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IMPROVING LAND-COVER CLASSIFICATION BY INCORPORATION OF MAP INFORMATION. A STUDY IN ANDALUSIA. SPAIN

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RESUMEN

Un área de unos 12 a 18 km alrededor de Antequera fue seleccionada para comprobar los resultados de una metodología que incorpora la información de la cartografía temática existente en el proceso de clasificación. El área presenta, a grandes rasgos, dos claros dominios geomorfológicos: un sector ligado a formaciones de terrazas fluviales y llanuras de inundación de edad cuaternaria y constituido por arcillas y arenas, junto a dos sectores montañosos ligados a la presencia de calizas, dolomías y margas de edad Mesozoica y Terciaria. Pastizal, matorral, pinos y rocas desnudas constituyen las clases no-agrícolas presentes en las áreas montañosas, junto con olivos y parcelas dispersas de cultivos extensivos, mientras las formaciones fluviales de morfología plana están, casi en su totalidad, cubiertas por una amplia diversidad de cultivos intensivos, la mayor parte de ellos bajo regadío.

Los mapas de Usos y Aprovechamientos (1:50000), Geológico (1:50000) y Topográfico (1:10000) constituyen las fuentes de información para los datos no-espectrales, mientras las cintas correspondientes a la imagen TM/Landsat de 15 de junio de 1984 proporcionan la información espectral. La principal limitación de las fuentes de información temática proviene de la insuficiente identificación de los cultivos, ya que ellos se recogen agrupados en categorias de usos y no individualmente. Por otra parte la complejidad de la zona de estudio, donde la diversidad de tipos de cultivos y el tamaño de las parcelas favorece la presencia de un alto procentaje de píxeles mixtos, da como resultado deficientes clasificaciones si sólo se utiliza la información espectral, exigiendo, por lo tanto, la incorporación de la información temática existente con el fin de mejorar los resultados de la clasificación.

El proceso de trabajo incluye, por lo tanto, en un primer nivel, la digitalización, rasterización y registro común de la cartografía tematica y de los datos procedentes de la imagen de satélite. Posteriormente una evaluación de la influencia de parámetros como altitud, pendiente, orientación y substrato geológico, fue llevada a cabo a través de la construcción de matrices de correlación, pixel a pixel. La forma en que los resultados de la correlación fueron incorporados al proceso de clasificación se basó en la aplicación de la Teoría de la Evidencia de Dempster-Shaffer. Los porcentajes de correlación entre el uso del suelo y las otras variables temáticas fueron convertidos en "evidential support", favoreciendo la categoría más probable como una función del contexto de altitud y litología asociada a cada pixel. Finalmente estos valores fueron utilizados como probabilidad previa en el algoritmo de máxima-probabilidad.

1. INTRODUCTION

The integration of Remote Sensing and Geographic Information Systems is currently arousing considerable interest. This paper describes the preliminary results of a research concerned with the incorporation of information contained in thematic maps in the image classification process. The main focus of the present investigation is on the methodology of converting the knowledge extracted from thematic maps into quantifiable measures and the incorporation of such knowledge into classification procedures. The study area is 12 x 18 Km in size, situated in the Antequera district of Andalusia, Spain; its UTM corner coordinates are: (347000, 108600) (NW), (347000, 96553) (SW), (364923, 96553) (SE) and (364923, 108600) (NE).

Information was extracted from land use (1:50.000), geology (1:50.000) and topographic (1:10.000) maps. Spectral data came from the June 15th, 1984 overpass of Landsat-5's Thematic Mapper (path 201, row 34, quadrant 4).

The study area can be roughly divided into two geomorphic units: a flat agricultural area, with elevations in the range 372 m to 544 m, and two hilly sub-zones, with elevations in the range 544 m to 810 m. The flat area is underlain predominantly by Quaternary clays and sandstones, whereas the hilly areas are formed by Triassic, Lower Jurassic and Tertiary limestones, dolomites, marls, clay, sandstones and conglomerates. The land use of the two units is also distinct; the flat area is basically occupied by irrigated and non-irrigated crops, whereas in the hilly areas pasture, scrubland, pines and bare rock are the predominant land cover classes.

However, olives and a small number of other crops are common to both units.

The land use/land cover categories used on the Mapa de Cultivos y Aprovechamientos (1.023) of the Spanish Ministry of Agriculture, published in 1978 with agrarian information from 1977, are presented in Table 1. From the table it is readily apparent that the map displays general groups of land use/land cover classes rather tan individual classes. That means the categories represent assemblies of terrain objetcs with different spectral responses rather than inidividual objetcs. An idea of the overlap between categories can be gained from Figures 1, 2 and 3. It can also be noted that it was necessary to do some adaptations, particulary by subdividing the unproductive class into different subclasses. From the graphs it can be seen that only town and farm houses in Figure 1, almonds and poplar in Figure 2 and areas of alternating fallow/crops in Figure 3 are separable on the basis of their spectral signature.

