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A diffusion model for the adoption of agricultural innovations in structured adopting populations

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Abstract

We introduce a new model for examining the dynamics of uptake of technological innovations in agricultural systems, using the adoption of zero-till wheat in the rice-wheat system in Haryana state, India, as a case study. A new equation is derived which describes the dynamics of adoption over time and takes into account the effect of aggregation (e.g. on a spatial and/or cultural basis) in the adopting population on the rate of adoption. The model extends previous phenomenological models by removing the assumption of homogeneity in the non-adopting fraction of the population. We show how factors affecting the per capita rate of adoption can be captured using cognitive mapping and simulate the dynamics of the adoption process.

Keywords: [Bass curve; adoption; innovation]

Introduction

The adoption of novel technologies and techniques is a major concern in agricultural extension and development work. It is a common experience that the adoption of an apparently useful agricultural technology is slower than predicted, or desired, by extension agents (Röling, 1988). One of the reasons behind this delay is the continuing pro-innovation bias of much extension research. That is, the implication that an innovation should be diffused rapidly, and that innovations should neither be re-invented, nor rejected (Rogers, 1995). Related to the pro-innovation bias is Röling's (1988) criticism on the general practice of the progressive farmer strategy in agricultural extension. In this strategy, change agents approach progressive farmers to deliver extension on relevant innovations, after which the innovation is supposed to spread to other segments of the farming community through word-of-mouth communication. Because farming populations are not homogeneous, rewards for innovations change over time, extension messages are distorted over time, and for numerous other reasons, innovations often fail to spread to all segments of the farming population. Traditional extension strategies tend to fail to give sufficient attention to socio-economic structuring and the degree of interconnectedness of the farming community, and also to differences in psychological characteristics of individual farmers (Röling, 1988).

Diffusion models may assist in gaining an understanding of the driving variables behind diffusion processes and allow, at least in theory, the prediction of the future adoption rate of innovations. Models of diffusion currently used in agricultural extension research are, of course, heavily simplified representations of the reality of diffusion processes (Rolling, 1988) and may be criticised for having little ability to predict future adoption of innovations (Mahajan *et al*., 1990). The Bass model is the most commonly used adoption/diffusion model (Bass, 1969) having originally been derived for applications in marketing science. Use of the

Bass model in agricultural extension is justified by the assumption that the launch of a new product on a market can be compared with the launch of an innovation in a farming community. Akinola (1986) provides a clear case study of the use of the Bass model in studying the adoption of pesticide use by Nigerian cocoa growers.

The Bass model recognises two sources of technological innovations. In agricultural extension, adoption of innovations through *external* factors is adoption initiated by factors outside the farming community, for instance by extension agents or mass media promotion. Adoption through *internal* factors is adoption resulting from inter-personal communication between farmers. Farmers adopting an innovation through external factors are sometimes referred to as (real) innovators, while farmers adopting through internal factors are referred to as imitators.

The Bass model (and similar models) deal with the adoption process at the population level. Such models neglect several important factors determining the adoption rate of innovations and reflect the pro-innovation bias of most other diffusion research. The Bass model, for example, assumes: that the market potential of new products/innovations remains constant over time; that the nature of the innovation does not change over time; that the diffusion of new innovations is independent of other innovations; and that the diffusion process is not influenced by marketing/promotion strategies, such as changing product prices, changes in advertisements, *etc*. (Mahajan *et al.*, 1990). As noted above, in real situations the market potential of innovations changes over time and distortion of information and reinvention of innovations changes the extension message and the nature of novel techniques. In addition, the distinction the Bass model makes between adoption through either external or internal factors may not reflect the reality of how farmers decide to adopt or reject an innovation. Few farmers decide to adopt a novel farming technique solely based upon information received from mass media or extension officers. Rogers (1995) estimates that the percentage of innovators in any population is between two and five per cent. External factors may create interest in and awareness of innovations, but the actual decision to adopt a new technique is usually not taken by the majority of farmers until information and practical experience from peer-farmers is received. Hence, external factors may facilitate the spread of innovative agricultural techniques through interpersonal communication, but are not convincing on their own.

Many of the limitations of the Bass and similar phenomenological[1] models can be overcome if a micro-level modelling approach is taken (Chatterjee & Eliasberg, 1990). However, although parameter estimation for micro-level models is straightforward in principle it may be far more time consuming, because of greatly increased data requirements, than for phenomenological models. Here, we present a compromise approach, which incorporates heterogeneity among individual adopters, but models the innovation-adoption process at the population level. The model is developed in ecological terms in an attempt to provide a cross-disciplinary exchange of concepts from production ecology to management science and *vice versa*.

Before a description of the derivation of the model and an analysis of its performance, the history of zero-tillage in the rice-wheat system in northern India is explained to show the complexity of the context in which adoption is taking place. The use of the technique of cognitive mapping (Kosko, 1992) is illustrated with reference to the rice-wheat system to show its value in capturing the potential dynamics of complex systems. The development of

[1] We use the term *phenomenological* rather than the term *aggregate*, which is more common in the economics/management science literature, to avoid confusion with the ecological use of the term *aggregation*.

cognitive maps for the rice-wheat system and their use in predicting the dynamics of model parameters is discussed in more detail in later sections of the paper.

History of zero-tillage in Haryana

Zero-tillage in wheat is a novel farming technique in Haryana. The technique allows farmers to drill wheat seeds directly into the stubble of the previous crop, which is usually rice, without any preceding soil cultivations. Zero-tillage has the advantage of saving labour requirements and soil cultivation costs during wheat sowing and reducing the emergence of the obnoxious weed *Phalaris minor* (Franke *et al*., 2001; 2003). Although the percentage of farmers practising zero-tillage is presently still small in Haryana (around 10%), zero-tillage is rapidly increasing popularity (Hobbs, 2002).

The first on-farm demonstrations of zero-tillage in wheat in Haryana were conducted in 1996 by Haryana Agricultural University. The extension workers concentrated their efforts on a dozen villages, where good relationships with progressive farmers already existed. Many of these farmers belonged to the Sikh caste. They are traditionally innovative and resource-rich farmers, who are often more able and willing than farmers from other castes to try out new farming techniques. Incentives, in the form of free use of zero-till machinery and free herbicides, were provided to farmers joining zero-tillage demonstrations. At the time zero-tillage was introduced in 1996, farmers in Haryana were having difficulty controlling the weed *Phalaris minor*, (Littleseed canary grass) whose control had drastically worsened due to the development of resistance against the widely applied herbicide isoproturon (IPU). The pressure that IPU-resistant *P.minor* exerted on farm income contributed to the farmers' willingness to experiment with zero-tillage. On the other hand, the complex mechanism by which zero-tillage affects *P. minor* population size was not well understood. This made many farmers sceptical about the use of zero-tillage as a means to control *P. minor*, impeding their willingness to adopt. Another hindrance to the acceptance of zero-tillage was the widely held conviction among farmers that extensive soil cultivation operations before wheat sowing are a necessity for good crop establishment. However, after the first on-farm demonstrations showed a considerable reduction in *P. minor* pressure and similar yield as fields under zero-till, willingness to adopt increased (Singh & Panday, 2002).

