occur in the model. This analysis is of course sensitive to the periodic oscillations due to boom-bust cycles in population, but this is partially averaged out by integrating over time lengths that are relatively long compared to the time periods shown in figure 3.

We do not notice any systematic time behaviours for the wave formations other than diagonal waves which show a tendency to diminish as the model evolves in time. Rabbit blobs and spirals once established will continually recur and appear to be the main contributors to the general population trends. Foxes will typically remain part of a wave or be part of general blobs and spirals. the attacking fox wavefront seems to be the major emergent fox-specific feature.

## 5 Transformation Matrix

A further interesting property of the spatially emergent pattern in our model is that they can transmute from one type to another. This is a generally slow process and is not easy to predict except in the most general terms. This can again be analysed by close observation, but we prefer to consider a statistical analysis.

One way to analyse the system is to look at the transformation probabilities as measured from model runs. The identified aggregates do transform from one identified classification type to another. Some are very long lived, some less so. Some very robust against change, other are more fragile.

Figure 5 shows asymmetries in the probability transformation matrix measured in our model. The values have been scaled arbitrarily and coloured from maximum (dark) to minimum (white). These have been averaged over the middle period of the run as shown in the table in section 4. The diagonal elements have been deliberately suppressed as clearly the most likely occurrence during 500 steps is for the cluster to remain the same type. However there are significant probabilities (shown as percentages) that a particular type will transform to another. For example a “thin diagonal” is very likely to change to a “diagonal wave”, a transitional cluster is quite likely to become a spiral.

These measured transition probabilities are consistent with the general abundance probabilities discussed above. Rabbit and mixed blobs and spirals are likely to occur and seem to play the dominant role in determining the rabbit populations. There is a strong interplay

Species Code	Probability “early” step 500-1000	Probability “Middle” step 1000-1500	Probability “later” step 2200 - 2700	Species Description
1	0.237293956	0.215424018	0.153591682	diagonal wave
2	0.024038462	0.033295390	0.011814745	thin diagonal wave
3	0.072115385	0.098178714	0.091209830	horizontal wave
4	0.098901099	0.044109277	0.064744802	vertical wave
5	0.154189560	0.112407513	0.211877757	rabbit blob
6	0.046359890	0.021058623	0.060649023	general blob
7	0.181662088	0.261240751	0.254725898	spiral/curve
8	0.185439560	0.214285714	0.151386263	transitional cluster

Table 1: Probabilities of occurrence of each macro-cluster type during different phases of a typical model run. (See Figure 4)

between blobs being attacked by waves and becoming spirals, or spirals of rabbits being left unmolested to rapidly become blobs.

## 6 Summary and Conclusions

We believe this situation of observing complex emergent patterns in a microscopically simple simulation model is not uncommon in many areas of computational science. Our approach has been to apply experimental scientific techniques and attempt to develop a vocabulary for describing the phenomena. We have also attempted to use more quantitative probabilistic methods to classify, describe and reason about the origins and specific behaviours of the emergent patterns. We think it likely that much future computational science will progress in this way using simulation techniques.

We have carried out a form of classification and analysis that may be of wider use in other models. Our use of the transformation matrix and asymmetries in it shows how sensitive our model is regarding the behaviour of spirals in particular.

An important question that arises from our analysis is that of whether our simulated system scale is large enough? It is not clear how scale dependent the spatial patterns we have obtained really are. We hope to be able to refine the efficiency of our system to enable larger systems but also to be able to explore longer simulation times. The time scaling [9] of these emergent patterns is also an open question.

We hope that our approach does represent a way of tackling the increasingly common phenomenon of **emergence** [13] in simulations in a practical and quantitative manner.

## Acknowledgements

The authors gratefully acknowledge the contribution of Helix supercomputer time by Massey University and the Allan Wilson Centre in the production of the data reported in this paper.

