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A METHODOLOGY FOR UPDATING AGRICULTURAL FOREST AND RANGE RESOURCE INVENTORY IN MEXICO

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I. ABSTRACT

This paper presents the experiences, results and conclusions of a two year research effort on the feasibility of updating Land Use-Land Cover maps through digital processing of Landsat data. The project has been conducted by the Dirección General de Geografía del Territorio Nacional (DGGTN), which has in charge the realization of the natural resources inventory of México's National Territory.

Several approaches for developing training statistics were used, and their advantages and shortcomings are discussed. A classification scheme and a general outline of an operational procedure for updating our Agricultural, Forest and Range Resource Inventory is presented.

II. INTRODUCTION

Since 1969, the DGGTN has been publishing topographic and thematic maps at several scales. The large scale thematic maps are made through interpretation of color or BW aerial photographs with the aid of information collected in the field. An intensive ground survey guarrantees that the interpreter becomes familiar with the land use activities and vegetation assemblages of the area under study. As a result of this Land Use-Land Cover maps exceed 96% accuracy, in spite of the complexities of agricultural practices and vegetative cover of México. But while the information content of our geological, hidrological, and soils maps does not become obsolete, the use of the land and its vegetative cover are highly dinamic phenomena. Because of the high cost of acquiring new photographic coverage over extensive areas, and bearing in mind the synoptic and repetitive coverage of Landsat images, it was decided to initiate a research and development project for updating our Land Use-Land Cover maps through digital processing of Landsat MSS data.

III. THE INVESTIGATION

With the aim of facing all those problems which should be solved if the methodology to be developed was to reach an operational status, it was decided to update a map whose ecological complexity was representative of the variability found in any 1:250 000 scale map, since this was the selected scale for the updating. In this way, the region between 21° and 22° North and 102° to 104° West was selected as the first test site. Two adjacent images were used, their ID numbers are 2792-61650 and 2793-62230, dated march 24 and 25 of 1977, respectively.

A. THE SUPERVISED CLASSIFICATION APPROACH

An analogic interpretation of the area was accomplished with the aid of a MinniAdditive Color Viewer and the 70 mm single channel negatives of the two adjacent Landsat images. The interpretation was plotted at 1:500,000 and taken to the field in order to correct errors. By comparing this manual interpretation with the corresponding aerial photographs, which were taken in 1971, it was possible to gain an insight into the geographical distribution and precise nature of the changes in land use and land cover conditions that had taken place in the area. With this information, it was then possible to define a set of training fields for each of the 12 categories that were to be represented in the updated map.

The whole area to be classified, comprised of over 5 million pixels, was divided into 8 subimages. Each of these subimages was classified with a different set of statistics, because some categories were absent from some subimages. This step was considered necessary because preliminary classifications had revealed spectral confusions between some irrigated fruit groves and some of the oak forests, between the low and deciduous tropical forests and the Mezquite stands, and between some steep and shadowed slopes and clear water bodies.

All the training fields of a category were grouped into a set of spectral classes, and the same was done for each category. Then each subimage was classified with a different subset of spectral classes, with a minimum distance to the mean classifier. A qualitative evaluation revealed a large number of errors of commission, and it was soon realized that some categories were not discriminable with spectral data alone. The classification scheme was adjusted accordingly, and the spectral classes of these not discriminable categories were merged. The class groups for classification were again edited and the subimages were classified with a minimum distance to the mean classifier and with a neighbor-weighted bayessian classifier (Baz,1977)[2].

Even though many training fields had been used to represent each category, the minimum distance classification did not perform well because the spectral variability of each category was not well represented in the training statistics. It could also be determined that the grouping into spectral classes needed to be done with a criterion of statistical separability. The bayessian classifier did not perform well because some of the spectral classes were not normally distributed.

These experiences point out that the supervised approach is not well suited for mapping land use; the main reasons are :

1. Updated and good quality reference material, such as high altitude color IR aerial photography, is needed for the precise location and identification of enough training fields so as to adequately represent the spectral variability of each category.

2. Special software is required for the editing of statistics into normally distributed classes.

3. These requirements become more critical if the area to be classified is large and with complex topography.

These results are in agreement with those reported by more experienced authors (Fleming et al., 1975; Fleming and Hoffer, 1977)[3,4].

