

## **DIGITAL MAPPING OF FARMLAND CLASSES IN THREE LANDSCAPE IN MEXICO**

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### **ABSTRACT**

The cartography of farmland classes allows generating land maps, using a methodology based on local knowledge, rapidly and at low cost, and with a greater number of cartographic units than conventional soil surveys maps. However, the results found when producing these maps with automated cartography techniques are contrasting. Precision and accuracy were evaluated in 324 computer generated farmland class (FLC) maps by applying the Inverse Distance Weighted (IDW) interpolation model. These maps were obtained by varying the sample size for the training, its spatial design, and the Power value of the interpolator. Moreover, the effort needed to obtain maps with acceptable reliability was quantified. The procedure was applied to FLC maps obtained from surveys with producers from three contrasting environmental zones in Mexico. The results show that the best sampling scheme in the three areas is the systematic sampling, and Power 8, giving the maps with the highest reliability. Through the criterion of map reliability and effort needed for sampling, the recommended sample size is 10% to 25% of the total plots.

**Keywords:** Map accuracy, IDW interpolator, soil sampling strategies.

### **INTRODUCTION**

A farmland class (FLC) is defined as a specific land area that includes all the directly or indirectly observable attributes of the biosphere, in time or space, and which are affected by their use or handling (Ortiz-Solorio *et al.*, 2005). Diverse studies on FLC have shown that it is a good alternative to relate them to physical and chemical soil properties (technical concept) and their formation factors, as well as color, texture, drainage,

agricultural practices, type of vegetation, and crop (Ericksen and Ardon, 2003; Barrera-Bassols *et al.*, 2006; Licona-Vargas *et al.*, 2006; Cruz *et al.*, 2008). Also, it is a rapid, inexpensive methodology which does not require high specialization of the personnel in cartography, as opposed to technical soil surveys (Ortiz, 1999). The maps generated under this approach have a high degree of precision and accuracy, as

mentioned by Lleverino *et al.* (2000). Also, the cartographic units delimited are more detailed than the Subunit or Subgroup levels of the World Reference Base or Soil Taxonomy, respectively (Ortiz-Solorio *et al.*, 2005). With regard to digital mapping of FLC, some studies have been done to automate cartography, with contrasting results. For example, Martínez (1993) and Ortiz (1999) mention that digital mapping of FLC cannot be done since the classes cannot be identified satisfactorily. On the contrary, Segura *et al.* (2004) got 80% reliability in their FLC map, but only when grouping land classes in the groups with and without residual moisture. Therefore, there is still to be found an automated technique to generate FLC maps with acceptable reliability.

Some factors taken into account to generate high quality computer assisted soil maps (technical maps) are: a) sample size to do the classification, b) spatial design of the sampling scheme, and c) the configuration of the interpolator or classifying algorithm, specifically regarding Power (it is an exponent which determines the weight assigned to each of the observations) with the IDW model.

Sample size is an important factor to carry out the classification since the precision of each class and global map precision depend on it (Foody and Mathur, 2006). In some cases, a value determined as  $30p$  is taken, meaning 30 pixels times the number of bands or layers ( $p$ ) that intervene in the classification. In other cases, it is established based on statistical models (Foody *et al.*, 2006; Carré *et al.*, 2007). An exploration can also be done determining percentages, for example, Grinand *et al.* (2008) analyzed sample sizes to generate CALM, from 10 to 90 % of the total area, and found that there are no changes in the map precision after 30%. Regarding spatial design of the sampling, Hengl *et al.* (2003) pointed out that by graphing two principal

components (topographical variables) on an X – Y plane (UTM coordinates) the best spatial arrangement or sampling design is obtained. On the other hand, Moran and Bui (2002) recommend the Area-Weight method, similar to a random design, but unlike the random design, it takes into account all classes, this is, the sample number per class is proportional to the area occupied by each one. Finally, the configuration of the interpolator or classifying algorithm affects the outline of the resulting maps. In the IDW model, Power plays an important role in the reliability of the created map. Robinson and Metternicht (2006) state that the best maps are obtained using Power 1, nevertheless Kravchenko and Bullock (1999) affirm that it is so with Power 4.

The main goal of this work is to create a methodology to generate high quality computer assisted FLC maps. The following specific objectives were established: 1) to evaluate the factors that intervene in the generation of computer assisted soil maps in digital mapping of farmland classes; 2) to quantify the sampling time needed to obtain maps with acceptable reliability.

