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COMPARING ENVIRONMENTAL IMPACT OF ALTERNATIVE CAP SCENARIOS ESTIMATED THROUGH AN ARTIFICIAL NEURAL NETWORK

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Comparing Environmental Impact of Alternative CAP Scenarios Estimated Through an Artificial Neural Network

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Abstract

The paper aims to assess environmental impact produced by alternative Common Agricultural Policy (CAP) scenarios in the Italian Marche region for the period 2000-2002. Scenarios concern alternative hypotheses about direct payments for arable crops related to Agenda 2000. For this aim, a Multilayer Feedforward Neural Network model (MFNN) was applied. Different from traditional models, MFNN is able to analyze complex patterns quickly and with a high degree of accuracy. Moreover, MFNN makes assumptions about neither the underlying population nor the existence of optimising behaviour and uses the data to develop an internal representation of the complexity characterising the system analysed. The results indicate that direct payments produced positive environmental effects compared to the hypothesis of absence of direct payments. Moreover, they show that it would have been even better, from an environmental point of view, if Agenda 2000 had been more radical in comparison to the 1992 Mac Sharry reform, by introducing decoupled direct payments.

Keywords: neural networks, Common Agricultural Policy, direct payments, environmental impact

J.E.L. Classification: C45, Q18, Q21

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Contents

1 Introduction

Agenda 2000 is a European agricultural policy reform introduced in 1999. It is an action programme whose objectives are to strengthen Community policies and to give the European Union a new financial framework for the period 2000-06 with a view to enlargement (European Commission, 1999). It covers four main, closely related areas: the reform of the common agricultural policy, structural policy reform, the pre-accession instruments and the new financial framework.

The main objective of the agricultural reform was to continue the reform process along the lines of the changes made in 1992. More specifically, the aims are: improving the European competitiveness on markets, taking great account of environmental considerations, ensuring fair income for farmers, simplifying legislation and decentralising the application of legislation, improving food safety, strengthening the Union's position in the new round of WTO negotiations and stabilising agricultural spending.

These objectives are pursued by two measures: modification of the common organisations of the markets in wine, arable crops (grains and oilseeds), beef and veal and milk and, secondly, introduction of measures of more horizontal nature (cross-compliance by which direct aids are bounded to the respect of environmental requirements and decentralized finance administration in favour of Member States).

In particular, to improve price competitiveness, Agenda 2000 introduced reductions in market support prices for arable crops, dairy from 2005 and beef. In order to allow farmers to adapt to the new pricing environment, the reduction in institutional prices was introduced gradually. Moreover, direct aid payments were introduced to partially offset the loss of income caused by the reduction in the market support prices, ensuring, at the same time, a fair standard of living for farmers.

The problem associated to direct payments is that their nature of payments coupled to production could cause that farmers are stimulated to increase production of capital-intensive crops in order to obtain additional aids (OECD, 2005, p. 9). This means that farmers are pushed to raise the level of soil exploitation through a massive recourse to mechanization and chemicals. The obvious consequence is an excessive environmental pressure, which originates well-known undesired effects (such as air and water pollution, decrease in soil fertility and landslide). However, the incentive of coupled direct payments to increase production might be attenuated by both cross-compliance and a reduction in support prices, which lowered the profitability of those commodities whose institutional prices have been modified downwards.

The aim of this paper is to estimate environmental impact produced by alternative Common Agricultural Policy (CAP) scenarios for the period 2000-2002. Impact is measured as a change in the extent of intensification (or extensification) of agricultural practices. Scenarios concern alternative hypotheses about direct payments for arable crops related to Agenda 2000. The area under study is the Italian Marche region. This is one of 20 regions in Italy. It is located in the Central-Eastern part and has a geographic area of 9,692 km^2, equivalent to 3.2% of the national territory. The Marche region is a good laboratory for analysing the CAP effects related to arable crops since the latter are widespread in the region. To have an idea about the importance of these crops, one can note that in 2000 the Usable Agricultural Area (UAA) cultivated with cereals and industrial crops (such as soja, rape and sunflower) was equivalent to about 55% of the entire UAA of the Marche region against 33% at a national level (ISTAT, 2005).

In order to estimate environmental impact, a Neural Network model is applied. This model can be included in the category of quantitative tools aimed at evaluating agents' behaviour and their response to external changes. This approach is often employed in economic applications for empirical analysis, both for classifying and forecasting (Kohzadi *et al.*, 1995; Herbrich *et al.*, 2000). However, its application for evaluating agricultural policy impacts is not widespread yet (Nuppenau and Thiele, 1997). Recently, it was used in Prosperi (2003) to estimate the impact on productive choices of a sample of farms of the Marche region produced by the regime of compensations for arable crops related to the Mac Sharry Reform. The study, which employed a Multilayer Feedforward Neural Network, concludes that the 1992 Reform favoured an extensification of agricultural practices and thus it produced positive environmental effects in the Marche region since it led to a reduction in the density of livestock and in the use of chemicals. However, it had marginal effects on the use of fuel and this was justified with the fact that fuel consumption, which is linked to the level of mechanization, depends on medium-long term choices.

The paper is organised as follows. In the second section, the methodology employed and its theoretical framework are discussed. The third section shows the main results produced by the application of the model. Finally, the last section summarises the results obtained and offers some reflection cues.

