Dynamical aspects in the adoption of agri-environmental measures

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1 Introduction

The present study was motivated by the question of adoption of agri-environmental measures (to be further noted AEM) by farmers in Europe. The European Union is presently proposing financial help to farmers who accept to modify their agricultural practices towards environmentally friendly practices such as input (fertilisers and pesticides) reduction, biological farming, set-aside etc. In practice, at some local level, farmers have to decide whether to accept a contract implying some financial help in exchange for the adoption of well defined agricultural practices in their farm. Such a reorientation of the Common Agricultural Policy from subsidies to production towards environmentally friendly practices involves a lot of changes, equivalent in amplitude to those induced by the technical revolution for farming in the beginning of this century or the green revolution in the less developed countries. We might expect that the present process will develop in time, hence the idea to use a dynamical approach similar to the one used in the study of technological change.

In fact, most modeling of innovation diffusion is presently based on the ideas that:

- a new innovation is always beneficial;
- the rate of adoption of the innovation is limited by the propagation of information from innovators to potential innovators (Degenne and Forsé 1994)[1].

The standard metaphor is then epidemiology, and innovation diffusion is treated as the propagation of an epidemics through a susceptible population; individual "infection" events are thus proportional to a frequency of encounters between infected and non-infected individuals. In the case of random encounter across the whole population, these hypotheses lead to a logistic equation and the well-known S curve for adoption.

We will here depart from these standard hypotheses. A first variant from the hypothesis of random encounter across the whole population is to suppose the existence of a social network : "efficient" encounters only occurs among connected individuals (Degenne and Forsé 1994). Some studies use empirical networks to study buying patterns of teenagers for instance (Farrell 1998). The absence of knowledge of actual patterns in most interesting situations lead researchers to work

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[1]a more complete bibliography can be found in Chattoe and Gilbert 1998

on 2d spatial lattices as models of social networks (Fölmer 1974). One can think of three kind of reasons to work with 2d spatial lattices.

- Relevance: lattices might be relevant to the case when space is the support of information transmission: one can imagine for instance farmers observing activities of their neighbours. Another case where space plays role is when the diffusion of a chemical or biological species plays a role in "profits" related to the adoption of the innovation. For instance pollution, obviously related to the adoption of polluting techniques, propagates in space (Weisbuch et al. 1996). The same relation is important between pests and the use of pesticides.

- Insight: 2d lattices allow to easily visualize simulation results and gain some insight in the important dynamical processes.

- Search for generic properties: imitation phenomena often results in collective behaviors with well characterised dynamical regimes and clear cut regime transitions when parameters are varied. We will search for these regimes and their transitions on 2-d lattices, conjecturing that these semi-quantitative properties are generic for a large class of more complex architectures (Weisbuch 1990).

We will then start from the 2d lattice metaphor, adding as a second feature the relative usefulness of the innovation. We want to take into account the fact that the innovation might not be equally beneficial for all agents. Some agents might be in a position such that the innovation is clearly beneficial and they should adopt it as soon as they hear about it for instance, while for others the extreme opposite is true: whatever other agents are doing, they should not adopt. In between, other agents might decide upon the choices made by their connected neighbours. In that respect, we are supposing that what makes sense to agents is what the others actually do; information by itself is not sufficient to make agents change their minds.

We then suppose that farmer adoption decision is motivated by technical and economical reasons on the one hand, plus social factors which include the dynamics of influences across social networks. The purposes of the study are several.

- We first want to describe and understand the dynamics of adoption of AEM. But we are facing two difficulties: we lack empirical data about the structures of social networks and about the time series of adoptions. One purpose of our modeling is then to characterise features of the dynamics that are specific of certain dynamical regimes, such as limits to adoption for instance, or patterns. These emergent features observed on the simulated systems could then be compared to static empirical data.

- One can also take a normative approach: at a global level, policy makers have to choose the level of financial incentives which would result in some uptake of AEM by a population of farmers. At the local level, agricultural advisers have to schedule the allocation of their information and persuasion effort among individual farmers. A better understanding of the adoption dynamics could help the administration to better control (in the sense of control theory) adoption, or at least to achieve acceptable level of uptake.

We have presently built and checked models based on the following hypotheses:

- 2 dimensional models in the case when adoption is not always beneficial, were studied by analytical methods for equivalent agents, and by also using numerical simulations in the case of distribution of agents characteristics.

- For the purpose of comparison, we also studied randomly connected networks: in our view, the degree of structuration of social networks is intermediate between these two extremes, and

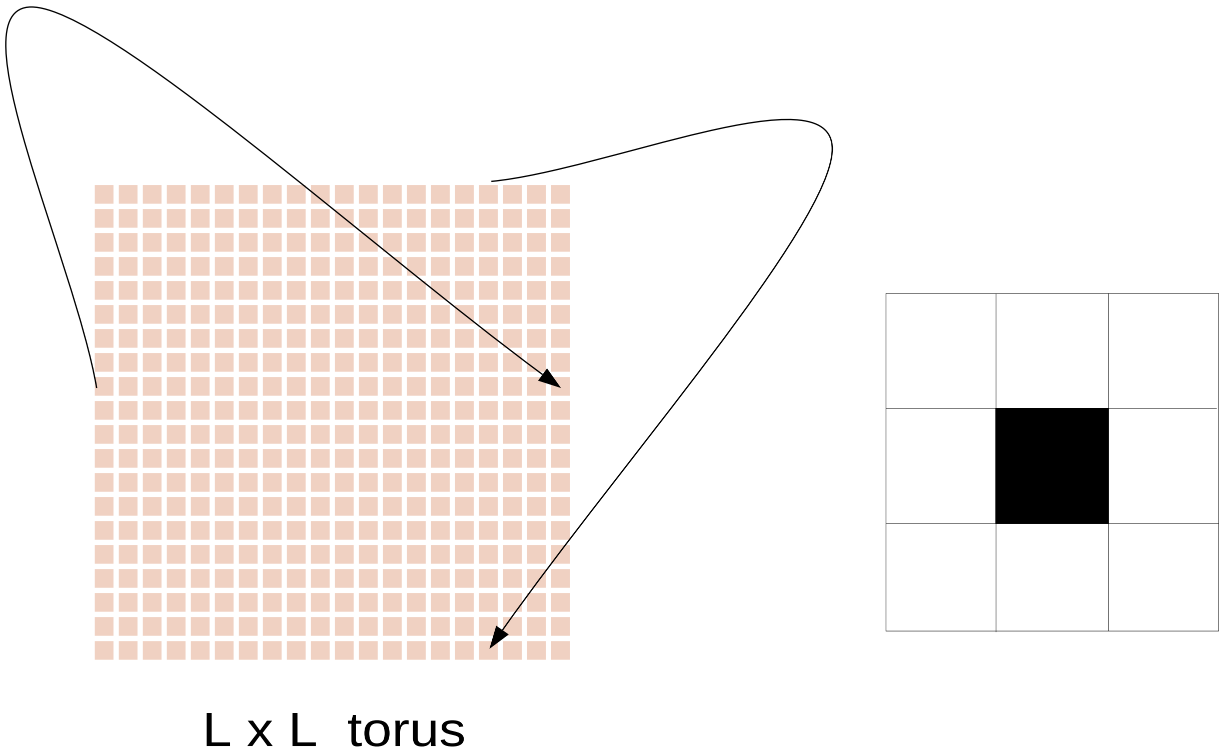

Figure 1: Model geometry: Periodic boundary connections are displayed on the left. The black cell in the middle of the right figure receives input signals from its eight neighbours (the white cells).

properties common to both 2d lattices and random nets have good chances to be generic, and thus applicable to social nets.

For the 2d simulations, the most relevant metaphor is 2 dimensional crystal growth on surfaces, rather than epidemiology. We will then use here the standard Ising model of statistical physics. Although first established to interprete ferromagnetism, this model and its variant are used in physics to describe all sorts of cooperative phenomena. Recent applications to social phenomena are described in Galam (1997), Kohring (1996) and Moss de Olivera et al (1999)[2].

We here discuss AEM adoption, but most of what we say applies as well to brand selection, technical change or adoption of any isolated cultural trait.

2 Adoption dynamics on a uniform 2d lattice

We start with a geography of farms lying on a flat-land at the nodes of a 2-D lattice, each farmer being connected to his neighbourhood (V) for information exchange about adoption. To reduce boundary effects periodic boundary connections have been chosen: the lattice is displayed at the surface of a torus [3].

Figure 1 displays the torus construction and the neighbourhood.

[2] There exists an abundant literature in physics discussing related phenomena at a formal level far above the discussions of the present paper. The above quoted papers and the book by Moss de Olivera et al (1999) are a good introduction to this literaure.

[3] One could also assume strict borders with no connections across.

At each time step farmers [4] have the choice to accept (state 1) or to refuse the contract (state 0)[5] according to some estimated utility functions [6]. We start from 'absolute utilities', or total incomes of the farm system, in the two cases when contracts are accepted (u_1) or refused (u_0).

In absence of neighbourhood, a "monadic" farmer could choose the option with the highest utility.

We propose to take into account social influence by adding a "social" term to the absolute utility function. The argument of the choice function, difference of 'effective utilities' is:

$$\Delta U = \Delta u + J(2f_1 - 1) \tag{1}$$

where $\Delta u = u_1 - u_0$ is the difference in absolute utilities, J is a scale coefficient, and $f_1 \in [0, 1]$, the proportion of choices 1 of the neighbourhood is defined as:

$$f_1 = \frac{v_1}{(v_0 + v_1)} \tag{2}$$

v_k being the number of neighbours which made choice k[7].