## **MATERIALS AND METHODS**

### **Study zones**

Three study zones were selected, with different climatic, lithologic, and topographic conditions. The first zone is located in the municipality of Villa Hidalgo, Zacatecas: extreme coordinates 101°45' WL and 22°24' NL, 101°42' WL and 22°18' NL; climate type BS<sub>1</sub>kw, semi-arid with mean yearly temperature between 12°C and 18°C; temperature during the coldest month varies from -3°C to 18 °C; temperature during the warmest month is below 22°C; with summer rains, and winter rain

percentage from 5% to 10.2% of the total annual rainfall (Garcia, 1988); parent material is mainly sedimentary rock such as sandstone, conglomerate, and lutite (INEGI, 1988); average slope is less than 5%.

The second zone is located in the municipality of Texcoco, Mexico: extreme coordinates 98°57' and 98°53' WL, 19°33' and 19°30' NL; climate type C (wo), temperate, sub-humid mean annual temperature from 12°C to 18°C; temperature during the coldest month from -3°C to 18°C; temperature during the warmest month is below 22°C; rainfall during the driest month less than 40 mm; summer rains with a P/T index below 43.2; winter rain percentage from 5% to 10.2% of the total annual rainfall (Garcia, 1988); it is a lacustrine alluvial plain; its geology corresponds to the Quaternary (INEGI, 1988); slope is less than 2%.

The third zone is located in the municipality of Papantla, Veracruz: extreme coordinates 97°17' WL and 20°17' NL, 97°10' WL and 20°14' NL; climate type Am (f), warm humid, mean annual temperature over 22°C, temperature of the coldest month over 18 °C; rainfall during the driest month less than 60 mm; summer rains, winter rain percentage over 10.2% of the total annual rainfall (Garcia, 1988); lithology is made up of lutites, sandstone, alluvial sediments and extrusive acid igneous rocks (INEGI, 1988); in the plains, the slope is 2%, and in the hillsides the slope varies from 14% to 72%.

### Cartography of the farmland classes

The FLC maps for each zone were generated through the methodology of Ortiz *et al.* (1990), which consists of 1) selecting a base map on which boundaries are drawn, the recommendation is to use with aerial photographs; 2) the farmers or

informants are selected of the study zone. It is important to mention that the informants can be divided into two groups; one for the cartography of FLC, and other for the characterization of the FLC, their problems, management techniques and even alternatives for improvement. Experience showed that the first group might be composed of two or three persons who are familiar with the entire area; 3) soil surveys around the area, accompanied by informants, with the corresponding aerial photograph in hand. The soil surveys walk around the area accompanied by informants, the following questions are made: Where does land class change? and how is it different from neighboring ones?

### Sample size and sampling scheme

As mentioned before, there are several ways to determine the sample size for training and sampling scheme. In this study, the number of points for the interpolation was determined based on proportions of the total land surface with the following percentages: 1, 5, 10, 15, 20, 25, 30, 40, and 50. Moreover, in order to find the best sampling scheme for each study zone, the three most common schemes were used: random, systematic, and random-stratified.

### Configuration of the classifier

The IDW model calculates the weight of the values according to the inverse relationship of the distance with the following equation (Lloyd, 2007):

$$\hat{Z}(X_0) = \frac{\sum_{i=1}^n Z(X_i) * d_{i0}^{-r}}{\sum_{i=1}^n d_{i0}^{-r}} \quad (1)$$

where the prediction of  $X_0$  is a function of  $n$  neighboring observations,  $Z(X_i)$ ,  $i = 1, 2, \dots, n$ ,  $r$  is an exponent that determines the weight assigned to each

observation, and  $d$  is the separation distance between  $X_0$  and  $X_i$ . As the distance between these two points increases the weight decreases. As the distance decreases, the weight increases. An important parameter of this model is the value of the exponent, or Power, where 2 is the most common value. Although, according to Gotway *et al.* (1996), the accuracy of the predictions with IDW increases as the Power increases. Because of this, in this research different Power values were used: 1, 2, 4, and 8 in IDRISI andes™.

#### **Computer assisted farmland class maps (CAFLCM)**

For each study zone 108 CAFLCM were generated, resulting from the application of the variations of each of the three factors considered in sections of sample size and sampling scheme and configuration of the classifier: Nine percentages for sample size, three sampling schemes, and four Power values (9x3x4). Thus, 324 CAFLCM were generated.