2 Methodology and Theoretical Framework

The methodology adopted is based on a Multilayer Feedforward Neural Network model, which is part of the family of Artificial Neural Networks (ANNs).

ANNs have several advantages compared to traditional methods of analysis. First, they have the ability to analyze complex patterns quickly and with a high degree of accuracy. Second, they make no assumptions about the nature of the distribution of the data. They are not, therefore, biased in their analysis. Rather than making assumptions about the underlying population, ANNs, with at least one middle layer, use the data to develop an internal representation of the relationship between the variables. Third, they perform well with missing or incomplete data. Whereas traditional regression analysis is not adaptive, indiscriminately processing older data together with new data, ANNs are able to readjust their weights as new input data becomes available (Krishnaswamy, *et al.* 2000). But much more important is that ANNs can be used to represent the complexity characterising social, economic and financial systems.

Indeed, ANNs can be framed within the theory of complex economic systems, which is applied by modelling artificial agents (Beltratti *et al.*, 1996; Esposti and Sotte, 2000).[1] This theory states that the economic system takes a dynamic and complex configuration, which is characterised by continuous and changing interaction among economic agents who, singularly or jointly, act in a given environment and in an unpredictable manner.

The agents are supposed to be unable to have full and perfect knowledge. Therefore, they tend to have behaviours inspired by limited rationality and based on imitation and self-learning rather than utility or profit maximization. Their actions are a result of a process of learning by doing, where experience is being acquired by trial and error. Behaviour often follows regular patterns inspired by a given routine, which comes from widespread knowledge shared by most agents who act in a given social and economic context. Since searching for information as well as modifying existing behaviour models require significant efforts and are risky, agents will tend to follow the routine until they face constraints or shocks and are thus forced to change their behaviour model (Dosi *et al.*, 1996).

Starting from the consideration that it is not feasible to represent this situation through a traditional theoretical model, completely, the scholars of behaviour suggest analysing complex systems through learning models, like ANNs, based on direct observation of an enormous number of experiences. From the analysis of this great volume of information, a learning model tries to identify some common patterns, which highlight the possible existence of a routine about the way the agents behave generally. The model, once it has been calibrated and tested adequately, can be employed successively to carry out simulations and to verify how a given system reacts in face of possible perturbations.

The context in which farmers operate can be effectively assimilated to a complex system and, therefore, it is a candidate to being studied by learning models. This system can be simplistically represented by three ambits which interact to each

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[1] However, like any statistical tool, there are some disadvantages related to the use of ANNs. For example, a first drawback is that there is no structured methodology available for choosing, developing, training, and verifying an ANN. Therefore, the results can be strongly affected by the characteristics of the ANN used. Second, ANNs are "black boxes" since it is very hard to give meaning to relationships in the hidden layers. Third, they are data-dependent, so the algorithms are only as good as the data shown to them (Meade, 1995). Forth, they can have long training times. Finally, they may fit a curve to some data even when there is no relationship. In other terms, they tend to under- or over- fit data (Krishnaswamy, *et al.* 2000), although there are several technical solutions to prevent from this problem occurring.

other and affect the behaviour of farmers (Prosperi, 2003). They are the operative context, public institutions and firm strategy. The *operative context* refers to operative conditions which cannot be modified by the farmer, at least in the short-term. These are natural features of the farm (i.e. localisation) and structural characteristics such as labour availability. *Public institutions* are responsible for policy and its implementation at a local level. Moreover, they interact directly with farmers by providing subsidies and imposing constraints. Finally, *firm strategy* concern short and long term planning decisions taken by the farmer, regarding for example land distribution and investments.

The next sub-sections are dedicated to illustrate the ANN, the data used and the structure of the ANN employed in this research.

2.1 Artificial Neural Network

An ANN is an information processing paradigm, which is inspired by the way a biological nervous system, like the brain, elaborates information. The key element of this paradigm is the novel structure of the information processing system. An ANN consists of a set of processing system, also known as neurons or nodes, which are highly interconnected with each other.

There are several kinds of ANNs. In this research, a multi-layer feed-forward ANN is employed. This architecture, which is the most used, is composed of three different types of layers each one constituted of several nodes: one *input layer*, whose function is just to load input data, one or more *hidden layers*, which represent the core of the architecture and one *output layer* (Fig. 1). All data propagate along the connections in the direction from the input layer to the output layer, hence the term "feed-forward".

The behaviour of an ANN is affected by the weights of the connections and on the type of the connections or rather the input-output function (transfer function) which links the neurones. This concept can be described as a directed graph in which each node j performs a transfer function f_j of the form:

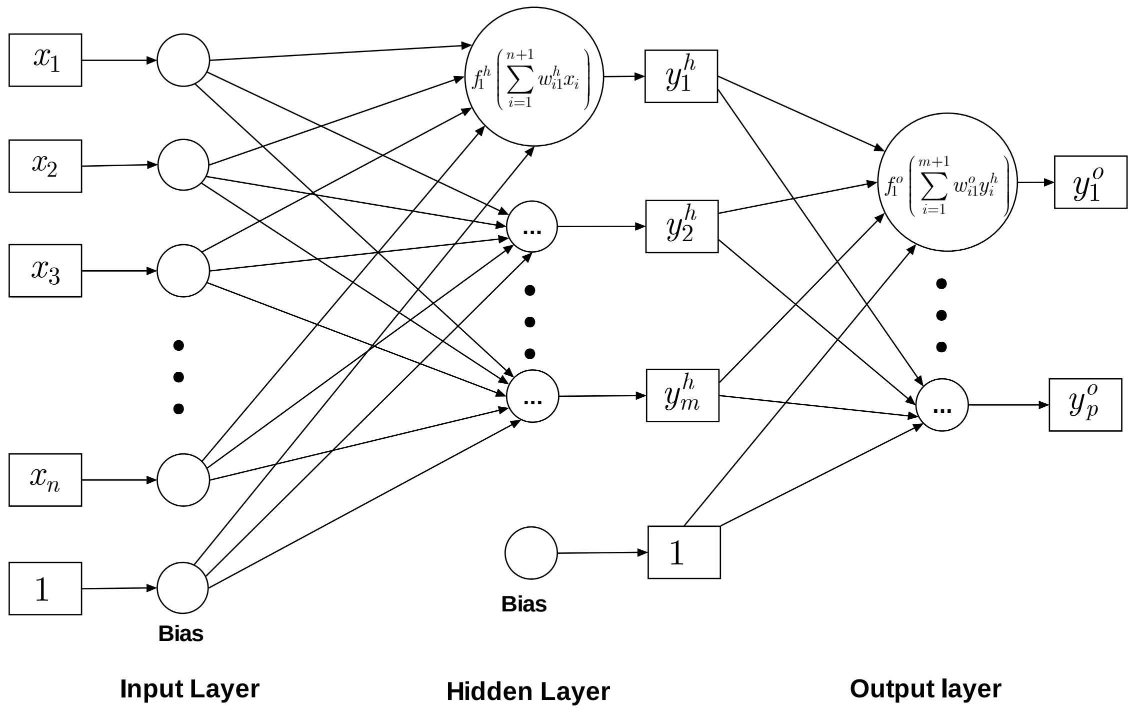
$$y_j = f_j\left(\sum_{i=1}^{n} w_{ij}x_i\right) \tag{1}$$

where y_j is the output of the node j, x_i is the i-th input to the node j, and w_{ij} is the connection weight between nodes i and j. The most used function is the sigmoid function which takes the form:

$$f_j = \frac{1}{\left(1 + e^{-X_j}\right)} \tag{2}$$

where $X_j = \sum_{i=1}^{n} w_{ij} x_i$. The sigmoid function is centred on zero but in many applications, it is preferable that the centre of every neurone is personalised by the neurone itself in order to guarantee bigger calculation flexibility. This can be obtained by adding a threshold (or bias) to X_j as follows: $X_j = \sum_{i=1}^{n} w_{ij} x_i - \theta_j$. To personalise the threshold (the point on which the sigmoid function is centred), it is needed that the threshold is learnt (i.e. it modifies itself during the learning process) like the connections weights between the neurones of the diverse layers. To do that, by a little trick, it is possible to consider this threshold as an additional input fixed at unity, which is connected to the input neurone through a weight to be learnt. So, the sum of the inputs related to the unit j becomes: $X_j = \sum_{i=1}^{n+1} w_{ij} x_i$.

Figure 1: Three-layer artificial neural network with bias neurones



Note: circles identify neurones whereas squares identify input and output data

An ANN is configured for a specific application, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist among the neurones. This is what happens with ANNs as well. Every ANN possesses knowledge which is contained in the values of the connection weights. Modifying the knowledge stored in the network as a function of experience requires a learning rule for changing the values of the weights. The most used learning method, which is here used, is the supervised learning. The latter is based on an external teacher which informs each output node about what its desired response to input signals should be.

Basically, the training or learning process is made up of the following steps: (1) providing the ANN with training examples, which consist of a pattern of values for the inputs units along with the desired pattern of values for the output units (teaching inputs); (2) determining the error between the actual output of the network and the desired output; (3) changing the weights of connections until the network produces a better approximation of the desired output or rather until the error is reduced to a given threshold. The training phase of a network is actually an unconstrained nonlinear optimization problem. The objective is to search an optimal set of connection weights in such a way that the errors of the network output are minimized.

In order to train the ANN, an enhanced version with momentum of the well-known *back-propagation algorithm* is adopted (Rumelhart *et al.*, 1986). In the first phase of the algorithm, an input pattern is presented to the network. The input is then propagated forward in the net until activation reaches the output layer. This represents the so-called forward propagation phase. In the next phase, the output of the output layer is then compared with the teaching input. The objective of the algorithm is to find an optimal set of connection weights which minimise the error among the desired and estimated outputs. This is made by the so-called generalized delta-rule (Beltratti *et al.*, 1996) which updates the connection weights by applying proportional and progressive adjustments to the difference (delta) between estimated and real outputs. In particular, the error between the output and the teaching input of an output unit j is used together with the output of the source unit i to compute the necessary changes of the link w_{ij}. To compute the deltas of units for which no teaching input is available (units of hidden layers), the deltas of the following layer, which are already computed, are used as in equation (3). In this way, the errors (deltas) are propagated backward, hence this phase is called backward propagation.

