

# Quantifiable Metrics for Complex Emergence in Spatial Agent-Based Models

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## Abstract

Spatial animat agents can be used to construct sophisticated spatially-rich macroscopic models to study complex and emergent phenomena based only on localised microscopic control parameters. We have developed a predator-prey based animat model that we have successfully used to explore collective behaviours including herding, battlefront formation, segregation and population control. We describe our model architecture and how such agent based models can support large numbers (around one million) of animat agents for multiple generations of coexistence. In studying collective phenomena using computer models it is important to develop quantifiable metrics and measurement apparatus in tandem with the model itself. We discuss some of the macroscopic metrics and statistical measurement approaches we have used to relate localised animat parameters to the emergent patterns of behaviour identified in our system. We show how these quantifiable approaches could be applied more generally to other agent-based models for decision support applications.

**Keywords:** spatial animat; complexity; emergence; quantifiable metric; decision support.

## 1 Introduction

Complexity and emergence [1, 2] are two deep concepts relevant to understanding the behaviour of multiagent systems. One approach to exploring these concepts quantitatively is to model a particular system and establish specific metrics based upon the macroscopic system properties and to try to relate these back to the model control parameters.

Spatial agents or animats [3] provide a means of exploring many complex and emergent behaviours of multiagent systems that would otherwise be inaccessible to quantitative experiments. A number of multiagent models have been developed for studying artificial life phenomena [4, 5] including [6, 7, 8, 9, 10]. These projects place an emphasis on the evolution of “digital organisms” and the corresponding emergent macro behaviours. They are not particularly concerned with the details of the lives of individual “animats” [11]. One exception is [12] where a hierarchy of animats is

established in which beetles need to eat worms and worms need to eat grass. However, this model does not study animat evolution and behaviour but focuses on the conservation and transfer of energy.

One of the main problems in modelling and exploring evolutionary behaviour through simulations [8] is the sheer size of the parameter space or fitness landscape that is usually encountered. It is extraordinarily difficult to apply brute-force search methods to the phase spaces of many biologically-inspired computing models. The notion of genetic algorithms makes use of biologically-inspired mechanisms to combine and adapt existing “solutions” to find even better ones. This approach can still take very large computational resources to run simulated evolutionary models for long enough to see statistically significant changes or dramatically new solutions. It also presupposes that the starting conditions are sensible solutions and that in effect the experimenters are looking in roughly the right place - or at least a plausible position in solution space. While real biological systems proceed using thermodynamically scaled system sizes and very long time scales, even for simple computational models, it is not sufficient to start somewhere completely random and “hope” to evolve a solution somewhere in phase space. We discuss an approach and a model that we have developed, whereby we can employ evolutionary inspired methods in a very controlled manner, starting from well defined areas of model space and with a parameter space that is heavily constrained.

Multi-agent systems have proved a very interesting tool for exploring evolutionary behaviour since it is possible to encode relatively simple rules into individual agents and to perform computational experiments involving many interacting individual agents. However even this approach has its limitations, not least due to the need for large numbers of individual agents in the system to have any hope of duplicating the phenomena thought to occur in real biological or sociological systems.

Popular science accounts of genetics [13] often fail to draw attention to the large number of components and time-scales involved in the evolution of real genetic systems [14]. A useful starting point for us was to identify a fundamental behaviour such as predation and build up a microscopic model around it. Our predator prey model [15, 16] has been refined over a period of several years. Instead of noting evolutionary behaviour (which is often difficult to measure) we have concentrated on making small, well-defined adjustments to the model and then analysing new animat behaviours. In particular we have documented fascinating emergent clusters such as the defensive spirals and other features discussed in [17] and a zoology of other emergent spatial patterns [18].

Few Artificial Life models have been used to study the effects of “higher-order” interactions such as altruism [19], trading [20], pack hunting [21], segregation [22] and swarming [23]. We have carried out one study of altruistic behaviour that strongly suggests that altruism can evolve naturally and provides benefits for altruistic groups. We have also experimented with trading among animats and attempted to find situations in which trading can benefit both the individual and the group. In this present article we review some of the macroscopic behaviours we have discovered in our model and consider them in terms of some quantitative metrics that we have developed.

In this article we focus on some quantitative metrics that give insight into what is happening in our population of interacting animats. Firstly we describe the details of our model system in section 2. Secondly we discuss some quantitative metrics that can be applied to this class of model in section 3. We present some selected results in section 4 including an analysis of what microscopic rules are used with what frequency by animats at different times in a typical run in section 4.1. In section 4.2 we present an analysis of the effect of one of the key global parameters of our model - the probabilistic success of breeding. In section 4.3 we present some analysis of the typical age at death of our animats. We discuss our results and some ideas for future work on various models in section 5 and offer some concluding remarks in section 6.