#### **Evaluation of map reliability**

One hundred pixels were considered for each farmland class to evaluate global precision of the CAFLCM with the confusion matrix in Equation 2 (Congalton, 1991). In this sense, precision was defined as the degree of closeness of results to the values accepted as true. Let  $x$  be an  $r \times r$  confusion matrix set out in rows and columns that express the number of sample plots (of which there are  $n$ ) predicted to belong to one of  $r$  classes relative to the true ground class (on the diagonal). The precision is calculated as follows:

$$Precision = \left( \frac{1}{n} \sum_{i=1}^r x_{ii} \right) \times 100\% \quad (2)$$

However, it is also important to evaluate the location of the classes, which is

directly related to the accuracy of each land class. For this, the K location index (defined as the success due to the simulation's ability to specify location perfectly), widely described by Pontius (2000) was used. The sample size to evaluate accuracy was the same as was used for precision. The sampling scheme used was random-stratified since it gives satisfactory results when evaluating map reliability (Congalton, 1988). Figure 1 show the general methodology used.

#### **Sample size determination by plot size**

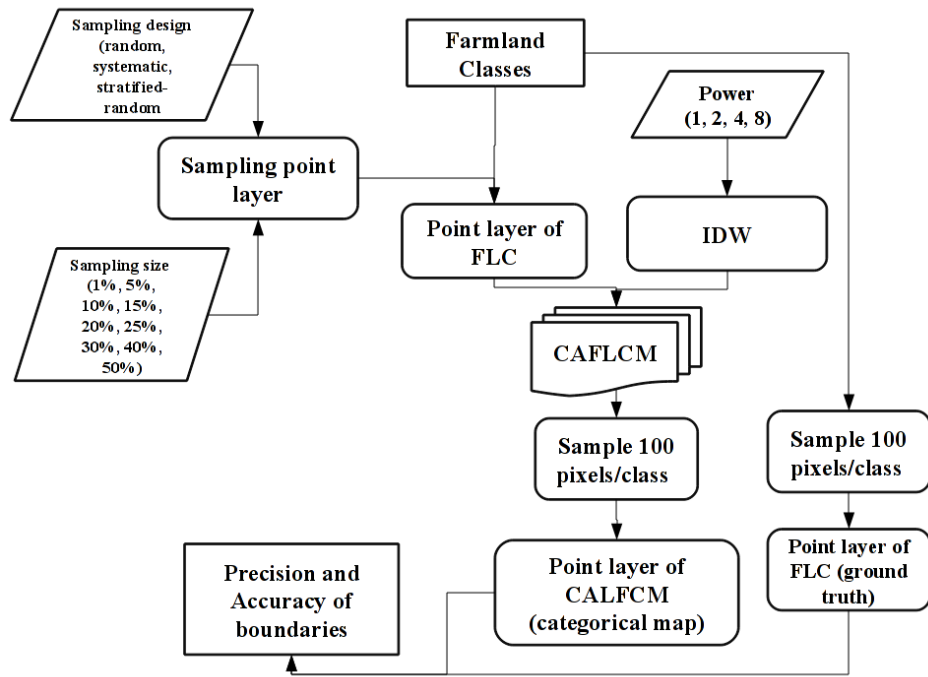
The definition of the sample size for the training in the generation of CAFLCM was done according to the number of pixels that have to be taken. However, this amount depends on the size to which the pixels are configured, which may not be practical in the field. Therefore, a second option is to consider the size of the plot to determine the size of the sample. The average plot size in Villa Hidalgo and Texcoco was 2 ha, and in Papantla it was 12 ha. The plot size was divided in the surface area of each zone to obtain the sample size (100% of the sampled plots). Moreover, this value was divided by 2, 4, and 10 to determine the sampling points shown in Table 1. The sampling scheme and Power defined in sections of sample size, sampling scheme and configuration of the classifier were used. The evaluation of reliability of the maps was done.

#### **Determination of sampling time**

To calculate the time that it would take to carry out the sampling according to the proportion of visited plots, the following formula was generated:

$$TP = S \times \sqrt{PS} \quad (3)$$

where  $TP$  is the time needed to traverse two consecutive points (hours),  $S$



**Figure 1.** General scheme of methodology. Farmland Classes (FLC); Computer Assisted Farmland Classes Map (CAFLCM).

**Table 1.** Sampling density per plot size.

Zone	Sampling plot (%)	Points	Point ha <sup>-1</sup>
Villa Hidalgo	100	916	1/2
	50	458	1/4
	25	229	1/8
	10	92	1/20
Texcoco	100	2087	1/2
	50	1044	1/4
	25	522	1/8
	10	209	1/20
Papantla	100	288	1/12
	50	144	1/24
	25	72	1/48
	10	29	1/120

is the average walking speed of a person (km hr<sup>-1</sup>), in this case 5,  $PS$  is the average size of the plot (km<sup>2</sup>).

$$ST = (TP + T)(SS - 1) \quad (4)$$

where  $ST$  is the sampling time (hours),  $T$  is the time spent stationary at a single point (hours), under the assumption that the farmer is only asked what land class that specific point belongs to, and some other characteristics, it takes 10 minutes or 0.167 hours as a constant,  $SS-1$  is the sample size, not considering the time needed to reach the first point.

