APPLICATION OF FUZZY SETS FUNCTION FOR LAND ATTRIBUTES MAPPING

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ABSTRACT

A study was conducted to evaluate the potential use of Geographical Information System (GIS) for mapping the biophysical resources of watershed. PC-based GIS soft-wares were used in the analysis, processing and mapping of spatial data. The conventional mapping technique that presents land attribute in form of polygon with abrupt change across class boundaries was improved using Fuzzy technique. This technique involves the generation of membership maps for each soil type based on the relationship between the soil type and it's forming factors like geology, elevation, slope gradient, slope aspect, slope curvature, and land cover. The fuzzy technique was found to be more appropriate than the conventional technique of mapping in expressing continuous and gradually changing soil or land attributes. Validation with observed soil or land attributes values indicated that root mean square error (RMSE) obtained for Fuzzy method was lower than that from the conventional method.

Keywords : Fuzzy set, membership function, mapping

INTRODUCTION

Soil maps produced through conventional surveys are the major source of soil spatial information for land evaluation or many management activities. Yet soil spatial information derived from conventional soil maps has been found to be inadequate for modeling at watersheds of mesoscale size. This inadequacy is largely due to subjective allocation of individuals to classes and polygon-based mapping practice employed in conventional soil map (Triantafilis *et al.*, 2001). The spatial distribution of soil landscape units were identified and delineated sharply to form soil polygons. The polygons delineated are used as uniform, basic spatial units of information (Burrough, 1989; Burrough *et al.*, 1997). Each individual of soil landscape is assigned to one class which referred as Boolean assignment (Zhu, 2000). Once assigned to a class, the local soil is said to have the typical properties of that class.

The traditional Boolean approach for mapping as described above has many limitations for efficient production of soil spatial information. Limitations are especially related to the use of a polygon-based model in delineating the unit. With the polygon-based model only soil bodies of certain size (scale dependent) are shown on the resulting soil map. Small soil bodies are ignored or omitted (Zhu *et al.*, 1997, 2001). Also, the soils in a given soil polygon are treated as homogenous bodies-changes in the soil property values only occur at the boundaries of the polygons. This creates a very inappropriate representation of spatial variation of soil properties. The traditional Boolean approach ignores important aspects of reality indicated by gradual and continuous spatial changes of soil properties and terrain characteristics across the landscape (Triantafilis *et al.*, 2001). Considerable loss information may occur when data that have been classified by this method are retrieved or combined using methods of simple Boolean algebra. This is because the Boolean approach allows only binary membership functions i.e. true or false. An individual is assigned to be a member or it is not a member of any given set as defined by exact limits. Therefore, vagueness in defining soil and terrain characteristics can not fully expressed. Boolean sets do not allow ambiguities and they are too inflexible to take account of genuine uncertainty (McBratney and de Grujiter, 1992). Nevertheless, the Boolean approach has advantage that it is exploratory and may lead to testable hypothesis about the nature of soil and landscape (Burrough *et al.*, 1992).

A more appropriate delineation of mapping units might be achieved by the use of fuzzy logic in combination with interpolation of data points by geostatistical or other methods (Burrough, 1989; Kollias, *et al.*, 1999). Fuzzy methods allow the matching of individuals to be determined on a continuous scale instead on a Boolean binary or an integer scale (Burrough, 1989, 1992). In contrast to Boolean sets, a fuzzy set is a class that admits the possibility of partial membership. Fuzzy set provides an alternative approach, expressing the vagueness of soil properties over a landscape.

Geographical Information System (GIS) as a computer system has proved to be a capable tool accommodating a fuzzy set application in mapping processes. In the GIS, the discontinuity of soil spatial data can be reduced that the soil or other landscape parameters can be presented as spatial continuum.

A study was carried out to develop the methodology of mapping land attributes using Fuzzy Logic in GIS and to analyze the relationship between soil and its environmental factors and map the soil spatial variability in the watershed.

METHODOLOGY

The study area was located between 14°03' – 14°35' Northern Hemisphere and 121°20' – 121°36' Eastern Longitude, about 60 km aerial distance South-East of Manila, capital of Philippines (Figure 1).

