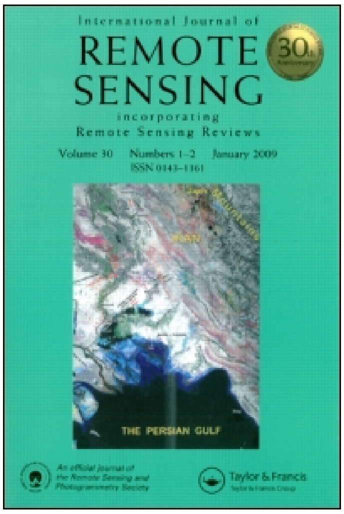

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Study of the potential of alternative crops by integration of multisource data using a neuro-fuzzy technique

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Study of the potential of alternative crops by integration of multisource data using a neuro-fuzzy technique

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This work proposes a neuro-fuzzy method for suggesting alternative crop production over a region using integrated data obtained from land-survey maps as well as satellite imagery. The methodology proposed here uses an artificial neural network (multilayer perceptron, MLP) to predict alternative crop production. For each pixel, the MLP takes vector input comprising elevation, rainfall and goodness values of different existing crops. The first two components of the aforementioned input, that is, elevation and rainfall, are determined from contour information of land-survey maps. The other components, such as goodness values of different existing crops, are based on the productivity estimates of soil determined by fuzzyfication and expert opinion (on soil) along with production quality by the Normalized Difference Vegetation Index (NDVI) obtained from satellite imagery. The methodology attempts to ensure that the suggested crop will also be a high productivity crop for that region.

1. Introduction

According to the global employment trends brief (ILO, 2007) the agricultural sector employs the second largest percentage (38.7%) of the world population, yet it only accounts for 4% (IMF, 2004) of the world's Gross Domestic Production (GDP). This is due to low agricultural productivity in many parts of the world. Hence increasing crop productivity is the primary aim of agricultural research work. Apart from enhancing productivity, increasing sustainability of the agricultural system is a prime requirement (Brady, 1994).

One of the problems of agriculture in India is that in many zones of the country crops are grown under a wide range of soil and climatic conditions that are not necessarily ideal for a particular crop (Mamoria, 1984; Ray *et al.*, 2005). Each crop requires a specific soil, climatic condition and physiography for best expression of its potential. The reasons for growing crops in environments other than the best suited ones often centre on the necessity of meeting household needs, non-availability of better alternative crops, availability of marketing infrastructure and constraints of inputs, including labour and other factors (Randhawa and Abrol, 1990). This leads to not only low productivity but also degradation of land resources.

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Thus, crop suitability analysis is a prerequisite to achieve optimum utilization of the available land resources for not only increasing productivity but also sustainable agricultural production. Information on current and previous land-cover, land-use practices, changes in land management over time and other factors have often been obtained by combining data from crop-land inventories and land-cover classification from satellite data. All this crop-related information is directed towards not only achieving the optimum yield over a region but also understanding the efficiency of agricultural practice. One such area of crop studies is alternative crop modelling, where different approaches (Biswas and Pal, 2005; Ceballos-Silva and Lopez-Blanco, 2003; Nisar Ahamed *et al.*, 2000; Panigrahy *et al.*, 2005; Sethi *et al.*, 2006) have been considered to suggest alternative crops for a region.

Generally Boolean logical approaches are followed in generating suitability information. However, the Boolean methods are designed to assign a unit area to a single class and no provision exists for assigning partial suitability to each of the appropriate suitability classes (Nisar Ahamed *et al.*, 2000). Under fuzzy logic, the soil at a given pixel (unit area) can be assigned to more than one soil class with varying degrees of class assignment (Burrough *et al.*, 1992). These degrees of class assignment are referred to as fuzzy memberships. Fuzzy logic (Zadeh, 2001) has been effectively applied as an alternative to Boolean logic, weighted linear combination, maximum limitation and other methods of suitability assessment in a number of recent applications (Burrough *et al.*, 1992; Gupta *et al.*, 2000; Nisar Ahamed *et al.*, 2000; Reynolds, 2001; Stathakis and Vasilakos, 2006; van Ranst *et al.*, 1996; Zhu *et al.*, 2001).

In recent years, Geographic Information Systems (GIS), neural networks and fuzzy logic techniques have been used in several hydrological and land-use studies (Dixon, 2005; Jiang and Eastman, 2000; Malczewski, 2006). Some work has also been reported in the literature on an expert knowledge-based fuzzy soil inference scheme (Shi *et al.*, 2004; Zhu, 1997). However, integration of remote sensing data along with soil and weather data through neural network modelling for alternative crop planning is a new concept.

In this context the study is carried out for integration of available soil, rainfall, elevation contour data and existing crop patterns along with vegetation conditions determined from remote sensing data using neuro-fuzzy techniques towards developing an alternative crop pattern plan for a rain-fed agricultural region. Although we have used land-cover classification data obtained from NATMO (National Atlas and Thematic Mapping Organization) maps, one can also use the detailed land-cover classification (Bendjebbour *et al.*, 2001; Sarkar *et al.*, 2005) as obtained from satellite data.