## RESULTS AND DISCUSSION

The number of farmland classes (FLC) varies in each area. In Villa Hidalgo, Zacatecas, there are five classes: Canelona, Chautosa, Colorada, Parda, and Pardusca on a surface area of 1831 ha (Figure 2a). In Texcoco, Mexico,

there are eight classes: Arena, Barro, Blanca, Cacahuatuda, Jaboncillo, Lama, Pantano, and Salina in 4174 ha (Figure 2b). Lastly, in Papantla, Veracruz, there are three classes: Arenal, Barrial, and Vega de Río in 3462 ha (Figure 2c). The soil properties for each farmland are shown in Table 2.

**Table 2.** Soil properties of FLC in three landscape in Mexico.

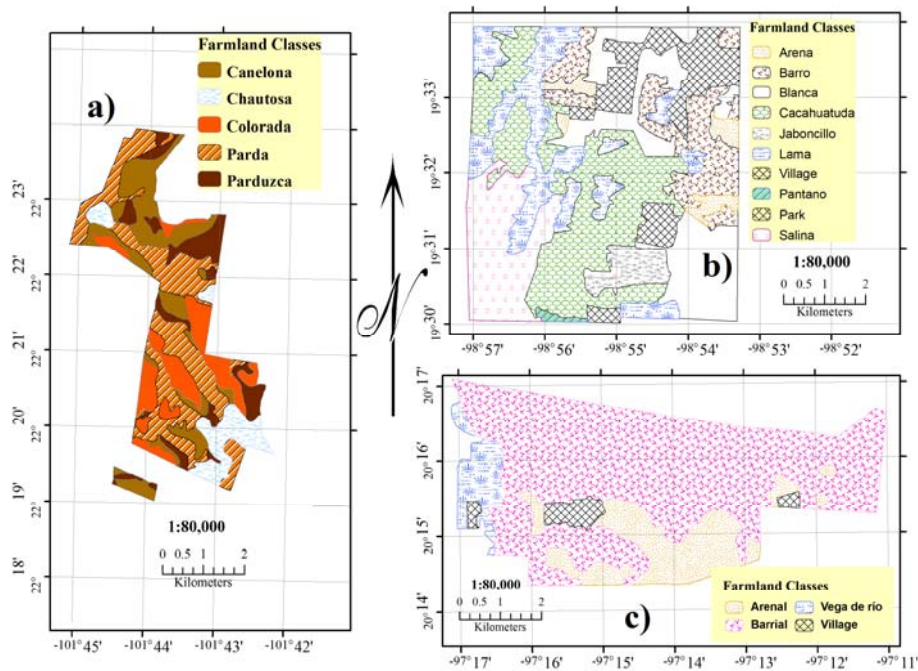
Zone	FLC	Texture	pH	OM (%)	EC (dS m <sup>-1</sup> )
Villa Hidalgo	Canelona	Sandy loam	6.5	0.9	0.2
	Colorada	Sandy loam	6.8	0.8	0.2
	Chautosa	Clay	7.9	1.5	2.2
	Parda	Clay	8.0	1.4	2.3
	Pardusca	Loam	7.3	1.0	1.0
Texcoco	Arena	Sandy	7.9	0.9	1.2
	Barro	Silty clay	7.6	1.8	0.8
	Blanca	Sandy loam	8.2	2.2	0.9
	Cacahuatuda	Clay loam	7.9	2.0	2.3
	Jaboncillo	Clay	10	1.0	69.0
	Lama	Loam	7.0	1.3	0.8
	Pantano	Silt	7.6	1.5	1.0
	Salina	Silt loam	9.3	1.2	67.7
Papantla	Arenal	Sandy loam	6.5	0.7	0.2
	Barrial	Clay	7.8	1.1	0.3
	Vega de Río	Clay	6.7	1.0	0.2

FLC= farmland classes; OM= organic matter; EC= electrical conductivity.

The behavior of precision and accuracy of the CAFLCM is similar for both parameters in all three study zones (Figure 3). The best sampling scheme was the systematic scheme for both precision and accuracy: 89% and 86% in Villa Hidalgo; 93% and 92% in Texcoco; and 98% and 95% in Papantla. In none of the

three zones were precision and accuracy less than 80% using this sampling design.