## 2 The Animat Model

Our multiagent system is based on the notion of multiple spatial agents or “animats” that coexist on a discrete square mesh. Each agent thus has  $(x, y)$  coordinates; a health state; an age; a gender; and a set of microscopic rules that govern its behaviour. The particular set of rules that an animat follows determines its species and we have constructed our model using the primary species split in terms of predators and prey. This notion allows us to set up systems with appropriate competing forces that establish a dynamic equilibrium and which display a very rich set of emergent spatial patterns and macroscopic behaviours. A unique feature of our multiagent system is the relatively large number of microscopic animats that we are able to simulate. We routinely model quite large-scale experiments on systems of up to around one million animats, evolving for time-scales of a few thousand steps. We are able to explore around  $\approx 10$  independent runs using a different stream of random numbers or microscopically different starting conditions to make ensemble averages for a particular set of control parameters.

Throughout this article we refer colloquially to predators and prey as foxes and rabbits. This gives a memorable symbolism for equations and the simulation software. However our individual animats are not necessarily representative of actual physical “rabbits” and “foxes” nor are they intended to be so.

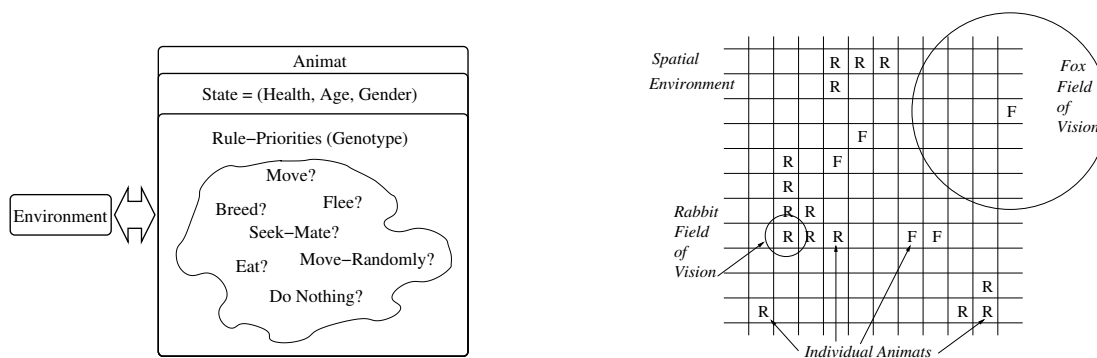


Figure 1: The internal workings of our spatial animat agents and the model world on which predator “fox” and prey “rabbit” species interact.

Figure 1 shows the outline of the model with individual animats containing an internal state and a genotypical rule embodying their microscopic behaviour preferences located on a spatial world map at particular  $(x, y)$  coordinates and interacting with their environment as embodied by their animat peers. The model contains two types of “animats” – predators that need to eat prey to survive and prey that need to eat “grass”. Grass is placed only in certain areas of the map, thus effectively containing the animat populations. Previous work [24] has shown that animat behaviour is not affected by the edges of the grassed region.

At every time step, each animat executes a rule. Some rules (for example “hunting”) are not always executed successfully. The effects of reducing the success rate of predators when hunting have been discussed in [21] and are also used in the experiments described below. Rules for predators are:

1. breed with an adjacent predator, if well fed
2. eat an adjacent prey animat, if hungry
3. seek another predator (as mate), if well fed

4. seek a prey animat, if hungry
5. move randomly (50% chance of succeeding)
6. do nothing

and the rules for prey are:

1. breed with an adjacent prey animat, if well fed
2. eat grass, if available and if hungry
3. move randomly (50% chance of succeeding)
4. seek another prey (as mate)
5. move away from other prey (to relieve overcrowding)
6. flee from a predator

Each animat always executes the first rule in its list for which the conditions are satisfied. We have experimented with changing the order of priority of the rules [15] and thus produced different sub-groups of animats where each sub-group has the same set of rules but with a different priority order.

The interaction of the animats as they follow their rules has produced fascinating emergent features in the form of macro-clusters often containing many hundreds of animats. We have analysed and documented these emergent clusters in [17]. The most interesting cluster is a spiral and several spirals and other battlefront patterns are visible in the figures in this article.

Our simulation model is implemented as relatively short ( $\approx 1000$  lines), but highly optimised C++ program. A number of look-up tables are employed for computationally expensive operations such as computing square roots for distance sorting and for determining which animats are within a particular animat’s field of vision and interaction. The spatial area of the model is organised into a coarse-grained grid and this allows us to optimise animat neighbour lookups [25]. We have also experimented with various parallel and synchronisation techniques to support speed-up of the model but also to ensure fairness and to avoid introducing any artifacts caused by the order in which animats are updated each time-step. We employ a multi-phase update cycle that avoids bias amongst animat updates [26].

We have tried to minimise the number of global and free parameters present in the model. Some we have been unable to avoid are the health value that animats gain from ingesting “grass” and the probabilistic success rates of reproduction. The former is a simple percentage fraction that can be tuned to adjust the animat bearing capacity of the land area of the global system and the latter adjust relative success rates of predator and prey populations and are discussed in section 4.2 below.