Formally, the delta-rule is as follows:

$$\Delta w_{ij} = \eta \delta_j y_i$$

$$\delta_j = \begin{cases} f_j'(X_j)(t_j - y_j) & \text{if } j \text{ is an output-unit} \\ f_j'(X_j)\sum_{k=1}^{n} \delta_k w_{jk} & \text{if } j \text{ is a hidden-unit} \end{cases} \tag{3}$$

where η is a learning factor (a constant) affecting the extent of adjustments and t_j is the teaching input (desired output) of output unit j. In the enhanced version with momentum, a percentage (momentum) of the previous change in weights is added to Δw_{ij}, in order to speed the convergence and to avoid local minima.

One typical method for training a network is to subdivide the data series into three disjoint sets: *training set*, *validation set* and *test set*. The network is trained directly on the training set. Its generalisation ability is checked on the validation set and its ability to forecast is measured on the test set. The ability of generalisation of a given network measures how well the network can treat unknown inputs, i.e. inputs about which the ANN was not trained. A network that generates high forecasting error on unforeseen inputs, but low error on training inputs, is said to have overfit the training data. Overfitting happens when the network is trained until reaching a minimum in the total squared error based on the training set. An overfit network has poor generalisation ability. In order to avoid this problem, one possible solution is to stop the training procedure once the total squared error calculated on the validation set rather than on the training set has reached a minimum.[2]

2.2 Structure of the Artificial Neural Network and Data Used

The ANN employed in this research is a Multilayer Feedforward Neural Network composed of three layers: input layer, hidden layer and output layer.[3]

The input layer is formed of 9 neurones which can be regrouped into the following categories: trend, natural characteristics, labour, land, capital and policy factors.

Trend is the year to which data refer. Three years are considered: 2000, 2001 and 2002. Natural characteristics only concern altitude (in meters above the sea level). Labour is represented by the number of total worked hours independently of the kind of labour. Land is composed of the following inputs: total UAA, UAA dedicated to cereals and UAA devoted to industrial crops. Capital is represented by total horsepower of available machines. Finally, policy factors are subsidies to cereals and subsidies to industrial crops.

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[2] In the Appendix, the enhanced version of the "vanilla" back-propagation algorithm, which includes momentum, is illustrated. The peculiarities of the algorithm developed by the Author are threefold. First, it is studied to be applied to more hidden layers. Second, it incorporates steps to check the total squared error on the validation set in order to avoid overfitting. Third, it is written in such a way that it is possible to implement it in any computer programming language with little effort.

[3] Indeed, rigid rules about the number of hidden layers to be used do not exist. It was proved that as the number of layers increases, stability and robustness of the architecture improve, but there is a bigger tendency towards memorising data and an increasing loss of generalisation and approximation. Therefore, since even simple structures constituted of only one hidden layer have demonstrated to reach a discrete degree of generalisation (White *et al.*, 1992), a group of three layers (one input layer, one hidden layer and one output layer) can be considered satisfactory.

The hidden layer is arbitrary composed of 9 units, the same number as the input layer.[4] For current purposes, this unobservable hidden layer is assumed to define organisational functioning of farmers.

Output layer is constituted of 2 neurones which are: purchase expenses related to fertilisers (CF) and pesticides (CP).

All variables were expressed per hectare of UAA.

Therefore, by the ANN, we attempted to estimate a complex non-linear function, which links the use of chemicals to a series of factors which are supposed to affect farmers' strategies. It has to be noted that no assumptions about the underlying relationships are made as well as no hypotheses about the existence of an optimising behaviour are introduced. The function related to output neurone p can be expressed as:

$$y_p^o = f_p^o\left[\sum_{j=1}^{m} w_{jp}^o f_j^h\left(\sum_{i=1}^{n} w_{ij}^h x_i + w_{n+1,j}^h \cdot 1\right) + w_{m+1,p}^o \cdot 1\right] + \varepsilon \tag{4}$$

where o refers to the output layer, h indicates the hidden layer, m is the number of hidden neurones and n in the number of input neurones.

The data used for the construction of the ANN come from the Italian FADN (Farm Accountancy Data Network) with reference to a constant group of 438 farms which operate in the Marche region for the period 2000-2002. The total number of observations amounts thus to 1,314.