The additional "social" term is interpreted in several ways in the standard literature on social choice :

- One might consider that several connected innovators experience an increase in the utility of innovation because of direct interactions. For instance, in the case information is necessary to the use of the innovation, new innovators can share the information. The same argument also applies to common struggle against pests or pollution.

- Another possible view, is to interpret the additional term as providing to an eventual adopter some extra information about the interest of the innovation. If agents were purely rational and knew exactly the possible advantages of innovation, they would decide according to their own appreciation of utilities. Since their knowledge about the innovation is imperfect, they might shift their expectation of utilities according to the choice of their neighbours. The factor J is a measure of the influence of their neighbours' choice with respect to their evaluation of utilities. The above interpretation is commonly used in the description of fads and herd behaviour (Föllmer 1974, Arthur and Lane 1993, Kirman 1993, Orléan 1995). It is the one we have in mind in the present paper.

From now on, we will refer to absolute utilities Δu and to effective utilities ΔU in the rest of the paper, although both quantities are actually differences between the utilities for different choices 1 or 0.

[4] We are choosing here parallel updating rather than sequential updating: all farmers are taking decision at each time step. The rationale for this choice, simultaneity of decision, is that there exist a yearly deadline for grant application, and that any imitation behavior is based on the observation of the changes induced by grant acceptance, or refusal, of neighbouring farmers. This is also consistent with the fact that farming is a seasonal activity; the "natural" time step thus represents one year.

[5] Although some AEMs allow a graded response from farmers, in the sense that they can accept the environmental friendly policy on part of their farm, the present paper only discusses all or none decisions, accept or reject for the whole farm.

[6] The wording does not imply that economic factors are the only ones taken into account by farmers: the utilities can also include considerations about time, pleasure, state of the environment, psychological factors such as fame or good relations with neighbourhood etc...

[7] The $J(2f_1 - 1)$ term is a summation of contribution of adopters, each contributing $J/(v_0 + v_1)$ and non-adopters, each contributing $-J/(v_0 + v_1)$.

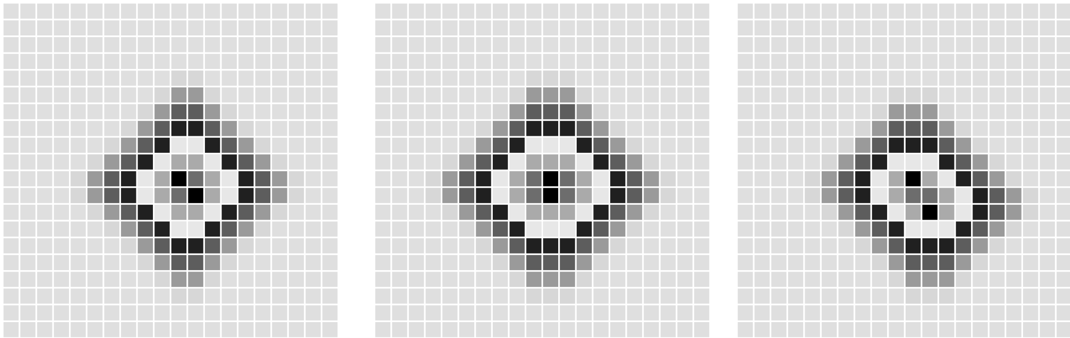

Figure 2: The figures show the first 6 time steps of adoption dynamics starting from a seed made of two adopters (the central pair of black cells). Gray level code time steps. The threshold for growth is 2 adopting neighbours.

2.1 Deterministic homogeneous model

Let us first consider the simple case where all agents have the same difference in absolute utilities Δu. We also suppose that the choice function of the agent is deterministic: an agent takes the choice with the highest utility - i.e. choice 1 when $\Delta U > 0$, choice 0 otherwise. The model is then a simple cellular automaton of the counter type (see e.g. Vichniac 1986[8], Weisbuch 1990): any cell takes a state 0 or 1 according to the number of its neighbours in state one. If this number is larger than a threshold, it takes state 1, and otherwise state 0. The threshold depends on the ratio between Δu and J times the total number of neighbours.

Let us take a square lattice, and a neighbourhood of 8. Let us assume without loss of generality that $J = 1$. Equations 8 and 9 give as a condition for innovation adoption:

$$\Delta u + \frac{v_1}{4} > 1 \tag{3}$$

When Δu is larger than 1, growth of adoption occurs in any condition in one time step.

For $0.75 < \Delta u \leq 1$, the threshold is one neighbour adopting. Any seed at state 1 in a ocean of 0 generates a cluster which grows to fill the lattice.

For $0.5 < \Delta u \leq 0.75$, the threshold is two neighbours. As seen on figure 2 any seed of two adopters distant by less than 2 grows to fill the lattice. Growth is fast, occurs regularly and growing domains have diamond shapes.

For $0.25 < \Delta u \leq 0.5$, the threshold is three neighbours. As the figure 3 shows, several configurations of three initial adopters are able to grow and fill the lattice. But one type of "corner" configuration has a very limited growth. Growth is slower and roughly isotropic.

Figure 4 shows the variation of the fraction of adopters in time starting from a seed of 2 and 3 contiguous adopters for thresholds of respectively two and three adopters. The lattice size is 20x20. Other simulations with larger lattices give the same S shape. Characteristic times (e.g. at fraction one half) scale in proportion of the linear size of the lattice and the approximate one half ratio in growth times between the two and three threshold conditions is maintained.

Four neighbours are necessary when $0 < \Delta u \leq 0.25$, but no initial configuration of four neighbours is able to grow and fill the whole lattice if isolated.

[8]The paper by Vichniac is a good indroduction to the cellular automaton approach to invasion

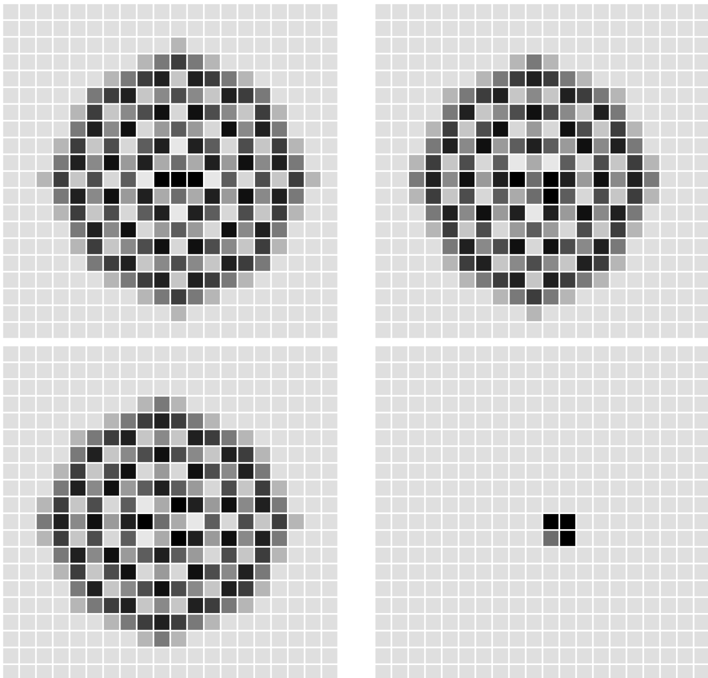

Figure 3: The figures show the first 16 time steps of adoption dynamics starting from a seed made of three adopters (the centered triplet of black cells). Gray level code time steps. The threshold for growth is 3 active neighbours. Note than one triplet is not a hopeful monster.

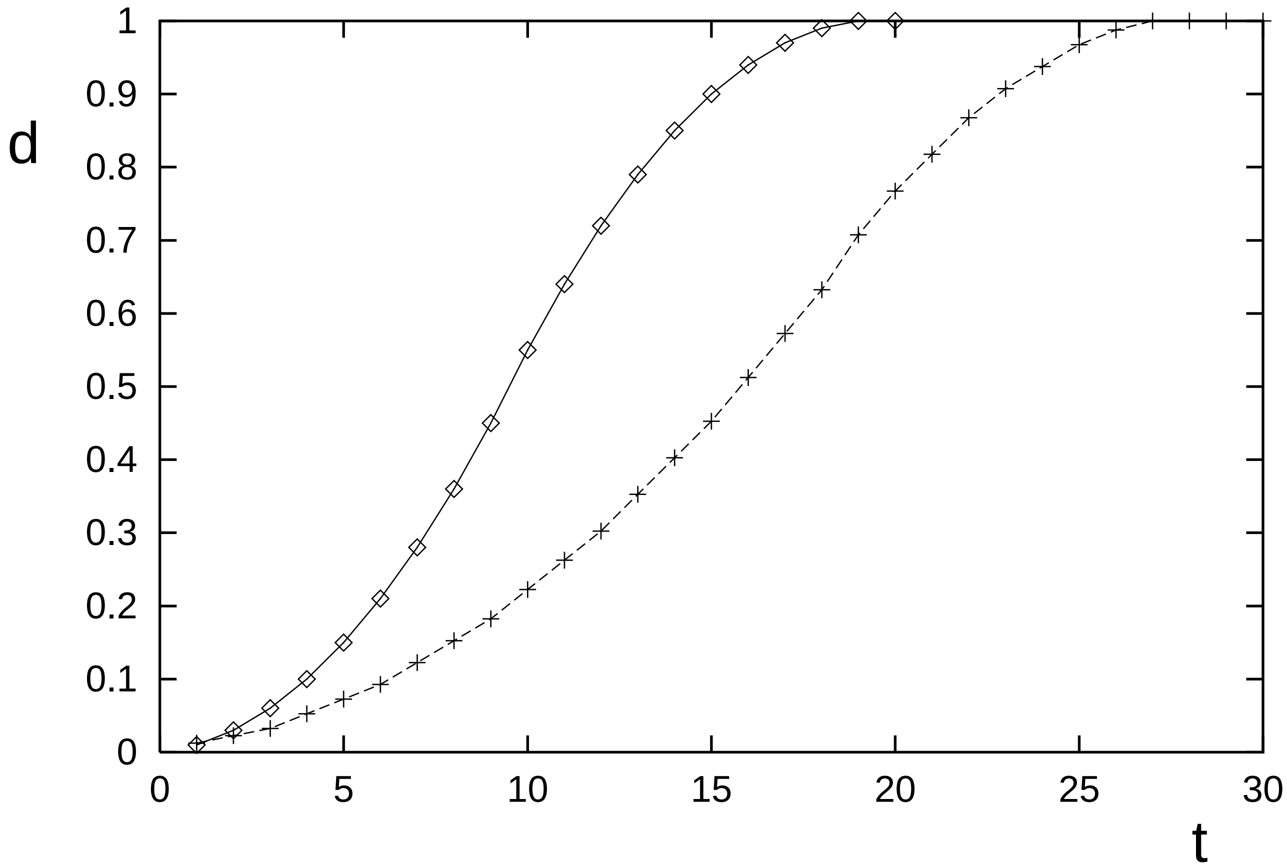

Figure 4: Time (x axis) evolution of the fraction of adopters (y axis) in a 20x20 grid, starting from a seed of two adopters for threshold of 2 ($\Delta U = 0.51$, continuous line) and three adopters for threshold of 3 ($\Delta u = 0.251$, dotted line).