### 3 Metrics

In terms of detailed model metrics, we first consider what rules are actually executed by animats in the population at a particular time epoch. We report on experiments to measure these frequencies explicitly in section 4.1 below.

A second key observable for the model system is the total population of animat species as it varies with time starting at model initialisation. Figure 2 shows a logarithmic plot of the populations

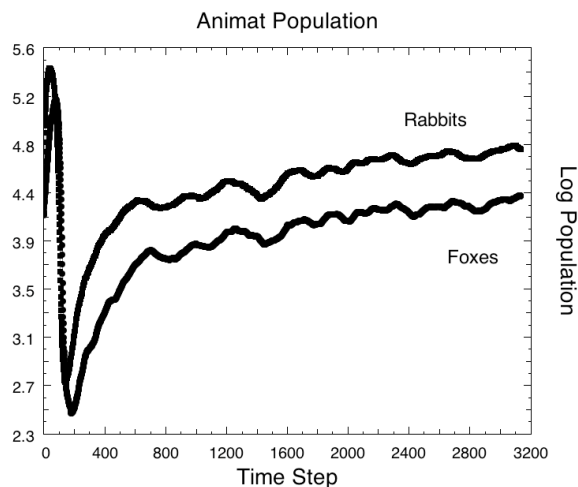


Figure 2: Populations of prey (top) and predators (bottom) shown on a logarithmic scale for a typical model run. The model is initialised randomly and displays a shock-recovery regime followed by a gradual convergence to a stable dynamic equilibrium with boom-bust periodic fluctuations superposed on a stable envelope function. Note the predator population consistently lags behind the prey curve.

of the two interacting species in the multiagent spatial environment. The plot shows the periodic oscillations superposed on a more slowly changing time envelope function. We are usually most interested in global parameter regimes that can be tuned so that the initial population configuration will eventually find a long-term sustainable dynamic equilibrium around a stable average population values. We discuss the role of the global model parameters in achieving this in section 4.2 below.

Figure 3 shows the effect of averaging the populations over many independent runs. The phase information is lost but we recover the envelope function and the average population values which indicate the trend to stability based on the carrying capacity of the model.

Thirdly, we consider the “age at death” of animats and describe the insights that metric gives into the life-cycle of a typical animat in section 4.3.

## 4 Results

In this section we present results and some analysis of quantitative metrics we can use to explore model behaviour in experiments involving the frequencies with which animats execute their possible rules; the role of global tuning parameters such as breeding and animat reproduction success rates; and the age distribution of animats when they “die.” All of these support understanding of the life-cycle of individual animats and how their microscopic behaviours can be related to the observed macroscopic patterns observed in the whole multiagent model system.

### 4.1 Rule Frequencies

Each animat has a priority list of rules and depending upon its circumstances it will succeed or fail to execute particular rules. A statistical analysis of the rule execution frequencies gives some

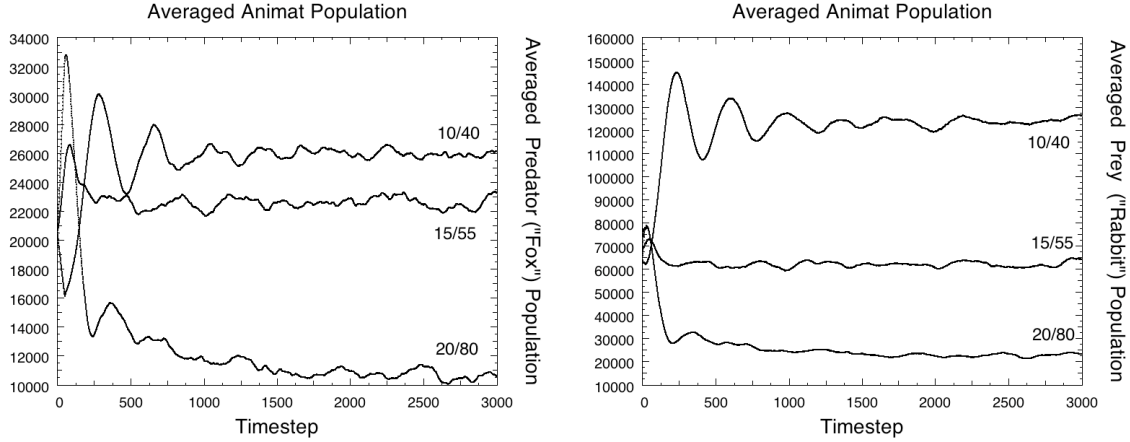


Figure 3: Averaged Populations over 10 runs, showing the tuning stability effect of the 10%/40%; 15%/55%; and 20%/80% breeding success rates for predator/prey animats respectively. The former (top curves) show runaway success and a high population and associated high density of animats. Careful tuning allows operation of the model in a more manageable regime.

insights into the life cycle details of the animats.