B. THE GUIDED CLUSTERING APPROACH

A portion of each subimage which accounted for the spectral variability present in the original subimage was clustered with a version of ISOCLS. Some of these training subimages were very long and narrow, consisting of a traverse across the environmental gradient found within the subimage. The identity of each spectral class was then ascertained and the complete subimage was classified with the spectral classes derived from the corresponding training subimage, with a minimum distance to the mean classifier and with a neighbor weighted bayessian classifier. Both algorithms performed well, with no significant difference in accuracy, but the minimum distance approach was five times faster.

The evaluation of the most complex subimage revealed that a large number of errors of commission were present. It was hypothesized that although the training subimage was representative, the clustering algorithm was not performing a good description of the spectral space of the data. Two features of the algorithm were thought to be the reasons:

1. The version of ISOCLS we were using required the number of clusters to be input by the analyst before starting. Although several runs were made for each training site, it is very possible that we classified with less classes than were necessary.

2. The initial clusters centers were positioned along a diagonal across spectral space and the eventual allocation of these centers proceeded gradually as the pixels were reassigned iteratively by the minimum distance criterion . It is possible that the spectral space lying further away from the diagonal was not well described by the algorithm.

A version of ISOMIX was then used to - cluster the training subimages. This algorithm works as follows :

1. Generates a set of initial cluster centers along a diagonal in spectral space.

2. Performs a minimum distance classification, and means and variances are computed.

3. Any cluster with a variance greater than a specified maximum is partitioned, and the new cluster centers are located at Xi-S and Xi+S, where "X" is the mean, "S" is the standard deviation and "i" is the channel whose variance exceeded the threshold. The -- means of the other channels remain the same, so the cluster splits in the direction of maximum variance only. This splitting proceeds until all clusters present have variances smaller than or equal to the threshold.

4. Another minimum distance classification is performed and new cluster centers and variances are computed.

5. The statistical distance between each pair of clusters is computed and those pairs with a distance smaller than a specified threshold are merged.

6. The new cluster statistics are computed and the separability distance matrix is -- printed.

Initially, this program used a statistical separability measure that did not consider the covariances and was found to be unreliable. - This measure was substituted by the Swain-Fu distance. The clustering was repeated and - the subimages were again classified.

After inspecting the 1: 24 000 line printer outputs, the classified subimages were -- submitted to a generalization algorithm which permitted that the smallest unit depicted in - the final product to be 3 mm on a side. A - skew correction factor was applied and the - subimages were plotted at the desired scale - of 1:250 000 with a Gould 5 200 electrostatic printer plotter.

Each subimage was registered to a possitive transparent overlay of the topographic map and the mosaic was thus assembled. Because the images were not geometrically corrected or georeferenced, small displacements of the water bodies were evident. On the -- other hand, several water reservoirs which - were not depicted in the topographic map were faithfully portrayed in the classified image. A quantitative accuracy assessment was not - possible because the images were from 1977, the aerial photographs were from 1971 and it was then 1979. Nevertheless, a survey of the area was conducted in 1980 and the classification was found to be as accurate and more detailed than the manual interpretation.

This guided clustering approach for developing training statistics was considered adequate for mapping land use and land cover in large and complex areas because it is less demanding of reference material and analyst involvement than the supervised approach, while at the same time an improvement in classification accuracy is attained.

C. THE MODIFIED-SUPERVISED APPROACH

With the aid of an interactive CRT dis-- play device it was possible to define complex polygons whose identity was well known. A - program named Point Cluster allows the clustering of data contained in different polygons. Because the clustering is performed on a polygon by polygon basis, the spectral variability of a category can be considered represented when the number of spectral classes is not incremented when adding more training fields.

No stratification was attempted in this approach. One statistics file was generated for each Landsat frame. Those classes that were computed from only a few pixels were deleted because most probably they were edge pixels or isolated items of another category, such as a line of trees within a grassland. After eliminating these less abundant classes a diver-- gence matrix was computed and the editing was accomplished according to separability criteria. This analysis permitted those spectral confu-- sions which had been detected to be quantified. It also acquainted us with the fact that there - was more variability in each land use category than had been suspected.

It was soon realized that the classifica-- tion scheme to be used had to be in accordance with the possibility to discriminate between certain land cover conditions with great accuracy, so as to rely less heavily on ground -- truth. It was necessary to build an unders-- tanding of the discriminating capabilities of - the Landsat MSS.