2. OBJECTIVE

The aim of the work reported here is to test a methodology to employ terrain information as an aid to classification. As already noted, land use information alone does not provide a satisfactory characterization of individual class signatures, making it impossible to generate a good classification using normal supervised techniques of image classification. In these unfavourable conditions, non-spectral terrain information can be of considerable value.

3. DATA PREPARATION

3.1. Map Information.

Nine topographic (1:10,000) maps were digitized and merged and a Digital Elevation Model (DEM) was created using LaserScan's software in the GIS Laboratory of the University of Nottingham, Department of Geography. From the DEM, elevation, slope and aspect were derived as separate raster files. The land use and geology maps were also digitized in vector format, structured as polygons and converted to raster. The five raster files with 25 x 25 m grid were then converted from 16 to 8 bit representation and transferred via an Ethernet link to the Nottingham Image Processing System.

3.2. Spectral Data.

The preprocessing of the spectral data consisted of geometric correction and removal of haze. Geometric correction was carried out by the polynomial least-square fit method, using 38 ground control points taken from topographic maps and accepting a least-squares residual of less than one pixel. The images were also re-sampled to a 25 x 25 m pixel size. Of the six reflective bands, band one and to a lesser extend band two were particulary affected by path radiance, wich gives hazy, low-contrast images. In view of the difficulty in identifying clear water or shadow areas, a reliable application of the regression method for path radiance correction was not possible. Therefore the haze was partially removed by setting the minimum value in each band to zero; in this case subtracting 33 from all pixels in band one and two gave acceptable results.

4. APPROACHES TO THE INCORPORATION OF EXTERNAL KNOWLEDGE

The incorporation of non-spectral information (i.e. that which is external to the image) in order to improve the classification of remotely-sensed images has been investigated by several authors. Hutchinson (1982) provides a review of the subjetc. The techniques described are:
Additional Channel: this procedure consists of adding non-spectral information as additional bands, so that the number of attributes of each pixel is increased. Althouh easily implemented, this technique requires considerably more computer time when several layers of map information are used, usually without significant classification improvement. Further difficulties are met when the data cannot be stastistically modelled for the application of the classification algorithms.

Stratification: the study area is sub-divided into smaller areas or strata, based on rules derived from external knowledge, so that the strata can be processed independently. The process is performed prior to classification with the purpose of increasing the homogeneity of the data sets to be classified or to separate different objetcs that are spectrally similar. Stratification is effective and easy to implement, but it is deterministic, that is, it does not handle uncertainty about the occurence of certain classes or the gradation between strata. Also, incorrect stratification criteria can invalidate the entire classification process.

Post-classification Sorting: the classified image is checked according to rules derived from ancillary data and individual pixel labels are modified accordingly. The advantages of post-classification sorting in relation to the previous strategy is that it deals only with problem classes and errors made in the selection rule can easily be corrected, as it is perfomed after classification. However, it is also a deterministic method and, one of the present major concerns which is the dimensionality of the data is not solved.

Prior Probabilities:this approach is described by Strahler (1980). The prior probability is based on an estimate of the proportion of the objetcs that fall into a particular class. Based on some kind of external source of information, the classes are weighted in accordance to their likehood of occurrence. The critical step in this approach seems to be the reliability of the number chosen to express the likehood of the class in a certain context. In Strahler's (op. cit.) example the prior probabilities values were determined by subdividing the topographic parameters in categories and recording the distribution of cover classes in these subdivisions. To incorporate more than one external parameter in the classification - elevation and aspect, for example -it is necessary to calculate the conditional probabilities contingent to all combinations of those parameters.

The use of prior probabilities is an interesting method of incorporating ancillary information into the decision rule. However, when many terrain parameters are to be taken into consideration a large set of joint priors would have to be used, thereby increasing the computing requirements considerably. Furthermore, development of GIS is providing a considerable volume of data which can hardly be treated by probabilistic methods either because they cannot be modelled by the Gaussian distribution or because of the prohibitive dimensionality of data. Therefore, investigations have been conducted lately on alternative methods, particularly the evidential approach.

Evidential Reasoning: this apprach is based on the Dempster-Shaffer (D-S) theory of evidence. The central idea of the theory of evidence is to manipulate pieces of evidenced derived from different sources, so that the evidence is accumulated by the pooling of observations or propositions. Applications of the D-S theory to remote sensing are discussed by Lee et al. (1987), Srnivasan & Richards (1990) and Wilkinson & Megier (1990). Let us suppose that there are three possible labels for a pixel: A, B and C. The set of possible labels is called the Frame of Discernment, represented by θ=(A,B,C). The D-S theory uses a number, in the range [0,1] inclusive, to indicate the belief on a subset (label or class in this case) of the Frame or Discernment, given a piece of evidence. This number expresses the degree to which the evidence supports a particular class and it is known as the mass of evidence committed to that subset. The mass attributed to each subset of the Frame of Discernment forms the Basic Probability Assignment (BPA).