Table 1 shows a number of interesting effects over the typical lifetime of the multiagent system. The values shown are the normalised frequencies of occurrence amongst animats in the population at time epochs around: 40; 90; 140; 250; 1000; 2000; and 3000 time steps. Averages are over ten independent model configuration runs and appear to be reasonable estimates to within two significant figures.

In a long term relatively stable population of animats the typical “male rabbit” animat appears to spend most of its time doing nothing, moving randomly and eating. Since breeding is a passive activity for male rabbits in our model, the breeding rule does not show up in the frequency measurements. Female rabbits do however spend a significant fraction of their time breeding. Note that there is a temporary crash in animat population as the model equilibrates after initialisation. The crash shows up in the rule execution frequencies around time-step **90** whereupon rabbits spend proportionately more time fleeing foxes when resources are generally scarce.

Both male and female predator foxes also spend a surprising amount of time doing nothing or moving randomly on average. Seeking prey and eating form the next most likely activities for foxes. While Female foxes bear the opportunity cost of breeding that their male counterparts do not, this has less impact on foxes than it does for rabbits.

The statistical results of table 1 can be compared with the visual results of typical animat system configurations shown in figure 4. Individual animats are illustrated as white (prey) and black (predators) against a green “grass” background that defines the viable area of the model. Sand coloured “desert” areas bound the grass and while animats are free to wander into the desert edge area they cannot survive longer than a generation there. We discovered these open boundary conditions [27] were a good way to avoid affecting the bulk behaviour of the model with artifacts such as reflections and so forth, while at the same time not artificially constraining the total size of the population. Prior to use of these boundaries the model would grow arbitrarily as animats spread out in unbounded space. This led to an  $O(n^2)$  slow-down of the model in computational terms and added nothing of new interest except a repetition of the phenomena already seen in the system sizes shown in figure 4.

		40	<b>90</b>	140	250	1000	2000	3000
Rabbit Male	Nothing	0.223	0.136	0.233	0.296	0.274	0.268	0.268
	Random	0.414	0.398	0.389	0.406	0.401	0.407	0.407
	Move away	0.090	0.075	0.051	0.074	0.083	0.083	0.083
	Breed	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Graze	0.173	0.201	0.204	0.183	0.183	0.181	0.182
	Seek mate	0.010	0.013	0.036	0.011	0.013	0.014	0.013
	Flee fox	0.090	0.177	0.087	0.031	0.046	0.047	0.048
Rabbit Female	Nothing	0.145	0.079	0.146	0.183	0.175	0.172	0.168
	Random	0.335	0.300	0.265	0.315	0.332	0.329	0.329
	Move away	0.129	0.105	0.114	0.121	0.126	0.123	0.123
	Breed	0.203	0.253	0.269	0.229	0.211	0.218	0.215
	Graze	0.123	0.144	0.137	0.124	0.126	0.125	0.131
	Seek mate	0.002	0.004	0.001	0.003	0.003	0.003	0.002
	Flee fox	0.062	0.114	0.068	0.025	0.028	0.029	0.032
Fox Male	Nothing	0.369	0.262	0.257	0.319	0.311	0.299	0.308
	Breed	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Eat	0.125	0.063	0.059	0.142	0.100	0.096	0.101
	Seek mate	0.068	0.031	0.036	0.087	0.049	0.049	0.050
	Seek prey	0.057	0.386	0.417	0.124	0.239	0.240	0.228
	Random	0.380	0.258	0.232	0.328	0.301	0.316	0.313
Fox Female	Nothing	0.339	0.246	0.223	0.344	0.283	0.289	0.292
	Breed	0.072	0.027	0.043	0.064	0.044	0.044	0.047
	Eat	0.127	0.064	0.069	0.130	0.098	0.094	0.100
	Seek mate	0.056	0.025	0.036	0.053	0.043	0.039	0.043
	Seek prey	0.061	0.392	0.443	0.134	0.245	0.243	0.222
	Random	0.344	0.245	0.186	0.274	0.287	0.291	0.296

Table 1: Normalised animat rule frequencies of execution as measured over ten independent runs of the model. Note the effects of the population crash around time-step 90, followed by relatively stable values thereafter. Note also the surprising amount of time individual animats spend doing nothing or moving randomly.

