DASYMETRIC MAPPING WITH IMAGE TEXTURE

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ABSTRACT

The conceptual framework of a dasymetric mapping method using IKONOS image is presented. The method uses homogenous urban patch as the spatial unit and models its population density using two components: the expected population density determined by the land use class and image texture, and the residual population density which is modeled by areal interpolation. This paper discusses the first component only. Gray-level co-occurrence matrix (GLCM) is used to describe image texture. Its utility to differentiate land use classes and the correlation with residential population density are examined. The results show although GLCM can differentiate residential from non-residential land use satisfactorily, the overall accuracy for Anderson Level III classification is only 58%. Some degrees of correlation exist between GLCM texture descriptors and population density, with a correlation coefficient around 0.45. The results suggest that other texture methods need to be examined if texture is to be utilized to estimate population density.

INTRODUCTION

Knowledge of the size and spatial distribution of human population in urban area is essential for many practical applications. In the United States, the decennial census is the primary source to obtain such information. However, census data are only released as the aggregates of spatial units (e.g. census tracts and counties) whose boundary may not be designed to reflect geographic distribution (Forster, 1985). This leads to two difficulties when utilizing census data: the modifiable areal unit problem (Openshaw, 1983) which refers to the dependence of the results of spatial analysis on the spatial basis of the data used; and inaccurate estimation of the spatial distribution of population because residents within a spatial unit may not be uniformly distributed.

To remedy these problems of census data, dasymetric mapping with remote sensing is usually employed. This method uses land use/land cover information extracted from remotely sensed images to obtain an improved estimation of where people actually live. An areal interpolation technique is then applied to disaggregate census population data into spatial units with homogenous land use (Mennis, 2003). In the past, various images have been examined for dasymetric mapping, such as aerial photographs (Anderson and Anderson, 1973), Landsat TM (Forster 1985), SPOT (Lo, 1995), and DSLP nighttime imagery (Sutton, 2001). Although the successes of these studies vary, one consensus reached is that for small-scale applications, spatial resolution of 0.5-5m seems necessary (Jensen and Cowen, 1997).

The advent of IKONOS imagery opened the opportunity for dasymetric mapping at small scale. Its panchromatic imagery of 1-m resolution enables the counting of individual dwelling units, while the 4-meter multispectral imagery clearly reveals the differences between residential communities. This paper examines the utility of 4-meter IKONOS imagery to refine the population data reported at census block group level. The conceptual design is to disaggregate census reporting units into homogenous urban patches (HUP) according to land cover/land use. The population density within an HUP is assumed uniform and modeled by the following equation:

$$D = m(C,T) + \varepsilon \qquad (1)$$

where D is the population density of a HUP. It is modeled using two components: m which is the expected population density and ε which is the residual population density. m is modeled as a function of the land use and the image texture of an HUP . ε is modeled by an areal interpolation method. This paper focuses on m only. In particular, it discusses the results obtained by applying Gray Level Co-occurrence Matrix (GLCM) to estimate residential population density.

DATA AND METHOD

Study Area

The study is focused on the urbanized area of south coast region in Santa Barbara County, California. The region is located 170 km northwest of Los Angeles in the foothills of the California Coast Range.The study area is about 300 sqkm in size and includes a total population of about 200,000. The area represents different types of land use including residential areas with different density and socioeconomic structure, commercial and industrial districts, and open spaces such as farm land and wetland.

Data

The study used three sets of data: (1) The census 2000 population data on block group level; (2) An 4-meter IKONOS imagery taken in August, 2000; (3) A digtial land use/land cover map in a modified Anderson III classification scheme. The land use/land cover map is widely deemed as very accurate and therefore serves as the ground reference data. Geometric and atmospheric corrections were conducted on the IKONOS image to create an accurate and nomralized image mosaic. An object-oriented land cover classification was performed using the eCogition software system (Baatz *et al.*, 2001). This results in three major land cover classes: buildings, green vegetation and the others which include roads, parking lots, bare soil, water bodies, and non-photosynthetic vegetation. The overall classification accuracy is 82.4% and the Kappa coefficient is 71.4%. Details on the pre-processing and land cover classification of IKONOS imagery can be found in (Herold *et al.*, 2002).

Homogenous Urban Patch (HUP)

The elementary unit of this study is homogenous urban patch (HUP) which corresponds to a polygon in the land use/land cover map. The concept of HUP is based on 'photomorphic region' widely used in aerial photographic interpretation (Peplies, 1974) and discussed by Barnsley and Barr (1997). Photomorphic regions are defined as image segments with similar properties in terms of size, shape, tone/color, texture and pattern. In urban area, these regions are termed 'homogeneous urban patches' (HUPs) and have the following characteristics (Herold *et al.* 2002):

(a) A HUP has a homogenous texture which is visibly different from that of the neighboring HUPs.

(b) A HUP may have several land cover types (e.g. built-up, vegetation etc.), but has only one land use (*e.g.* commercial).

(c) A HUP should be adequately large for texture analysis based on spectral reflectance values. Very small homogenous areas are not appropriate for urban land-use characterization.