2. The framework

Our objective in proposing an alternative crop-pattern over a region has been carried out on the basis of information available from different independent sources. There are several sources of data:

(i) data available from land-survey maps about the geographical features of the region such as land elevation data (elevation in metres above sea level), rainfall distribution data (mm rainfall), soil type data (type of representative soil for a region as per pixel specification), existing crop pattern (type of representative crop for a region as per pixel specification), etc.;

(ii) data available from satellite imagery which are used to find out different kinds of information for a region over time, such as the NDVI (Normalized Difference Vegetation Index) distribution over a region;
(iii) knowledge about specific ideal crop production conditions obtained from experts in the agricultural field.

The region under observation is the district Bankura (bounded by latitude 22°46′ N to 23°38′ N and longitude 86°36′ E to 87°47′ E) in West Bengal, India (see figure 1).

The contour data on elevation and rainfall in land-survey maps are converted into raster data by the kriging interpolation technique, while digitized versions of soil patterns and existing crop patterns are available as raster data. The information so obtained, such as (i) interpolated elevation information, (ii) interpolated rainfall information, and (iii) crop productivity measures resulting from integration of soil

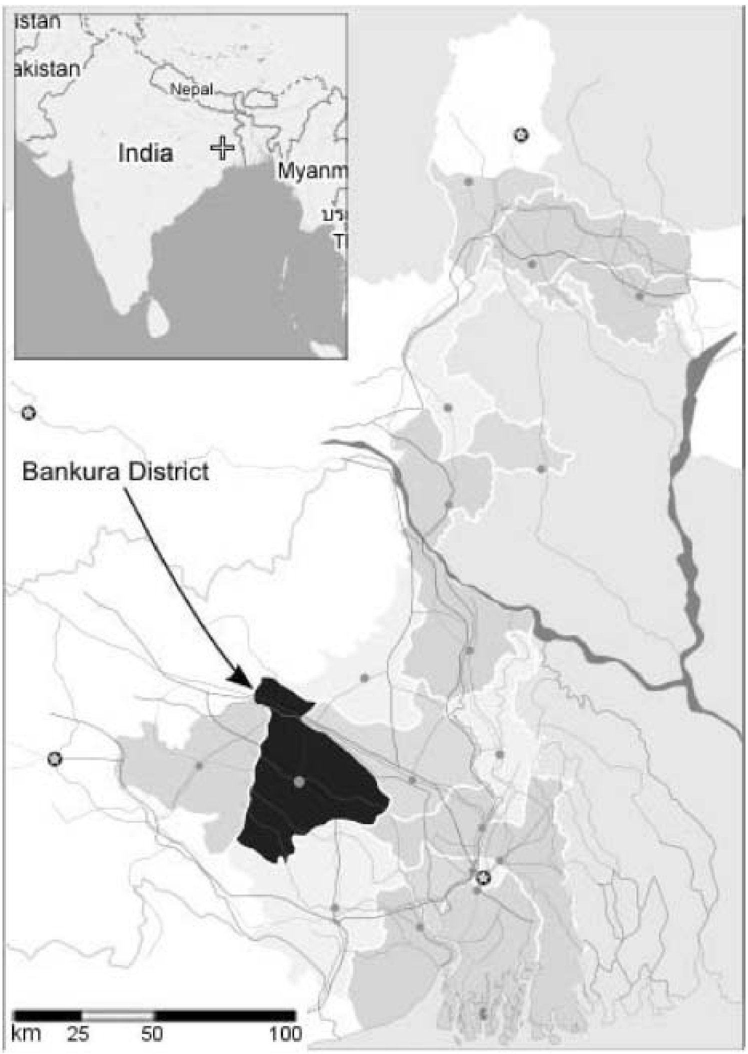


Figure 1. Location of Bankura.

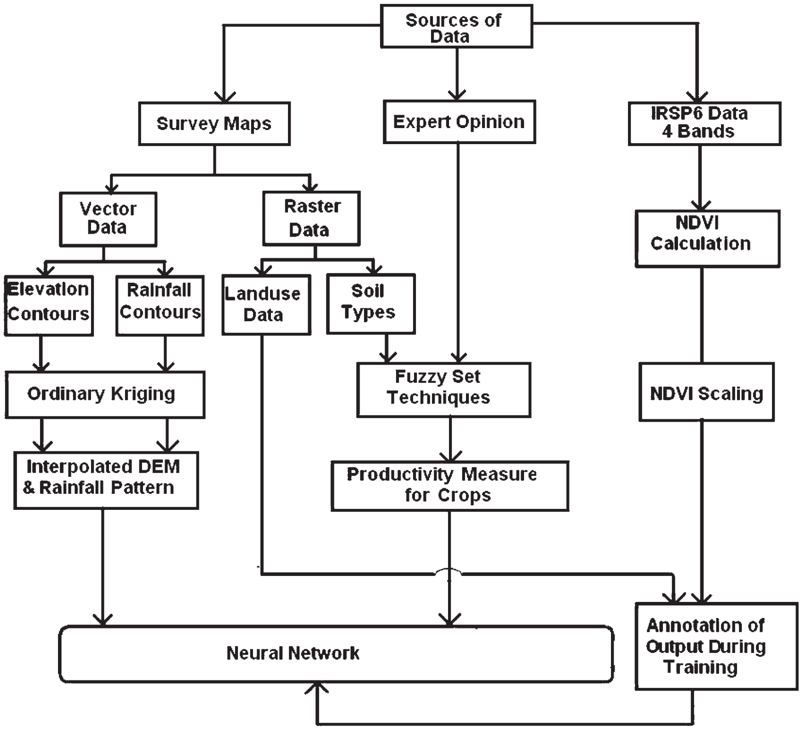


Figure 2. Schematic diagram of the methodology.