If a source of knowledge of the area of interest suggests 30% evidence that the pixel should be labelled A, 50% for B and 20% for C, our BPA would be m{A,B,C}=<0.3, 0.5, 0.2>. It is a requirement that the sum of the mass in a frame of discernment must be equal to unity. However, if we do not rely entirely on our source of information or if we are not willing to commit ourselves completely on the support for each label, we can allow our uncertainty to reduce our commitment to, for instance, 80%. We would then change our previous BPA to {0,24, 0,40, 0,16} for A, B and C, respectively. The difference (1- {0.24 + 0.40 + 0.16})= 0.2 is the measure of our uncertainty or ignorance. In the theory, the uncertainty is indicated by committing mass to entire Frame of Discernment (θ), thereby indicating an inability to decide between any of the competing labels. Our BPA will now be m(A,B,C,θ)= {0.24, 0.40, 0.16, 0.2}.

The great advantage of the theory of evidence is that it is able to combine bodies of evidence. Using Dempster's Rule of Combination a Bel 1 (with basic probability assignment m1) is combined with Bel 2 (with basic probability assignment m2) to give a new function (Bel). The combination notation is $\oplus$ and Bel 1$\oplus$Bel 2 = Bel.

The combination rule is:

$$m(X) = K^{-1} \sum_{Y \cap Z = X} m1(Y)m2(Z)$$

where K is a normalizing constant

$$K = 1 - \sum_{Y \cap Z = 0} m1(Y)m2(Z)$$

The combination of BPA m1 (m1(A), m1(B), m1(C), ...m1(θ)) and BPA m2 (m2(A), m2(B), m2(C), ...m2(θ)) is calculated by considering all products in the form m1(Y)m2(Z) where Y and Z are individually varied over all subjets of Bel 1 and Bel 2. The resulting function is a new BPA with sum equal to one.

The BPA representing the combination of m1 and m2 apportions the total amount of belief among the subsets of θ by assigning m1(Y)m2(Z) to the set intersection of Y and Z. Thus for every subset A of θ, Dempster's Rule defines m1(A) $\oplus$ m2(A) to be the sum of all products of the form m1(Y)m2(Z) where Y and Z are selected from the subsets of θ in all possible ways, such that their intersection is A. The operation yields the same value regardless of the order in wich the functions are combined. The normalization step ensures that no mass is committed to the null set (when there is no intersection between the subsets). The evidential reasoning approach to the handling of multi-source data analysis is promising, particulary when categorical spatial data are to be incorporated to the classification.

5. THE COMBINATION OF PROBABILISTIC AND EVIDENTIAL APPROACHES

The evidential approach, as an alternative to the more traditional probabilistic techniques, can be applied to external as well as to spectral data. In the case of spectral data, portions of evidence are assigned according to scene/energy interactions -for example, the relationship between the spectral reflectance of an objetct in different wavelengths, the comparison of the reflectivity of different objetcs in the same band or assessment of seasonal variation of multi-temporal data (Ferrante et al., 1984). However, in the present work the approach was to apply the already tested and recognized probabilistic classification scheme for the spectral data combined with the evidential approach for the external information. The technique is the same proposed by Strahler (op.cit.), with the difference that the prior probability for each combination of terrain variables was worked out on the basis of evidential reasoning. This was accomplished by the following procedure:

1. Correlation of Terrain Variables.

The first step was to find the amount of correlation between the terrain variables (elevation, slope, aspect and geology) with the land use classes. Having all these information digitized and registered with the same grid resolution (25 x 25 m) it was possible to check the distribution of land use categories in the terrain pixel by pixel. Only elevation and geology showed a consistent correlation with land use.

2. Elevation.

The 438 m elevation range was subdivided in 10 interval (Table 2) and the number of pixel of each land use class falling in each category was computed. Two correlation matrices were obtained, one representing the percentage distribution of each land use category across the elevation intervals (correlation lu_ele, Table 9) and another showing the distribution of land use pixels in each elevation interval (correlation ele_lu, Table 12).

3. Geology.

The geology map was simplified by grouping lithologies into eight categories, taking into account the stratigraphy and the terrain morphology associated to them (Table 3). A reasonably good correlation was found after subdividing the area into two - below and above 548 m elevation. Tables 10 and 11 express the percentage distribution of each land use class in the geological categories for lower and upper areas (correlation lu_geo_1 and lu_geo_h). Tables 13 and 14 show the distribution of land use pixels in each geological category (correlation geo_lu_1 and geo_lu_h).