The sample size for training of the interpolator does have an influence on precision and accuracy of the CAFLCM (Figure 4). In Villa Hidalgo, we recommend 10% of the total pixels (2265) to do the interpolation, since the results

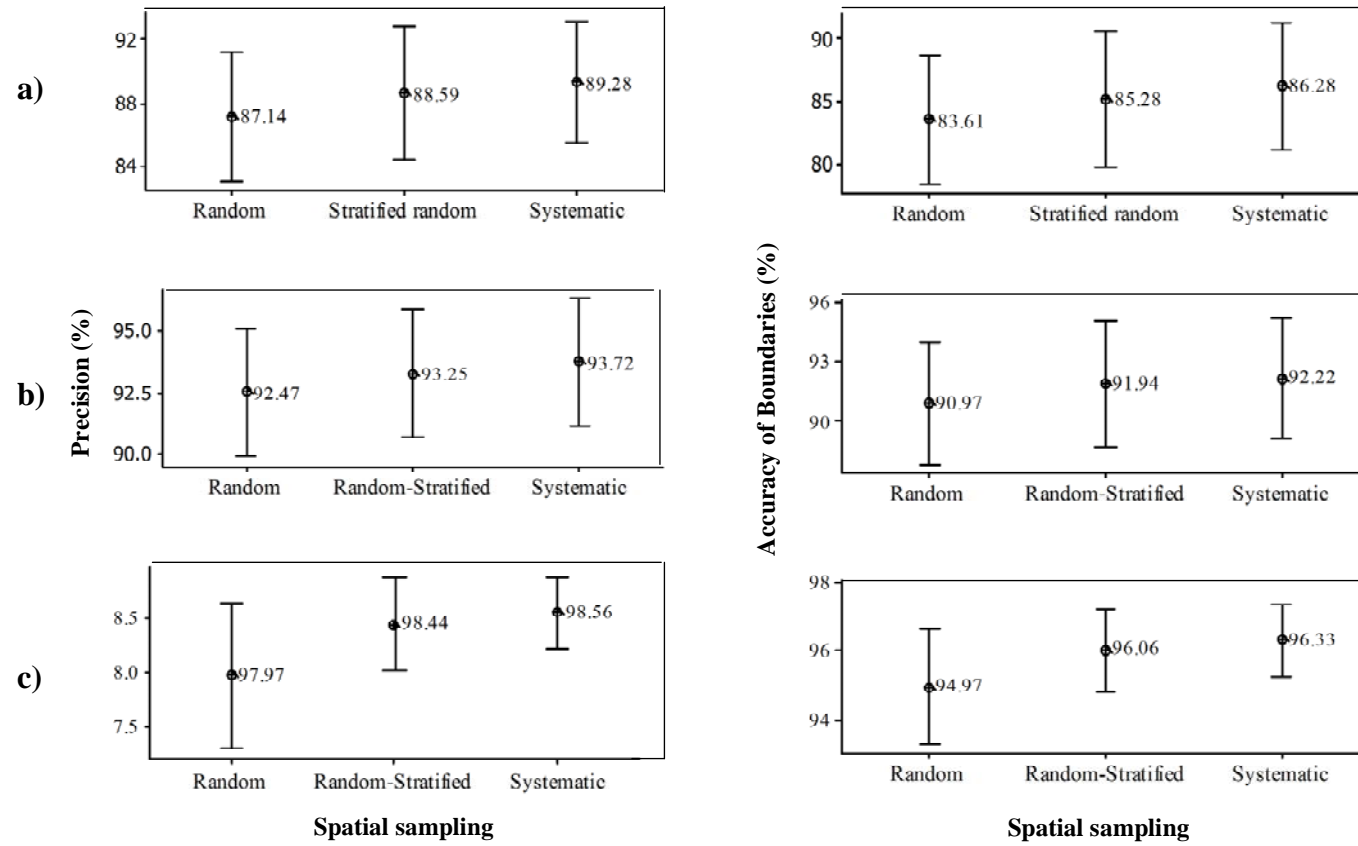


**Figure 2.** Farmland Classes maps a) Villa Hidalgo, Zacatecas; b) Texcoco, Mexico; c) Papantla Veracruz.

obtained are similar to those of a 50% sample size (11325). In Texcoco, 15% of the total pixels (7716) were enough to carry out the computer assisted classification, obtaining over 95% reliability of the maps. Nevertheless, 5% of the total pixels (2572) is also acceptable, since the CAFLCM would have over 85% precision and accuracy. Like in the case of Villa Hidalgo, the CAFLCM of Papantla can be done with 10% of the sample (4262) to feed the interpolator and obtain maps with acceptable reliability. Also, like in the case of Texcoco, a smaller sample can be used; in this case 1% of the total pixels (426) and the maps would have over 85% reliability. On the other hand, Moran and Bui (2002) obtained these same results of precision and kappa index with 50%