Growth patterns from different initial conditions of early adopters can also be monitored by simulation (see figures 2 and 3).

Symmetrical computations, with the possibility of growth of non-adopter regions in a "sea" of adopters, can of course be done for negative values of Δu.

2.2 Statistical approach to minimal density of initial adopters

If we start from a random distribution of initial adopters[9] , growth depends statistically on their initial density when $0 < \Delta u \leq 0.75$ as we can see in figure 6 obtained by averaging simulation[10] results. For low initial densities, seeds made of several neighbouring adopters might not be present in a finite sample. In other words, the same initial density of early adopters might result in completely different outcomes, total invasion of adoption or no growth. As we discuss further, the relevant parameter is not the average density, but its actual spatial distribution, and actually the existence of "hopeful monsters"; furthermore average rate of adoptions might poorly characterise the actual situation. In the present case, we are observing an all or none outcome and can deduce the fraction of 0 or 1 outcome from the average adoption curve. For the more complicated cases that we discuss in the next section, one has to use histograms of of adoption rates for a large number of simulation (figure 9). At this stage, let us notice that we observe here a large dispersion of results for random distributions with the same average characteristics, a typical feature of complex systems in the neighbourhood of criticality.

The computation of the probability of hopeful monsters - those initial clusters of adopters susceptible to invade the whole lattice - is straightforward, but involves some delicate combinatorics. Let us give the simplest example for the case of threshold 2. Hopeful monsters are pairs of adopters separated by a distance of at most 2 (figure 5 on the left). Any early adopter has then a probability p to have another specific adopter as a neighbour which is:

$$p = 24/N \tag{4}$$

where 24 is the number of cells available as "useful" neighbours and N is the total number of lattice sites. If m early adopters are randomly generated in successsion, the probability $\mathcal{P}$ that none of the m early adopter has any "useful" neighbour can be written

$$\mathcal{P} = (1-p)(1-2p)(1-3p)......(1-(m-1)p) \tag{5}$$

since the mth early adopter has a $(m-1)p$ probability to "land" in the vicinity of another early adopter already present on the lattice. p being small, this probability $\mathcal{P}$ remains close to one as long as m is small. For large m values, $\mathcal{P}$ goes to zero exponentially. We can estimate the magnitude of m such that $\mathcal{P}$ is intermediate by approximating $1 - ip$ by $exp(-ip)$. The probability is then written:

$$\mathcal{P} = exp - (\frac{p\ m\ (m-1)}{2}) \tag{6}$$

[9]We can think of initial adopters as exceptional agents which Δu is larger than one; another interpretation in terms of policy or advertising, is that special efforts have been applied by agricultural advisers or sales-persons to convince them to adopt.

[10]The simulation computer program is the direct translation of the model described in this paper. In general adoption is "sticky": once a farmer has adopted, he remains an adopter. A variant from this rule was run, taking into account the fact that adopters only commit for adoption for a period of five years. In fact, for deterministic version of the program (i.e. except for section 4.3), this makes negligible difference on growth. We use two versions of the program. One version has a graphical on-line display allowing to visualise adoption kinetics. Figures 2 and 3 were generated from this version. The other version without graphical interface, allows statistics and loops on parameters values. Figures 6 to 11 were generated from this version.

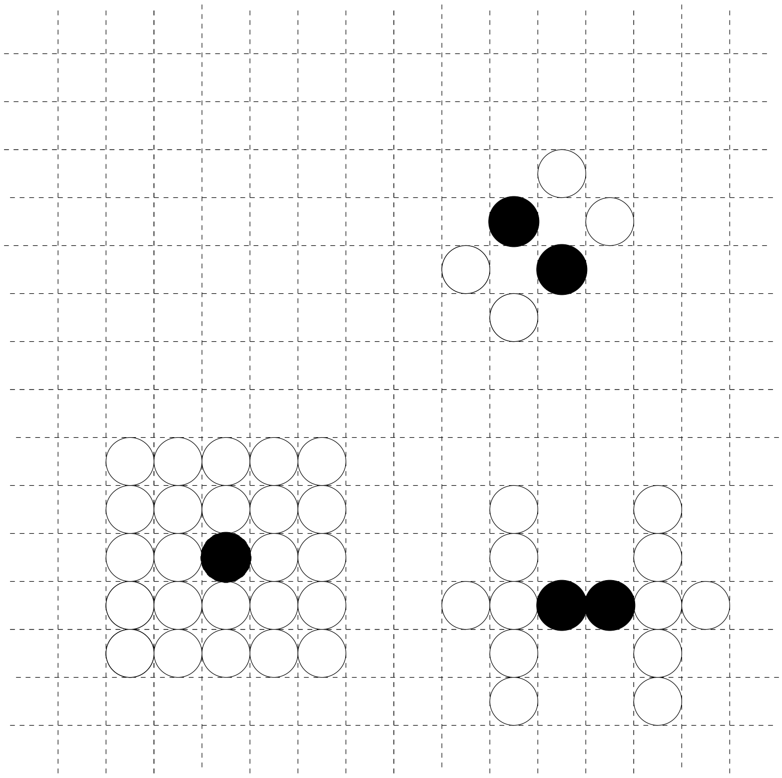

Figure 5: Hopeful monsters. The configuration on the left represents the possible initial configurations (seeds) of a hopeful monster when the threshold is 2 active neighbours: one of them is the black circle and the white circles are all possible positions of the second one (the "destiny" of three of these monsters are represented on figure 2). The two other configurations, on the right, correspond to a threshold of 3: white circles are all possible positions of the third active site according to the relative positions of the first pair of active sites represented in black (the "destiny" of three of these monsters are represented on figure 3).

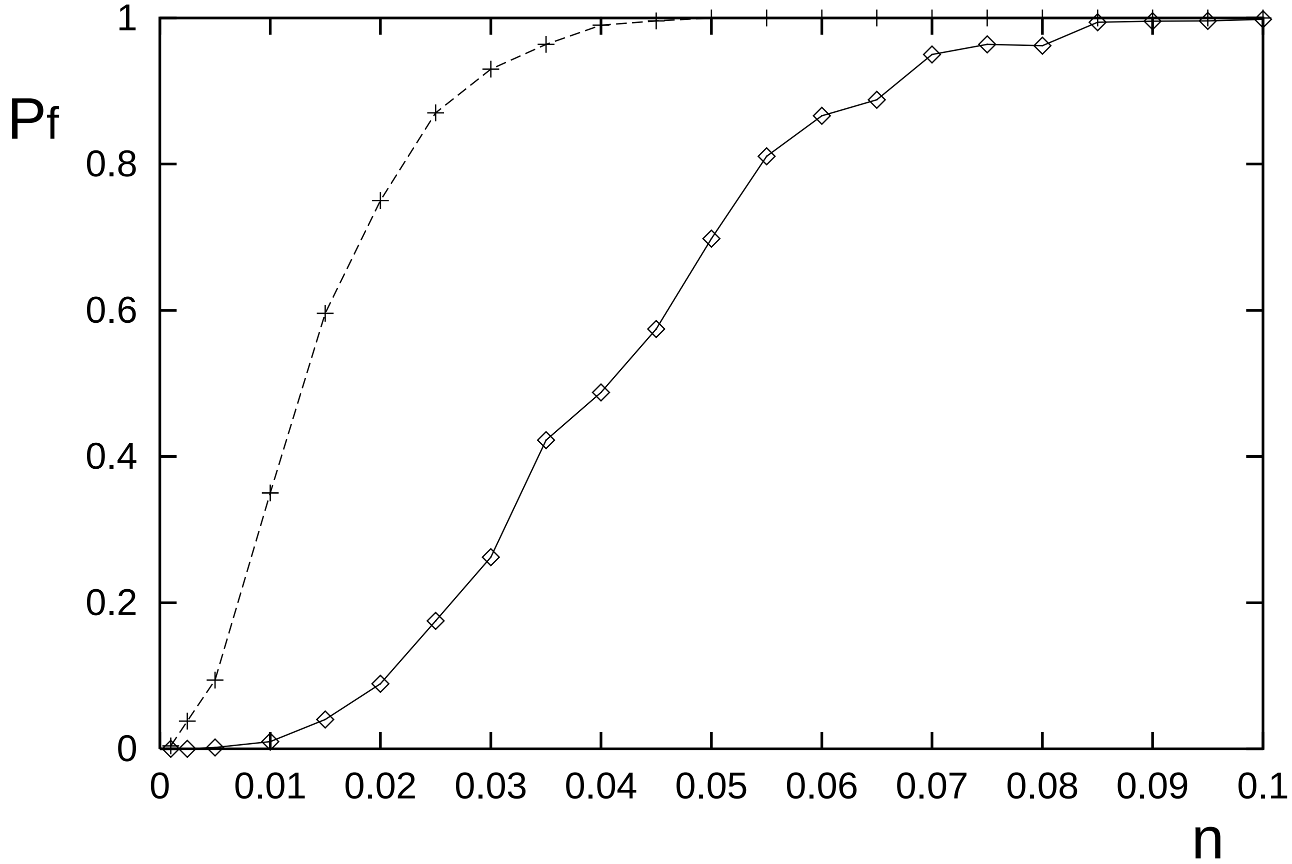

Figure 6: Probability (y axis) that all agents adopt at "infinite" time as a function of density of early adopters (x axis) for threshold of 2 ($\Delta U = 0.51$, dotted line) and for threshold of 3 ($\Delta U = 0.251$, continuous line). Each dot represents an average obtained with 500 samples.