type, expert opinion and NDVI data per pixel, serve as the inputs of the neural network (see figure 2). The neural network is trained using samples of the existing crop pattern. The output of the neural network are the different crop quality (viz. healthy, medium, poor) indicators per pixel.

3. Preprocessing for the input of the neural network

As said earlier, the vector data obtained from elevation and rainfall contour maps are converted into raster form by an optimum local interpolation method; it is to be noted that the proposed methodology described in this work would also allow the use of satellite data based preconstructed DEM and rainfall distribution maps, such as Shuttle Radar Topography Mission (SRTM) elevation maps. For interpolation we had chosen the method of ordinary kriging. We justify the choice for this method of interpolation as follows.

3.1 *Ordinary kriging*

This technique has the advantage that it takes into account the local variation of the variable under consideration. A variogram, which represents the relationship between the mean square difference between sample values of the variable and their distances, is used to determine the value at the unsampled location. An experimental variogram is first found by calculating the variance of each point in the set with respect to each of the points and plotting the variances versus distance between the points. From this experimental variogram, a model variogram is obtained by smoothing the plot of points with a suitable mathematical function. This model variogram is finally used to determine the weights needed for local interpolation – see Burrough and McDonnell (1998), for details. An important feature of this technique is that the variogram can be used to calculate the expected error of estimation at each interpolation point since the estimation error is a function of the distance to surrounding scatter points.

3.2 *Utilization of soil class data by a fuzzy logic implementation*

In order to extract meaningful information from soil data, conversion of this qualitative data to quantitative form is necessary. To do so, a fuzzy-logic technique is applied involving different determining factors of crop-production. As the number of different components in soil are generally given as an interval and the role of these factors over the crop-production is mostly qualitative, fuzzy logic is chosen as a tool. The principal task is to integrate the data related to crop-production and composition of soil obtained from experts and derive a quantitative productivity measure of each crop on a particular area as raster data. The steps of the processing are detailed here.

The crops considered in the region of investigation are of five types, viz. paddy, potato, pulses, vegetables and mustard. The determining factors are taken as pH, air-content and humus-content in the soil. For each crop and for each determining factor, membership functions are constructed. All these data are normalized in the range [0, 1] and the productivity of the crops is classified as healthy, poor and absence of the crop. That information, i.e. the determining factors and the likely range of values for the corresponding membership function, are collected from the experts (see table 1 for paddy and mustard). The steps are illustrated here by the example of mustard.

Soil containing 0–25% of humus is bad for mustard. Hence the value of the membership function corresponding to humus for poor mustard is kept at 1 in the interval 0–0.25 (see figure 3*a*) and at all other places it is zero. A Gaussian curve is used for the construction of the membership function and also for all subsequent membership functions a Gaussian curve is used.

Similarly, more than 45% of humus is good for mustard. The membership functions for air-content (figure 3*b*) and pH, shown in figure 3(*c*), also follow a similar pattern. The membership values are shown in table 2.

On the basis of the weights of different factors as obtained from the expert, the rule-base is constructed. Actually here no explicit weights are used, rather the priority of different factors is found and on that basis the rule-base is formed. For mustard, pH is the most important factor. Hence good pH content will lead to

Table 1. Data obtained from experts for paddy and mustard.

Attribute	Paddy	Mustard
Humus(healthy)	>50%	>45%
Humus(poor)	<20%	<25%
pH(healthy)	6–8	6–8
pH(poor)	0–4.5	<4
pH(medium)	>9	>9
Porosity(healthy)	65–85%	75–90%
Porosity(poor)	<50%	<45%
Porosity(medium)	>90%	>95%