In 1998, alternative herbicides for the control of *P. minor* were launched on the Indian herbicide market, and since then the control of isoproturon-resistant *P. minor* has greatly improved. Consequently, the introduction of new herbicides decreased the relative advantage of zero-till over conventional tillage by reducing *P. minor* pressure. However, by 1998 it had been realised that adoption of zero-tillage gave a considerable reduction in soil cultivation and labour costs. This economic advantage soon became the main driving variable behind the adoption of zero-tillage, and from 1998 onwards, diffusion of zero-tillage through interpersonal communication began to take off. The innovation was spreading to other farmers living in the neighbourhood of those villages initially targeted by the extension workers. Farmers could now purchase their own zero-till drill through a local manufacturing company and no further incentives were provided to farmers to adopt zero-tillage. At this stage, a high degree a trialability (farmers could easily try out the innovation by cultivating a small area of their land with a hired zero-till drill) and a high degree of observability of the innovation in the field favoured rapid diffusion. Diffusion through interpersonal communication soon became a more important means of spreading the innovation than the activities of relatively small team of university extension workers (Franke *et al.*, 2003). The size of the extension team involved in promoting zero-tillage existed of around ten people, while the size of the farmer population potentially adopting zero-tillage is several million

Extension about zero-tillage was also provided through mass media broadcasts, for example through television and radio programs on farming and farming newsletters. These media were highly effective in creating awareness of zero-tillage among the entire farmer community. However, farmers, who were aware of the innovation through mass media, generally lacked willingness to adopt until further information and practical experience from their peers was received (Franke *et al*, 2003). Presently, zero-tillage is widely adopted in the surroundings of the villages where university extension workers introduced the innovation, while outside these areas the fraction of adopters in the population is still low. In areas with a low adoption rate, many farmers are aware of the availability of zero-tillage, but lack confidence in the technique. The university extension team may still play an important role in accelerating the rate adoption by organising demonstrations of zero-tillage in these areas.

The likelihood of adoption depends not only on farmers' geographic location, but also on their socio-economic position. The main economic advantages of zero-tillage, *e.g.* reduced soil cultivation and labour costs, are higher for farmers with larger landholdings and a higher degree of mechanisation, as compared with small farmers using animal draft power. Small farmers already have minimal soil cultivation costs, and hiring a tractor and a zero-till drill may increase cultivation costs. In addition small farmers have relatively more family labour per hectare of land available than large farmers and are therefore less interested in the time and labour savings resulting from adopting zero-tillage.

The degree of interconnectedness of the farming community in Haryana appears to be another relevant factor in the adoption of zero-tillage. In common with other village-based rural communities strong family ties and the prevalent caste system divide farmers into social groupings (Jodhka, 1998). Farmers have strong contacts with peer-farmers belonging to the same grouping and tend to communicate less with farmers belonging to other groupings. Some groupings had a tradition of innovativeness, while others are more conservative. As mentioned above, Sikh farmers were among the first farmers to adopt zero-tillage. Generally, Sikh farmers intensively exchange information on farming and the technique, after its introduction, rapidly diffused among Sikh farmers. Farmers from other castes were much slower to adopt zero-tillage, irrespective of their geographic location. Apparently they had less contact with Sikh farmers who had adopted zero-tillage and were less willing to accept information on farming from Sikh farmers.

In the next section the new diffusion model is derived and the use of cognitive mapping for capturing a quantitative description of the farming system is described. The final section of the paper discusses the implications of the model for diffusion of innovations in a development setting.

DERIVATION OF A NEW DIFFUSION MODEL FOR ADOPTION OF TECHNOLOGY

The Bass model

Starting point of the new model is the Bass model. The Bass model distinguishes between diffusion through external factors and internal factors. The number of new adopters resulting from interpersonal communication is described as a constant fraction (*β*) of the product of farmers who have adopted (*A*) and those who have not adopted (*N*-*A*). According to the model, the cumulative number of adopters, adopting through *internal* factors follows a sigmoid curve with time.

The numerical equation for the number of adopters through internal factors can be written as:

$$\frac{dA}{dt}_{\text{internal}} = \beta \cdot A_t \cdot (N - A_t) \qquad (1)$$

Where:

A_t is the total number of adopters at year t.

A_{t+1} is the total number of adopters at year $t+1$.

N is the maximum potential number of adopters.

β coefficient of internal diffusion; indicating the chance of adoption as a fraction of the possible interactions between non-adopters (*N*-*A*) and adopters *(A)* at time t.

Equation 1 is the familiar logistic growth curve, which is widely applied in studies of biological population dynamics (May, 1973; Begon *et al*., 2000). The adoption rate through external factors is modelled as a fraction (α) of the farmers who have not adopted:

$$\frac{dA}{dt}_{\text{external}} = \alpha \cdot (N - A_t) \qquad (2)$$

Where α is the coefficient of external diffusion; *i.e.* the fraction of the total of farmers who have not adopted, adopting through external factors at time, *t*.

The coefficient of external diffusion is relevant in situations in which the initial adoption of innovations is induced by extension agents and mass media promotion, targeting all farmers who have the potential to adopt the innovation (*N*): that is, if $A_0 = 0$ then $A_1 = \alpha \cdot N$. Since the adoption rate through external factors is proportional to the number of non-adopters, the rate will be highest when no farmers have adopted and will decrease over time with a growing number of adopters.

The Bass model combines equation 1 and 2 and may be written as:

$$\frac{dA}{dt} = \alpha \cdot (N - A_t) + \beta \cdot A_t \cdot (N - A_t) \qquad (3)$$

Sultan *et al.* (1990) found that for fifteen different applications of the Bass model, the average coefficient of external diffusion (α) was 0.03, while the average coefficient of internal diffusion (β) was 0.38. This suggests that, generally, the diffusion process is affected more by factors such as word of mouth than by mass media influence.

A novel diffusion model: an ecological analogy

Diffusion processes which rely on personal contact to spread an innovation are analogous to infectious processes in the spread of a disease; indeed Rogers (1995) uses the word "contagious" to describe the adoption/diffusion process. In common with many simple models of disease and population dynamics, the commonly used diffusion models assume homogenous mixing of the population through which the disease (or innovation) is spreading. However, one of the key factors in determining the rate of such processes is the contact rate between those who have already adopted (infected individuals in the case of disease) and those who have not already adopted (uninfected individuals by analogy). The contact rate between adopters and non-adopters, for a fixed number of adopters, is lower if those adopters are aggregated physically and/or socially, so that a large number of their interpersonal contacts are with other adopters. It is this aspect of the diffusion process which current models do not take into account and for which the new model has been derived. Alternative modelling approaches which consider contact rates directly are widely used in human health studies and would also be potential starting points for the derivation of enhanced population level adoption/diffusion models (see for example, Black & Singer, 1987).

The effect of non-homogenous mixing (or aggregation) on population dynamic processes has been widely considered in the applied ecology literature (Nachman, 1981; Waggoner & Rich, 1981; Madden *et al*., 1987; Kuno, 1988; Yang & Te Beest, 1992; Hughes *et al*. 1997). These studies present various mathematical models population dynamic processes which account for non-homogenous mixing of infected and uninfected individuals.