Computing a characteristic m_c such that the argument of the exponential is one gives

$$m_c \simeq \sqrt{\frac{N}{12}} \tag{7}$$

We used for simulations a 20x20 square lattice. The prediction from expression 14, $m_c \simeq 6$ corresponding to a density of initial adopters $n_c \simeq 0.015$, is verified by the numerical simulations.

3 Deterministic models with distributions of farmers characteristics

We have no reason to assume that all agents share the same characteristics. After all, we have in mind farmers whose income, expenses and criteria of choice vary largely.

We will model the variety of agents characteristics by introducing some randomness in the distribution of utilities and connections of the agents. We will first deal with *frozen disorder, i.e.* we suppose that some distribution of characteristics is chosen at the beginning of a simulation and that all chosen parameters are kept constant for the time of the simulation. Such models are then deterministic. We will refer to another source of variation, random change of agents parameters with time as *random noise*, to be discussed in the next section, on probabilistic models.

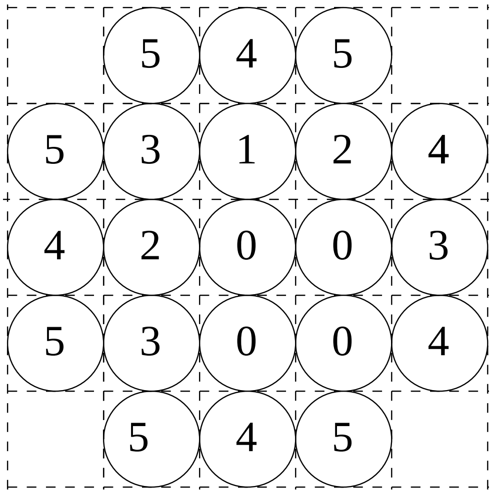

Figure 7: Interfacial growth from clusters. Numbers inside circles indicate times of adoption. Growth from the central square of circles (labeled 0) could not occur if all thresholds were three, but when a seed (labeled 1) with a lower threshold of two is present at the interface it adopts at time 1. Adoption of others neighbours at later times indicated by the labels is then allowed by the presence of the seed.

3.1 Inhomogeneities in utilities

Let us first study the influence of a distribution of different Δu among agents. We have chosen to add to the average Δu_a, a random term drawn from a Gaussian distribution with a given width σu. The random term is constant in time.

A direct on-line examination of computer simulations show that growth is favored by the random terms in the region of intermediate average Δu_a. Initial clusters that would otherwise disappear or be limited to small regular size have "seeds" on their periphery, due to agents with Δu larger than average. Interfacial growth can then proceed from these seeds. The process is illustrated on figure 7. Depending upon the density of initial adopters and the spread of the distribution of Δu, growth can fill most of the lattice or remain limited to only a fraction of it. Averaged statistics taken for 500 samples are presented in figure 8; they show the increase of the final fraction of adopters d_f with the magnitude of the random terms in conditions when average Δu and initial densities n would not permit growth without these random terms (for the sake of comparison, the same pairs of average Δu and initial densities n, 0.24, 0.05 and 0.48 , 0.01 are used in the following simulations figures 8, 9, 10, 11 and 12).

In fact, as earlier mentioned, these curves averaged over many simulations only give partial information: an average of $d_f = 0.5$ could correspond to half densities being 0 and half being 1 (perfect bimodality), or to the opposite case of a distribution uniform on [0,1]. We investigated the issue by plotting the corresponding histograms of d_f for points represented in figure 8 and found that intermediate values of the average final densities can correspond to very different distributions as observed on histograms represented in figure 9.

The bins for the histograms were the ten decimal intervals plus the two extremal discrete bins corresponding to $d_f = 0$ and $d_f = 1$. Once more, the most striking feature to observe is the dispersion of results for equivalent randomness distributions. The distribution of utilities is insufficient to predict the outcome of the imitation process; for this purpose one would have to know the precise spatial distribution.

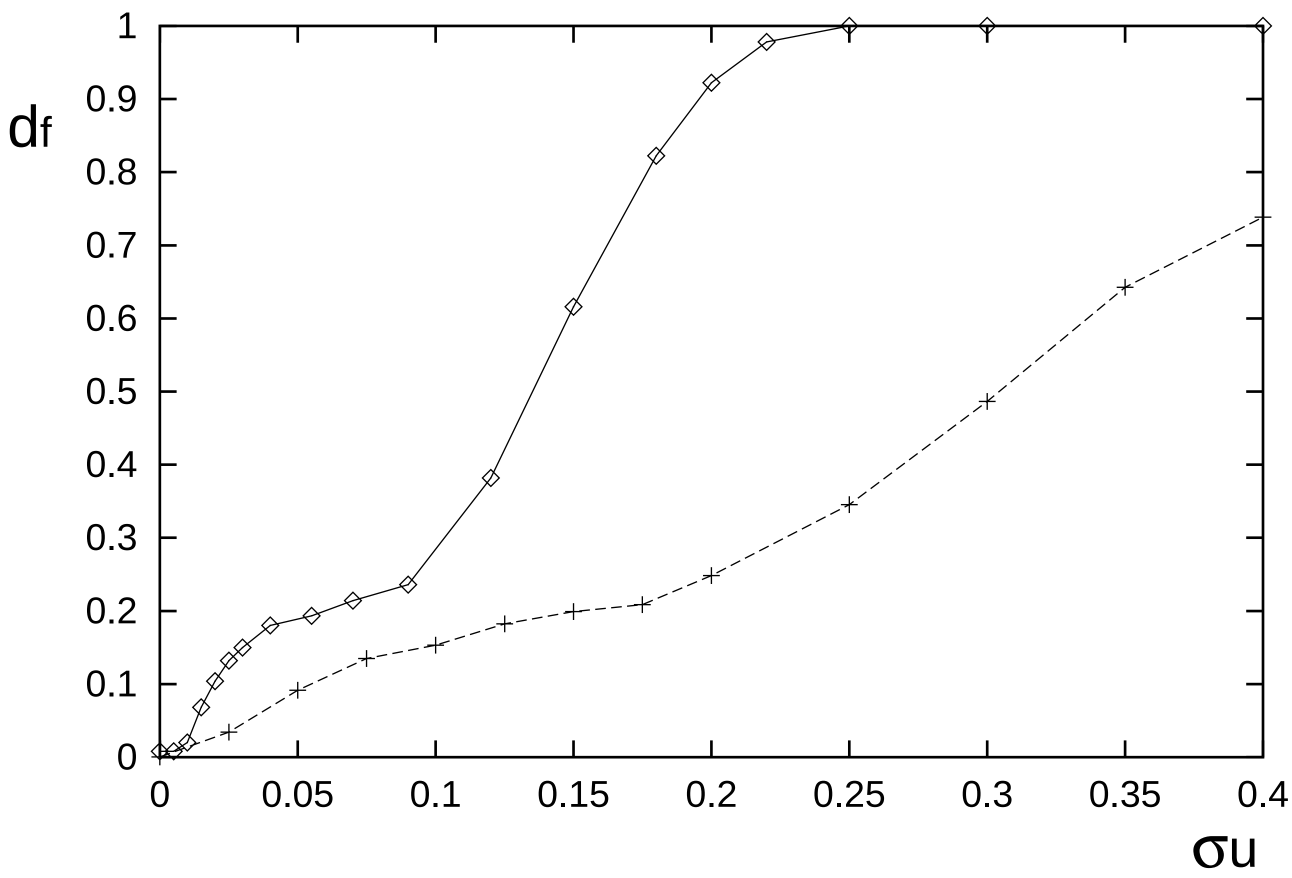

Figure 8: Average fractions of adopters at "infinite" time as a function of width of distribution σu (x axis). Averages are taken from 500 samples. For average $\Delta_a u = 0.24$ (dotted line), initial densities of adopters are $n = 0.05$ and for $\Delta u_a = 0.48$ (continuous line), $n = 0.01$.