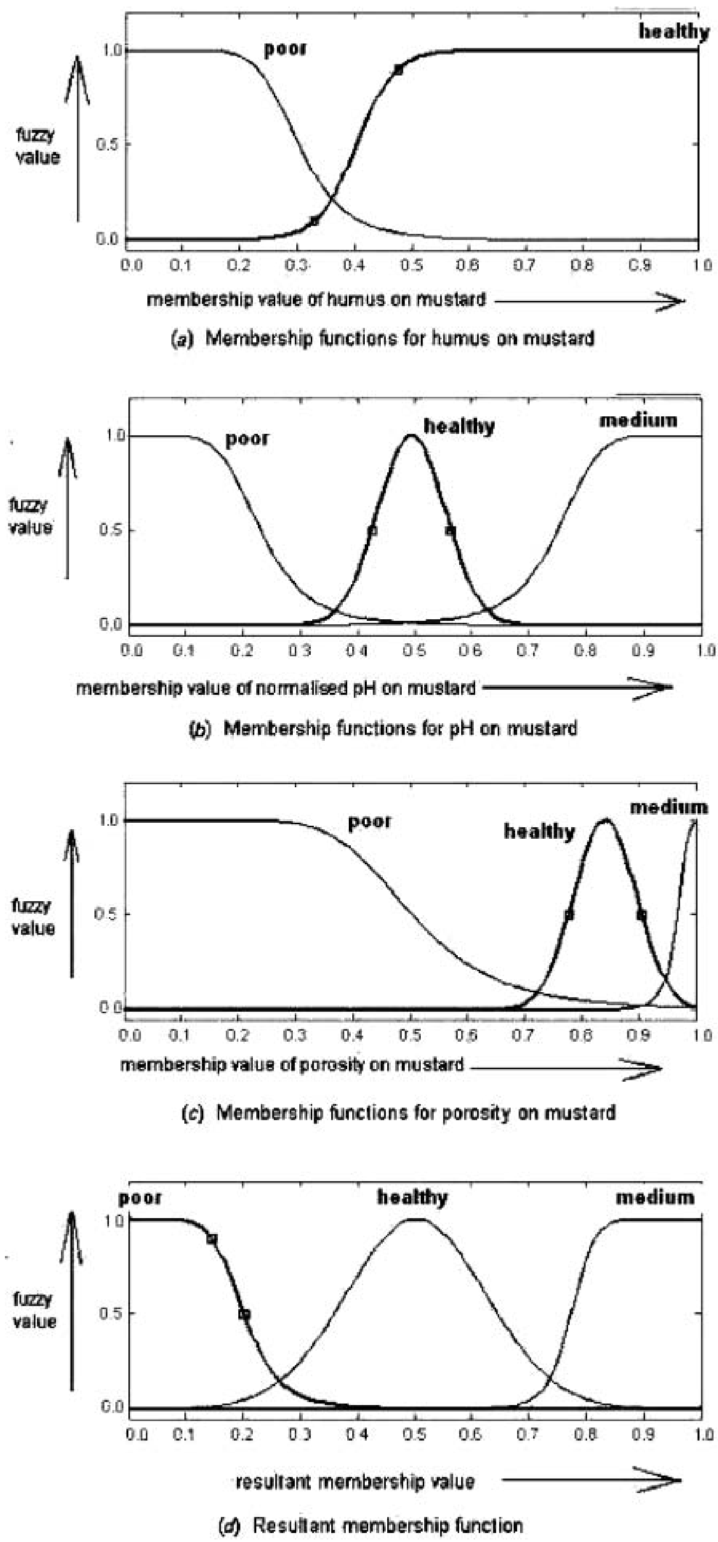


Figure 3. Membership functions for fuzzy calculation.

Table 2. Membership values of different values for Mustard.

Factors/Quality	Poor	Medium	Healthy
Humus	0.0–0.3	not defined	0.5–1.0
normalized pH	0.0–0.25	0.75–1.0	0.4–0.6
Porosity	0.0–0.6	0.9–1	0.75–0.9

Table 3. Rule-base for Mustard.

Humus	pH content	Porosity	Quality of Mustard
Healthy	Healthy	Healthy	Healthy
Healthy	Healthy	Poor	Medium
Healthy	Healthy	Medium	Medium
Healthy	Poor	Healthy	Poor
Healthy	Poor	Poor	Poor
Healthy	Poor	Medium	Poor
Healthy	Medium	Healthy	Poor
Healthy	Medium	Poor	Poor
Healthy	Medium	Medium	Poor
Poor	Healthy	Healthy	Medium
Poor	Healthy	Poor	Poor
Poor	Healthy	Medium	Poor
Poor	Poor	Healthy	Poor
Poor	Poor	Poor	Poor
Poor	Poor	Medium	Poor
Poor	Medium	Healthy	Poor
Poor	Medium	Poor	Poor
Poor	Medium	Medium	Poor

healthy mustard with a higher probability compared to other good factors. Deficiency of pH would lead to poor mustard irrespective of the goodness value of the other factors. Porosity and humus are relatively less important factors and deficiency of only one of them leads to medium quality of mustard. The whole rule base for the mustard is shown in table 3.

Subsequently the amount of different factors present in different soils is found (which is also based on expert opinion). By combining the above-mentioned data, the goodness values (productivity measure) of a particular soil for different crops are found. The method is elaborated by the example of mustard with membership values and rule base as shown in tables 2 and 3. These productivity measures are normalized between 0 and 1. The goodness values of different crops for different soils is shown in table 4. As a neural network is used for further processing, it is not

Table 4. Quantitative values with respect to productivity performance of different soils for different crops.

soil type/crop type	Paddy	Mustard	Pulses	Vegetable	Potato
Younger alluvial	0.584	0.656	0.659	0.649	0.659
Older alluvial	0.59	0.504	0.504	0.504	0.504
Red gravelly	0.238	0.432	0.433	0.435	0.433
Red sandy	0.254	0.433	0.435	0.437	0.439
Red and yellow	0.242	0.436	0.433	0.433	0.430
Lateritic	0.255	0.443	0.438	0.431	0.433

required to defuzzify the values. The fuzzified values themselves can be used directly for the neural network input.