Some of the models in these areas of application make use of Lloyd's Index of Patchiness (LIP) to account for the effects of aggregation on the rate of population increase (analogous to rate of innovation adoption). LIP was originally intended as a measure of the patchiness of a meta-population of plants or animals and is derived from the variable 'mean crowding' (Lloyd, 1967). Mean crowding is defined as "the mean number per individual of other individuals in the same quadrat". If the quadrat size coincides with the individual's ambit, mean crowding is the average number of individuals with which an individual interacts. In sampling studies LIP is calculated as the ratio of mean crowding to mean density per quadrat.

To transfer the use of LIP to diffusion of innovations in agriculture, 'mean crowding' is taken to be the number of other adopters an individual adopter interacts with within his/her ambit. An adopter's ambit is assumed to be the area within which the adopter typically interacts with other farmers, and within which diffusion of an innovation might occur as a result of personal contacts. In the current case it is difficult to define precisely what geographical area an ambit constitutes. For the purposes of the present study, an individual's ambit is taken to be a village and its immediately surrounding farms.

As interpersonal communication is the dominant factor accounting for the speed and shape of the diffusion of an innovation (Rogers, 1995), Bass's equation for diffusion through interpersonal communication alone is used as the starting point for the development of the new model. The coefficient of external diffusion is omitted for two reasons. First, interest in the present context is in studying the dynamics of uptake of innovations after they have been introduced. Secondly, as already noted above, during diffusion of agricultural innovations, such as zero-tillage, few farmers adopt as a direct result of contact with change agents or other external influences. However, extension *via* mass media is helpful in facilitating interpersonal diffusion by raising awareness of innovations and this aspect of its impact and is included in the section dealing with cognitive mapping, in which we consider variables affecting the attractiveness of an innovation and the rate of adoption.

To adapt the diffusion model for aggregation effects, we need to redefine equation 1, describing the adoption curve for innovations. The following equation has the advantage that it is less sensitive to changes in population size compared with equation 1, in which the innovation rate increases exponentially with increasing population size.

$$\frac{dA}{dt} = r \cdot A \cdot (1 - \frac{A}{N}) \qquad (4)$$

Where:

r is a rate parameter summarising the capacity of the innovation to spread, analogous to the coefficient of internal diffusion (α), and

$(1 - \frac{A}{N})$ is the population fraction of non-adopters

A high value for LIP means that the adopters are aggregated. This aggregation decreases the number of contacts an adopter has with non-adopters. This is equivalent to saying that increasing levels of aggregation reduce the effective population fraction of non-adopters. If LIP has a value, *x* say, an adopter would interact on average with *x* times as many adopters as expected under a random pattern of adopters (*i.e.* under homogeneous mixing of adopters and non-adopters). Stating this formally we can include LIP in equation 4 as follows:

$$\frac{dA}{dt} = r \cdot A \cdot (1 - \frac{LIP \cdot A}{N}) \tag{5}$$

If LIP is stable over time, the maximum number of adopters corrected for LIP, *N'*, would behave as follows:

$$N' = \frac{N}{LIP} \tag{6}$$

According to equation 6, at high values of LIP the diffusion process would come to an end at relatively low levels of adoption. However, ecological analyses of diffusion processes (Yang *et al.*, 1991; Yang & TeBeest, 1992; Madden *et al.*, 1987) show that LIP changes over time. Transferring these ecological results to the present context we might expect that aggregation levels (*i.e.* LIP) to decrease as the fraction of adopters increases. Therefore, LIP should be calculated as a function of the number of adopters. This leads to a general form of the new diffusion model given in equation 7.

$$\frac{dA}{dt} = r \cdot A \cdot \left(1 - f(A) \cdot \frac{A}{N}\right) \tag{7}$$

Finally, it is necessary to define a form for the function *f*(*A*) in equation 7. Unfortunately, there are limited data available on the behaviour of LIP over time for ecological data and none that we know of for diffusion processes in the current context. However, as an initial attempt to derive *f*(*A*) we may proceed heuristically.

It is known that the maximum value of LIP occurs in the hypothetical situation in which adopters and non-adopters are completely segregated. The maximum value of LIP is, then, determined by the ratio of the maximum number of adopters per village to the number of potential adopters per village. When the number of adopters (*A*) approaches the maximum number of adopters (*N*), adopters will no longer be aggregated (relative to the non-adopters), and therefore LIP will approach the value of 1. The theoretical maximum value of LIP at any value of *A* can thus be defined as:

$$LIP_{\max}(A) = \frac{\frac{N}{q} - 1}{\frac{A}{q}} = \frac{N - q}{A} \qquad (8)$$

where:

q is the total number of villages.

If the number of individuals per village is relatively large, LIP_{max} approaches $\frac{N}{A}$. For example, if the number of individuals per village exceeds 100, the approximation of LIP_{max}, as $\frac{N}{A}$, deviates less than 1% from the real value of LIP_{max}. Since in the rural community in Haryana a farmer's ambit usually consists of several hundred farmers, it would be reasonable in the current case to estimate LIP_{max} as $\frac{N}{A}$.

Having established that the actual value of LIP for any A varies between 1 and the maximum value of LIP for that value of A, we now assume that the function LIP(A) is a constant fraction of $LIP_{max}(A)$ minus an asymptote $LIP_{max} = 1$. If the value for LIP is known at a certain adoption fraction (A/N), LIP as a function of A can be calculated as:

$$LIP(A) = 1 + \frac{LIP_{\left(\frac{A}{N}\right)} - 1}{LIP_{\max\left(\frac{A}{N}\right)} - 1} \cdot \left(\frac{N}{A} - 1\right) \tag{9}$$

Substitution of equation 9 into equation 7 leads to the expression for the new diffusion model.

$$\frac{dA}{dt} = r \cdot A \cdot \left[1 - \left(1 + \frac{LIP_{\left(\frac{A}{N}\right)} - 1}{LIP_{\max\left(\frac{A}{N}\right)} - 1} \cdot \left(\frac{N}{A} - 1\right)\right) \cdot \frac{A}{N}\right] \tag{10}$$

The performance of the model was examined using data from a socio-economic survey to farmers' practices in the rice-wheat system of Haryana (Franke *et al.*, 2003). Only data from those districts within Haryana where farmers practised zero-tillage were used. In these districts, the overall adoption rate of zero-tillage, sometimes practised along with other tillage techniques, was 19%. The estimated adoption rate of 19% was probably a slight overestimate of the actual adoption rate, due to bias related to the interviewers' preference to conduct interviews with progressive farmers in villages with relatively high socio-economic standards. Data from 25 villages, where two or more farmers were interviewed, were included to test the effect of aggregation on adoption rate of zero-tillage.

Estimation of LIP from survey data

Of the 25 villages providing data used to parameterize the model, 11 hosted farmers using zero-tillage, while in the remaining 14 villages, none of the interviewed farmers had implemented zero-tillage, indicating that adopters were aggregated. The average adoption fraction in villages with at least one person practising zero-tillage was 0.50, while the average adoption fraction of all 25 villages was 0.23. Assuming that the average number of farmers per village in villages where zero-till was practised was equal to the average number of farmers per village in villages without zero-till, and bearing in mind that the number of farmers per village was relatively large (>100), LIP at the given adoption fraction approaches: $\frac{0.50}{0.23} = 2.17$.