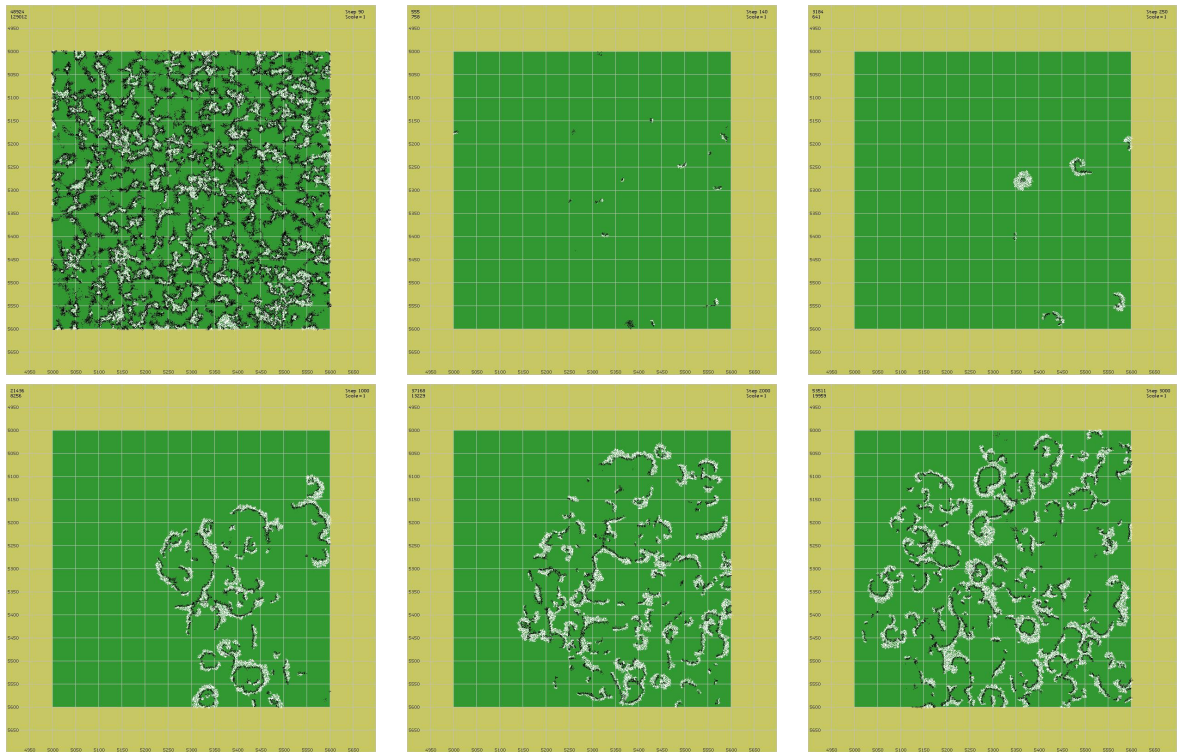


Figure 4: Step 0090, 0140 0250, 1000, 2000, 3000 showing the initial population crash followed by a recovery and long term dynamic equilibrium involving the formation and dissipation of battlefront patterns including spirals. Animats are shown as white(pre) and black (predators) and the viable grassed environment is green, surrounded by open “desert” boundaries. The spatial grid is a guide to the length scales of the model system.

As the figures show, the initial population is started randomly and is too large and too over-crowded for the land capacity of the system and therefore crashes. The system is then seen to make a gradual recovery to a relatively stable dynamic equilibrium. In later stages of the model localised clumps of rabbits and foxes can grow and diminish and with sufficient space between spatial clusters, there is time for new breakaway clusters to form and for some to vanish without having a runaway effect on the population as a whole. The long-term dynamic equilibrium state of the model is one of cluster formation, cluster erosion, breakaway groups, and the formation and dissipation of a variety of battlefront formations including spiral patterns. This dynamic boom-bust phenomenon is discussed further in section 5.

The length scales present in the long term model appear to be largely independent of the detailed starting configuration. Complex patterns including spiral clusters and other formations occur regularly. We believe specific lengths such as the size of the spirals typically formed are implicitly controlled by model parameters such as the vision range of individual animats (nearest neighbour distances for rabbits and 50 spatial units or pixels for foxes). All animats in the model can only move at most one spatial unit per time step.

Another global parameter we were forced to introduce was the probabilistic success rate of breeding. This is a global probability imposed on all breeding rule executions. Without this constraint the model system can completely crash with the whole population dying out and therefore unable to ever recover. A single value provides a useful parameter to encapsulate and abstract likely effects such as birth difficulties, providing shelter for young and other sub-microscopic details which would add un-necessarily to our list of adjustable model parameters.

## 4.2 Adjusting Breeding Success Rate

The global probabilities for breeding success can be adjusted and we have experimented with a range of values.

Figure 5 shows a set of typical model configuration snapshots alongside population graphs that have been averaged over ten model runs at the same time epoch of 3000 time-steps after initialisation. The probabilistic successes of breeding for predators/prey is shown for three different cases. In the top case predators have a 10% probability of successful reproduction and prey have a 40% success rate. This leads to a surfeit of rabbits and the model is seen to be spatially cluttered with dense rabbit formations and foxes enjoying rich pickings. The population graph shows classic boom-bust periodic oscillations superposed on relatively stable average populations of around 120,000 rabbits and 20,000 foxes.