4. Neural network

The aim here is to suggest a model of alternative crops from available data, viz. soil, rainfall, elevation and land use. As described in §3, all are suitably converted into surface data, i.e. for each point on the map, data related to these four fields are available in quantitative form. The quality of crops produced is made available from NDVI maps. By means of these the neural network is trained and subsequently is used to suggest the crops that can be produced for the entire region under study.

4.1 *Neural network construction*

The ANN (artificial neural network) model proposed here is a multilayer perceptron (MLP) with four layers: one input layer, one output layer and two hidden layers. See Haykin (1994); Rumelhart *et al.* (1986) for a discussion of the structure, functioning, and operation of ANNs.

We have a total of seven performance measures, viz. elevation, rainfall, and five performance measures for each of the crops corresponding to the encountered soil type. These are the input to that neural network. Hence the input layer of ANN has seven nodes.

Let k be the number of crops that grow in the region under consideration. The alternative crop suggested for any pixel will be one of these k crops. The input layer is configured in the following manner: two nodes for elevation and rainfall and k nodes for the performance measure of the k crops depending on soil type. The performance measures of these k crops are to be determined from a table analogous to table 4 (which exhibits these performance measures for $k=5$). For each of the k crops there are three output nodes, corresponding to healthy, medium and poor quality of crops. The number of nodes in the output layer is thus $3k$. As mentioned earlier, the region under study has five main crops, viz. paddy, potato, mustard, vegetables and pulses, so the value of k is five. Again they can be classified into three categories: healthy quality, poor quality and no production. Hence the number of nodes in the output layer is 15. The number of nodes in the two intermediate hidden layers is determined by trial and error. In our case, the final neural network constituted is 7 : 21 : 30 : 15 (see figure 4).

4.2 *Utilization of NDVI in output labelling*

The space-based remote sensing data provide a large amount of information about crop condition and growth. In optical remote sensing, the typical reflectance pattern for healthy vegetation shows high absorption due to chlorophyll at wavelength 650 nm (red region) and high reflection due to leaf internal structure at wavelength 750 nm (near-infrared, NIR region). These differential vegetation responses at different spectral regions have been used to develop various arithmetic formulae, commonly known as vegetation indices (VI). These VIs have been found to have a very good relationship with various crop-growth indicators like leaf-area index (LAI), biomass, stress, etc. (Walko *et al.*, 2000). VIs are also indirectly related to fractions of absorbed PAR (photosynthetically absorbed radiation), canopy photosynthesis, stomatal conductance, land-surface albedo and crop yield. Multitemporal vegetation index data have been found to be useful in land-cover