At an adoption fraction of 0.23, the approximation of LIP_{max} is 4.35 (from equation 8).

The total number of adopters, *N*, was estimated as the product of the number of villages (25) and the average number of farmers per village. This second value was estimated as 500, on the basis of information gathered from local farmers and HAU extension staff, giving a value for *N* of 12500.

The effect of the initial level of aggregation on the progress of innovation uptake

The cumulative number of adopters in the 25 villages and the rates of adoption were examined for four situations:

(1) $LIP_{\left(\frac{A}{N}=0.23\right)} = 2.17$ (aggregation based on observation)

(2) $LIP_{\left(\frac{A}{N}=0.23\right)} = 1.0$ (no aggregation, equivalent to homogenous mixing)

(3) $LIP_{\left(\frac{A}{N}=0.23\right)} = 1.085$ (50% aggregation compared with situation 1)

(4) $LIP_{\left(\frac{A}{N}=0.23\right)} = 3.255$ (150% aggregation compared with situation 1)

Adoption progress curves for equation 10 were obtained by numerical integration using a Runga-Kutte method implemented either in the FST modelling environment (Windows ver. 1.06, Kraalingen *et al*., 1999) or in Mathcad (ver. 2001i (Professional), Mathsoft Inc. Cambridge MA 02141, USA). The FST code and/or the Mathcad worksheets are available on request from the authors. For comparison of the qualitative effects of different levels of aggregation on the rate and progress of adoption, the rate coefficient, *r*, in equation 10 was set to 0.38 (based on the results of Sultan *et al.* (1999) reported above).

Figure 1 shows the adoption curves for the four different initial levels of aggregation (Fig.1(a)) and the rate of adoption against time (Fig. 1(b)). It can be seen that an increasing the level of aggregation among adopters leads to an increase in the time taken to reach the final fraction of adopters and also in the maximum rate of adoption during the adoption process. With the value of $r = 0.38$, the time required to reach 80% adoption in situation 1, the observed aggregation level, is delayed by 3.3 years as a result of aggregation compared with a situation in which there is random mixing of adopters and non-adopters. The relative increase in time compared with random mixing of adopters and non-adopters was 43%. Doubling the aggregation level, (situation 4), would extend the time required to reach 80% adoption by another 11 years (relative increase compared with random mixing: 207%).

<FIGURE 1 NEAR HERE>

Aggregation (LIP) as a function of the adoption fraction over time (equation 9) is shown in Figure 2. It can be seen that a 50% increase in the initial level of aggregation, as compared with the observed value, results in the pattern of adopters remaining aggregated (LIP>1) until close to then end of the adoption process. Analysis of equation 9 showed that a value of LIP(A) = 1.0 was obtained after 21 years starting from a position with 50% more aggregation than the observed value. For the observed level of aggregation, the model predicted that the homogenous mixing of adopters and non-adopters would occur after 10 years.

<FIGURE 2 NEAR HERE>

In their discussion of the relative merits of phenomenological versus individual-based diffusion models Mahanjan, *et al*. (1990) noted that "*…all potential adopters do not have the same probability of adopting the product in a given time period*." Individual-based models such as those proposed by Chaterjee & Eliashberg (1990) attempt to address this issue by modelling the processes of decision/adoption at an individual level. Although such approaches can give accurate fitting of adoption curves to observed adoption data (Chaterjee & Eliashberg, 1990) they require information on the behaviour of individual adopters which may not be easy to collect. The approach reported here is an attempt to find a compromise between the individual-based approach and the original Bass diffusion model. Specifically, the model uses information which can be collected, by direct observation, on the aggregation of the innovation within the adopting population to estimate an additional shape parameter for the diffusion model. The parameter, based on the ecological concept of patchiness, (Lloyd, 1967) specifically accounts for the way in which physical or social grouping within the adopting population might delay the adoption of an innovation by making the probability of adoption non-constant over those yet to adopt.

The proposed model has properties which make it useful for the context in which it was developed. First, it is known that, in common with other groups of adopters, farmers are more likely to adopt an innovation when either they can try it out before committing to it, or they can observe someone else trying it (Rogers, 1995). This effect has already been observed with the adoption of zero-tillage in India (Singh & Panday, 2002). Clearly, the opportunities for non-adopters to observe adopters trying a new method are reduced in circumstances where adopter and non-adopters do not mix homogeneously in the population. Caste, religion and wealth all act as sources of aggregation within Indian villages and may lead to non-homogenous exchange of information about, or access to, technological innovations (Jodhka, 1998). Second, detailed information on the adoption/decision process of adopters, a prerequisite for constructing a micro-level model and information which may be difficult to collect in a development context, is not required for the model presented here. Third the model is well-suited to situations in which the population of adopters consists of distinct social groups (*e.g.* villages) since the aggregation parameter is estimated simply from the mean and variance of the number of adopters per group (*i.e.* per village in the current context). Since such social structuring is a common feature of peasant agricultural systems, the current model may provide a basis for improved forecasting of technology adoption in development studies compared standard diffusion models.

Mahanjan *et al*. (1990) discussed the difficulties in obtaining parameter values for diffusion models in advance of the diffusion process reaching an advanced stage. In principle, the model presented here may not be as severely affected in this respect by lack of data as other diffusion models. First, the model's basic structure is that of the logistic equation in which the inflection point occurs at the mid-point in time of the diffusion process. This may make it possible to estimate the rate parameter, *r*, from a relatively short time series of data. Deviations from a symmetrical adoption curve arise in the current model as a result of the time-varying function of aggregation in the adopting population. Thus, although the rate parameter might be estimated as if the diffusion curve were symmetrical about its inflection point, the actual curve may be asymmetrical. Furthemore, the time-varying parameter (LIP) which affects the shape of the curve may be estimated from a single observation period, as illustrated above, provided reasonable estimates can be made of the number of potential adopters in each group, and the total number of potential adopters in the population.

Irrespective of whether parameter estimation for the proposed model proves to be easier than for other diffusion models or not, the principle use of the model is likely to be strategic rather than tactical in any case. That is, in common with other relatively simple models of complex processes (May, 1973) the main use is likely to be in understanding how the dynamics of the process might change in response to changes in a few key parameters. In such analyses, the interest is often in qualitative changes in the predicted behaviour of the system in response to changes in parameter values rather than in precise numerical analysis of particular fits of the model to data. The analysis of the model clearly indicated that extension effort to reduce the aggregation of adopters would result in increased adoption rates.

In the current context, we considered it justifiable to focus attention on a diffusion model which accounted for diffusion as a result of "internal" pressure only, rather than by both "internal" and "external" pressure. This decision was justified partly by the results of Sultan *et al*. (1990) who found that the coefficient of internal adoption pressure was an order of magnituide higher than that for external influence in a meta-analysis of 15 adoption studies. It was also based on our own observation (Franke *et al*., 2003) that a majority of Haryana farmers have been exposed to the concept of zero-tillage through mass media coverage, but only those who have had direct experience of the method have actually adopted it.