4. Support and Belief.

In deriving the evidence it was assumed that the correlation values relate to the support in favour of a particular land use label, given the pixel's topographic and geological context. For the ele_lu and geo_lu correlation, the mass was calculated by taking the percentage support directly from the respective matrices (Tables 12, 13 and 14) and applying equation 1. For the lu_ele and lu_geo the mass was calculated by equation 2 to express the evidence as a function of the horizontal distribution in the respective matrix.

$$m_{ij} = S_{ij}\ (1\text{-unc})/100 \qquad (1)$$

Where **S** is the support for class **i** in category **j** taken directly from the matrix and unc is the uncertainty assumed.

$$m_{ij} = \frac{S_{ij}\ (1\text{-unc})}{\Sigma S_{ij}} \qquad (2)$$

Example

Table 4 shows mass derived from Table 9 (lu_ele) for elevation class 5 and mass from table 11 (lu_geo_h) for the geology category 1, with 5% uncertainty. Their combination forms Belief1. It can be observed that Belief in classes 11 and 8 is boosted as they have good support in both matrices while Belief in the other classes has decreased. In the same way, masses from correlation ele_lu and geo_lu are combined to form Belief2. The combination of Belief1 and Belief2 yields the final Belief which is the pooling of all evidence involved. This value is taken as the prior probability.

The Algorithm

The following modifications were introduced on the maximum likehood algorithm:

Read the elevation and geology files as additional bands.
Read the Belief (elevation, geology, land use).
For each pixel:
If Belief equals zero then
do no take that land use class into consideration.
Otherwise
add the Belief to the classification process as a prior probability according to equation 3.
Choose k which minimizes (3)

$$Lk\ (X_i) = \log |D_k| + (X_i\text{-}m_k)'D_k^{-1}(x_i\text{-}m_k) - 2\log P_k \qquad (3)$$

where

$\mathbf{L_k}$: the likehood function for the kth class
$\mathbf{X_i}$: the observation vector associated with ith object
$\mathbf{D_k}$: dispersion matrix of the training samples for Kth class
$\mathbf{m_k}$: the mean vector for the kth class
$\mathbf{P_k}$: the a priori probability fot he kth class, in our case given by the belief in each class.

As the priors range from 0 to 1, the logarithmic term in (3) will be negative. The closer the belief is to zero, the higher the absolute value of this logarithmic term. As negative numbers they are actually added in equation 3, so that the higher priors will tend to minimize $\mathbf{L_k}$, thus increasing the likehood for that class. The final decision though will depend on both the distance of spectral vectors from the mean vector and the belief involved.

6. RESULTS

Accuracy of classification was assessed by computing the distribution of the cover class pixels in the whole land use map in relation to the whole classified image. The **class accuracy** was determined by the percentage of pixels belonging to class **i** in the land use map and classified to class **i**. **Omission** error is formed by pixels belonging to class **i** but belonging to another class in the land use map. As all pixels were tested the total number of omission and commission is the same. The **overall accuracy** is the proportion of pixels correctly classified in relation to the total number of pixels of the image, and the mean of class accuracy was called the **mean accuracy**.

Table 5 shows the accuracy of the classification generated by the standard maximum-likehood algorithm using all six bands and equal prior probabilities. Table 6 represents the accuracy of classification by the modified maximum-likehood algorithm of the same bands using prior probabilities. The comparison between the two tables is an eloquent expression of the magnitude of the improvement. There is an improvement in classification accuracy for every class, with the exception of class 1 (vineyard). The overall accuracy jumped from 23.72% to 51.19%.

7. DISCUSSION

It is important to bear in mind that this research was carried out with insufficient information for a good classification, because several land use classes are in fact formed by spectrally heterogeneous objetcts. Even for those classes assumed to be well defined and identified in the reference map, such as olives and vineyard, the accuracy is poor, probably because there is a good deal of generalization and imprecision on the map.

The difficulties due to the lack of information are to some extent positive as an exercise on how to weight the evidences to end up with a number for the prior probabilities that express the likehood as a function of the geomorphic context of the pixel, as this is essencially an heuristic method. In our work it was first thought that the evidences derived from the horizontal distribution of pixels (matrices lu_ele and lu_geo) were the best expression of the true likelihood of the pixels and should be sufficient. The classification based only on those evidences, allowing 5% uncertainty, did improve the accuracy for every class (Table 7) but the overall accuracy remained low. This is due to the inequalities of the classes as far as size is concerned. Therefore, the smaller classes had a substantial improvement whereas the larger ones very little, and the rate of omission and commission errors remained high. This fact pointed to the need to take the size of the classes into account. This was accomplished by including the evidence derived from the vertical distribution of pixels (matrices ele_lu and geo_lu). The effect of adding these two sets of evidences in and keeping 5% uncertainty can be seen in Table 8. The overall accuracy increased substantially but for several classes the accuracy actually decreased because the evidences were biased towards the larger classes. The balance was found by increasing the uncertainty of the ele_lu and geo_lu derived evidences to 30%, which means commiting less belief on that source of evidence, while keeping the same (5%) for the lu_geo and lu_ele evidences, as presented in table 6. That reduced the overall accuracy in relation to table 8 but the class accuracy is much better balanced.

8. CONCLUSION

The modification of the maximum-likelihood algorithm to incorporate map information was proved effective to improve classification. This incorporation was made possible due to the use of evidential approach to combine evidence derived from maps in a way that they could eventually be translated to a number which expresses the prior probability of each pixel as function of its geomorphic context. The convergence of all evidences to a single number greatly facilitates the application of the prior probabilities technique proposed by Strahler (1980) by reducing the computation and by the flexibility of allowing to weight the sources of information, i.e., setting different levels of confidence.