A similar set of runs with the same spatial size of model but with 15%/55% reproduction success rate probabilities allows a fox population of around 25,000 which is enough to nearly halve the stable rabbit population to around 62,000. Further increases to the success rates for fox reproduction to 20% can be compensated for by increasing the rabbit reproduction rate to 80% and a stable fox population of around 12,000 feed off a rabbit population of around 25,000.

We can therefore tune the bulk average behaviour of the model in terms of numbers of animats in the average viable population. It should be noted that the spatial mixing and separation that are key components of this system give rise to spatial fluctuations across the whole system. At any given time-step one region may be “booming” while another is “busting” and it is an interesting emergent property of the model how these spatial fluctuations can combine either in phase (constructively) or out of phase (destructively).

The 10%/40% regime shown at the top of figure 5 shows a remarkable synchronisation of the boom-bust fluctuations over ten independent runs of the model. We hypothesise that this is characteristic of a dense model configuration, where information can be propagated right across the whole model

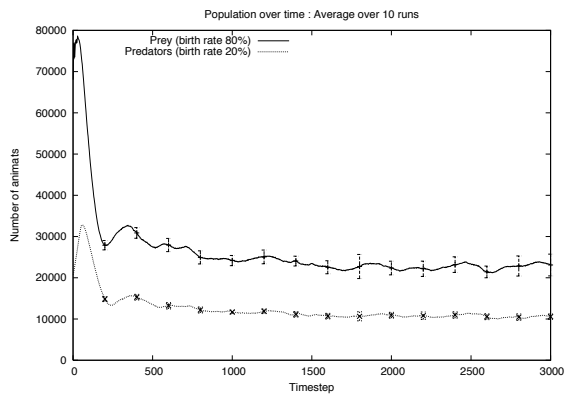
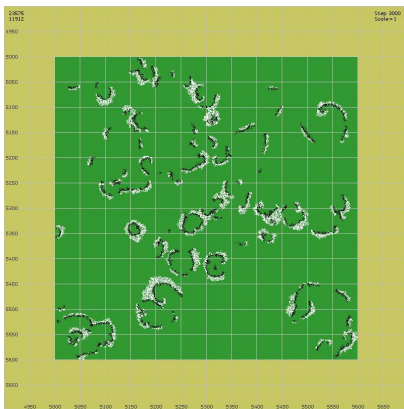
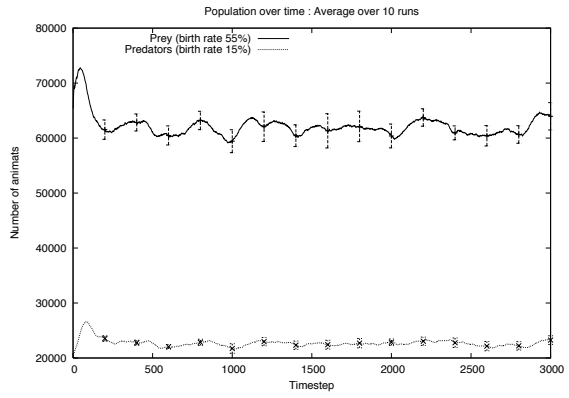
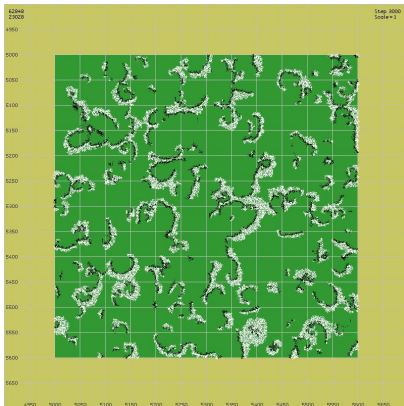
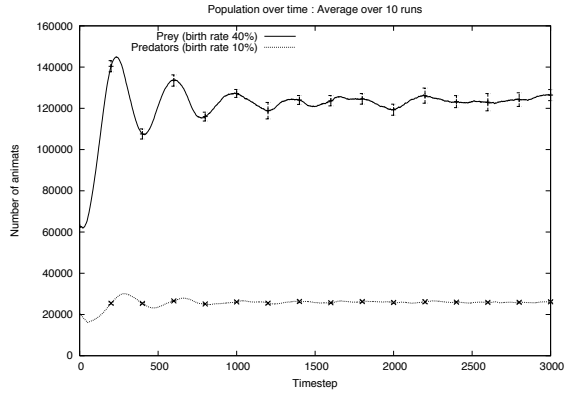
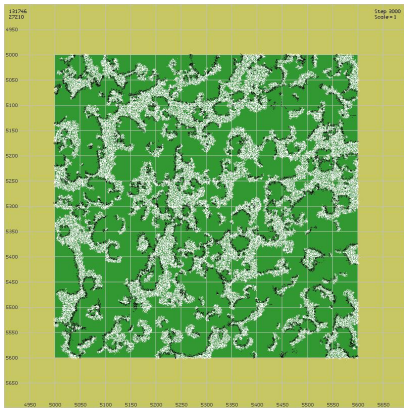


Figure 5: Snapshots after 3000 steps with 10%/40%; 15%/55% and 20%/80% breeding rates for predators/prey respectively. The success rate of predator breeding is seen to be critically linked to animal density and overall population.

system through normal animat interactions. The remaining two cases where there is a lower average spatial density also show periodic fluctuations but as can be seen they are much more smeared out by the averaging effect across the ten separate runs than for the dense case.