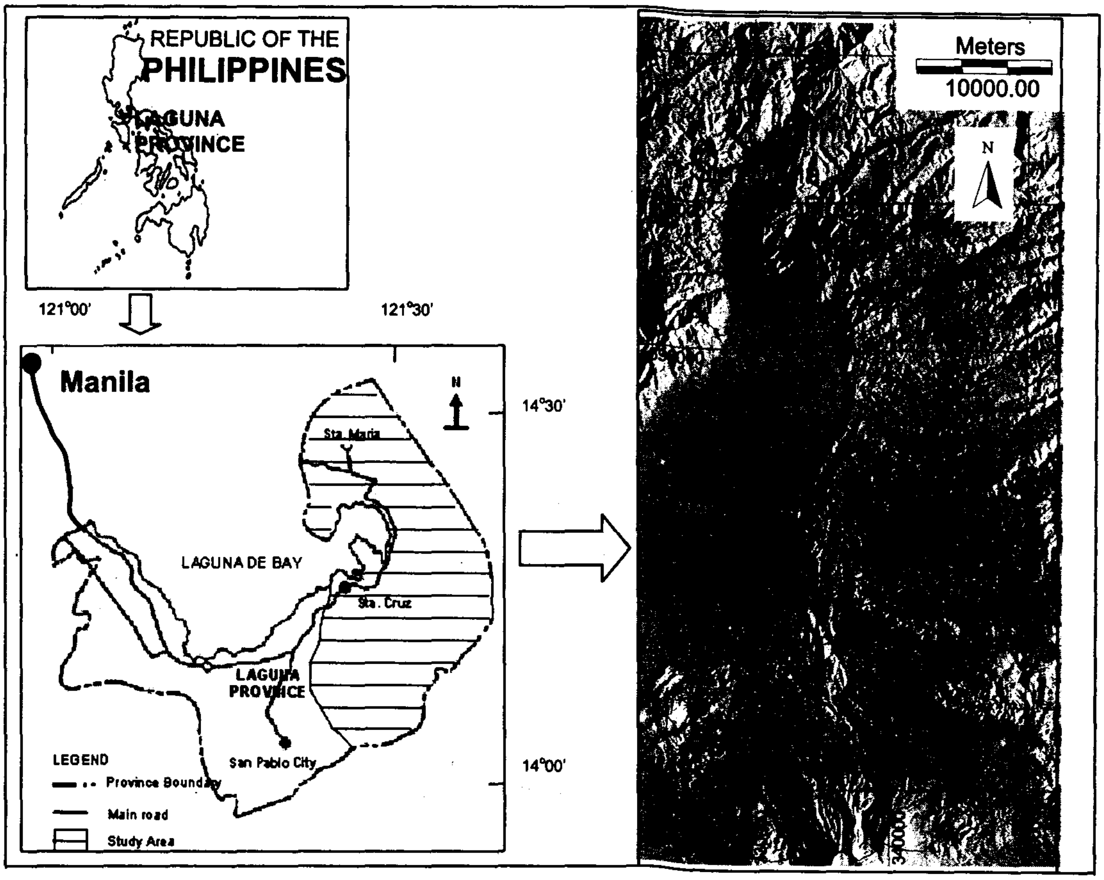
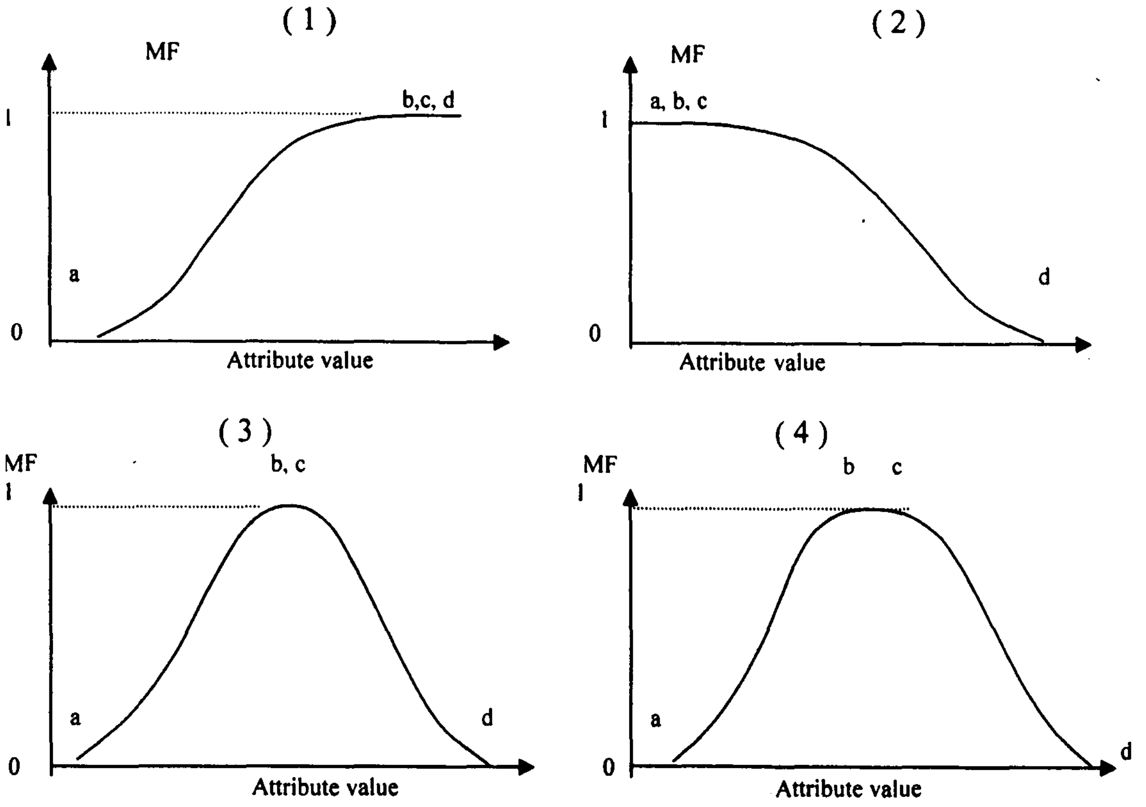