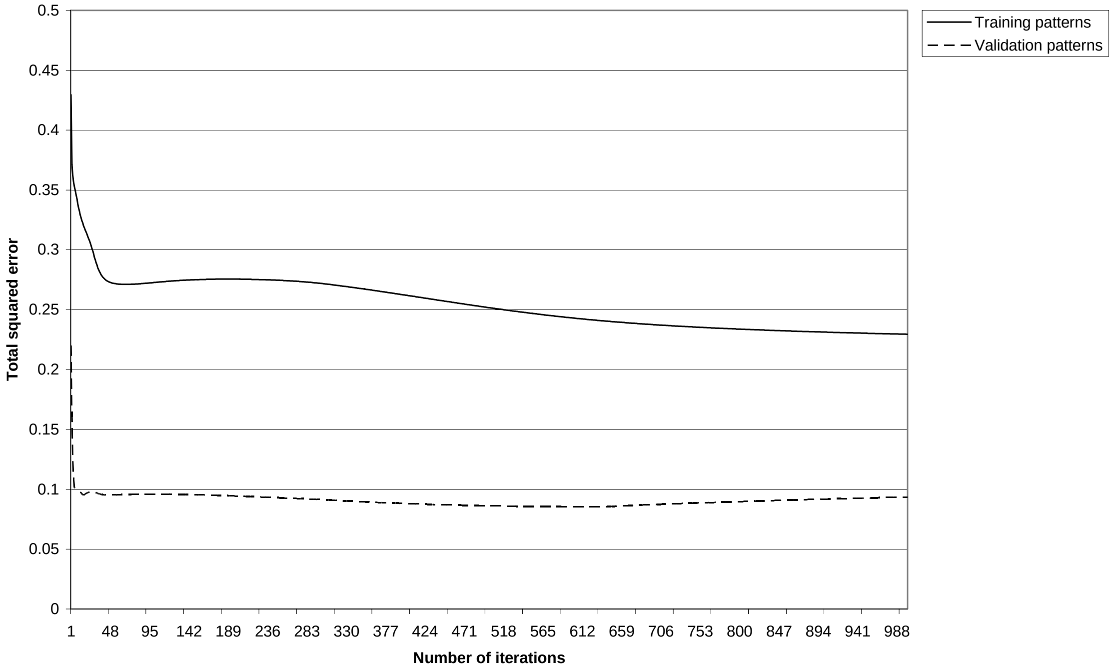
The time-series was subdivided into 3 groups: training set, validation set and test set. The former is constituted of 999 observations (i.e. 333 farms observed over a period of 3 years). The second one is composed of 201 observations. The test set is constituted of the remaining 111 observations. Before feeding the ANN, input and output data were normalised to take values between 0 and 1.

During the training of the net, the total squared error on validation pattern (see Figure 2) never went down under a certain threshold. Therefore it was decided to stop the procedure as 1,000 iterations were made. At the end of training, the validation error was less than 0.1 and was even lower than training error. This assures a good capability of generalization. To evaluate the ability of the ANN to forecast on the test set, we measured both the correlation coefficient and the determination coefficient using, for every output variable, the observed output as dependent variable and the estimated output as independent variable. It results that the correlation coefficient was 0.83 and 0.77 about CF and CP, respectively.

[4] Different numbers of hidden neurones were tested. However, a number of 9 hidden neurones proved to produce better results.

The determination coefficient was, instead, 0.69 and 0.60. The results indicate that the ANN is sufficiently good at making simulations.

Figure 2: Trend of Total Squared Error for training and validation patterns



Source: Author's elaboration

3 Empirical results

Three policy scenarios were compared: baseline scenario, decoupled-direct-payments-based scenario (scenario 1) and null-direct-payments-based scenario (scenario 2). Baseline scenario is the situation as it was in the period considered. Scenario 1 is based on the hypothesis that direct payments are decoupled to production. More specifically, this scenario supposes that farms received in the period analysed a three-year average sum of the actually received direct payments, similarly to that which happened with the introduction of single payment scheme starting from 2004 according to the 2003 Fishler reform.[5] Finally, scenario 2 is a radical situation which assumes absence of direct payments.

To estimate impact generated by alternative scenarios, the ANN was run on the entire sample available by changing the input parameters related to policy (direct payments for cereals and industrial crops). In scenario 1, direct payments for each

[5] Council Regulation (EC) No 1782/2003 of 29 September 2003.

year were fixed to the average of direct payments received in the three years considered. In scenario 2, direct payments were instead zeroed.[6]

The results are shown in Table 1, Figures 3 and 4. In Table 1, results are provided both as a total and regrouping farms according to their localization (flat, hill, mountain) and size (small, medium and large).[7] Results related to the baseline scenario are observed values calculated from the database. On the contrary, the results associated to alternative scenarios are expressed in terms of percentage difference between outputs estimated by running the ANN on observed inputs and those estimated by executing the ANN on inputs associated to every scenario.

Analysing baseline scenario, it results that the farms localised in flatter territories tend to adopt more intensive agricultural practices. This is an expected result which depends on the morphological characteristics of flatter soils, which are well suited to mechanization and to an intensive use of chemicals. Moreover, it turns out that medium and large farms are those which make more use of chemicals.

Results produced by the application of scenario 1 indicate that decoupling direct payments leads to an average reduction in the use of fertilizers by 2.0% and in the consumption of pesticides by 7.4%. Therefore, the results show that unlinking direct payments to production brings about a decrease in the degree of soil exploitation. This can be related to the fact that receiving income independently of the produced quantity of commodities removes the stimulus to increase production in order to receive additional income.

[6] According to the Lucas' critique (Lucas, 1976), given the presence of mutual interactions between the behaviour of private operators and policy makers, the former could change following public intervention or expectations of public intervention. In other terms, public choices could affect the reactivity of privates or rather they could change the parameters of the functional form of private behaviours which, in the model adopted, correspond to the weights of the connections between neurons. This is that which could happen considering alternative scenarios since the ANN was trained only with reference to the baseline scenario. However, we feel that the risk that the interrelationship among private and public operators affects results significantly is absent or negligible. This is because the ANN was trained keeping a sufficiently good capability of generalization, which implies that it is able to respond to unforeseen changes with relative accuracy.