Cognitive map construction for examining the dynamics of the rate coefficient, r

The rate coefficient, *r*, can be considered as a parameter expressing the attractiveness of the innovation, analogous to the infectiousness of a disease, and is likely to depend on Roger's (1995) attributes of innovation rate: relative advantage, compatibility, complexity, trialability and observability. Also, mass media may affect the diffusion coefficient *r*, by facilitating interpersonal diffusion and so increasing the 'infectiousness' of the innovation.

It might be expected, by analogy to the epidemiological context, (van der Plank, 1963; Campbell & Madden, 1990) that *r* will not be constant over time. Sufficient data are not available to undertake a quantitative analysis of the question of how *r* will vary over time. This situation is quite common in the development of models in systems analysis and we present here a method which allows initial progress to be made based on expert opinion. The method has the advantage of focussing the attention of the researcher on the interactions which occur between different components of the system under investigation.

Cognitive map construction and interpretation: a simple example

A cognitive map represents logical and causal connections between actions, objects or concepts which together describe a larger entity, system or concept. In a cognitive map, the concepts/objects/actions are typically represented by boxes of various shapes and causal relationships between them are represented by arrows. The arrows are annotated with '+' and '-' signs to indicate causal increase or decrease respectively. In cases where the relative strength of the causal relationship can be estimated the '+' and '-' signs can be replaced by values between -1 and 1 to produce what is known as a Fuzzy Cognitive Map (FCM, Taber, 1991; Kosko, 1992, 1993). The numerical values can be related to linguistic quantifiers such as; 'never', 'sometimes', 'often', 'always', 'little', 'some', 'a lot', which makes the technique easy to use in gathering expert opinion. The data to be translated into an FCM can be gathered either from face-to-face interview or from written material in which the concepts under consideration are discussed. A FCM represents a view of the way in which a particular feature of the world works and can be used to make inferences about the expected behaviour of this feature of the world through the application of straightforward matrix algebra.

The first step is to translate the causal connections in the map into a square matrix. If the map contains *n* concepts, the matrix will have *n* rows and *n* columns, one row and one column representing each concept. Each column of the matrix contains the values of the causal effects of a concept on each of the other concepts in the map (which are represented by the *n* rows of the column). In order to generate inferences from the FCM, an *n* x 1 vector of initial values is multiplied to the matrix to generate a vector of output states. Repeated multiplication of the output vector to the matrix may result in a stable pattern of activation of the concepts emerging (known as a stable limit cycle) or a single stable steady state may be obtained (in which the *pattern* of activations of the concepts remains constant), or chaotic patterns of activation may arise (Taber, 1991; Kosko, 1992). The technique is directly analogous to the construction and interpretation of community projection matrices in population ecology (May, 1973; Caswell, 2001). A simple example based on expert opinion of the issues which determine a farmer's decision to plant potatoes in preference to wheat in the rice-wheat system is shown in Figure 3(a). The causal statements underlying the FCM are given in Table 1. The expert opinion predicts a cyclical oscillation in the production of potatoes within the system as the feedback between potato supply and price fluctuates.

Examination of the output from the cognitive map (Figure 3(b)) shows that the qualitative aspects of the predicted system behaviour agree with the stated expert opinion.

<TABLE 1 NEAR HERE> <FIGURE 3 NEAR HERE>

A FCM for the adoption of zero-tillage in the Haryana rice-wheat system

In the current context, discussions regarding the factors influencing the uptake of zero-till technology in Haryana were conducted with various local experts and farmer groups in Haryana in 1999, 2000 and 2001. A set of causal statements was produced by the project team from field notes made during these discussions. The FCM shown in Figure 4 was produced from these statements. The list of factors (states) in the FCM is given in Table 2 together with the initial activation levels used in the projections. The set of causal statements is given in Table 3, with their weights. The aim of the map FCM was to capture the main factors which affect the attractiveness of zero-tillage and might therefor affect the value of the parameter, *r*, in the diffusion model.

<TABLE 2 NEAR HERE> <TABLE 3 NEAR HERE>

The effects of aggregation on the rate of adoption were included in the FCM as shown in Figure 4. To examine the dynamic nature of the *r* parameter without aggregation, the causal connections between aggregation and other states were set to zero. This is analogous to the assumption of homogenous mixing in the farmer population. The FCM was also used to examine the predicted dynamics of the system with different initial levels of aggregation corresponding to the situations described above, with and without the effect of government intervention. Intervention was removed from the projections by setting its activation level to zero. The FCM analyses were carried out using the Fuzzy Thought Analyser (FTA, ver. 1.03 for Windows^{TM}, Fuzzy Systems Engineering., Poway, CA, USA). Adaptations to the diffusion model resulting from the observed dynamic nature of the *r* parameter are described below.

<FIGURE 4 NEAR HERE>

Cognitive map dynamics

Examination of the dynamics of the system suggested that a fixed attractor would be reached in a relatively short time. Overall, seriousness of the *Phalaris minor* was predicted to decrease, but herbicide resistant *P.minor* was predicted to increase. Concurrent with the period of increase in resistant *P.minor*, farm income was predicted to fall, before showing a recovery to approximately its initial value. These predictions of the behaviour of the system broadly agree with its observed behaviour over the last eight to ten years. The input of state intervention *via* fuel and fertilizer prices and by supporting mass media information on zero-tillage, was found to make little difference to the eventual level of adoption of zero-tillage, but did lead to a slightly higher level of profitability in the system. Thus, the final activation for the state "profit" was 0.48 in projections in which intervention was included and 0.43 in projections where it was omitted.

The rate coefficient, *r*, was found to reach a stable value within a few cycles of the FCM, irrespective of the presence of Government intervention, or the initial level of aggregation among adopters, although the final value of the parameter did depend on the presence of Government intervention in the system. The stable value of *r* was 10.5% higher in the case where intervention affected other states, than the case where no intervention was present. (Figure 5). <FIGURE 5 NEAR HERE>

The use of cognitive mapping allowed an examination of the overall context within which adoption of zero-tillage is taking place in northern India. The cognitive maps generated projections of changes within the system which are in agreemnent with observed data. For example: an increase a gradual replacement of normal *Phalaris minor* with isoproturon-resistant *P.minor*; a period of decrease in farm income associated with the increase in IPU resistant *P.minor* followed by a period of recovery in farm income. Given the qualitative agreement between the projections from the FCM and the observed behaviour of the system, it was of interest to examine the dynamics predicted for the rate parameter, *r* in the diffusion model.

The FCM projection suggested that the rate parameter would quickly increase to a stable value. If required the diffusion model given in equation 10 can be extended to include variable rather than constant rate parameter. A possible parameterisation for such a model is given in equation 11.

$$\frac{dA}{dt} = \left(b \cdot \left(1 - e^{-a \cdot \frac{A}{N}}\right)\right) \cdot A \cdot \left[1 - \left(1 + \frac{LIP_{\left(\frac{A}{N}\right)} - 1}{LIP_{\max\left(\frac{A}{N}\right)} - 1} \cdot \left(\frac{N}{A} - 1\right)\right) \cdot \frac{A}{N}\right] \qquad (11)$$

The new rate parameter in equation 11 is expressed as a function of the fraction of adopters (*A*/*N*). The new parameter, *b*, is the upper limit to which *r* tends, while *a* is a rate parameter which determines the time taken for *r* to reach its stable value. Numerical integration of equation 11 with values for *a* and *b* selected to mimic the projections from the FCM analysis varied little from the analysis based on equation 10, with constant *r*. Generally, if the rate parameter reaches a constant value early in the diffusion process, results from equation 11 are similar to those for equation 10 and it is not clear that worthwhile benefits in explanatory power will be gained from the additional burden of extra parameter estimation.