Figure 1. Location of the study area

Fuzzy Approach was applied to map soil spatial variation in the study area based on environmental variables as soil formation factors. The soil formation factors considered were followed the soil formation factor of Jenny (1941) namely geology (parent material), topography (represented by elevation, slope gradient, aspect, wetness index, and distance from river), and canopy coverage (represented by normalized differenced vegetation index, NDVI). The knowledge on the relationships between soil series and the soil formation factor was obtained by extracting the attributes from the soil formative factor layers with the soil layers used as a definition image. These were done using Extract module in IDRISI. The relationships were then represented in form of membership function as a measure of favorableness of the factor for the soil types.

Memberships functions used for fuzzy membership classification were based on the approach that utilizes a bell-shaped curve (sigmoidal) as shown in Figure 2. This approach consists of two basic functions: asymmetric and symmetric. The first function, an asymmetric model, was used where only the lower and upper boundaries of a class have practical importance. This function consists of two types: asymmetric left (Type 1) and asymmetric right (Type 2). For example, with regard to relationship between slope and Typic Tropaquepts, the steeper the slope the less favorable the site for the soil type, with the most favorable slope is level to nearly level (0 -1%) so that it is appropriate to use an asymmetric right types. The symmetric models also consist of two types: one that uses a single point (Type 3) as a central concept, while the other employs a range of ideal points (Type 4).



a = membership rises above zero, b = membership becomes zero
c = membership falls below 1, d = membership becomes 0
MF = vertical axis = value of the membership function

Figure 2. The Membership function: 1) increasing-sigmoidal function (the value of b, c, d are identical), 2) decreasing-sigmoidal function (the value of a,b, and c are identical), 3) symmetric-sigmoidal (b and c are identical), and 4) symmetric-sigmoidal (b and c are not identical)

The membership function type and the values of membership function parameters used for any soil series were determined based on data characteristics (statistics parameters and frequency distribution function) of attribute value of soil formation factors in every soil series. Cross tabulation between each soil type in current soil map with every soil formation factor maps were done to obtain the frequency distribution function as the basis for determining the membership function parameters. All fuzzy membership function operations were done on maps in raster format using Fuzzy module in IDRISI Software.