## References

- [1] Christoph Adami. *Introduction to Artificial Life*. Springer-Verlag, 1998. ISBN 0-387-94646-2.
- [2] Peter Cariani. *Emergence and Artificial Life*. In J.D.Farmer C.G.Langton, C.Taylor and S.Rasmussen, editors, *Artificial Life II*, SFI Studies in the Sciences of Complexity, pp 775–797. Addison Wesley, 1991. ISBN 0-201-52571-2.
- [3] Ferber, J. “Multi-Agent Systems An Introduction to Distributed Artificial Intelligence”, Addison-Wesley, 1999, ISBN 0-201-36048-9.
- [4] K.A. Hawick, C.J. Scogings and H.A. James. “Defensive Spiral Emergence in a Predator-Prey Model,” in *Proc. Complexity 2004*, Cairns, Australia, Dec. 2004, pp 662–674, Editors: Russel Stonier and Qinglong Han and Wei Li.
- [5] H.A. James, C. Scogings and K.A. Hawick. “A Framework and Simulation Engine for Studying Artificial Life,” *Research Letters in the Information and Mathematical Sciences* ISSN 1175-2777, Information and Mathematical Sciences, Massey University, Albany, North Shore 102-904, Auckland, New Zealand, May 2004. CSTN-007.

	Thin Diagonal Wave	Horizontal Wave	Vertical Wave	Rabbit blob	Mixed blob	Spiral/Curve	Transitional Cluster	
Diagonal Wave	0	3	3	3	2	2	1	6
Thin Diagonal Wave	0	0	3	4	1	2	2	4
Horizontal Wave	8	1	0	0	2	6	2	4
Vertical Wave	9	2	0	0	2	6	2	4
Rabbit blob	3	0	1	2	0	1	8	2
Mixed blob	7	1	5	6	2	0	6	7
Spiral/Curve	2	1	1	1	8	4	0	8
Transitional Cluster	11	0	2	3	3	4	10	0

Figure 5: Covariance or Transformation matrix between aggregate patterns. The percentage probability of an aggregate pattern type (left) changing into another (top). The diagonals are shown as zero to indicate no change. Off diagonals are dark indicating a high significant probability or white to indicate a low insignificant probability. Note particularly the asymmetries in the matrix.

[6] H.A. James, C.J. Scogings and K.A. Hawick. "Parallel Synchronisation Issues in Simulating Artificial Life," in Proc. 16th IASTED Int. Conf. on Parallel and Distributed Computing and Systems (PDCS), pp, 815–820, Boston, November 2004.

[7] Manual and Semi-Automated Classification in a Microscopic Artificial Life Model, K. A. Hawick and H. A. James, Proc. IASTED International Conference on Computational Intelligence, (CI 2005), July 2005, Calgary, Canada.

[8] Roles of Rule-Priority Evolution in Animat Models K.A.Hawick, H.A.James and C.J.Scogings Proc. Second Australian Conference on Artificial Life (ACAL 2005), Sydney, Australia, 2005.

[9] Leo P. Kadanoff. *Statistical Physics Statics, Dynamics and Renormalization*. World Scientific ISBN 981-02-3764-2

[10] S. Levy, *Artificial Life The Quest for a New Creation*. Penguin. ISBN 0-14-023105-6, 1992.

[11] Lotka, A.J. "Elements of Physical Biology", Baltimore: Williams & Wilkins Co, 1925.

[12] Jean-Arcady Meyer and Stewart W. Wilson, editors. From animals to animats : proceedings of the First International Conference on Simulation of Adaptive Behavior, volume 1, Paris, France, 1990. MIT Press, Cambridge, Mass.

[13] Ronald, E.M.A., Sipper, M. and Capcarrère, M.S. "Testing for Emergence in Artificial Life", in Advances in Artificial Life: Proc. 5th European Conference on Artificial Life (ECAL'99), Switzerland, 1999 Ed. Dario Floreano and Jean-Daniel Nicoud and Francesco Mondada, Pages 13-20, Pub Springer ISBN 3-540-66452-1.

[14] T.S. Ray. An approach to the synthesis of life. Artificial Life II, Santa Fe Institute Studies in the Sciences of Complexity, xi:371-408, 1991.

[15] Tools and Techniques for Optimisation of Microscopic Artificial Life Simulation Models, C.J.Scogings, K.A.Hawick and H.A.James, Massey University Technical Note CSTN-033, April 2006.

[16] D'Arcy Wentworth Thompson, On Growth and Form, Cambridge University Press, 1942.

[17] Volterra, V. "Variazioni e Fluttuazioni del Numero d'Individui in Specie Animali Conviventi", Mem. R. Accad. Naz. dei Lincei, Ser VI, Vol 2, 1926.