Conclusions

By appealing to the analogy between innovation diffusion models and population growth models it is possible to derive extended diffusion models that specifically take account of non-homogeneous mixing between adopters and non-adopters in a population. The aggregation parameter which enters the standard diffusion model can be interpreted against the background of the population and innovation(s) under investigation and can be estimated from single-point observations of the adoption process. The resulting model can be used to examine the effect of use of a fixed level of extension effort to promote adoption when between a small number of intensively supported locations (for example demonstration or Monitor Farms) and a larger number of more dispersed initial adopters.

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Annex of Figures/Tables

Table 1. Expert opinions on the factors determining the long-term use of potato as an alternative crop in the Haryana rice-wheat system

Statement no.	Statement
1.	Sometimes as a result of the problems associated with rice-wheat farmers plant potatoes

2. A high potato price will make farmers try potato as a crop because the price makes the rice-wheat problems more apparent

3. A high potato price makes potato an attractive crop in itself and makes farmers plant potato

4. When lots of farmers plant potatoes, a potato glut occurs

5. A potato glut reduces the price of potato, leading to fewer farmers planting them next year

6. *The situation described in statements 1-5 leads to a cyclic pattern of boom and bust in the planting of potato in the rice-wheat system*

Table 2. Initial levels of activation in a Fuzzy Cognitive Map (FCM)of factors affecting the rate of adoption of zero-tillage in wheat in the rice-wheat system in northern India

State/Concept	Abbreviation used in FCM	Initial Activation
Phalaris minor	Pminor	0.80
IPU-tolerant *Phalaris minor*	rPminor	0.40
Rate coefficient of adoption	r	1.00
Number of adopters	A	0.23
Cost of Fuel	Fuelcost	0.6
New herbicides	Newherb	0.2
Diversification	Diversif`	0.1
Government intervention	Interven	1.00 (0.00)[1]
Value of rice/wheat crops	Cropval	0.5
Cost of fertilizer	Ureacost	0.6
Profit	Profit	0.5
Ability to invest in new methods	Invest	0.3
Low interest rates	Lowint	0.3
Aggregation	Aggreg	0.5 (0.00, 0.25, 1.00)[1]
Cost of adopting zero-till	ZTcosts	0.7
Mass-media	Massmed	0.95

promotion of zero-tillage		
Lack of familiarity with zero-tillage	Nofamili	0.77
Belief in need for tillage	Needtill	0.80`
Risk aversion to adoption	Toorisky	0.80

[1] Alternative initial values used in different projections are shown in parentheses

Table 3. Causal statements linking states associated with the rate of uptake of zero-tillage in the rice-wheat system of northern India

Statement no.	Statement	Weight
1.	Adoption of zero-tillage reduces *Phalaris minor* infestation	-0.60
2.	Use of new herbicides reduces *P.minor* infestation	-0.75
3.	Presence of *P.minor* results IPU-tolerant *P.minor*	1.0
4.	Adoption of zero-tillage reduces IPU-tolerant *P.minor*	-0.60
5.	Use of new herbicides reduces IPU-tolerant *P.minor*	-0.75
6.	Presence of P.minor increases attractiveness of zero-tillage*	0.6
7.	Presence of IPU-tolerant P.minor strongly increases attractiveness of zero-tillage	1.00
8.	High fuel prices strongly increase increases the attractiveness of zero-tillage	1.00
9.	Diversification reduces the attractiveness of zero-tillage	-0.60
10.	Ability to invest increases the rate of adoption	0.95
11.	High costs of zero-tillage machinery reduce attractiveness of zero-tillage	-0.75
12.	Lack of familiarity with the technique reduces the attractiveness of zero-tillage	-0.60
13.	Belief in the need for tillage redcues attractiveness of zero-tillage	-0.75
14.	Risk averse attitudes reduce the attractiveness of zero-tillage	-0.75
15.	A positive rate coefficient leads to an increase in adopters	1.00
16.	Intervention generally increases fuel costs	0.60
17.	Increase in crop value (rice/wheat) leads to increase in use of new herbicides	0.90

Table 3 (cont'd.)

18.	Occurrence of IPU-tolerant *P.minor* leads to use of new herbicides	0.75
19.	Occurrence of *P.minor* stimulates diversification in cropping system	0.45
20.	Occurrence of IPU-tolerant *P.minor* stimulates diversification in cropping system	0.75
21.	Increase in crop value (rice/wheat) decreases diversification	-0.90
22.	Intervention generally increases crop value (rice/wheat)	0.90
23.	Intervention generally decreases fertilizer costs	-0.75
24.	High fuel costs reduce profitability	-0.75
25.	High crop values (rice/wheat) increase profitability	1.00
26.	High fertilizer prices decrease profitability	-0.80
27.	Profitability stimulates investment	0.90
28.	Low interest rates stimulate investment	0.95
29.	Intervention reduces interest rates for farmers' loans	0.50
30.	Increase in the number of adopters reduces aggegation among adopters	-1.00
31.	Increase in the number of adopters reduces costs of adoption of zero-till	-0.90
32.	Intervention supports the use of mass media promotion of innovations	0.70
33.	Increase in the number of adopters leads to decrease in lack of familiarity of zero-till among farmers	-0.75
34.	Aggregation among adopters maintains a lack of familiarity of zer-till among adopters	0.80

Table 3 (cont'd.)

35.	Mass media promotion reduces lack of familiarity of zer-till among adopters	-0.60
36.	Increase in the number of adopters reduces belief in the need for tillage	-0.75
37.	Aggregation among adopters maintains a belief in the need for tillage	0.80
38.	Lack of familiarity with zero-tillage maintains a belief in the need for tillage	0.95
39.	Aggregation among adopters leads to maintenance of a risk averse attitude to adoption of zero-tillage	0.80
40.	Lack of familiarity with zero-tillage leads to maintenance of a risk averse attitude to adoption of zero-tillage	0.90

Figure Legends.

Figure 1. Predicted adoption curves (a) and corresponding rates of adoption (b) over time for the adoption of zero-tillage in wheat in the northern Indian rice-wheat system. The dynamics of adoption are described by a modified logistic curve which accounts for non-homogenous mixing of adopters and non-adopters.

Figure 2. The behaviour of the predicted level of aggregation in the adopting population over time, for different assumptions about the observed level of aggregation at a single time point early in the adoption process.

Figure 3. A simple example of capturing expert opinion in a fuzzy cognitive map (FCM). (a) Causal statements linking concepts (boxes) are shown as arrows. The direction of causation is indicated by the shape of arrowhead (►, increase), (♦, decrease) and by, respectively, + and – signs. (b) The projected dynamics of the FCM shown in (a) as a Markov process after translation of the FCM into a projection matrix. Shaded squares indicate presence of the corresponding state in the time step of the projection, open squares indicate absence of the concept in a time step. The sequence is initiated by high potato prices, but no other active concepts.