The result of these fuzzy membership operations was a membership map for every soil series in the study area. This means that the soil at a given pixel (point) could be assigned to more than one soil class with varying degrees of class assignment.

The spatial distribution of any soil properties could then be derived on the basis of the resulted membership maps using linear and additive weighting function as proposed by Zhu (2001) as follow:

$$C_{ij} = \left(\sum_{k=1}^{n} S_{ij}^{k} V_k \right) / \left(\sum_{k=1}^{n} S_{ij}^{k} \right)$$

Where Vij is the estimated soil property value at site (i,j), Sij is the similarity value of soil type k at site (i,j), Vk is the typical value of a given soil property of soil type k, and n is the total number of prescribed soil categories in the study area.

RESULT AND DISCUSSION

Soils of the study area were characterized using two different approaches. The first approach was to derive the spatial distribution of the soil characteristics from conventional soil map. In this approach, each soil polygon was assigned the typical soil property value (in this case mean value) of its respective assigned soil series. The second scheme was using a fuzzy approach by generating fuzzy membership maps for every individual soil series.

Fuzzy membership maps represent similarity of the soils in a given area to the prescribed soil series and showed the spatial gradation of soils with membership values ranging from 0 through 1.

Figure 3 showed membership maps for selected soil series (Bugarin Series and Sampaloc Series) in the Northern part of the study area. The membership maps display membership values for the individual soil series. The higher the membership value, the higher the probability that the corresponding site or point can be characterized as that soil unit. The figures showed that both soil series covers more or less the same area with different membership value. This means that the soil information at any point or any site was not represented by information of just one single soil series as it was done under conventional approach. The figures also showed that the membership values of a soil series The membership maps were used to derive soil attribute values over the study area. Figure 4 showed the soil depth distribution derived from membership maps and conventional soil map. It was clear from the figures that the soil depth derived from membership maps follows somewhat similar general pattern to that derived from conventional map. However, the soil depth map derived from membership maps exhibited much greater spatial detail-the values tended to change gradually from place to place as indicated by gradually changed colors. In the other hand, the soil depth derived from the conventional map showed a uniform distribution over large area as polygons. There was no variation of the soil depth value within each soil series but it changed suddenly as it cross the unit boundary (indicated by sudden changed colors). This was because, on a conventional soil map, the value of soil depth at a given location was the typical value of prescribed soil series for the location (the mean value). Consequently, there was only one value for every soil series. This was a great generalization and inappropriate, especially for the soil type that has very large coverage such as Lusiana and