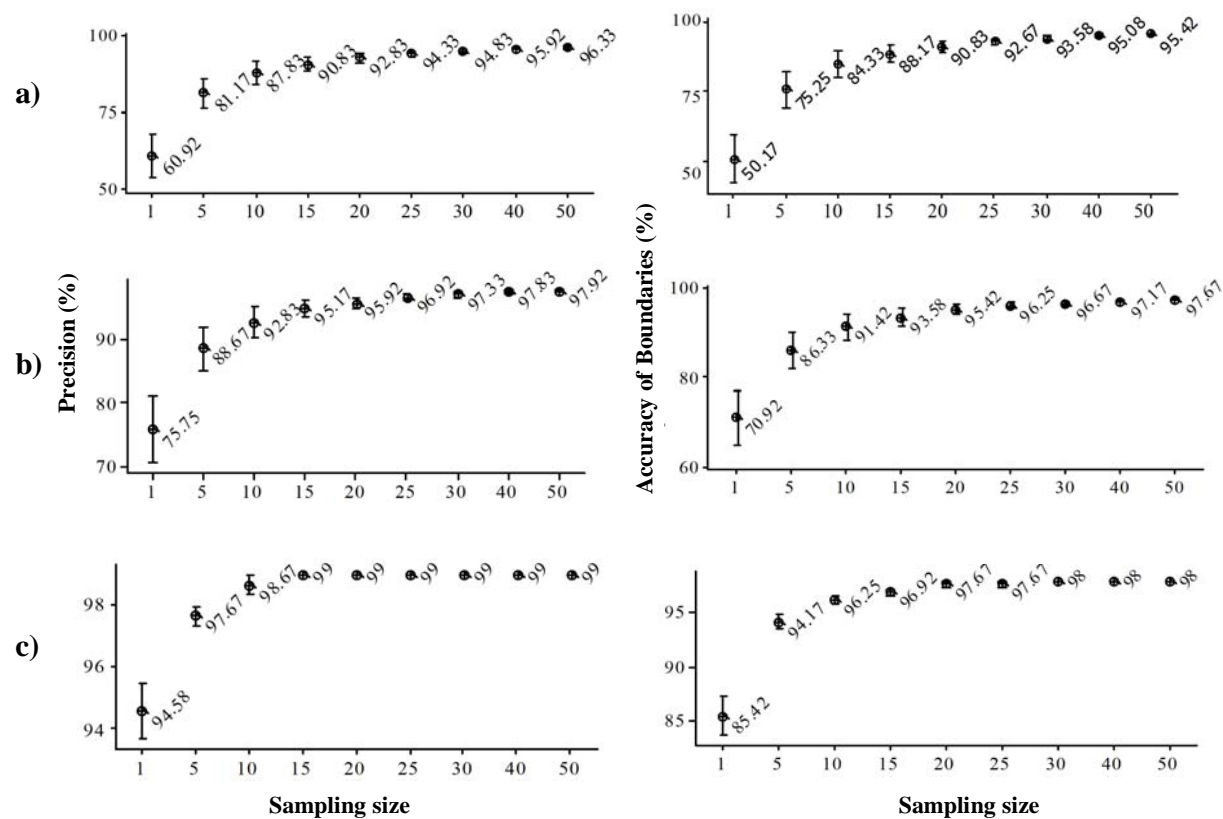
sampling density and using a decision tree as classifying algorithm. Using this same sample size, Grinand *et al.* (2008) obtained 65% and 63% precision and kappa index in their land maps.

The influence of the Power on the reliability of the CAFLCM varies with each study region (Figure 5). For Villa Hidalgo and Texcoco the difference between Power 1 and Power 8 is more than 6% and 8%, respectively. Contrarily, the CAFLCM of Papantla had a difference below 1%. Generally speaking, the best maps were obtained using Power 8, unlike what was found by Robison and Metternicht (2006), whose land maps with the greatest reliability were those using Power 1, as compared to Power 2, 3, and 4. Then again, Kravchenko and Bullock (1999) obtained their best maps using