Figure 4. A fuzzy cognitive map of the rice-wheat system in northern India with particular attention to concepts which might affect the rate of adoption of zero-tillage. The identities of the concepts are given in Table 2, together with their initial values. Causal statements are indicated by the arrows joining concepts as either (►) increase, or (♦)decrease and are listed in Table 3.

Figure 5. The projected behaviour of the rate parameter, *r*, in the fuzzy cognitive map shown in Figure 2 under different assumptions about the initial level of aggregation among adopters and the presence of government intervention in the economics of the cropping system.

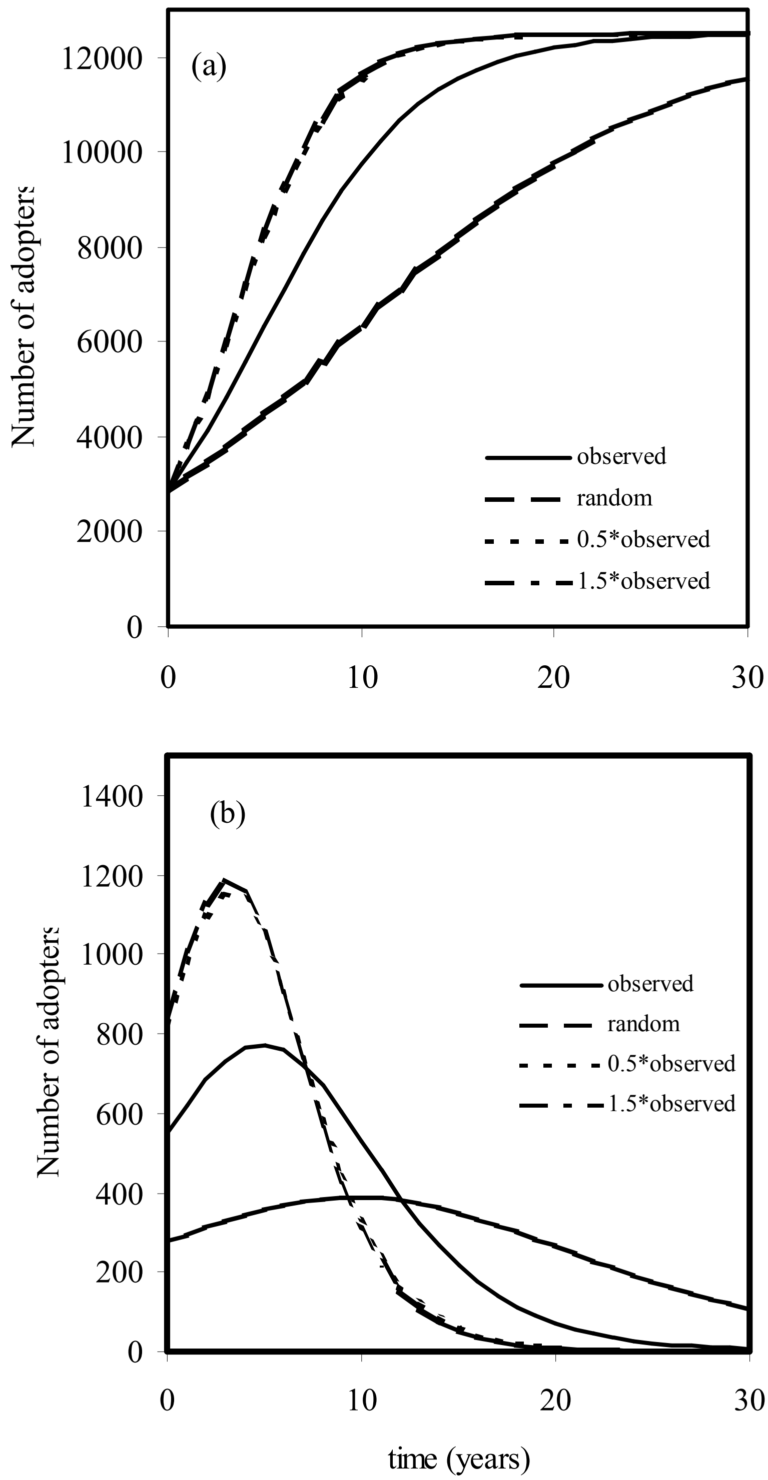

(a)
Number of adopters
observed
random
0.5*observed
1.5*observed
0
2000
4000
6000
8000
10000
12000
0
10
20
30
(b)
Number of adopters
observed
random
0.5*observed
1.5*observed
0
200
400
600
800
1000
1200
1400
0
10
20
30
time (years)

Fig 1

Fig 2

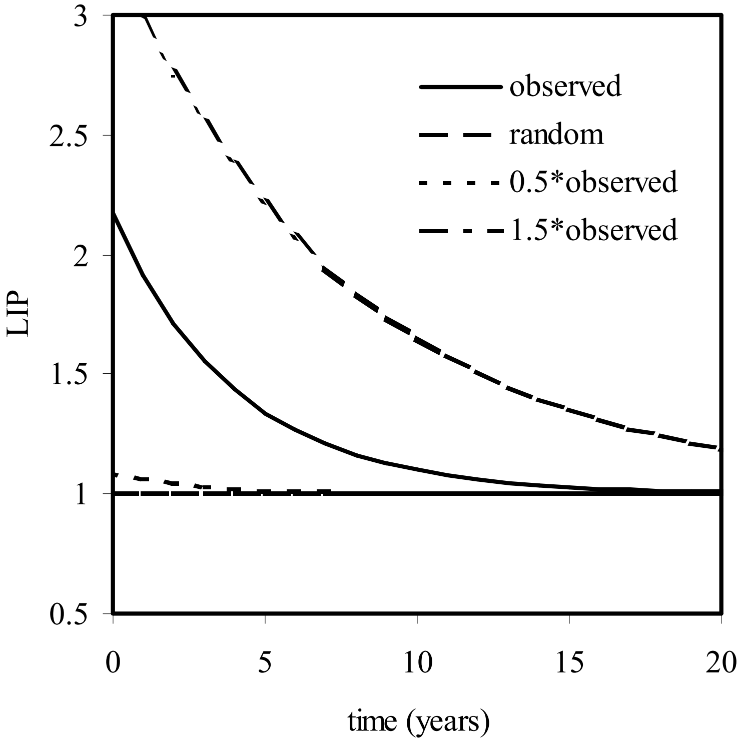
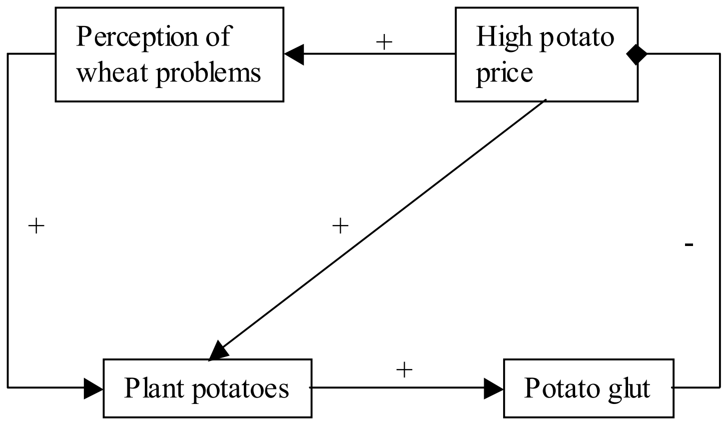
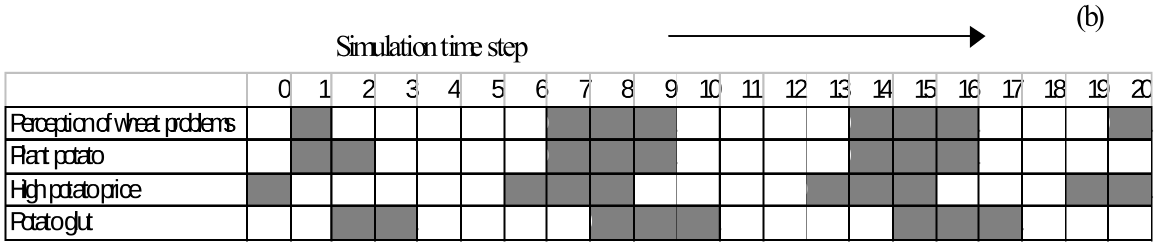