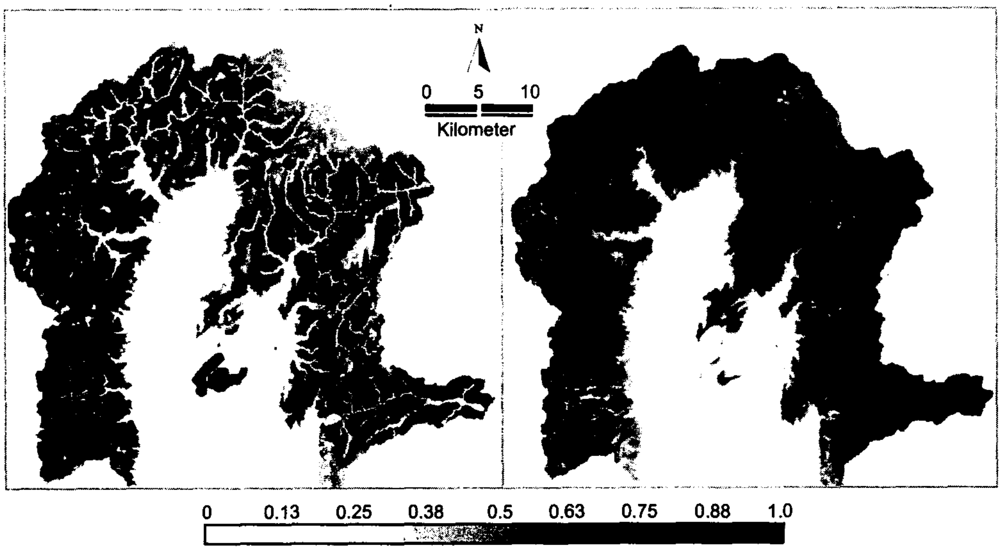


Figure 3. Membership map of Bugarin Series (left) and Sampaloc Series (right) at Sta. Maria and Romero river catchments (Darker color indicates a higher membership value)

Figure 4. Soil depth of the study area derived from membership maps (left) and conventional map (right). Boxes indicate the sample areas for complex topography (box 1) and flat lowland (box 2)

The real values of the soil property at certain location might be very different from that of the typical values of the prescribed soil series. The trend that the soil attribute map derived from membership maps showed more spatial details than the conventional map was especially obvious in the area with obvious environmental differences such as hilly-mountainous areas that have complex topography (Figure 5). In the hilly and mountainous areas, the environmental gradient is very strong. In this condition the GIS techniques employed seemed to be able to capture the environmental differences for characterizing the soil formative environment. Therefore the membership maps showed more spatial detail of soil distribution as compared to conventional map.

In flat-lowland area, fuzzy approach was failed to give a better spatial distributions in comparison with the existing soil map (Figure 6). The relationship between soil types and their formative factors was not so clear in the area. Various soil series present in the area with weak environmental gradient where geology and topography are similar. In the area along St. Maria river, for example, there are many soil series were identified, where in fact, geology formation, geomorphology, and topography of the area are uniform (recent alluvium, broad alluvial plain, and level to nearly level slope). Accordingly, the GIS techniques used were not able to differentiate and provide enough details on the soil formative environments. Therefore, the relationships developed based on the existing data in the area were not so accurate. The result suggested that the assessment of fuzzy membership values was crucial to proper fuzzy model. In this study, fuzzy memberships were based on the knowledge extracting from the current/available soil and its formative factors data. The membership maps only provide added flexibility for representing soil spatial variation. Other methods of extracting knowledge of soil-environmental factor relationship seemed to be necessary to obtained better result.

To evaluate the accuracy, two selected soil properties: soil depth and A-horizon depth derived from membership maps and conventional map were plotted against the observed values. The root mean square error (RMSE) was then calculated and used as indicator, as proposed by Grunwald *et al.*, (2001). The RMSE was calculated as follows:

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(xi - yi)^2}{n}}$$

Where xi is observed values, yi is values derived from map, and n is the number of sample observation.