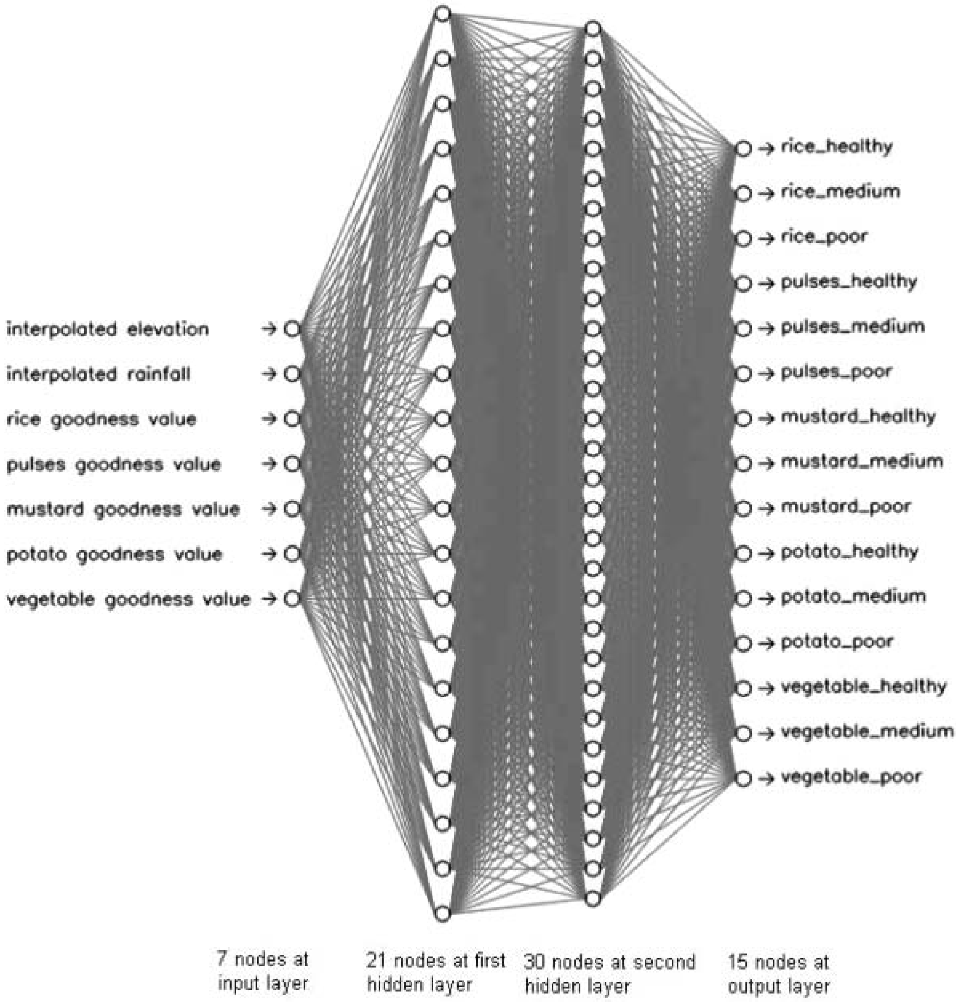


Figure 4. The neural network topology.

classification (Lambin and Ehrilch, 1995), detection and categorization of subtle forms of land-cover change (Lambin and Strahler, 1994) and analysis of vegetation dynamics (Holben, 1986).

Among the vegetation indices, the most commonly used is the NDVI developed by Rouse (1974). It has been found that crop-yields are highly correlated with NDVI around the time of maximum green leaf biomass development (Tucker *et al.*, 1980). In India district-level yield estimation models have been developed for crops like wheat, sorghum, mustard, cotton, etc. using NDVI as input (Dadhwal and Ray, 2000). Our objective here being to integrate several factors along with an index that characterizes a crop's yield as high or low, we select the NDVI as a useful index.

The satellite image available here is from AWiFS onboard the IRSP6 (Resourcesat-1) satellite. AWiFS operates in four spectral bands, viz. green (0.52–0.59 μm), red (0.62–0.68 μm), near-infrared (0.77–0.86 μm) and short wave infrared (1.55–1.70 μm); with 56 m spatial resolution, 10-bit radiometric resolution and five days revisit period, the AWiFS provides huge capability for agricultural applications. AWiFS data of 14

February 2005 have been used which corresponded to maximum vegetative growth of winter season crops in our study area, i.e. the Bankura district in the state of West Bengal, India.

We have assumed the following NDVI scaling scheme in this instance for determining the quality of crops during neural network training, which matched with the field observation. Since we are only proposing a methodology, other NDVI scaling schemes (as deemed appropriate for other regions) may also be used to suggest different crop conditions. In India, various studies have shown that district level yields of rice, potato and mustard were linearly related to NDVI derived from single/multidate satellite based remote sensing data and the empirical models have been developed for yield prediction (Dadhwal and Ray, 2000). This suggests a linear scaling of crop quality such as the following:

- healthy crop NDVI$>$0.35;
- medium crop 0.25$<$NDVI$\leqslant$0.35;
- poor crop NDVI$\leqslant$0.25.

4.3 *Neural network training*

We illustrate the neural network training procedure using an example pixel. For a pixel labelled 'paddy' in existing land-use data, we classify the pixel as healthy productivity paddy from the NDVI scheme 1 if $NDVI>0.35$ for that pixel. For such input the target output of the neural network will be 'one' for healthy productivity paddy output node and also for no production output nodes for the other crops. All other output nodes are set to 'zero'. Likewise the values of output nodes are set for other pixels.

The nonlinear activation function used is a logistic function. The algorithm used for ANN is the back-propagation algorithm (Rumelhart *et al.*, 1986) with momentum and adaptive learning parameters. For proper termination of the algorithm, the mean square error is used as a criterion and in this case, the mean square error obtained is of the order of 10^{-4}. A function based on the gradient descent algorithm is used for training the network. The training was done with 10% (which is 1585 pixels) of the total pixels (15 851 pixels) chosen randomly. The values of the learning rate and momentum used in the back-propagation algorithm were respectively 0.1 and 0.8.