The approach to set the initial support for each label was essentially numeric and derived from the correlation between land cover/land use and other terrain parameters available. This is not meant to be an universal approach but it looks applicable to areas where there is some correlation between land-cover an terrain parameters. If that is the case then this methodology can be used, particulary in regional surveys to set the decision rules in a fairly representative area with sufficient availability of information and then extrapolate them to the neighbouring region. In view of the flexibility of the evidential approach, which poses no restriction on the size of the Frame of Discernment and allows to differentially weight the evidences according to confidence on its source, this methodology can be easily adapted to many situations to alleviate the difficulties found in the incorporation of data that do not fit the Gaussian model or would require excessive computation if treated exclusively by probabilistic approach. The classification algorithm used in this research in fact reduced the computation time from 03:14:19 hours for the unmodified maximum-likehood to 02:20:24 hours for the modified algorithm, using a VAX 11/730 computer.

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Table 1

LANDUSE/LANDCOVER CATEGORIES

Vinyard (*vinedo de transformacion*)
Poplar (*Chopo y Alamo*)
Apple/Pear (*Manzano/Peral*)
Vegetable Gardens (*Huerta*)
Town (*Improductivo*)
Pasture (*Pastizal*)
Almonds (*Almendro*)
Non-intensive Agric. Occupation (*Labor Extensiva*)
Rotation fallow/crops* (*Barbecho Blanco*)
Irrigated Crops** (*Cultivos Herbaceos*)
Pasture/Scrubland (*Pastizal/Matorral*)
Pasture/Scrubland/Baresoil(*Pastizal/Matorral/Improd*)
Pines/Scrubland (*Pino Carrasco/Matorral*)
Scrubland/Mediterranean Oak (*Matorral/Encina*)
Barerock (*Improductivo*)
River gravels (*Improductivo*)
Farm buildings (*Improductivo*)
Rotation crops/pulse*** (*Barbecho semillado*)
Olives (*Olivos*)

*yearly rotation of fallow and cultivated land
**this category encompasses different kind of herbaceous crops, in this area cultivated under irrigation
***seasonal rotation of crops and fixing nitrogen plants with some fallow periods

Table 3

GEOLOGIC CATEGORIES

Cathegory	Age	Lithologies
1	Triassic	Clay,sandstones,dolomites,ofites
2	Low Jur	Dolomites,breccias
3	Low Jur	Limestones
4	Mid Jur	Limestones,marls
5	Upp Jur	Marls,calcarenites,limestones
6	Tertiary	Sandstones,conglomerates
7	Quaternary	Terraces
8	Quaternary	Alluvial

Table 5

ACCURACY OF CLASSIFICATION WITH EQUAL PROBABILITIES

CLASS	N. OF PIXELS	%CORRECT	OMISSION	COMISSION
1	1320	40.53	785	28468
2	1096	38.14	678	19951
3	845	45.33	462	14091
4	2685	48.68	1378	14045
5	3365	65.79	1151	2903
6	2740	20.33	2183	18091
7	987	45.80	535	21871
8	7574	27.63	5481	24748
9	3406	13.21	2956	17842
10	122237	14.72	104245	8592
11	35186	17.65	28974	5030
12	1949	36.84	1231	9910
13	8044	42.93	4591	12855
14	408	74.75	103	3076
15	756	75.53	185	4482
16	682	12.46	597	19515
17	875	42.29	505	5228
18	66593	22.10	51878	14318
19	83401	34.53	54696	17518

Total number of pixels 344149
Total omission/comission 262524
Mean of class accuracy 37.85%
Overall accuracy 23.72%

Table 7

CLASSIFICATION ACCURACY WITH PRIOR PROBABILITIES
(using lu_ele/lu_geo evidences only with 5% unc)

CLASS	NO. PIXELS	%CORRECT	OMISSION	COMMISSION
1	1323	46.26	711	26732
2	1096	42.30	628	12755
3	845	59.23	342	15440
4	2688	57.66	1138	13119
5	3367	69.85	1015	2643
6	2740	27.88	1976	11856
7	987	53.09	463	19234
8	7574	38.62	4649	15155
9	3406	38.55	2093	9511
10	122247	31.82	83347	14417
11	35191	38.26	21728	6083
12	1949	64.14	699	7051
13	8044	60.04	3214	4884
14	408	79.51	84	1936
15	756	87.57	94	2201
16	682	51.17	333	14591
17	876	62.97	324	4832
18	66594	34.34	43725	21171
19	83419	34.38	57736	17708

Total number of pixels 344191
Total omission/comission errors 221299
Mean of class accuracy 51.49
Overall accuracy 35.70

Table 2

ELEVATION CATEGORTES

Category	Elevation Range (meters)
1	372-415
2	415-458
3	458-501
4	501-544
5	544-587
6	587-630
7	630-673
8	673-716
9	716-759
10	759-810