[7] On the basis of ISTAT definition, for Italian central regions (the Marche region is one of them), flat corresponds to an altitude which is equal or lower than 300 metres above the sea level. Hill refers to an altitude which is included in the interval 300-700 metres above the sea level. Finally, mountain corresponds to an altitude which is bigger than 700 metres above the sea level. With reference to the size, the following discriminating criterion was adopted: small farms are those with UUA which is lower than 20 ha; medium farms are those with UUA which is included in the interval 20-50 ha and, finally, large farms are those with UUA which is bigger than 50 ha.

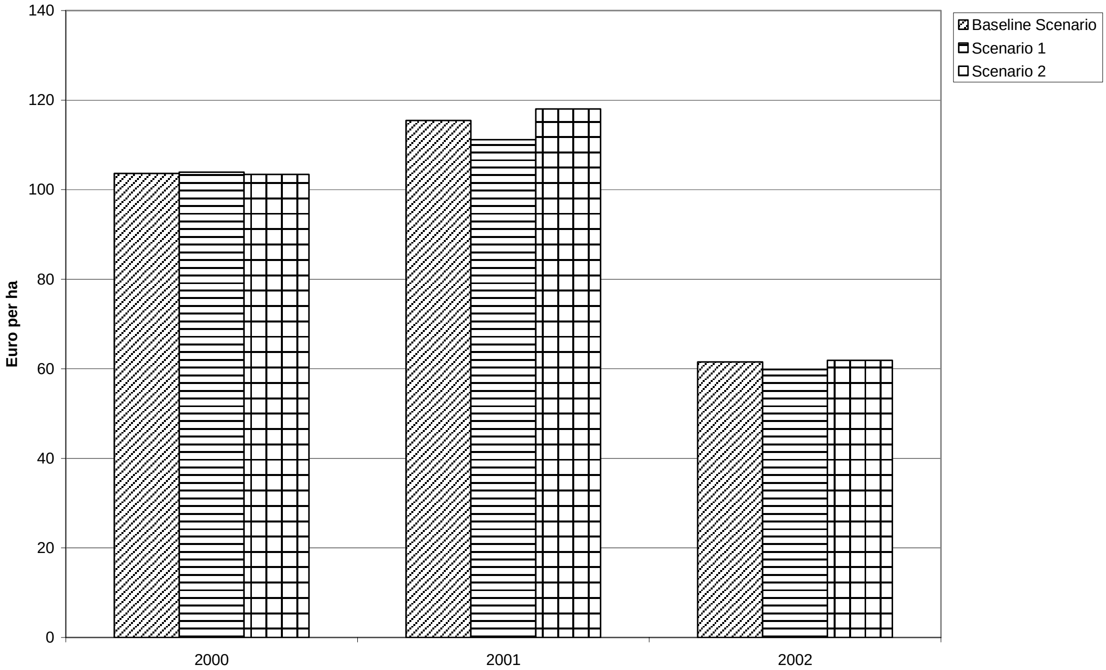
Table 1: Environmental impact produced by alternative policy scenarios related to Agenda 2000, Marche, 2000-02 (annual average values)

Variables per scenario	Localisation			Size			Total
	Flat (846)	Hill (435)	Mountain (30)	Small (764)	Medium (391)	Large (156)	(1311)
Baseline scenario							
CF (€ per ha)	103.4	79.7	15.4	35.1	210.8	85.9	93.5
CP (€ per ha)	49.2	24.6	0.7	16.3	87.1	37.4	39.9
Scenario 1 – decoupled direct payments (% difference)							
CF	-1.6	-3.1	-0.1	-1.5	-2.1	-3.1	-2.0
CP	-7.0	-8.9	0.0	-4.3	-7.5	-12.9	-7.4
Scenario 2 – null direct payments (% difference)							
CF	0.7	1.7	-0.1	0.5	1.1	1.3	1.0
CP	6.1	9.6	0.0	3.4	7.1	12.6	6.8

Legend: CF = Consumption of fertilizers; CP = Consumption of pesticides
Note: among parentheses, the number of observations is shown.