One approach to understanding the periodic boom-bust fluctuations is to transform the population samples shown into a frequency representation using a Fast Fourier Transform. Each of the  $l = 1, 2, \dots, M$  independent population curves  $\mathcal{P}_{R,i}(t), \mathcal{P}_{F,i}(t)$  can be transformed to a frequency  $\omega$  representation using:

$$\mathcal{P}_{l,j}(\omega) = \int_{-\infty}^{+\infty} \mathcal{P}_{l,j}(r) e^{2\pi i \omega t} dt, l = 1, 2, \dots, M; j \in R, F \quad (1)$$

The frequency histograms can be averaged for the  $M$  sample runs and the dominant frequency  $\omega^*$  identified without combining and therefore destroying the associated phase information. It appears that the model always gives rise to a similar oscillatory train of boom-bust oscillations, largely independent of the starting configuration, but the exact time at which the model settles down to this behaviour does vary between runs. This offset time is what we mean by “phase” in this context. Hence the need to average, independent of phase to obtain representative period measurements.

We find that the period calculated in this way is  $380 \pm 20$  and this appears to be almost independent of the breeding rate.

### 4.3 Analysis of Animat Age at Death

Animats can “die” either of starvation or of old age. We have generally used the extreme ages for prey and predators as 20 and 50 time-steps respectively. Prey can of course also be “eaten.”

Figure 6 shows the histogrammed ages of animats when they died in a typical model run. There is an interesting difference between prey and predators in that the distribution is uniformly flat for predators indicating that all ages are roughly equally likely and we hypothesise that this is due to the uniformity of the prey landscape - on average. Predators can starve or die of old age and there is no particular bias in the spatial landscape to favour one age group over another. There is no particular difference between the age profile of male and female predators. However there is a significant difference in the profiles for female and male prey animats. We find that on average there is significant tendency for female prey to live less long than males. The distribution tails off with a similar shape but showing fewer long lived females.

We hypothesise that the relative longevity of males is due to the “opportunity cost” of breeding for females. A female animat cannot execute any other rule when the breed rule succeeds. A male animat however is more passive. While a male must be present for a female to successfully breed, at the same time-step the male can successfully execute some other rule. Thus on average a female has a slightly decreased likelihood of doing something useful that contributes to survival such as eating or fleeing predators. We hypothesise that it is in fact the latter (fleeing) that is more important to the survival of prey on average since there is no corresponding effect for female predators, even although the fleeing rule is relatively rarely executed.

## 5 Discussion

Our model shows a number of emergent macroscopic spatial effects and we have tried to relate these to detailed observations of the microscopic behaviours. Population and ecological models are often

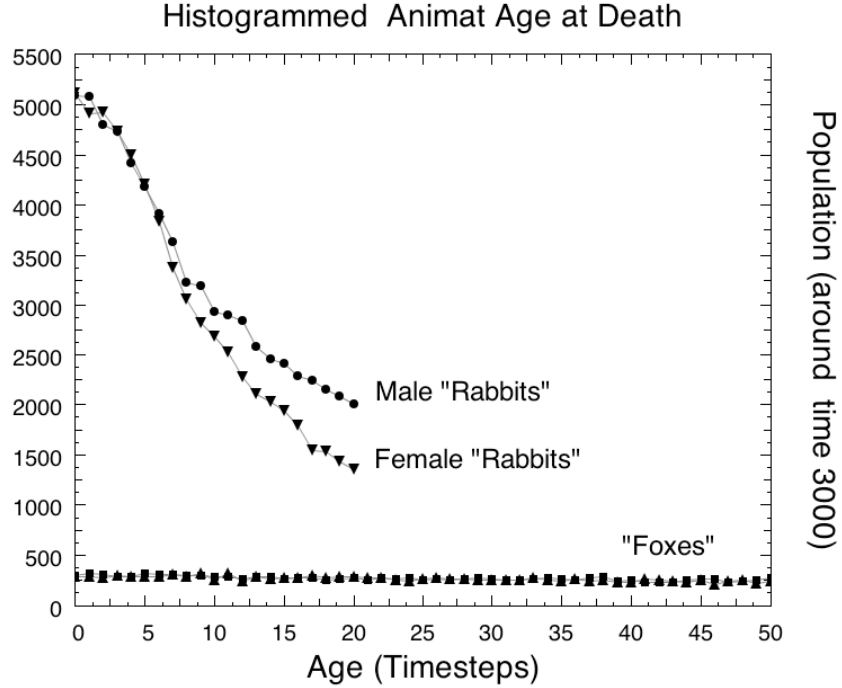


Figure 6: Ages on death around step 3000 with 10/40 breeding rates

compared to the bulk behaviour predicted by models based upon differential equations. A noted example in the literature concerns the populations of the Canadian Lynx and its prey species [28].