Table 4

EVIDRNCES FROM CORRELATION LU_ELE(m1),LU_GEO(m2)

CLASS	*m1(i,5)*	*m2(i,1)*	*Belief(i,5,1)*
1	0.0000	0.0000	0.0000
2	0.0000	0.0000	0.0000
3	0.0000	0.0000	0.0000
4	0.0014	0.1188	0.0393
5	0.0378	0.1188	0.0785
6	0.0435	0.0489	0.0431
7	0.0000	0.1188	0.0378
8	0.1123	0.1158	0.1555
9	0.0153	0.0085	0.0084
10	0.0000	0.0000	0.0000
11	0.2234	0.1061	0.2561
12	0.1580	0.0230	0.0799
13	0.1851	0.0261	0.0629
14	0.0695	0.1188	0.1127
15	0.0606	0.0000	0.0193
16	0.0000	0.0000	0.0000
17	0.0000	0.0000	0.0000
18	0.0147	0.0880	0.0410
19	0.0271	0.0830	0.0494
unc	0.0500	0.0500	0.0159

Table 6

CLASSIFICATION ACCURACY WITH PRIOR PROBABILITIES
(unc 5% for lu_ele/lu_geo and 30% for ele_lu/geo_lu)

CLASS	NO. PIXELS	%CORRECT	OMISSION	COMMISSION
1	1323	33.18	884	16017
2	1096	40.15	656	6408
3	845	54.20	387	10388
4	2688	52.79	1269	6155
5	3367	68.84	1049	1862
6	2740	21.02	2164	4978
7	987	45.80	535	11871
8	7574	31.58	5182	8194
9	3406	38.02	2111	3898
10	122247	62.06	46375	28388
11	35191	59.55	14236	10000
12	1949	58.18	815	3873
13	8044	64.32	2870	3013
14	408	76.47	96	1221
15	756	82.01	136	1475
16	682	24.63	514	2579
17	875	58.86	360	3480
18	66594	39.66	40182	24082
19	83419	42.26	48186	20156

Total number of pixels 344191
Total omission/comission errors 167988
Mean of class accuracy 50.19
Overall accuracy 51.19

Table 8

CLASSIFICATION ACCURACY WITH PRIOR PROBABILITIES
(lu_ele/lu_geo and ele_lu/geo_lu evidences with 5% unc)

CLASS	NO. PIXELS	%CORRECT	OMISSION	COMMISSION
1	1323	11.19	1175	3856
2	1096	13.32	950	279
3	845	22.25	657	1154
4	2688	28.35	1926	1540
5	3367	64.39	1199	1049
6	2740	7.52	2534	1077
7	987	16.82	821	1546
8	7574	21.22	5967	3190
9	3406	38.67	2157	2193
10	122247	84.26	19238	42446
11	35191	69.72	10656	13435
12	1949	41.66	1137	2172
13	8044	68.56	2532	2010
14	408	52.94	192	306
15	756	72.62	207	897
16	682	0.15	681	24
17	875	41.49	512	1644
18	66594	40.37	39728	27178
19	83419	52.88	39308	25581

Total number of pixels 344191
Total omission/comission errors 131577
Mean of class accuracy 39.28%
Overall accuracy 61.77

Table 9

CORRELATION LANDUSE-ELEVATION(lu_ele)

(Distribution of every landuse class in elevation categories)

CLASSES	ELEVATION CATEGORIES								
	1	1	3	4	5	6	7	8	9	10
1	0.23	59.88	36.43	3.47	0.00	0.00	0.00	0.00	0.00	0.00
2	99.18	0.82	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	36.05	61.64	1.82	0.19	0.00	0.00	0.00	0.00	0.00
5	5.29	9.98	59.64	19.72	5.20	0.18	0.00	0.00	0.00	0.00
6	19.96	24.53	25.18	2.59	5.99	8.03	12.08	1.64	0.00	0.00
7	0.00	61.40	29.99	0.00	0.00	8.61	0.00	0.00	0.00	0.00
8	1.33	26.63	33.34	15.08	15.43	7.30	0.24	0.65	0.00	0.00
9	0.00	30.74	17.91	0.76	2.11	1.50	4.29	23.66	10.51	8.51
10	52.59	45.37	1.91	0.13	0.00	0.00	0.00	0.00	0.00	0.00
11	3.43	6.19	11.79	11.93	30.71	22.81	9.22	1.68	1.18	1.06
12	0.00	0.00	2.26	4.36	21.86	22.42	22.83	22.52	3.75	0.00
13	0.00	0.00	6.90	22.56	25.44	19.56	18.47	6.38	0.68	0.00
14	0.00	0.00	0.00	1.23	9.56	24.75	47.30	17.16	0.00	0.00
15	0.00	0.00	0.00	0.00	8.33	27.65	59.92	4.10	0.00	0.00
16	99.71	0.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17	0.11	21.14	78.74	0.00	0.00	0.00	0.00	0.00	0.00	0.00
18	44.90	34.16	11.83	2.11	2.03	1.87	2.52	0.59	0.00	0.00
19	13.82	42.19	20.06	6.36	3.72	4.99	5.35	2.95	0.48	0.09