This modified-supervised approach has -

several advantages over the strictly supervised approach, because the training fields need not be homogeneous and so larger polygons can be defined faster and with less analyst involvement. Another advantage is that the training fields spectral variability is adequately represented by the spectral classes derived by the algorithm, thus making the manual editing unnecesary. On the other hand, an algorithm that computes the statistical separability within each pair of spectral classes is required in order to determine the spectral confusions between informational categories. The modified supervised strategy seems to be well suited for certain applications where only one or a few informational classes are sought for, and/or in the analysis of small areas.

C. THE UNSUPERVISED CLASSIFICATION APPROACH

A very interesting algorithm (SEARCH) was used for this approach. It proceeds as follows:

1. Reads in a matrix of 3x3 pixels and computes its statistics.

2. If the standard deviation is within the specified lower and upper bounds and its coefficient of variation is smaller than a specified maximum, the statistics are stored in a location of a buffer file. Then another 3x3 pixel window is read into memory.

3. Once the maximum number of stats that can be allocated in the buffer file is reached, the pair of stats with the smallest separability measure are merged. This allows room for another set of statistics to be held, so another 3x3 field is sought. This collect one-merge two process is repeated throughout the desired amount of data. As many files or subsets of a file, as desired, may be input to produce the same stat file. This feature makes this program specially well suited for the mono-cluster blocks approach to developing training statistics.

4. After all data has been input a command is given to cause the stats to be merged until the smallest separability measure between any pair of stats is greater than a desired value (NASA, 1980)[11].

After a SEARCH through a complete frame was terminated, a maximum likelihood classification was performed.

The identity of each spectral class was then ascertained by analyzing their spatial distribution and their mean values and covariance matrix. The spectral classes were grouped into informational categories, which were then printed with a different pattern with a Versatec electrostatic printer-plotter. A "cheap" geometric correction was applied without the use of control points. Again the classified image did not register precisely with the topographic overlay, but no systematic errors in scale were apparent.

This unsupervised classification yielded very interesting results. First of all it confirmed the existance of the already determined spectral confusions and most important it revealed that there were several "topographic expressions" of each type of cover. Although in many instances these spectral variations were found to be determined by slight or modest variations of the cover itself, in other cases a very homogeneous type of cover was represented by several spectral classes. Because the effect of aspect and slope on vegetation is a day to day fact for a photointerpreter, we believed that all spectral classes were representing different vegetation assemblages. Nevertheless, the topographic effect on the spectral response from nadir pointing sensors has been demonstrated even for a uniform sand surface (Holben and Justice, 1979)[8].

The unsupervised approach to classification is a good way to gain an insight into the spectral content of an image. In the analysis of small areas it can define spectral classes which might turn out to bear high informational value. On the other hand, the unsupervised approach has high computation requirements and also good ancillary data must be available for an adequate identification of the spectral classes, specially if the area considered is large and complex.

IV. THE METHODOLOGY

A. THE ENVIRONMENTAL STRATIFICATION STRATEGY

Though a stratification before classification seems to make subsequent computer processing more efficient by allowing the analyst to keep to a minimum the number of spectral classes with which he is working at any one time, the complex ecological gradients that prevail in most of México, make it very dif--

ficult to accomplish even a very general stratification. The great differences in elevation encountered within a distance of only a few kilometers determines that conifer forests and tropical forests, as well as the various intermediate types can be intermingled in such a way, so as to preclude the stratification from solving many spectral confusions between cover types which because of their different economic value or ecological significance should be portrayed as a separate category on a map. This is the case of the confusion between some forested mangroves and coconut plantations, which may lay next to each other along many kilometers throughout the coastal plains. Another example is the confusion between grasslands with a very low cover and very open shrub formations. These two cover types may also be confused with agricultural lands that were devoid of vegetative cover at the time of satellite overpass. Although other examples can be brought forth, the aforementioned suffice for understanding the importance of the influence that both geographic location and time of data acquisition have on the possible level of categorization that can be attained through spectral pattern recognition. This brings to mind that the seasonal behavior of the different cover types can be taken advantage of, and much more valuable information can be extracted from the images by the so called "multitemporal analysis". Nevertheless, every experienced photointerpreter knows that in México the contrasting ecological conditions originate a great variety of land use activities and practices. This has an impact on the level of classification that can be achieved in any geographical region at any one time. As a general rule, the broader the area considered, the less informational value is conveyed by any one spectral class.