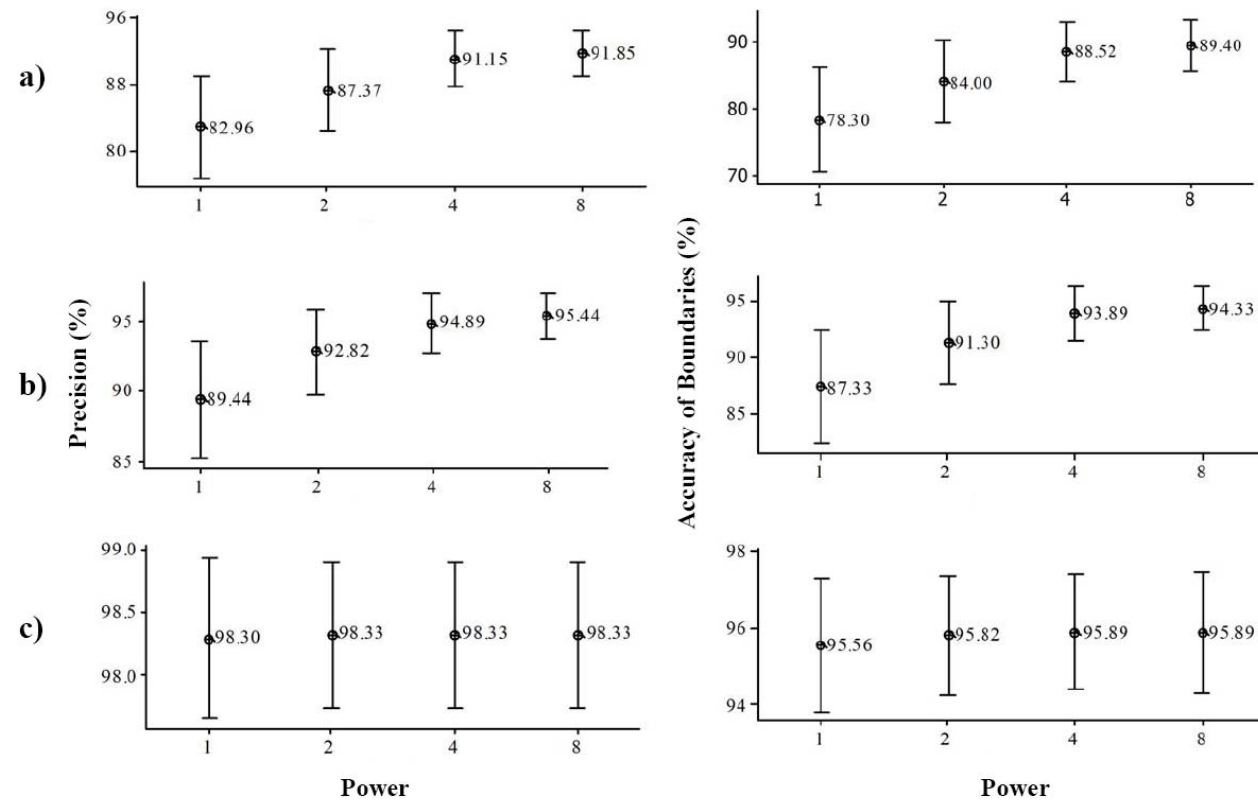


**Figure 3.** Precision and accuracy based on the sampling design. a) Villa Hidalgo, Zacatecas; b) Texcoco, Mexico; c) Papantla, Veracruz.





**Figure 4.** Precision and accuracy based on sample size. a) Villa Hidalgo, Zacatecas; b) Texcoco, Mexico; c) Papantla, Veracruz.



**Figure 5.** Precision and accuracy based on the Power. a) Villa Hidalgo, Zacatecas; b) Texcoco, Mexico; c) Papantla, Veracruz.

Power 4, followed by Power 1, 3, and 2 because the grid size for soil sampling was varied and this influenced the Power values.

To determine the sample size according to the average plot size that will generate CAFLCM with acceptable reliability, the systematic sampling design and Power 8 were chosen for the interpolation. The results of this analysis are shown in Table 3.