Table 10

CORRELATION LANDUSE-GEOLOGY-LOWER AREA(lu_geo_l)
(Percentual distribution of every landuse class in the geologic categories for the area below 544 meters)

CLASSES	GEOLOGIC CATEGORIES							
	1	2	3	4	5	6	7	8
1	7.47	0.00	1.66	0.00	0.00	25.04	65.84	0.00
2	0.00	0.00	0.00	0.00	0.00	1.09	9.67	89.23
3	0.00	0.00	0.00	0.00	0.00	0.00	75.74	24.26
4	8.01	0.00	0.00	0.00	0.00	8.01	57.47	26.50
5	40.18	0.00	0.00	0.00	1.04	36.46	15.88	6.43
6	15.33	0.00	1.37	0.00	0.00	54.77	28.53	0.00
7	27.49	0.00	0.00	0.00	1.33	7.10	64.08	0.00
8	59.54	0.00	0.00	0.00	0.00	10.40	30.06	0.00
9	18.78	0.00	0.00	0.00	1.84	6.71	67.91	4.75
10	0.34	0.00	0.00	0.00	1.29	1.62	70.60	26.15
11	54.28	2.78	0.81	0.00	0.00	22.63	18.68	0.83
12	76.58	0.00	0.00	0.00	0.00	4.50	18.92	0.00
13	0.00	39.38	24.90	21.23	0.00	0.00	14.48	0.00
14	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
16	0.00	0.00	0.00	0.00	0.00	0.00	7.18	92.82
17	0.46	0.00	0.00	0.00	18.06	4.11	22.17	55.20
18	4.66	0.25	0.83	0.45	6.89	7.20	76.07	3.65
19	11.10	0.73	1.02	0.47	5.56	20.09	59.82	1.22

Table 11

CORRELATION LANDUSE-GEOLOGY- HIGHER AREA(lu_geo_h)
(Percentual Distribution of every landuse class in geologic categories for the area above 544 meters)

CLASSES	GEOLOGIC CATEGORIES							
	1	2	3	4	5	6	7	8
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	41.17	0.00	3.51	0.00	0.00	49.74	4.29	1.30
7	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	97.45	0.00	0.00	0.00	0.00	2.55	0.00	0.00
9	7.14	0.00	0.00	0.00	0.00	86.76	0.00	6.09
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	89.30	0.00	0.00	0.00	0.00	10.54	0.12	0.03
12	18.50	0.00	0.00	0.00	0.00	81.50	0.00	0.00
13	2.20	17.77	49.60	0.06	0.00	21.23	1.14	0.00
14	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	0.00	0.13	99.87	0.00	0.00	0.00	0.00	0.00
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
18	74.05	0.00	0.00	0.25	1.14	11.97	5.57	7.01
19	69.91	0.58	0.14	0.48	0.53	21.12	6.70	0.54

Table 12

CORRELATION ELEVATION-LANDUSE(ele_lu)
(Distribution of landuse classes in every elevation category)

CLASSES	ELEVATION CATEGORIES								
	1	2	3	4	5	6	7	8	9	10
1	0.00	0.65	1.19	0.31	0.00	0.00	0.00	0.00	0.00	0.00
2	0.98	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.77	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.79	4.09	0.33	0.03	0.00	0.00	0.00	0.00	0.00
5	0.16	0.27	4.94	4.43	0.90	0.04	0.00	0.00	0.00	0.00
6	0.50	0.55	1.70	0.47	0.84	1.32	2.66	0.83	0.00	0.00
7	0.00	0.50	0.73	0.00	0.00	0.51	0.00	0.00	0.00	0.00
8	0.09	1.65	6.21	7.63	6.02	3.32	0.14	0.91	0.00	0.00
9	0.00	0.86	1.50	0.17	0.37	0.31	1.17	14.93	27.45	39.46
10	58.25	45.38	5.74	1.09	0.00	0.00	0.00	0.00	0.00	0.00
11	1.09	1.78	10.20	28.04	55.64	48.14	26.05	10.93	31.90	50.88
12	0.00	0.00	0.11	0.57	2.19	2.62	3.57	8.13	5.60	0.00
13	0.00	0.00	1.36	12.12	10.54	9.44	11.93	9.50	4.22	0.00
14	0.00	0.00	0.00	0.03	0.20	0.61	1.55	1.30	0.00	0.00
15	0.00	0.00	0.00	0.00	0.32	1.25	3.64	0.57	0.00	0.00
16	0.62	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17	0.00	0.15	1.69	0.00	0.00	0.00	0.00	0.00	0.00	0.00
18	27.10	18.62	19.38	9.39	6.98	7.46	13.48	7.22	0.00	0.00
19	10.44	28.79	41.15	35.43	15.97	24.99	35.81	45.67	30.83	9.66