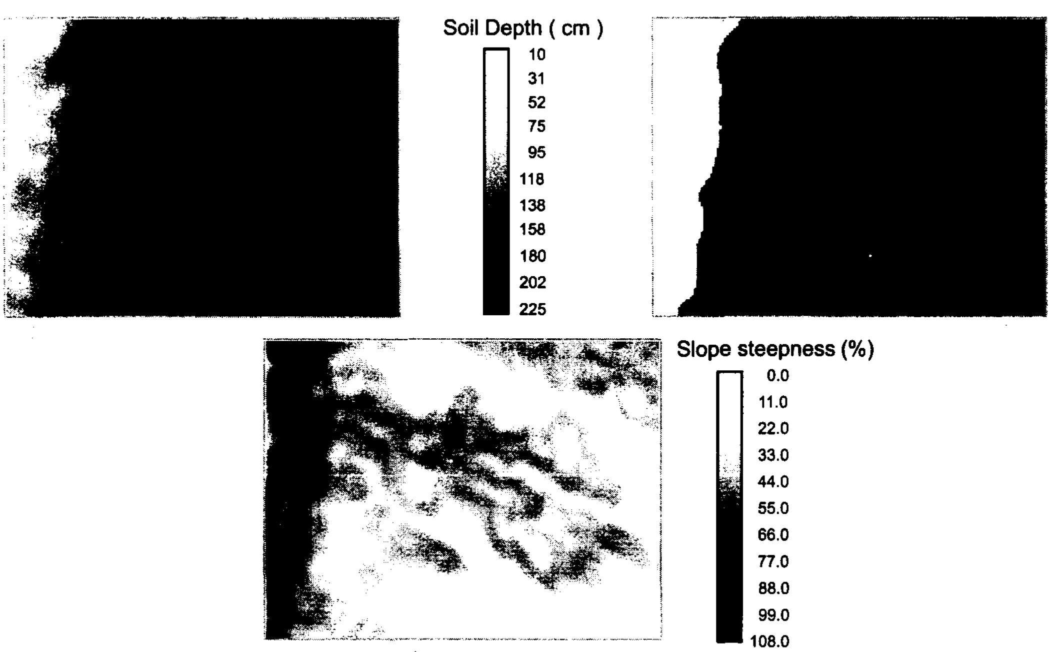


Figure 5. Maps of soil depth on a complex topography: a) derived from membership maps and b) from the conventional soil map. c) the corresponding slope gradient of the area

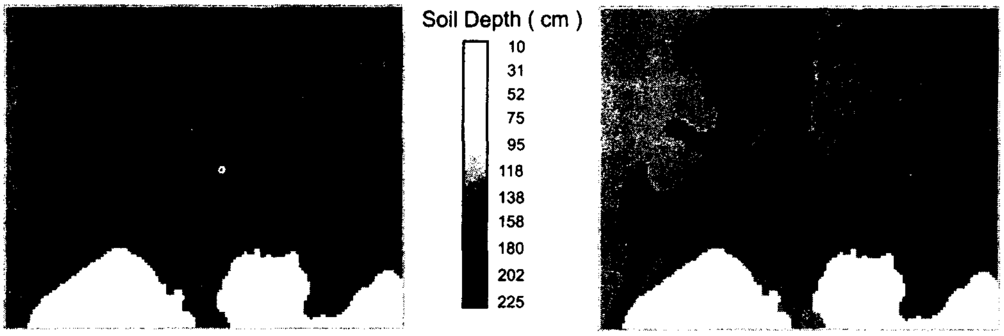


Figure 6. Soil depth on a flat lowland area derived from fuzzy membership maps (left) and from conventional soil map (right)

Scatter plots of the observed values for the soil characteristics and the values derived from membership maps and conventional maps and their corresponding RSME were presented in Figure 7. The two figures showed that the soil depths derived from fuzzy membership maps were less scattered than those derived from conventional map. It indicated that the soil depth from fuzzy membership maps were more closely associated with the field-observed soil depth than the corresponding depth obtained from the conventional soil map. The soil characteristics derived from membership maps are more accurate than those derived from conventional map. Lower RMSE values obtained for the soil characteristics derived from membership maps supported the result. Figure 8 showed the relationship between slope and soil depth. This figure also showed that the soil depths derived from fuzzy membership maps were less scattered with better relationship than those derived from conventional map. In addition, the soil depths were also more stratified along some values, which were actually the typical values of the prescribed soil type. Although the soil depth did not seem to relate to slope gradient very well as indicated by low correlation coefficients, the correlation between the depths from fuzzy membership maps and slope gradient was much stronger than that between the depths from the conventional map and slope gradient. It supported the fact that fuzzy membership maps had less attribute generalization than the conventional soil maps.

(A) (B)