In Texcoco and Papantla, with 10% of the sampled plots, 209 and 29 respectively, map precision was over 80% and accuracy was over 65%. Contrastingly, in Villa Hidalgo only global precision (62%) is acceptable with 92 points, and accuracy barely reaches 53%. In general, no more than 300 points are necessary to obtain CAFLCM with

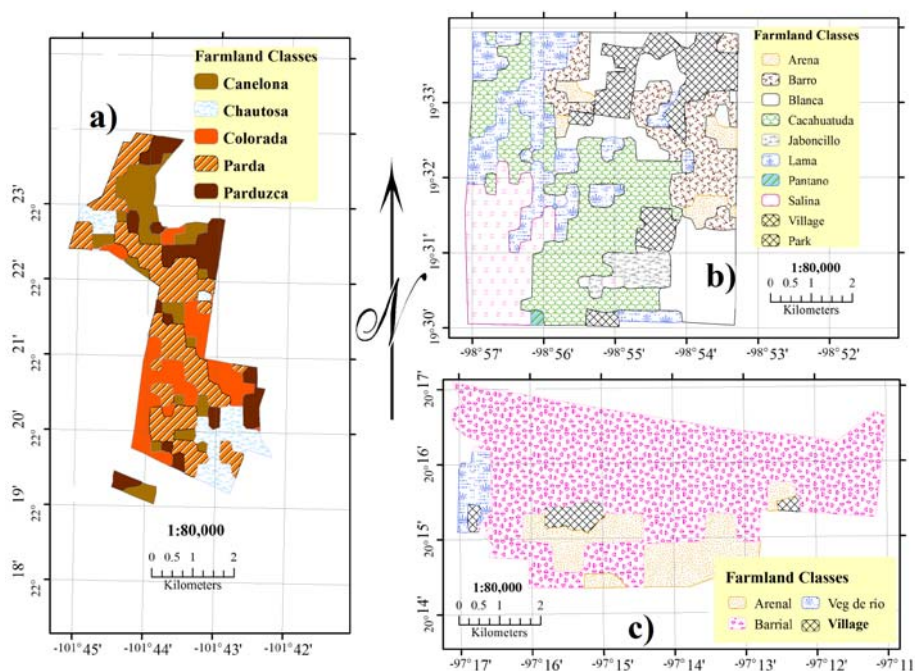
over 75% precision and 70% accuracy. On the other hand, Foody and Mathur (2006) recommend 90 points for each class. Therefore, considering this recommendation the sampling size in Villa Hidalgo would be 450 points, in Texcoco 720 points, and in Papantla 270 points. For this study, it is equal to 49%, 35%, and 94% of the total sampled plots for each zone, respectively. The sample size varies because the recommendation of Foody and Mathur (2006) did not take into account the plot size. Small plot requires more than a larger sample size and vice versa. In addition, Foody and Mathur (2006) used support vector machine to classify, the sampling scheme was random and used the remote sensing data as input variables.

**Table 3.** Precision and accuracy, and their effort in function of sampling density, considering plot size.

Zone	Sampling plot (%)	Precision (%)	Accuracy of boundaries (%)	Sampling time (hours)
Villa Hidalgo	100	90	87	800
	50	84	79	533
	25	75	72	361
	10	62	53	219
Texcoco	100	94	94	1823
	50	91	90	1217
	25	86	84	824
	10	80	78	500
Papantla	100	94	87	545
	50	91	79	374
	25	89	74	258
	10	85	68	174

The effort required increasing precision and accuracy of the CAFLCM of Villa Hidalgo from 62% and 53% to 75% and

72% is 11 and 7 hours, respectively, for each percentage point. However, in order to increase from 75% and 72% to 84%



**Figure 6.** Farmland Classes maps generated with IDW model (with 25% number of points of sampled plots). a) Villa Hidalgo, Zacatecas; b) Texcoco, Mexico; c) Papantla, Veracruz.

and 79%, the effort increases to 19 and 25 hours. Likewise, to reach maximum precision and accuracy when sampling all the plots, the sampling time is 44 and 33 hours for each percentage point in each parameter. The same behavior is true for the other two zones, this is to say, the effort needed to increase precision and accuracy increases as it nears 100% of the sampled plots for both criteria of map reliability (Table 3).

## CONCLUSIONS

Automated cartography of farmland classes was applied in areas with different

environmental conditions and local farmland classes, which allows to evaluate the methodology used under contrasting conditions. An important factor in the sampling design was to consider plot size, which is related with their handling, which in turn has influence on the identified farmland class. This can be observed in the distribution of their boundaries.

In general, the recommended sample size varies from 15 to 20% of the sampled plots to obtain maps with 68% to 80% reliability. This would take from 22 to 45 days (8-hour work days) in areas from 2000 to 4000 ha, all in function of the plot size (it was estimated on the basis of equations 3 and 4.). The best sampling

plan was the systematic scheme and Power 8 for all three zones because maps were obtained the most precision and accuracy.

The IDW does not use predictors or input variables for modeling compared algorithms commonly used in digital mapping soils like support vector machine, artificial neural network, decision tree, thus reducing setup time and cost, especially because the IDW does not use remote sensing data, the interpolation is not complex and the IDW is in most programs of geographic information systems.

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