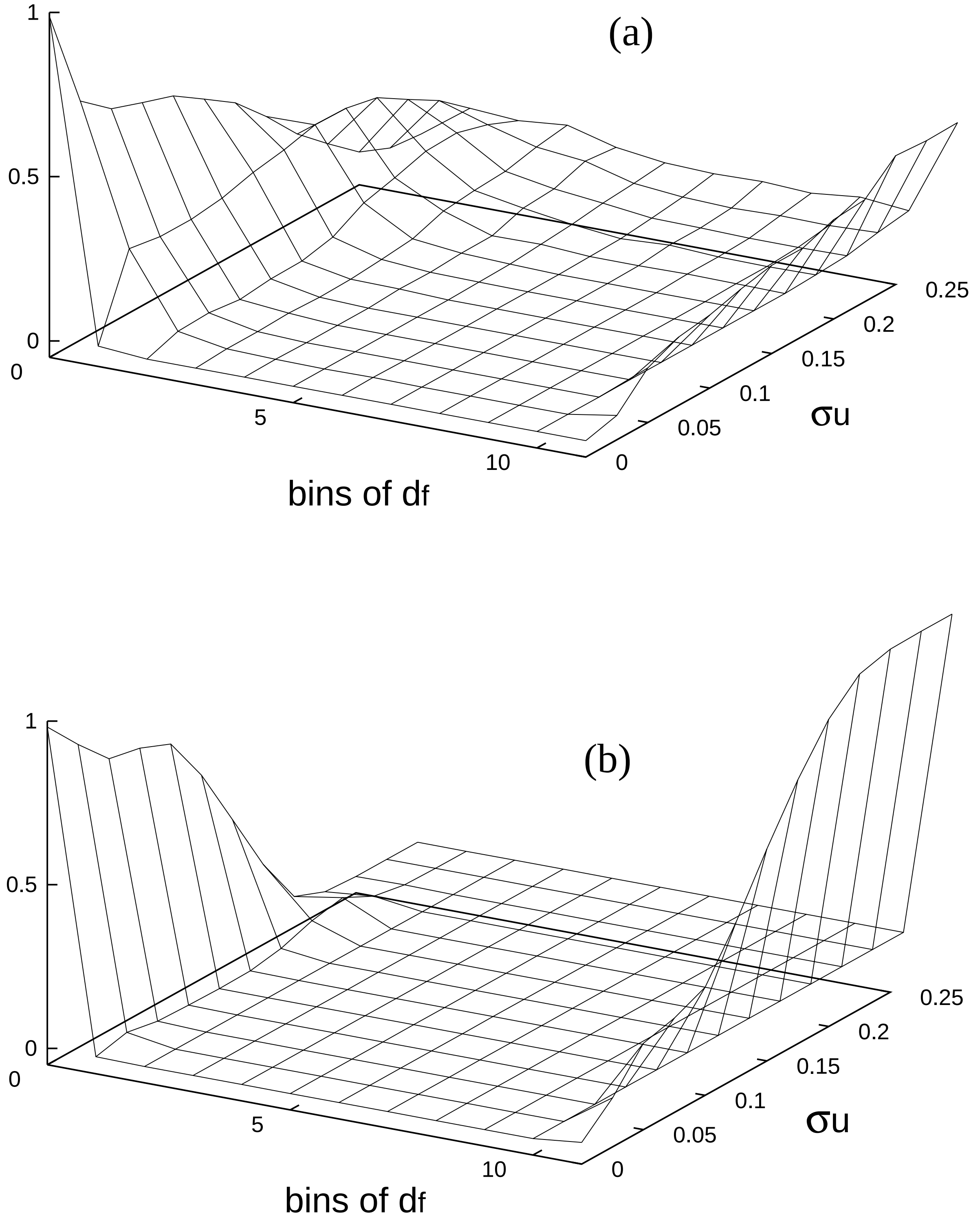

Figure 9: Histograms of fractions of adopters d_f at "infinite" time as a function of width of distribution σu (y axis). Averages are taken from 500 samples. Initial densities are the same as for figure 8. The bins along the x axis are the ten decimal intervals plus the two extremal discrete bins corresponding to $d_f = 0$ and $d_f = 1$. a) the upper histograms correspond to $\Delta u_a = 0.24$; b) the lower ones to $\Delta u_a = 0.47$.

- When $\Delta u_a = 0.24$ the gradual increase in average d_f corresponds to a gradual filling of the intermediate bins when σu increases and reaches a magnitude comparable to Δu_a (figure 9a). As checked by direct examination of adoption dynamics, the disorder in utilities allows interfacial growth and appearance of big clusters of adopters; but this process most often stops before filling the whole lattice.

- But when $\Delta u_a = 0.47$ nearly all samples are in the extremal bins, which implies that whenever growth starts it invades the whole lattice. The total invasion process is of course favored by large values of σu.

The online observations explains the phenomenon. $\Delta u_a = 0.48$ is close to a threshold for growth of two neighbours (0.5). All the cells on the periphery of a cluster are then "candidate" interfacial seeds for surface growth since they already have two adopting neighbours. They are "actual" seeds when their Δu is larger than 0.5. Let us consider the configurations of hopeful monsters of figure 5 corresponding to a seed of 2. In the case of a diagonal pair of neighbours for instance, the number of possible interfacial seeds (opportunities) are $s1 = 2$ at the first step and $s2 = 8$ at the second step [11] (figure 2 is an illustration of the situation from the second step on) . Averaging over all 24 hopeful monsters we get 1.66 opportunities for the first step and 6.33 for the second step. We can compute the probability π of filling a site with two occupied neighbours.

$$\pi = 1 - erf(\frac{0.02}{\sigma u}) = 1 - q. \tag{8}$$

Where q is the probability that the site stays empty and erf is the error function. The argument of the error function represent the probability that the random term is smaller than 0.02, the quantity needed to complement Δu to 0.5, thus allowing adoption. The probability $P1$ that at least one site among $s1$ opportunities at the first step is an actual interfacial seed is then:

$$P1 = 1 - q^{s1}. \tag{9}$$

The probability $P2$ that any site among $s2$ opportunities at the second step is actual interfacial seed is then:

$$P2 = 1 - q^{s2}. \tag{10}$$

These expressions show that when σu is large enough to give a non negligible probability of adoption at the first step, the chances are high that the process carries on to the second step which offers nearly four times more opportunities. For instance when $P1 = 0.3$, the above expressions give $P2 = 0.75$. Chances carry on increasing at further steps, hence the observation that if growth starts, its ends by filling the lattice (figure 9b).

On the opposite, $\Delta u_a = 0.24$ is close to a threshold for growth of three neighbours (0.25). Only the re-entrant corners or lines of at least three adopters, are then possible seeds for surface growth. Computation of opportunities at the first two steps on the hopeful monsters give a ratio of opportunities of two between the second and the first step. This slower increase in opportunities is also observed at further steps. Initial growth does not then guarantee that the whole lattice will be invaded. Finite size clusters remain at large times, and intermediate d_f bins are observed in the histograms (figure 9a).

[11] The corresponding figures are 4 and 8 for a horizontal pair of neighbours, 1 and 6 horizontal pair of next nearest neighbours, 1 and 4 for diagonal pair of next nearest neighbours and 1 and 5 for the remaining case.

3.2 Inhomogeneities of influence

We might expect the connection structure and intensities to vary between neighbours. One can then think of a random, non-symmetrical, matrix of connections among neighbours. We have chosen a slightly more regular structure which takes into account the ideas of influence and influential leaders. We suppose that some agents because of their social status, supposed wisdom, or more simply because of their wealth, are more influential than others (see for instance Latane and Nowak (1997)). The social term of equation (8) influencing agent i is then generalised to:

$$\frac{\sum_j J_j S_j}{\sum_j J_j} \tag{11}$$

where J_j is the social influence of agent j and S_j is a state variable which takes value + 1 for choice 1 (adopt) and -1 for choice 0 (non-adoption). Simulations were done for Gaussian distributions of influence with width σJ. Average J were 1. Once more, for statistical purposes, 500 samples were taken for each set of parameters. We again observed a lot of dispersion in the adoption fraction for equivalent distributions of randomness.

To compare the results with those of the previous section (width in σu), we have to figure out the change in J which produces the same effect on an agent i, via changes in effective utilities ΔU, as a change in absolute utilities Δu. Since agent i is influenced by eight neighbours, the effectiveness of changes in J are roughly[12] in a ratio one eighth with changes in Δu. We have then chosen to scale up by a factor 8 the σJ simulation parameter with respect to previous simulation in σu. On the other hand, since agent j acts on eight neighbours, the spatial range of the effects of influence increase is much larger than when absolute utility is increased, which we observed in the simulations.

Simulations show that the main difference between the effect of randomness in J with respect to randomness in Δu is the appearance of islands of resistance to adoption organised around influential leaders (which can occur either as strong individual leaders or even small clusters of self re-enforcing but not necessarily very strong leaders). In contrast a strong deviation in Δu can only lead to isolated resistant individuals, unless of course there exists some spatial correlation in the distribution of absolute utilities, a feature not studied in our simulations.

- When $\Delta u = 0.24$ we observed the same gradual increase in average d_f corresponding to a gradual filling of the intermediate bins as when σu increases. But clusters sizes are bigger, as observed by the fact that bins of higher d_f are filled (figure 10a). This reflects the increase of spatial range mentioned earlier. The $d_f = 1$ bin stays almost empty, a fact related to islands of resistance around non-adopting influential leaders.

- When $\Delta u = 0.47$ nearly all samples are in the extremal bins when σJ start increasing, with a gradual increase in the $d_f = 1$ bin. But this effect stops when $\sigma J \simeq 1$ and the distribution get centered around the $d_f = 0.9$ bin. Once more this is due to the existence of islands of resistance around non-adopting influential leaders.

3.2.1 Lognormal distributions of influence

Gaussian distributions are commonly used in scientific papers for many "good" reasons, such as central limit theorem and the possibility of exact computations. Empirical data in economics and social sciences often display different distributions. Using RICA/FADN data, we checked

[12] a more careful differentiation of equation 11 shows that the one eighth factor is a lower bound, valid in the neighbourhood of symmetrical influences.