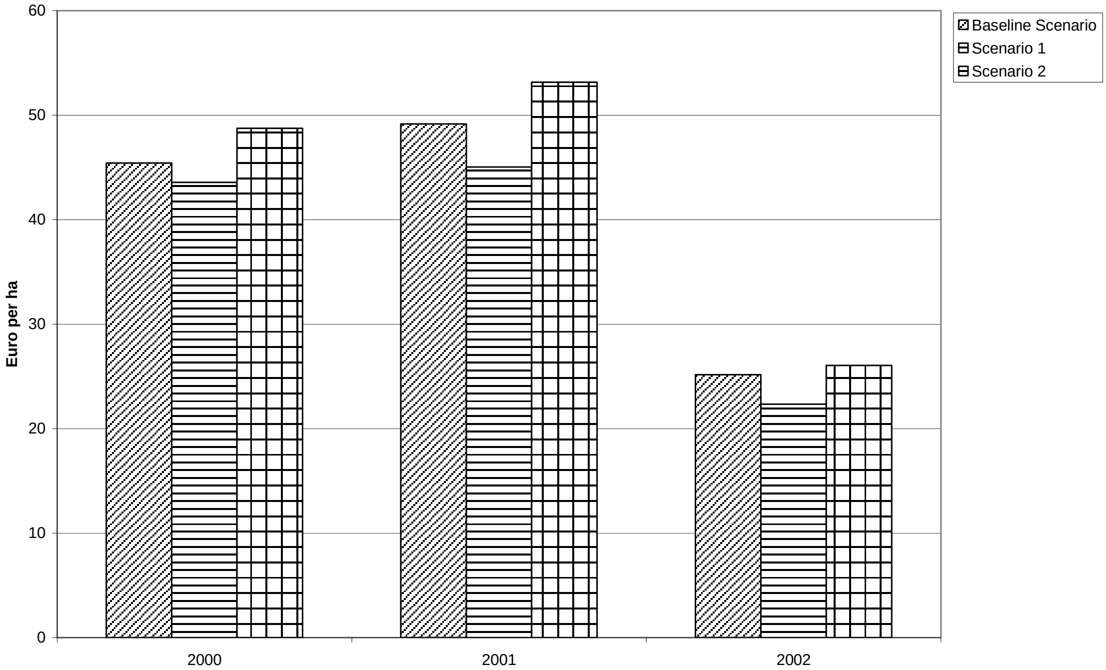
Source: Author's elaboration

Figure 3: Impact on consumption of fertilisers produced by alternative policy scenarios related to Agenda 2000, Marche



Source: Author's elaboration

Figure 4: Impact on consumption of pesticides produced by alternative policy scenarios related to Agenda 2000, Marche



Source: Author's elaboration

All farms of any size reduce the use of chemicals. However, larger farms tend to decrease exploitation to a bigger extent than the others, probably because, considering that they receive higher direct payments every year, they can afford to reduce the level of productive intensification to a larger extent.

Looking at the localisation, the effects produced by decoupling are more evident for farms located in hill and flat. This is because in these areas, crops entitled to receive direct payments are widespread and, as a result, any modification of policy regime produces larger effects. Hill farms decrease the use of chemicals to a larger extent than the flat ones and this can be due to a different crop vocation. While flat farms have a natural vocation for arable crops for morphological reasons, hill farms, which have a vocation for Mediterranean crops, have been specialised in arable crops just for economical reasons. This means that any change in policy regime produces bigger repercussions to hill farms than flat farms.

With reference to scenario 2, we note an average increase in the use of fertilisers and pesticides by 1.0% and 6.8%, respectively. Therefore, the results show that whether direct payments had not existed, farms would have increased the level of intensification of agricultural practices. The explanation could be that, in absence of supplementary income subordinated to the respect of environmental conditions, farms are pushed to increase production in order to reach or even to overcome the level of income which one would receive thanks to direct payment system.

Excluding mountain farms, the increase in the use of chemicals involves all the farms independently of the size and of the localisation. With reference to the size, larger farms are those increasing the use of chemicals to a larger extent. This increase is likely to be motivated by the need to recover the loss of income generated by the elimination of direct payments, which is surely bigger than that suffered by smaller farms. In terms of localisation, it turns out that the increase in consumption of chemicals involves only the farms located in hill and flat. In effect, mountain farms show different dynamics: their use of fertilisers slightly decreases whereas that of pesticides remains unaltered. Thus, mountain farms are not affected significantly by this change in policy. As mentioned above, the explanation can be attributed to the territorial distribution of crops entitled to receive direct payments, which privileges hill and flat zones.

Reversing the reasoning which turns out from a reading of the results associated to scenario 1 and 2, it is possible to assess environmental impact produced by direct payments in the Marche region for the period 2000-02, in comparison with alternative situations. In this way, we can argue that coupled direct payments compared to the hypothesis of decoupled direct payments brought about an average increase in the use of fertilizers and pesticides by 2.0% and 7.4%, respectively. This result can be ascribed to the incentive, provided to farmers by the coupled nature of direct payments, to increase production in order to obtain higher income. However, it can be also asserted that the system of direct payments restrained farmers from increasing levels of soil exploitation. Specifically, the use of fertilisers and the consumption of pesticides kept lower by 1.0% and 6.8%, respectively, than that which would have happened if direct payments had not existed. This is likely because, owing to cross-compliance, it was possible to receive additional income only keeping a respectful behaviour of environment.

Further results derive from an analysis of the use of chemicals over time (Figures 3 and 4). The results related to alternative scenarios were derived applying the percentage differences between results estimated by running the ANN on real inputs and estimates obtained by running the ANN on inputs associated to alternative scenarios to observed data of baseline scenario. It turns out that, in the period considered, purchase expenses of fertilisers and pesticides raised from 2000 to 2001 and then strongly decreased in 2002, reaching lower levels than in 2000. Therefore, under Agenda 2000, the extent of environmental impact induced by agricultural production decreased. In this regard, direct payments contributed to this reduction. This can be deduced by observing that their suppression (scenario 2) would have brought about bigger consumption of chemicals every year especially with reference to pesticides. However, it is also true that the decision of decoupling direct payments would have generated even better environmental effects.

4 Concluding remarks

The analysis has employed a Multilayer Feedforward Neural Network to estimate environmental effects produced in the Italian Marche region for the period 2000-02 by alternative CAP scenarios, which concern different hypotheses about direct payments for arable crops.