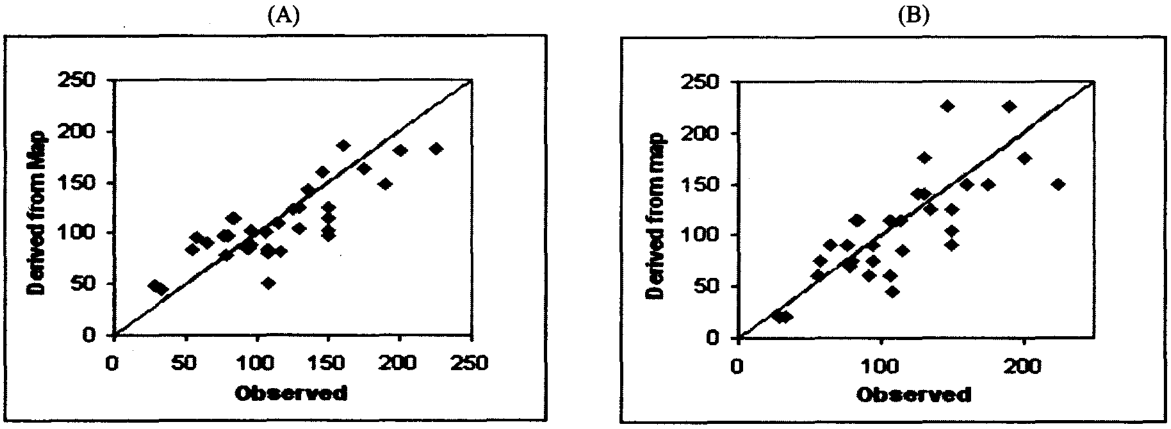


Figure 7. Scatter plot of soil depth in cm derived from membership maps (a) and conventional map (b) against observed

(A) (B)

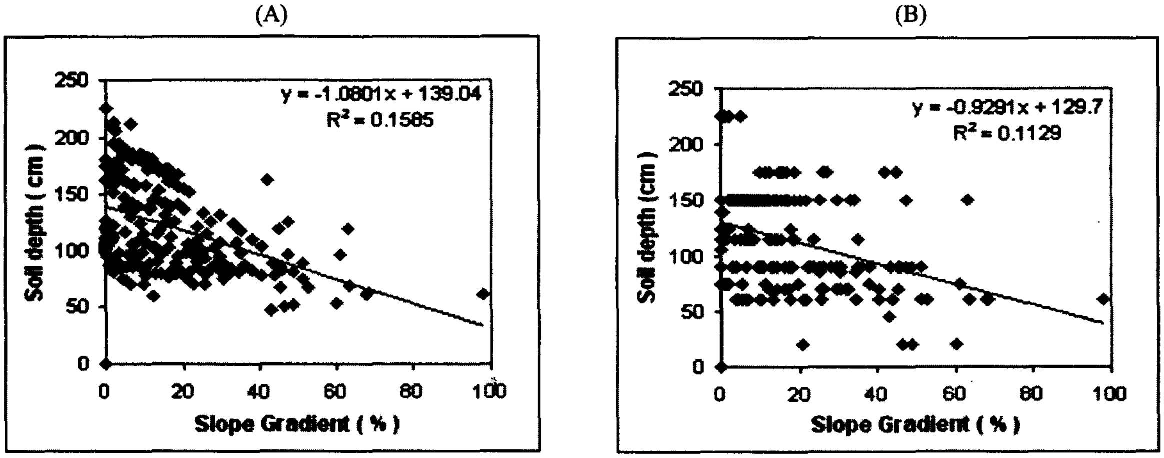


Figure 8. Slope-soil depth relationship a) soil depth derived from fuzzy membership maps, b) soil depth derived from conventional map

The comparison described above indicates that the spatial distribution of soil attributes can be better reflected by fuzzy membership approach than by soil conventional map. This result agrees with the result of many other researchers (McBratney and Odeh, 1997; Zhu, *et al.*, 1997; Lagacherie *et al.*, 1997). Nevertheless, the quality of soil information from fuzzy membership approach could suffer from the potential errors. Since the derivation of the soil properties used the assigned soil properties of prescribed soil class with weighted average operation, the internal variation of each soil type are not taken into consideration.

CONCLUSSION

The use of fuzzy technique to derive soil properties provides more detail spatial variation, especially on the area where environmental difference is high. In the area with low environmental difference, the fuzzy approaches were not so effective. Fuzzy technique was found to be better than conventional technique of mapping in expressing continuous and gradually changing soil or land attributes. Validation with observed soil or land attributes values indicated that root mean square error (RMSE) obtained for Fuzzy method was lower than that from the conventional method. The quality of the spatial information produced using the fuzzy approaches depend very much on the quality of the environmental condition characterized in GIS and the soil-environmental relationship extracted from the existing data.

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