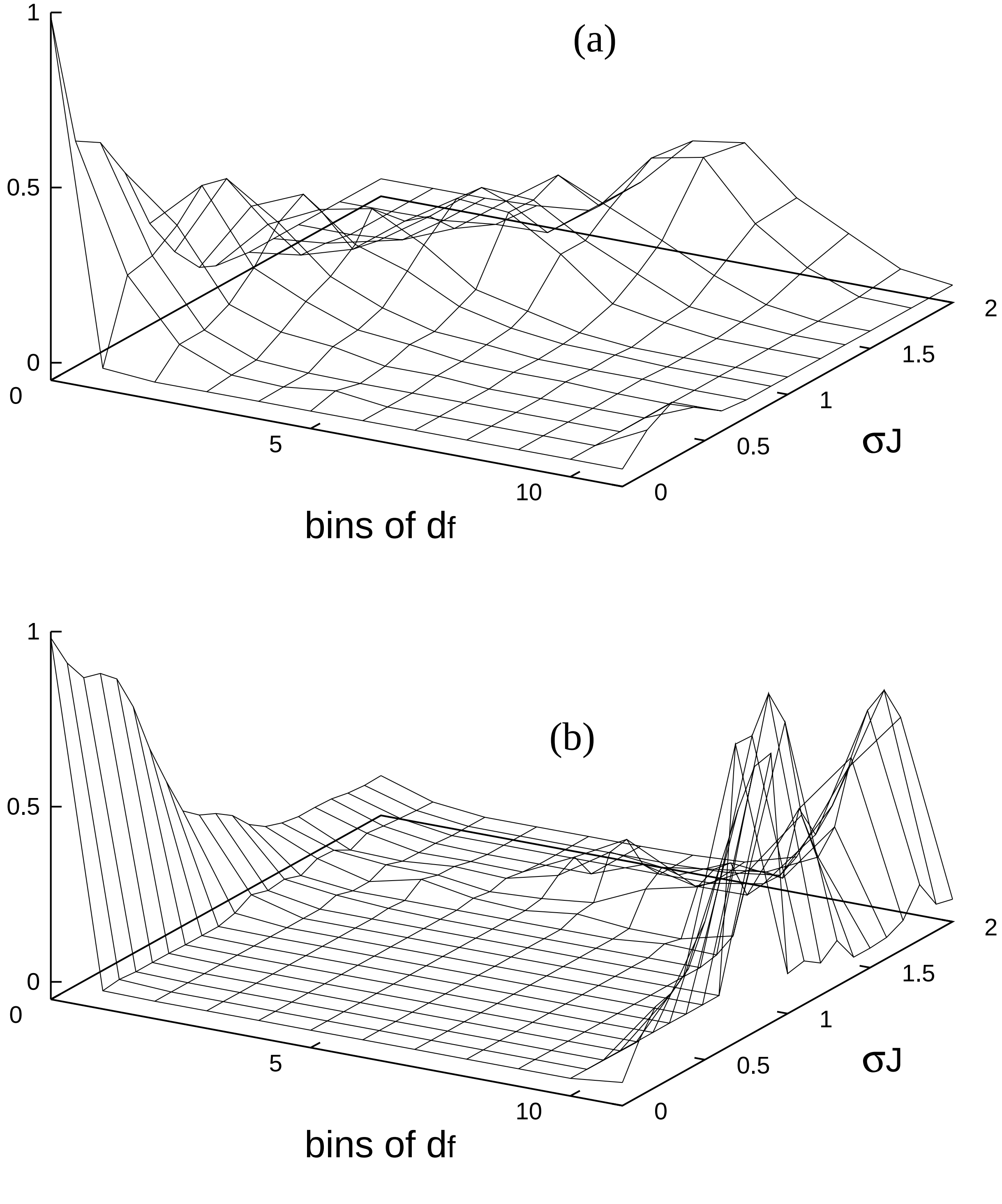

Figure 10: Histograms of fractions of adopters d_f at "infinite" time as a function of width of distribution σJ (y axis). Averages are taken from 500 samples. Initial densities are the same as for figure 8. The bins along the x axis are the ten decimal intervals plus the two extremal discrete bins corresponding to $d_f = 0$ and $d_f = 1$. a) the upper histograms correspond to $\Delta u = 0.24$; b) the lower ones to $\Delta u = 0.47$.

that income distribution for cattle breeders in central France obey a lognormal distribution and tested by simulation the dynamics of adoption with these distributions of influences. This would be a reasonable choice if influence were indeed strongly correlated with income. Since lognormal distributions have more extreme samples than Gaussian distributions of equal standard deviation, we expect even stronger impact of influential leaders. This is indeed observed in histograms (not presented here).

- When $\Delta u = 0.24$, bins of low d_f are the most important: influential seeds favour initial growth. But resistance to further growth appear due to island of resistance around influential leaders.
- When $\Delta u = 0.47$ the same relative increase in populations of bins of low d_f with respect to Gaussian distributions is observed.

Although lacking reliable empirical data for Δu, we also tested lognormal distributions of Δu, with results even closer to those obtained for gaussian distributions.

3.3 Random noise

We might also suppose that unknown and fluctuating phenomena change the value of ΔU: farmers health problems, epidemics, annual weather fluctuations, political events. These events change the perception of farmers and might make them take decisions that they would not have taken under "normal" circumstances. In economic decision theory, these random processes are often taken into account by using a "logit" probabilistic decision function (Anderson et al(1993)), better known to physicists as Maxwell-Boltzmann distribution. We have been using until now a deterministic threshold function for choice: adopt when $\Delta U > 0$. The logit function only provides a probability of adoption. The farmer decision becomes a random variable with a probability to adopt:

$$P(1) = \frac{1}{1 + \exp(-\beta \Delta U)} \tag{12}$$

β can be considered as a rationality or confidence coefficient. Large values of β correspond to probabilities close to one or zero except in the immediate neighbourhood of $\Delta U = 0$; the model is then close to our previous deterministic approach. On the other hand when β is small, intermediate probability values are observed for a large range of ΔU; this is the case when the agents miss information and are therefore less confident in the choice they make. Noise level is measured by the inverse of β which is proportional to the width of the probability distribution ($\beta/4$ is the slope of the probability distribution when $\Delta U = 0$).

At equivalent levels, the effect of noise on fractions of adopters at infinite time is more dramatic than the effect of frozen disorder since interfacial seeds have more occasions to appear and help in further growth of clusters of adopters[13]. Of course, for low noise level, large values of β, they take more time to appear and growth is slow. We report here two kinds of simulations, based on a different interpretation of the notion of seed.

- Let us consider the initial seed as due to agents that have a large absolute utility $\Delta u > 1$. The seed will always remain at state 1, and all the neighbouring cells will transit to state 1 with probability one, sometimes. Total invasion can be predicted for the absolute utilities and initial densities that we are using, and the only question is when: we are interested then in

[13] To be more specific, the utilities of the cells on the interface are sampled only once at the beginning of the simulation in the case of frozen disorder, and at every time step in the case of random noise: hence the increase in chances for adoption.

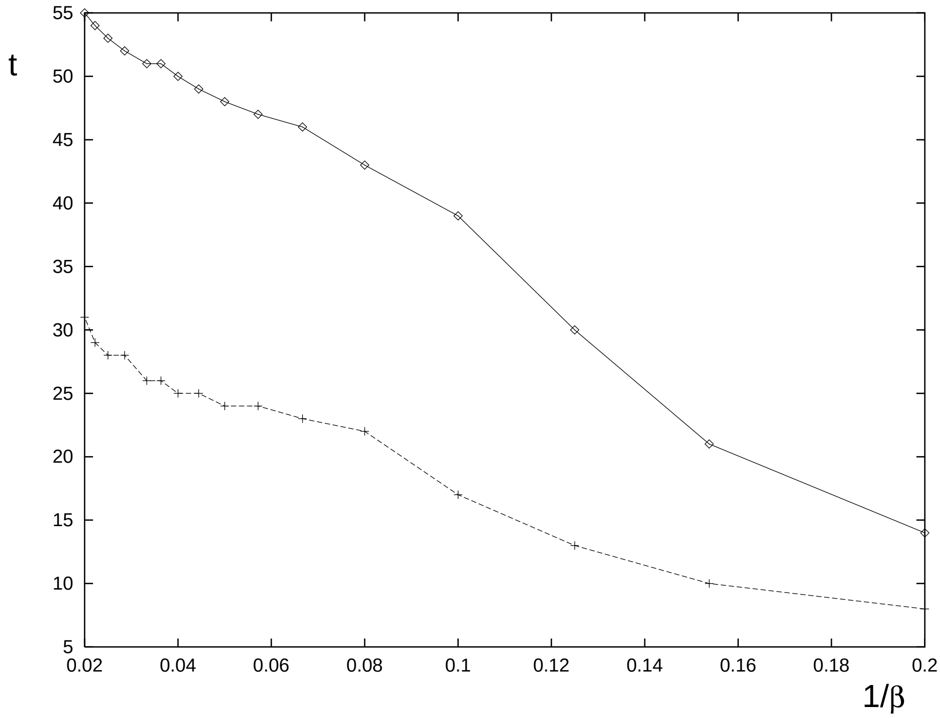

Figure 11: Time for complete invasion of adopters versus random noise parameter $1/\beta$ for sticky early adopters (see text). Continuous line corresponds to $\Delta u = 0.24$, dotted line to $\Delta u = 0.47$

times to reach total invasion. Simulation data on total invasion time are presented on figure 11.

- Let us suppose that the initial seed is made from agents that have chosen adoption the first year, but that they are free to cancel their commitment after a given amount of time, say five years as in the case of many AEM's. In that case, if enough neighbours haven't adopted (and thus support the early adopters choices by increasing their ΔU) during this finite amount of time, they will cancel their contract. Total invasion is certainly not ensured: simulation data showing adoption fraction at infinite time are presented in figure 12. The very fast increase of adoption fraction with random noise is due to the ratio in opportunities effect described in the section on inhomogeneities in utilities.