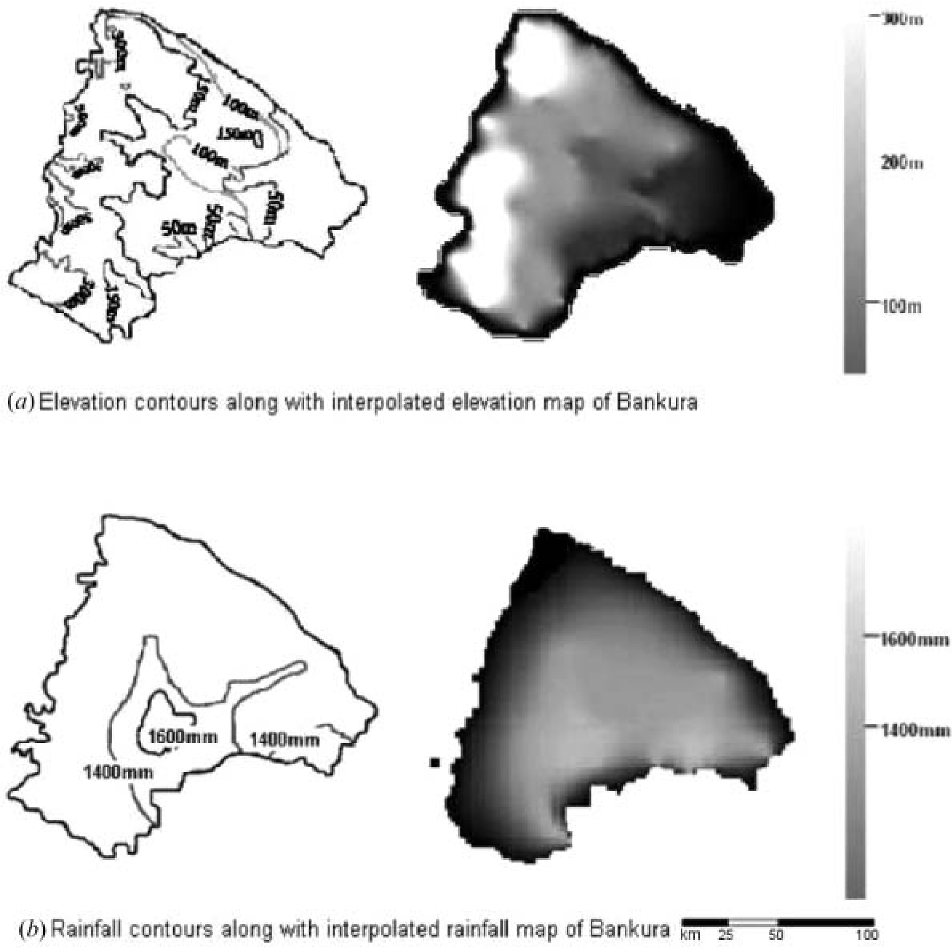
After completion of the training phase of the neural network, each pixel is tested as follows: the seven input measures are fed into the neural network and output node values are noted. The alternative crop suggested for the particular pixel will be the one whose 'healthy' output node has the highest value (excluding the already existing crop and also maintaining a certain threshold).

5. Experimental results

Our proposed alternative crop model, based on the neural network methodology, has been applied to the region under study. We first describe the findings of quantitative inputs to the neural net as obtained in the study area.

The contour data for elevation and annual rainfall, as well as their interpolated form as generated following §3, are exhibited in figure 5 which shows that the elevation extends to 300 metres and rainfall covers are as high as 1900 mm.

The second source of data is NDVI data obtained from the Advanced Wide Field Sensor (AWiFS) onboard ResourceSat-1 (also known as Indian Remote



(*a*) Elevation contours along with interpolated elevation map of Bankura

(*b*) Rainfall contours along with interpolated rainfall map of Bankura

Figure 5. Elevation and rainfall data.

Sensing Satellite-P6, IRSP6); pass date: 14 February 2005. The subscene under investigation has been isolated from a four-quadrant image by latitude and longitude information. Since the NDVI data is obtained in the winter crop season (November–February), the alternative crop pattern plan is appropriate for the winter crop season only.

Another input data source from the survey map is soil data (see figure 6). As described in §3.2 the productivity measures are determined and have been furnished in table 4. For example, in order to determine the productivity measure for mustard with respect to different categories of soil we have first drawn the membership functions corresponding to each attributes, viz. humus, pH and porosity. On the other hand, the ranges of values of different attributes for different soils have been collected from experts. For these ranges of values, using the rule-base as described in table 3, along with membership functions, these productivity measures for different soils (exhibited in table 4, column 2) are determined. We use fuzzy logic techniques for this. The elevation, rainfall raster data and productivity measures for each of the crops have been used as input to the neural network, while existing crop patterns

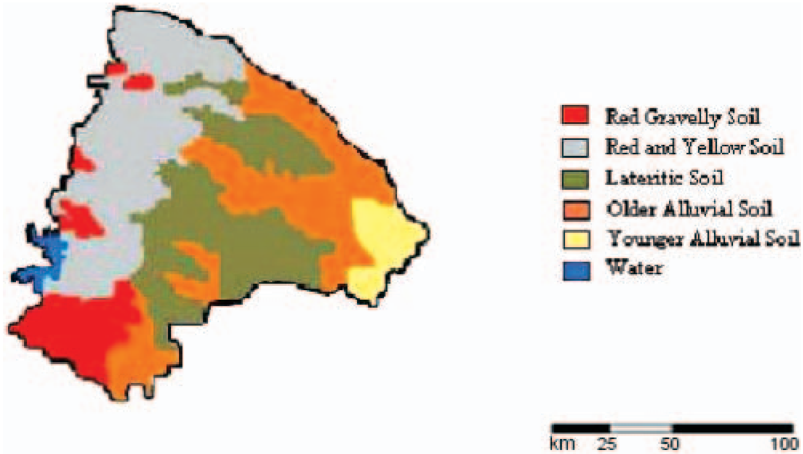


Figure 6. Soil type distribution of Bankura.