Our microscopic model can usefully be compared with the Lotka-Volterra predator-prey model [29, 30]. This model is based on a system of two coupled differential equations. Let  $R(t)$  be the number of prey (“rabbits”) at time  $t$  and  $F(t)$  the number of predators (“foxes”). The uncoupled equations for predators and prey in a non-interacting world are then:

$$\frac{dR}{dt} = |a|R \quad (2)$$

$$\frac{dF}{dt} = -|g|F \quad (3)$$

so that unmolested by predators, the prey grow exponentially in number, and the predators starve through lack of prey and die off exponentially. The two controlling rate constants are positive numbers shown by the absolute value symbols in equations 2 and 3. We drop this hereafter, and assume  $a \geq 0, g \geq 0$ . It is of course interesting to consider what happens when the two populations do interact, and ignoring spatial distribution effects, we model this through a coupling term assumed to be proportional to the product  $RF$  which is related to the probability of a predator-prey encounter. We then obtain:

$$\frac{dR}{dt} = aR - bRF \quad (4)$$

$$\frac{dF}{dt} = hRF - mR \quad (5)$$

We now have some parameters to adjust. These will depend upon the frequency or probability of encounter between our species in the spatial model. It is a matter of future work to incorporate the spatial diffusion properly, but we can investigate some simple bulk behaviour for the system once it is roughly equilibrated.

Solving this equation numerically, one can obtain equilibrium periodic solutions ( $a = 2; b = c = g = h = 1$ ) where the rabbit population reaches a high mean value with boom-bust periodic oscillations superposed on it. The fox population attains a lower mean oscillating value that lags behind the rabbit booms.

Our spatial animat multiagent model does indeed show this **average** effect after some long term spatial fluctuations. It remains to link the equation parameters to the microscopic properties of our animat model, using diffusion constants. Some work on this has been reported using partial differential equations [31] although it remains to see how the spatial part of the equations can be factored out analytically. A numerical study of the spatial Lotka-Volterra and a careful search of its parameter space would be a valuable future area of work for making comparisons with discrete agent models such as our own.

Other cellular automaton models [32, 33] can also be compared with agent systems and we have investigated similarities and differences between our animat model and statistical mechanical models such as the Ising and Potts system [22]. Generally it appears that the use of intelligent agents adds a richness and set of emergent properties that are not easily captured by the energy equilibria-seeking behaviour of these statistical physics models. This observation seems to go beyond consideration of the thermal and initial configuration randomness as both these effects can be included in simulated Potts systems using appropriate Monte Carlo simulation techniques such as the canonical or grand canonical ensemble approaches [34].

## 6 Summary and Conclusions

We have described our spatial multiagent model consisting of predator and prey animats coexisting in a spatial environment. We have given details of the model including our novel mechanism for encoding animat behaviours as rule priority lists. We have presented some visual snapshots of the model configurations and shown how these can be related to quantitative metrics such as populations; individual rule execution frequencies; animat densities; and animat age distributions.

We found that the bulk behaviour of our model is consistent with differential equation based models of populations such as the Lotka-Volterra system, but that the spatial richness and emergent structures can not be so easily explained [35].

It has been observed that the flow of energy through a non-closed system associated with corresponding decreases in entropy [36] are critically linked with the presence of life forms [37]. Energy is not conserved in our model system – it is not intended to be as it is not a closed system. This interplay of energy flow, the creation of information and the associated emergence of complex spatial structures present deeply interesting and fundamental questions about artificial life forms that it may be possible to explore further with simulated multiagent systems.

We have explored the life-cycle of a typical animat in our model. It is a surprising observation that a large fraction of animat time is spent doing nothing or moving about randomly and that the behaviours that appear more influential such as eating and breeding occupy minority fractions of animat time. This is of course an average effect. The environment for animats is defined solely in terms of the spatial substrate or background formed by other animats. Otherwise, animats perceive no spatial features on the landscape. We have experimented separately with boundaries and have implemented corridors of grass down which animats can be herded. Nevertheless animats remain

remarkably insensitive to their landscape and are only significantly affected by the presence or absence of their peers.

We might hypothesise that not all animats play important individual roles in the model as a whole. Nevertheless the silent dull majority are necessary to define the spatial structure of the model as a whole against which the “shakers and movers” can have a measurable effect.

There are analogies with sociological and military spatial patterns and structures and those found in our model. Although we have concentrated on statistical and general concepts, we believe the techniques we report upon may be applicable to specific and practical simulation models of physical and social phenomena.

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