The probabilistic approach above described is only one among possible approaches to uncertainty, which might not be the most appropriate to the present case. It is not clear that adoption decisions would be immediately taken on time fluctuations that are recognised as such by farmers. Furthermore, most fluctuations are not symmetrical in their effects: epidemics e.g. favor non adoption of AEMs for pesticides reduction, while drought and products price fluctuations (under decreasing returns assumptions) probably work in the other direction with respect to set aside and fertiliser reduction AEMs. The risk aversion approach, i.e. incorporating a bias term in the absolute utilities, might better take into account farmers' "wisdom". In conclusion, the inclusion of probabilistic terms might make sense, but the uncertainty coefficient β is probably much higher (i.e. uncertainty is much lower) than a direct evaluation of the time fluctuations of primary empirical

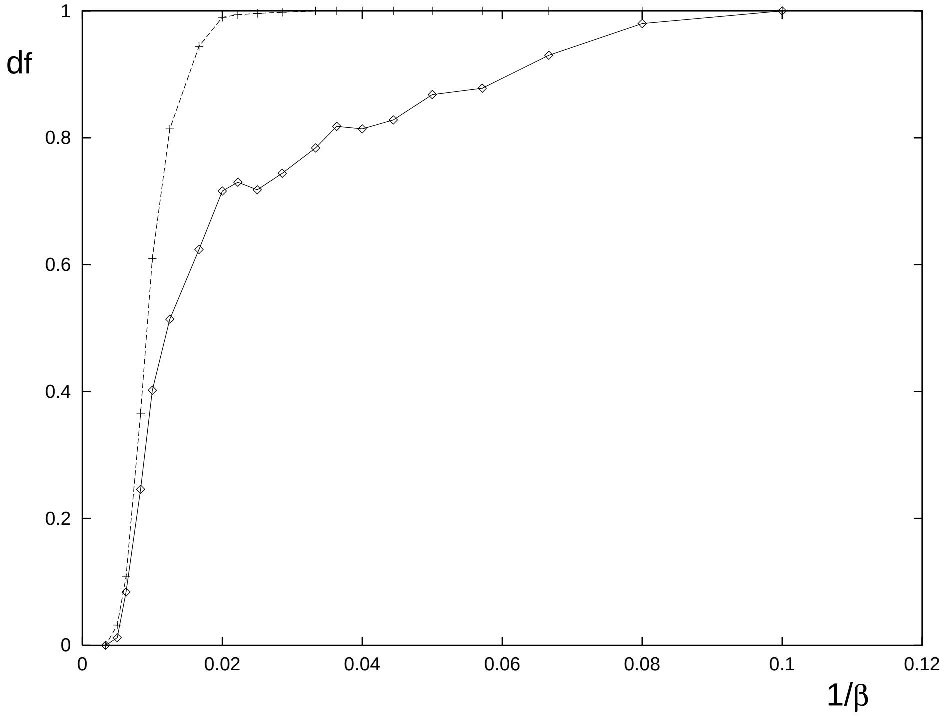

Figure 12: Fraction of adopters at infinite time versus random noise parameter $1/\beta$ for possibly reversible early adopters. Early adopters can reverse their choice after five year if they have no followers. Continuous line corresponds to $\Delta u = 0.24$, dotted line to $\Delta u = 0.47$

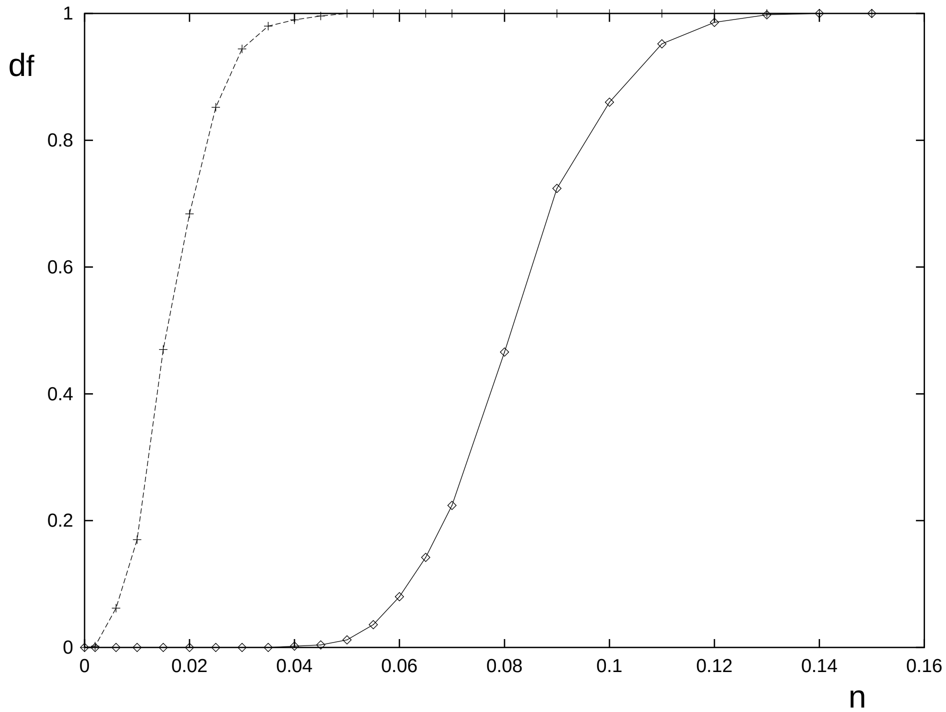

Figure 13: Adoption fraction on random nets as a function of density of early adopters (x axis) for threshold of 2 ($\Delta U = 0.51$, dotted line) and for threshold of 3 ($\Delta U = 0.251$, continuous line). Each dot represents an average obtained with 500 samples.

data (weather, prices, yields) would indicate.

4 Random networks

As mentioned in the introduction, we have little knowledge of real social nets. A number of the features that we observed could be related to our choice of a 2-d connection topology which is probably much more regular than real social nets. To test what might remain of our observations in more realistic implementations, we went to the other extreme and worked with random networks. We chose nets with non-symmetric randomly established connections, constant connectivity $k = 8$ and $N = 400$ vertices for the sake of comparison with our previous simulations. Similar results were obtained with average connectivities of 8. Because the connection structure of random nets is closer to a tree than to low dimensional lattices, the size of the neighbourhood of a node increases exponentially with the distance to the node. When growth occurs, invasion proceeds much faster on random nets than on lattices, e.g. less than five time steps.[14]. We first studied growth as a function of density of early adopters and then the influence of inhomogeneities of utilities.

[14]For a tree, growth time would be $logN/log(k-1)$

4.1 Minimal density of early adopters

Simulations done for conditions similar to those done for lattices (section 2.2) show the increase of average adopters fraction as a function of the density of early adopters (see figure 13)[15] . They correspond to either growth or no growth. They show more abrupt transitions than for 2d-lattices. As mentioned above, this is because of the exponential increase of available vertices for growth in random nets, to be compared with the corresponding linear increase in 2-d.

As for lattices, hopeful monsters also determine whether growth will occur in random nets, but they are more difficult to represent. A simplified analytical approach will still give some approximate prediction for critical initial densities n_c. Let us establish the recursion relation obeyed by the number of adopters S_t at time t. For threshold 2, e.g. $\Delta u = 0.5$, the M_t agents who adopt at time t, are those with at least 2 "parents": in other words, they need to have at least 2 input connections with earlier adopters which number is S_{t-1}[16]. In fact, earlier adopters can be decomposed in those who adopted at time $t-1$, M_{t-1}, and those who adopted at any time earlier S_{t-2}. A new adopter at time t can either have 2 parents among M_{t-1} or one in M_{t-1} and one in S_{t-2}, but not 2 in S_{t-2}, otherwise it would have been born earlier. By computing the average number of connections to a pair of nodes chosen randomly in a set of a given size, we obtain:

$$M_t = \frac{(k-1)(k-2)N}{2N^2}(M_{t-1}^2 + 2M_{t-1}S_{t-2}) \tag{13}$$

Where we have neglected any number of adopters with respect to the total number of agents, which is valid at the beginning of the growth process. Noticing that the parenthesis is a difference of two squares, the following recursion relation is then obtained for S_t:

$$S_t - S_{t-1} = \frac{(k-1)(k-2)N}{2N^2}(S_{t-1}^2 - S_{t-2}^2) \tag{14}$$

N disappears when we change from numbers of adopters S_t to their density $s_t = S_t/N$.

$$s_t - s_{t-1} = \frac{(k-1)(k-2)}{2}(s_{t-1}^2 - s_{t-2}^2) \tag{15}$$

If we now suppose the existence of a critical density n_c below which adoption cannot proceed by lack of parents, s_t should follow an exponential dynamics in the neighbourhood of n_c:

$$s_n = n_c * \alpha^n \tag{16}$$

Using the above ansatz in the previous equation predicts the critical density when $\alpha = 1$:

$$n_c = \frac{1}{(k-1)(k-2)} \tag{17}$$

The same method for threshold 3 gives:

$$n_c = \sqrt{\frac{2}{(k-1)(k-2)(k-3)}} \tag{18}$$

The above figures, and the predicted scaling, independence of N and dependence from k, are confirmed by simulation results.

[15]For average rather than constant connectivities, the curves are slighly upward shifted

[16]S_{t-1} is the sum of all agents that adopted at time $t-1$ or earlier.