(from NATMO maps) along with the NDVI scaling scheme serve during the training of the neural network. Finally the alternative crop suggestion has been generated for each pixel and is exhibited in figure 7(*b*).

The alternative crop suggestion methodology that has been proposed does not depend entirely on expert opinion. In fact, it requires corroboration from land-use data. For instance, let us say two points A and B have the same elevation and rainfall conditions. The expert opinion claims that the conditions are best suited for paddy. However, the land-use pattern shows that mustard is the current crop at both points. In this case, the neural network will not find any paddy as output crop in the above conditions during training. Hence, paddy will not be suggested as an alternative crop. This is to account for the factors other than the ones we have considered (which might be reflected in the current land use). On the other hand, if A has paddy growing in it and B has mustard, then B will have paddy as a possible alternative crop. Thus, to put it briefly, the alternative crop that our methodology will suggest has to be supported by both expert opinion and existing land-use. This, however, means that some points will not have any alternative crop suggestions. It is important to note that alternative crops will be suggested at a point only when it is supported to a certain extent by both expert opinion and existing land-use. Thus, our methodology ensures a high-productivity alternative crop suggestion.

The suggested alternative crop pattern shows that most pixels which did not have paddy as the existing crop have paddy as the alternative crop. This is because the overall conditions in the region are well-suited for paddy. Some pixels where paddy is the existing crop have received different alternative crops depending on the soil types and rainfall conditions there. For example the current mustard (deep blue) growing region has been found suitable for healthy paddy (red) and the reverse is observed in the adjoining region lying below it (see figure 7*c*). Some additional healthy pulse growing regions have also been identified.

Some pixels remained unclassified as they did not have any of the ‘healthy’ output nodes (except the one corresponding to the existing crop) stimulated beyond the threshold value. This is mainly because the aim of this methodology (as already mentioned before) is to generate a ‘high-productivity’ alternative crop suggestion. Thus, any suggestion will have to be supported by both expert opinion and land-use in that region. Some pixels might have had support from either of the sources, but

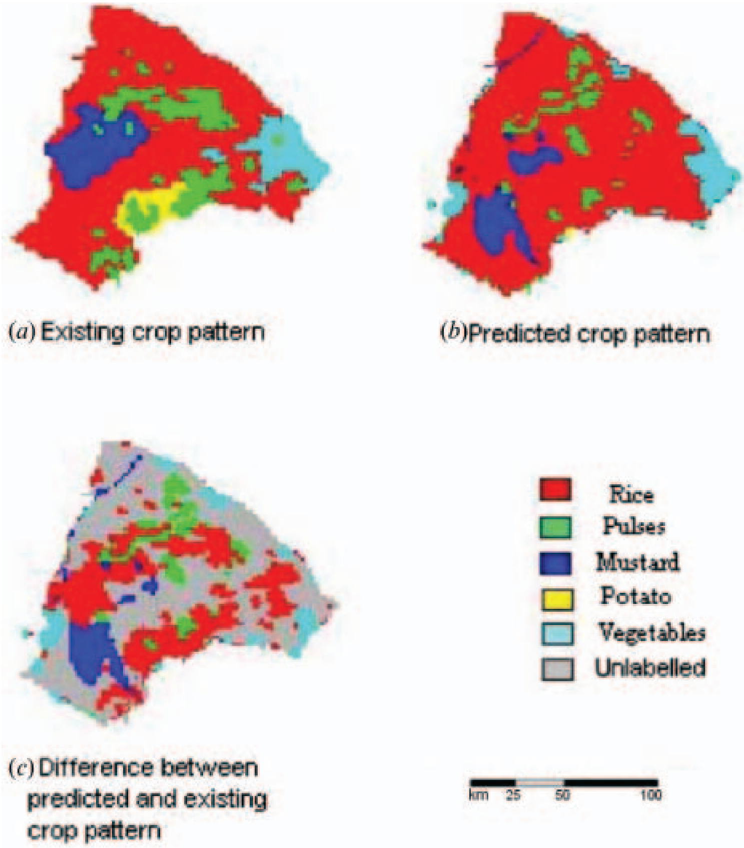


Figure 7. Existing and predicted crop pattern.

not from both and hence are not classified by the ANN. However, those pixels which were not classified by the ANN were marked with the existing crop label (see figure 7*b*) in the predicted crop pattern. The difference of the predicted and the existing crop pattern has been exhibited in figure 7(*c*). This experiment describes alternative crop suggestions only for those pixels that have high productivity ensured by the ANN, as exhibited in figure 7(*c*).

6. Conclusions

The proposed methodology uses neuro-fuzzy techniques integrating various quantitative and attribute data for determining alternative crop pattern prediction. Along with multisource inputs it uses expert opinion along with NDVI (from satellite data) for determining goodness of crop which was subsequently used for training the ANN. Finally for each pixel an alternative crop suggestion has been obtained with the adapted ANN. Thus the proposed experiment attempted to quantify through a methodological framework and in this sense, it can perform better than conventional 'semantic' methods.

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of data from different sensors, ref. 10/4/416, February 27, 2003. The authors would like to thank the referees for their useful comments and suggestions.

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