The results demonstrate that the system of direct payments prevented farmers from intensifying production and this can be attributed to cross-compliance. However, this result raises a question relative to the future of the CAP. Indeed, if the path undertaken by CAP reforms keeps also in the future, a progressive dismantlement of direct payment system is expected. But the absence of income support constrained to environmental conditions could push farmers to intensify production to recover the loss of income induced by the disappearance of direct payments. For this reason, if one of the policy objectives is to protect and to valorise environment, it is important that future reforms introduce adequate incentives expressly oriented to environmental protection.

A last consideration is that decoupling direct payments would have guaranteed a lower level of exploitation since there would not have been the incentive exerted by coupled direct payments to increase production in order to obtain additional income. This also induces us to conclude that the choice of the Fishler Reform to adopt a single payment scheme decoupled to production is likely to produce positive effects from an environmental point of view.

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A Appendix: Enhanced Backpropagation Algorithm for multi-layers ANNs with Overfitting control

Let consider h layers, of which layer 1 indicates input layer, layers from 2 to h-1 are hidden layers (generally only one layer) and layer h expresses output layer.

Denote with:

m^l	the number of neurones of the layer l;
y_j^l	output of neuron j of layer l (note that $y_j^1 = x_j$, which is input j or rather output of input neurone j);
$d_{z,j}$	desired output of neuron j;
$w_{ij}^{(l-1),l}$	weight of connection of neuron i of layer l-1 with neuron j of layer l;
f_j	the sigmoid transfer function of neuron j, $f_j = \dfrac{1}{\left(1+e^{-X_j}\right)}$;
X_j	the sum of inputs for neurone j as $\sum_{i=1}^{m^l+1} w_{ij}^{(l-1),l} y_i^{l-1}$;
η	a constant which expresses the learning rate affecting the extent of adjustments (typical values are 0.1..1.0; generally, 0.5 is used);
α	the momentum (learning) parameter and it results that $\alpha \in [0,1)$ (normally this value is set to 0.9);
ε	target error;
s	the number of examples in the training set;
v	the number of examples in the validation set.

The pseudo-code algorithm is as follows:

Normalising inputs and target outputs (for example between 0 and 1);
Generating random connection weights (generally between -1 and 1);
Loop epochs

{
Set epoch error to zero;
#On-line Training
For each example z $(z = 1, 2, ..., s)$

{
#Running the net on the training set (Forward phase)
For each layer l $(l = 2, ..., h)$

{

For each neuron j $(j = 1, 2, ..., m^l)$

{

calculating the relevant output of the neuron, as follows: $y^l_{z,j} = f_j\left(\sum_{i=1}^{m^{l-1}+1} w^{(l-1),l}_{ij} y^{l-1}_{z,i}\right)$

Note that $y^{l-1}_{z,i} = 1$ for $i = m^{l-1} + 1$;

}

}

#Backpropagation phase

For each layer l $\left(l = h, h-1, ..., 2\right)$

{

For each neuron j of the layer l $\left(j = 1, 2, ..., m^l\right)$

{

Calculating the derivative error as follows:

$$\begin{cases} \delta^l_j = y^l_{z,j}\left(1 - y^l_{z,j}\right)\left(y^l_{z,j} - d_{z,j}\right) & \text{if } l = h \\ \delta^l_j = y^l_{z,j}\left(1 - y^l_{z,j}\right)\sum_{k=1}^{m^{l+1}} \delta^{l+1}_k w^{l,l+1}_{jk} & \text{if } l < h \end{cases}$$

For each neuron i of the layer *l-1* $\left(i = 1, 2, ..., m^{l-1} + 1\right)$

{

Adjusting the connection weights as follows:

$\Delta w^{l-1,l}_{ij}\left(t\right) = -\eta \delta^l_j y^{l-1}_{z,i} + \alpha \Delta w^{l-1,l}_{ij}\left(t-1\right)$

where $y^{l-1}_{z,i} = 1$ when $i = m^{l-1} + 1$

$w^{l-1,l}_{ij}\left(t\right) = w^{l-1,l}_{ij}\left(t-1\right) + \Delta w^{l-1,l}_{ij}\left(t\right)$

}

}

}

}

For each example z $\left(z = 1, 2, ..., v\right)$

{

Set the validation error to zero;

#Running the net on the validation set

For each layer l $(l = 2, ..., h)$

{

For each neuron j $(j = 1, 2, ..., m^l)$

{

calculating the relevant output of the neuron, as follows: $y_{z,j}^{l} = f_j\left(\sum_{i=1}^{m^{l-1}+1} w_{ij}^{(l-1),l} y_{z,i}^{l-1}\right)$.

Note that $y_{z,i}^{l-1} = 1$ for $i = m^{l-1} + 1$

If layer is output layer $(l = h)$ then:

calculating the average squared error between the actual output and the desired output and updating the example validation error, as follows: $E = E + \frac{1}{2}\left(y_{z,j}^{l} - d_{z,j}\right)^2$

}

}

Set epoch error to validation error if this latter is bigger;

}

Repeating until the epoch error is equal or less than a given ε or epoch equals a maximum number;

}

Running the net on the test set using the weights estimated;

Calculating a fit measure estimating the gap between predicted output calculated and real output on the test set;

Modifying the structure of the net and repeating the procedure until the value of the fit measure is satisfactory.