observed
random
0.5*observed
1.5*observed
LIP
3
2.5
2
1.5
1
0.5
0
5
10
15
20
time (years)

Fig 3

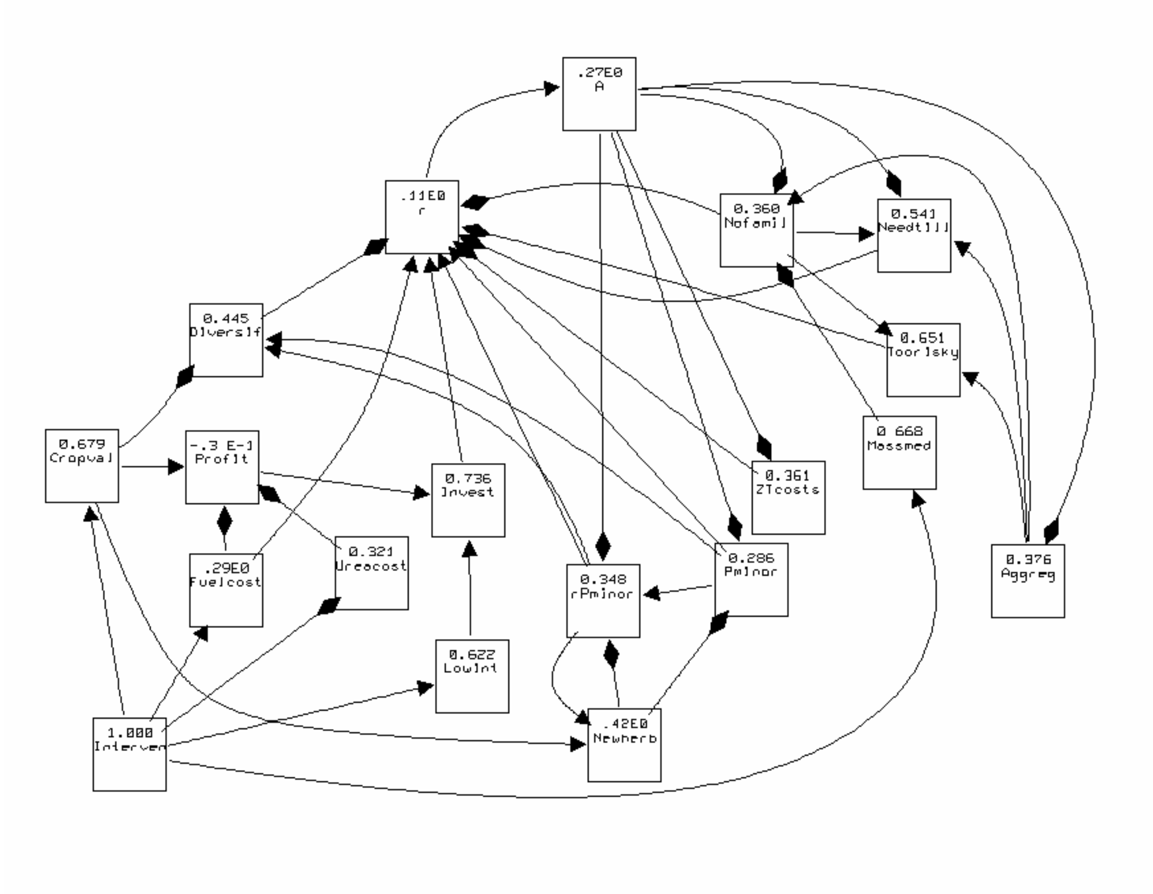

Perception of wheat problems
High potato price
Plant potatoes
Potato glut
+
+
+
+
-

(a)


Simulation time step
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Perception of wheat problems
Plant potato
High potato price
Potato glut

(b)

Fig 4



.27E0
A
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r
0.360
Nofamil
0.541
Needtill
0.445
Diversif
0.651
Toorisky
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Cropval
-.3 E-1
Profit
0.736
Invest
0 668
Massmed
0.361
ZTcosts
.29E0
Fuelcost
0.321
Ureacost
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rPminor
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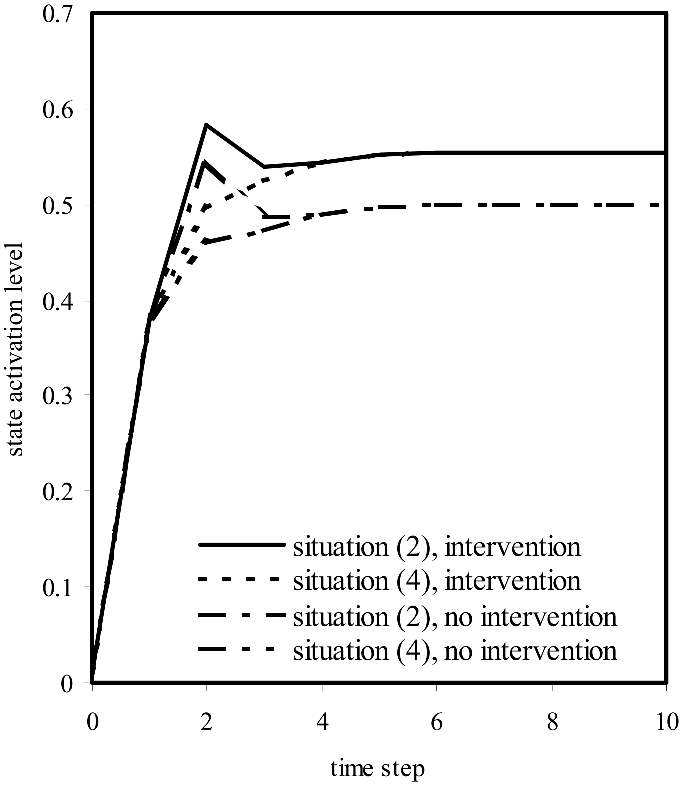
Pminor
0.376
Aggreg
0.622
LowInt
.42E0
Newherb
1.000
Interven

Fig 5


0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
state activation level
0
2
4
6
8
10
time step
situation (2), intervention
situation (4), intervention
situation (2), no intervention
situation (4), no intervention