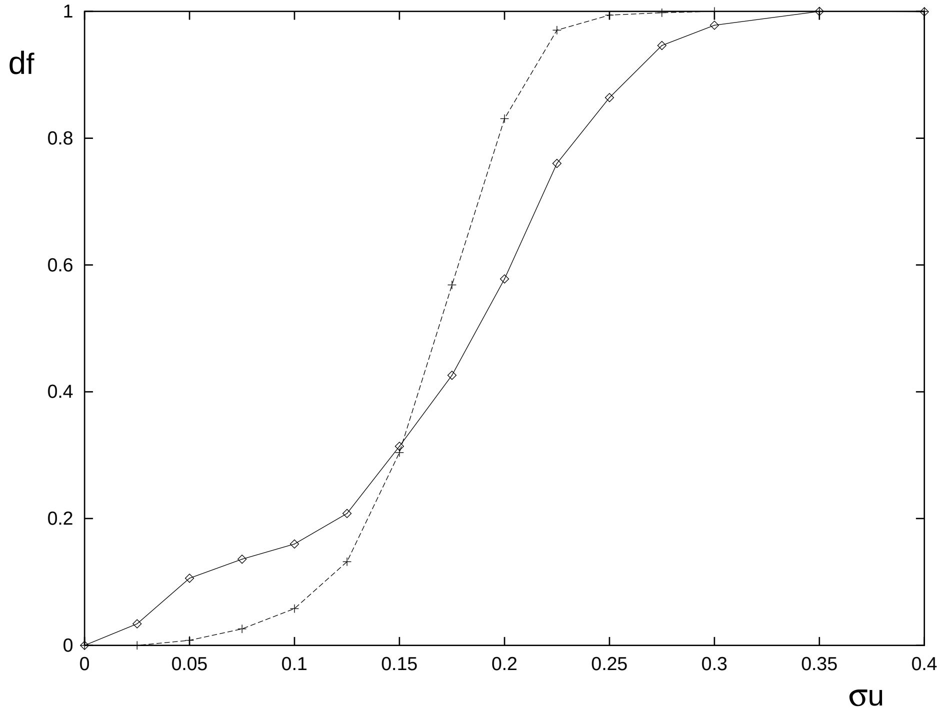

Figure 14: Average fractions of adopters at "infinite" time as a function of width of distribution σu (x axis) for random networks. Averages are taken from 500 samples. For average $\Delta_a u = 0.24$ (dotted line), initial densities of adopters are $n = 0.1$ and for $\Delta u_a = 0.47$ (continuous line), $n = 0.02$.

4.2 Inhomogeneities in utilities

We checked that inhomogeneity in utilities also favour growth for random nets. Simulations done for average Δu_a and density of early adopters which would not allow growth for homogeneous utilities display it when randomness is introduced, as observed in 2-d lattices, for the same reasons. In comparison with 2-d lattices, the main difference is that intermediate bins of histograms are flat for all values of Δu_a. All the information is then contained in the average fraction of adopters displayed on figure 14 (simulations done for a gaussian distribution of utilities). This average value corresponds to the fraction of initial configurations that allow full invasion. Once again, a large dispersion of outcomes is observed for a large range of the disorder parameter σu.

4.3 Other simulations

We also made simulations to test the influence of inhomogeneities of influence and had results which closely resembled those for 2d-lattices, with even less populated intermediate bins of the histograms.

A number of simulations where also done for symmetrically connected random nets, which gave essentially similar results to those obtained with asymmetric random nets.

5 Discussion and conclusions

The above simulations and computation give clear and simple results because we have chosen simple connection structures. In real life, social networks have certainly a more intricate structure. The question then arises about which dynamical features might be relevant and important for adoption of agri-environmental measures in farmers communities. We will then first discuss the robustness of the presented results in connection with models assumptions and then possible controls of the adoption process by administrations in view of these results.

5.1 Models assumptions

The models are based on two main assumptions concerning 1, the individual decision process, 2, the social network.

- All criteria that could influence farmers' decisions, economic profit, work time, psychological factors, even social influences are lumped into a single variable, utility. Such a simplification might depress cognitivists coming from Artificial Intelligence but it is reasonably adapted to our limited aims: we are interested in the decision and its consequences on adoption by other agents, not in the actual decision process, of which very little is known. (Alternate views, insisting on the importance of a finer description of the decision process are discussed in Chattoe and Gilbert 1998). A real difficulty though, is the evaluation the utility function as a sum of e.g. economic, psychological and time terms: if we use financial units, how do we measure time and psychological assets? by salaries and contingent analysis? Even economic profits are difficult to assess: adopting an AEM such as reduction of fertiliser input requires a full readjustment of production. Differences in profits result from difference in income and in inputs for different production conditions based on best agricultural practice (Lazzari 1998).
- In our view, the biggest issue is our ignorance about relevant social networks. Our knowledge on social networks is pretty limited to a few "cas d'ecole " in sociology such as personal networks, classroom friendship networks (see e.g. the Social network analysis web site), or data from ethnology (e.g. Levy-Strauss 1949); we don't know much about social networks

in Western world rural areas: a book edited by Darré (1994) gives a few examples. This is one reason why the epidemiology metaphor is so commonly used. Furthermore, the relevant network is probably not the same for decisions concerning domestic, economic or political issues. Empirical data collected in relation to some specific issue might not be relevant for other issues. Even decisions on adoption of proposed AEM could imply different connection structures according to the type of AEM. Consider e.g. local AEMs such Environment Sensitive areas scheme in the UK, national AEMs such as input reduction or some special AEMs such as maintenance of local cattle races. Furthermore, social network often involve loosely entangled sub-networks with tighter inner-connection as discussed in AIDS epidemics (Hyman and Stanley 1988) or Florentine history (Padgett 1993). Anyway, we have seen that the concepts we developed and the results we obtained on lattices are applicable, with careful generalisation, to sparse random networks, i.e. with a number of influence connections per agent larger than one on average, but much smaller than the total number of agents in the network as we checked in the section on random nets [17].

5.2 Summary of the main results

The main result, which might appear as counter-intuitive to a decision maker or even to a statistician, is the large dispersion of outcomes when randomness is introduced, for a wide range of parameters: a global characterisation of randomness by a probability distribution is not sufficient to predict uptakes, which can vary from 0 to 100 percent. This predicted dispersion could be a "zero hypothesis" explaining the large uptake difference observed in apparently similar contexts: for instance, large uptakes of AEM contracts have been observed in Lombardia and nearly no uptakes in Piemonte, two neighbouring Italian provinces with apparently similar characteristics. This sensitivity to the actual sampling of local variables is explained by the notions of clusters of adopters and of "hopeful monsters":

- Early adopters are those which would adopt even in the absence of neighbours.
- At any time, adoption occurs at the perimeter of clusters of adopters.
- The latter fact implies the necessity of hopeful monsters: initial configurations of neighbouring adopters in number sufficient with respect to absolute utilities so that growth of adoption clusters can proceed.
- A minimal utility, with a rather abrupt threshold of 0.25 in our model, is necessary to observe cluster growth, but growth dynamics and even chances for growth at a given density of early adopters depend on the magnitude of utilities well above the threshold.
- Randomness in utilities, influences and even external "noise " always favour growth.

5.3 Control aspects

In terms of global policy, the "financial" gains of the grant should be large enough to ensure participation of enough "early birds" (early adopters). Furthermore, if the funding agency aims at having a large fraction of adopters in a reasonably short time scale, say three years, the financial support and accompanying rules should be at a level well above the minimum level ensuring the appearance of early birds. The agency is also facing some kind of an "uncertainty principle ": ideally, the agency should be able to adjust the support level knowing the distribution of farmers

[17] A counter-example would be the case when most agents are directly connected to each other.

and social network characteristics, but we have observed that this is not the case because of the strong dispersion of results for equivalent distributions. A much more thorough knowledge would be necessary for actual optimisation of the agency financial effort. This dispersion is one more reason for the agency to increase its support above optimality[18] . A second approach is fine tuning, which we discuss in the next paragraph.

There might indeed exist possibilities for local adjustments. Local agricultural advisers can choose between a uniform campaigning effort, broadcasting and visiting all farmers equally, and a selective schedule. Let us model the effect of the counselor on individual farmers by some extra term in the utility function. Best results would be obtained if the counselor exerts his information and persuasion effort on pivotal individuals. We can think of three kinds of pivotal individuals of which two are evident:

- Those early adopters, whose utility is close to the threshold from below, and thus ready for adoption, and who are also close enough in the social network to realise a hopeful monster configuration.
- The influent leaders.
- The third type comprise dynamically influent farmers: when these agents are just outside the adoption cluster, they are able to trigger the growth of another layer of adopters because their interest for adoption Δu is large enough to allow them to adopt in the vicinity of the interface, but not to be an early adopter.

We can then imagine a fine tuning and scheduling of the adviser effort which would consist in visiting some of the pivotal agents, in the beginning of the program to convince possible early birds, and candidates for interfacial seeds at those times where they are in the immediate vicinity of the adoption cluster. Programming the effort should also take into account farmers influence on their neighbours. Of course, this supposes a lot of knowledge about agents readiness to adopt and actual social structure.

Rather that taking the full rationality view implied by such a thorough knowledge, we might take the procedural rationality view: in the absence of a priori specific and thorough knowledge could advisers devise simple and efficient ways to plan their visits and effort which would go along the previous lines? Such would be the case for instance, if their schedule were based on recommendations of previously visited farmers of whom to visit next. This scheme would follow the influence links[19] at the right time provided that the recommended person is visited after adoption by the recommending person, i.e. just when he has a good chance to be on the edge of an adopting cluster. This would be more efficient that both uniform and random effort. From the descriptive approach, we can also survey the actual practices of advisers to check whether they use such schemes, or others, which would be beneficial according to our theoretical predictions.

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[18]Rather than aiming at average results, a political institution is risk averse and has to avoid the probability of bad results; when the results of a policy can be expected to have a large dispersion, the agency has to aim higher

[19]with the restriction that influences might not be reciprocal.

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