Table 13

CORRELATION GEOLOGY-LANDUSE-LOWER AREA(geo_lu_l)

(Percentual Distribution of landuse classes in every geologic category for the area below 544 meters)

CLASSES	GEOLOGIC CATEGORIES							
	1	2	3	4	5	6	7	8
1	0.43	0.00	1.15	0.00	0.00	1.26	0.47	0.00
2	0.00	0.00	0.00	0.00	0.00	0.05	0.06	2.54
3	0.00	0.00	0.00	0.00	0.00	0.00	0.35	0.53
4	0.94	0.00	0.00	0.00	0.00	0.82	0.83	1.85
5	5.58	0.00	0.00	0.00	0.33	4.40	0.27	0.53
6	1.32	0.00	1.41	0.00	0.00	4.10	0.30	0.00
7	1.08	0.00	0.00	0.00	0.12	0.24	0.31	0.00
8	14.73	0.00	0.00	0.00	0.00	2.23	0.92	0.00
9	1.38	0.00	0.00	0.00	0.31	0.43	0.62	0.21
10	1.82	0.00	0.00	0.00	15.97	7.52	46.74	83.15
11	26.40	16.78	4.71	0.00	0.00	9.56	1.12	0.24
12	0.37	0.00	0.00	0.00	0.00	0.02	0.01	0.00
13	0.00	47.95	29.15	44.35	0.00	0.00	0.18	0.00
14	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
16	0.00	0.00	0.00	0.00	0.00	0.00	0.03	1.65
17	0.02	0.00	0.00	0.00	1.60	0.14	0.11	1.26
18	12.62	8.37	27.05	25.86	43.13	16.95	25.50	5.88
19	33.28	27.00	36.53	29.79	38.54	52.29	22.18	2.17

Table 14

CORRELATION GEOLOGY-LANDUSE-HIGHER AREA(geo_lu_h)

(Percentual Distribution of landuse classes in every geologic category for the area above 544 meters)

CLASSES	GEOLOGIC CATEGORIES 1	2	3	4	5	6	7	8
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.82	0.00	0.73	0.00	0.00	3.51	2.37	1.87
7	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	4.81	0.00	0.00	0.00	0.00	0.45	0.00	0.00
9	0.32	0.00	0.00	0.00	0.00	13.70	0.00	19.66
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	55,27	0.00	0.00	0.00	0.00	23.36	2.08	1.50
12	0.87	0.00	0.00	0.00	0.00	13.73	0.00	0.00
13	0.33	92.14	78.20	84.78	0.00	11.30	4.74	0.00
14	1.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	0.00	0.09	20.49	0.00	0.00	0.00	0.00	0.00
16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
18	8.99	0.00	0.00	2.17	40.60	5.18	18.91	61.99
19	26.83	7.77	0.57	13.04	59.40	28.88	71.89	14.98

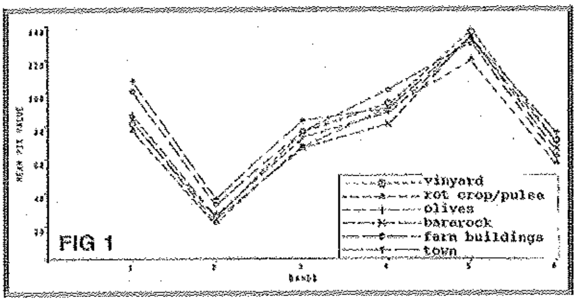

Figure 1.

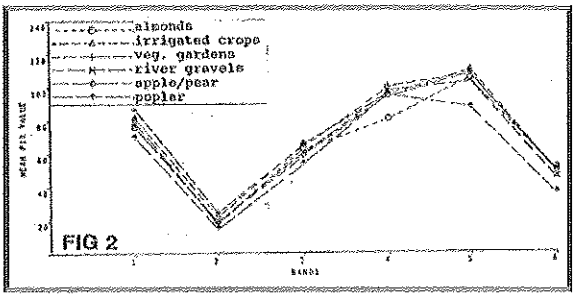

Figure 2.

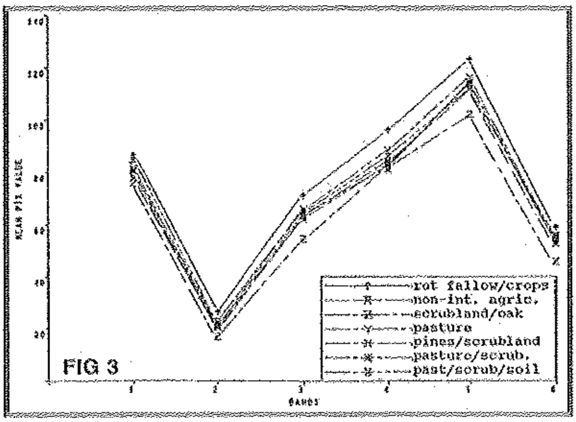

Figure 3.

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