As an alternative approach to the stratification before classification strategy, it is believed that an experienced photointerpreter can identify and correct any missidentification present in the classified image with enough speed and reliability so as to be considered operational, at least while geographical data banks can be operationally implemented in the digital classification process. So, having a human interpreter relabeling some of the units can greatly improve the informational value of the future map. This is of prime importance for some of the activities that Land Use maps are used for.

B. THE CLASSIFICATION STAGE

The mono-cluster with several blocks strategy for developing training statistics has proven to be satisfactory in all instances and has been recomended for use in all Latin America by very experienced authors (Hoffer and Bartolucci, 1980)[7].

On the selection of the classification algorithm much can be said, but we will only say here that from the available options either a maximum likelihood or a mimum distance to the mean algorithm should perform well with a representative set of training statistics (Hixson et al., 1980)[6].

C. THE CLASSIFICATION SYSTEM

In order to define a classification scheme which can be efectively used in a national level, it was decided to update three 1:250 000 maps, in the following order :

1. The region between 19° and 20° North, and 104° to 106° West. This area is typical of the climatic gradient between the temperate high altitude mountain ranges and the Pacific coastal plain.

2. A map that is representative of the ecological variations present in our subhumid and arid environments. The exact location still has to be defined.

3. A map within the hot and humid region. The exact location still has to be defined.

Although the definitive classification system must await the accumulation of experiences derived from working in other ecological environments, it is now defined that it must be hierarchical, such as the one developed by Anderson et al. (1976)[1].

This hierarchical structure should allow to present maps at 1:50 000 with a level II categorization and the 1:250 000 maps with a level I, with a unique correspondence between them.

The classification system which is tentatively suggested for México is as follows :

1. Agriculture : crops, orchards, ploughed and fallow fields, etc.

2. Forest : areas with a tree canopy closure over 15%, may have shrub, herbaceous and/or grass understory.

3. Shrub : areas with a shrub vegetative cover exceeding 24%; less than 15% tree cano py closure, may have herbaceous or grass un derstory.

4. Grass : areas with a grass cover of 25% or more; less than 15% tree canopy closure; there may be intermixed herbaceous spe cies and/or isolated shrubs.

5. Open shrub and/or grass : areas with a 5 to 25% vegetative cover; may be a com-- plex mixture of shrubs, grasses and/or herba ceous species.

6. Wet and/or flooded lands: areas that were wet and/or flooded during data acquisition. This condition may vary with season.

7. Water bodies.

8. Aquatic vegetation : includes water - hyacinth, non-forested mangroves, swamp vegetation and other floating or rooted aquatic types.

9. Barren : areas with less than 5% vegetative cover; may be predominantly bare non -agricultural soil, sand bars, beaches, rock outcrops, etc. Many man made features may fall in this category also.

Although the informational categories may seem to be very general, it is now considered more important to be able of monitoring the - alterations suffered by our forested areas than to continue seeking for the spectral reflectance differences that are necessary for a classi fication into forest types described by the spe cies composition of the community. The same holds true for the many shrub formations and the aquatic vegetation types.

Perhaps the most striking feature of this system is the absence of an urban category. - The reason for this is that the urban areas in México are very different from each other with regard to spatial organization, materials of -- which they are composed of and amount of ve getation present. While in some big cities the landscape is dominated by concrete, other -- small cities appear like forests to the view of the sensor, and still others are composed of - houses which are built from clays and/or other materials from the surroundings, thus presenting a very similar spectral response as that of local bare soils. On the other hand, our - Remote Sensing Department is conducting a -- project for updating the large scale urban maps with airborne MSS data.

Although this level I categorization is mo re a land cover than a land use system, many land uses can be inferred by an experienced - analyst with the aid of ancillary information, - such as the already existent Land Use map. It is believed that a manual interpretation of the classified image can guarrantee a level I categorization with an accuracy exceeding 85%. -- This human interpretation after spectral pattern recognition, along with a less generalized grou ping of the spectral classes, should allow a le vel II categorization which is yet to be defined.

D. ACCURACY ASSESSMENT

Accuracy of land use-land cover interpre tation or classification is a complex issue, -- both in its definition and measurement. A -- map is a graphic interpretation and represen-- tation of a complex surface that often contains abstractions. Without field checking the total map, exact accuracy cannot be verified. Cost considerations dictate that a sampling strategy which is statistically valid be employed for -- field checking. It is important that users understand that any accuracy estimate based on sampling requires confidence intervals which are dependant on the number of points selected per map.

Financial and termporal limitations, combined with the problem of adequately representing important minor classifications in the --- areal sample, have tended to focus the attention of researchers involved in land use-land - cover surveys towards some form of stratified random sampling technique rather than a stric tly random sample. The major difference bet ween the two approaches is that with the stratified random sampling the areal sample space es divided into strata and each stratum is trea ted as a separate sub-universe in which ran-- dom sampling is employed (Kelly, 1970)[10]. Although stratified random sampling techniques - have been readily accepted as the most appropiate method of sampling in land use studies, the problem still remains on the selection of the best sample size for each category.

Another issue which deserves examina-- tion is the fact that when field surveying an - area where land use-land cover changes have taken place after data acquisition, what may - have been a correct identification may not be confirmed by the field observation, thus lea-- ding to a recorded error in the classification accuracy estimate.

The procedure we have adopted for evaluating the accuracy of the classifications is as follows :

1. Stratify the areal sample space by -- land use-land cover category.

2. The number of sample points for each category is determined by considering the interpretation accuracy level prescribed in the criteria for adopting the classification system and then by consulting the tables published - by Genderen, van et al. (1978)[5].

3. The predetermined sample points are randomly distributed within each category by placing a large sheet of millimeter graph paper under the base map and using a random number table to generate the coordinates of - the sample points, which are then plotted in the base map. Because certain factors may make it impossible to visit some places, more points than are necessary are generated.

The areal distribution and coverage of some categories may be too small to permit the generation of enough random points. In this case, most or all of the areas where the category is present are visited.

4. During field checking the points, a - data collection sheet is used. The standard format facilitates subsequent data analysis.

5. The results are presented in a confusion matrix, where the errors of commission and omission for each category are easily -- distinguished. This confusion matrix is analyzed to determine if the errors are random or subject to a persistent bias.

6. Having computed the porcentage of - correctly classified sample points, the classification accuracy upper and lower 95% confidence limits are determined by consulting - the relevant table published by Hord and Brooner (1976)[9]. This values are given as an estimate of the overall classification accuracy.

The accuracy assessment that is now -- beeing conducted by the Land Use Department of the DGGTN has given results which suggest that accuracy improves when sample points - that fall in areas with only one pixel on a side are rejected. The accuracy estimate improves further if areas with only two pixels - on a side are also rejected. The reason for small areas to be erroneously classified may very well be the influence of background on - target reflectance as a result of scattering by the atmosphere (Turner, 1975)[12]. In any case, the smallest unit to be portrayed in the - final maps must be 250 meters on a side, so a generalization algorithm will be applied to - the classified images. The generalization algorithm generates one pixel for every 5x5 pixel matrix of classified raw data. In this way, many errors in the assignment of small areas will be neglected.

V. CONCLUSIONS

1. A stratification into physiographic or cover type areas of similar characteristics - seems to make subsequent computer processing more efficient by allowing the analyst to keep to a minimum the number of spectral -- classes with which he is working at any one time. On the other hand it is some times -- nearly impossible to divide a Landsat frame - into a small number of relatively homogeneous regions. The complex topography of our territory precludes the stratification strategy from solving many pervasive spectral confusions.

2. An alternative approach to the stratification before classification strategy is to manually correct any missidentifications. This - can be done in the field and/or indoors with - the aid of peripherical information.

3. A substantial improvement in classification accuracy can be achieved by developing an effective and representative set of training statistics. The recommended approach is the monocluster blocks strategy.

4. The contrasting environmental conditions originate in turn a great variety of land use activities and vegetation assemblages. This has an impact on the level of classification - that can be achieved in any one geographical region. The broader the area considered the less informational value can be conveyed by - any spectral class.

5. Another issue of prime importance - for an operational land use-land cover mapping program is the development of a locally adapted classification scheme that meets the informational needs of a more enlightened decision making process.

6. It is concluded that computer-aided -- analysis techniques, in conjuction with the wide expertise of human interpreters is the best approach to an operational methodology for --

updating renewable resources inventories.

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