The HUP concept is fundamental to subsequent examination of the relationship between image texture and population density. Compared to other spatial units such as quadratic filtering window (kernel) or pixel, HUP has the advantage that it allows the characterization of thematic-defined, irregularly shaped areas (Barnsley and Barr, 1997). Automatic delineation of HUP boundary is a separate issue and is not discussed in this paper. For this study, the HUP boundaries were obtained by overlaying the land use/land cover reference map with IKONOS image. Figure 1 gives an example of HUP boundaries.

(a). IKONOS image (b). Land use map (c) Homogenous urban patches

Figure 1. An example of the HUP boundaries

Gray Level Co-occurrence Matrix (GLCM)

A key component in the proposed dasymetric mapping method is the function to estimate the $m(C,T)$ term in equation 1. $m(C,T)$ is the expected population density of a HUP. It is assumed to depend on two variables: image texture and land use class. To describe image texture and determine land use class, the Gray Level Co-occurrence Matrix (GLCM) was used. GLCM tabulates the frequency of one gray tone appearing in a specified spatial linear relationship with another gray tone within the area under investigation. Each element in GLCM is the estimated probability of going from gray level *i* to gray level *j* given the displacement vector which consists of a direction and distance. Details on GLCM can be found in Haralick and Dinstein (1973).

The GLCM analysis in this study uses an isotropic displacement vector. This is because the purpose of texture analysis is to examine whether texture can be used to describe residential population density. The population density of a HUP is correlated with the number of buildings but not the spatial arrangement of the buildings, therefore the direction factor in the displacement vector is assumed to be isotropic. For the distance vector, there hardly exists theoretical guidance to the selection of it and empirical experiment is necessary. Due to the intensive computation cost associated with GLCM, distance factor varying from 1 to 9 pixels were examined. For an isotropic displacement vector with a distance of *h*, the frequency of going from pixel *i* to pixel *j* is counted as follows: for each pixel *i* in an HUP, find the quadratic window of 2*h* x 2*h* centered around the pixel. If the boundary of the window consists of pixels not belonging to the HUP, pixel *i* is excluded from GLCM calculation. Otherwise, for each gray level *j*, find the number of pixels with this intensity in the window boundary and update the (*i*, *j*) entry in GLCM . This process is applied to every pixel in the HUP and the result is a GLCM which can be normalized to obtain the normalized GLCM.

Six texture descriptors were calculated from the normalized GLCM. Together they form a vector to describe the texture of a HUP. Each texture descriptor can capture some characteristics of a texture, but none of them is optimal. The texture descriptors were listed in Table 1.

Table 1. GLCM-based texture descriptors

Texture descriptor	Description
Energy $= \sum_{i,j=0}^{N_g-1} g^2(i,j)$	Measures texture uniformity, *i.e.* pixel pair repetitions. High energy occurs when the distribution of gray level values is constant or period.
Entropy = $-\sum_{i,j=0}^{N_g-1} g^2(i,j)\ln g(i,j)$	Highly correlated to energy. Measures the disorder of an image. Entropy is high when an image is not texturally uniform.
Contrast = $\sum_{i,j=0}^{N_g-1} (i-j)^2 g(i,j)$	Contrast measures the difference between the highest and lowest values of a contiguous set of pixels. Low contrast image features low spatial frequencies.
Correlation = $\sum_{i,j=0}^{N_g-1} (i-u)(j-u)\, g(i,j) / \sigma^2$	Measures the linear dependency in the image. High correlation values imply a linear relationship between the gray levels of pixel pairs.
Variance = $\sum_{i,j=0}^{N_g-1} (i-u)^2 g(i,j)$	A measure of heterogeneity. Variance increases when the gray level values differ from their mean.
Homogeneity = $\sum_{i,j=0}^{N_g-1} \frac{1}{1+(i-j)^2} g(i,j)$	Measure image homogeneity. Sensitive to the presence of near diagonal elements in a GLCM.

where N_g is the number of gray levels, $g(i,j)$ is the entry (i, j) in the Gray Level Co-occurrence Matrix and

$$u = \sum_{i,j=0}^{N_g-1} i.g(i,j)$$ and $$\sigma^2 = \sum_{i,j=0}^{N_g-1} (i-u)^2 g(i,j)$$

GLCM applies to gray level images only, therefore two gray level images were prepared. One is the near infrared band (*i.e.* band 4) of the IKONOS image. This band is selected because a standardized principal component analysis shows that the infrared band is the most significant single band and accounts for 74.3% of the total information in the multispectral image. The other gray-level image is based on the normalized vegetation difference index (NVDI) value of each pixel. The NDVI value is calculated by

$$NDVI = \frac{band4 - band3}{band4 + band3} \tag{2}$$

and scaled to become an integer between 0 and 255. In the following sections, these two images will be referred to as NDVI image and NIR image respectively.

Classification scheme and classifiers

To classify an HUP into residential and non-residential classes, the HUPs are first classified according to a modified Anderson level II classification scheme and then labeled as residential or non-residential. Training and test sites were randomly sampled from the study area. Table 2 shows the details of the classification system.

Table 2. Definitions of land use classes

Level I	*Level II*	*Description and characteristics*	*# of training samples*	*# of test samples*
Residential	Low density single-unit (LSU)	Detached housing located in high income, low population density area. Large buildings with irregular spatial arrangement, large parcel size with vegetation as the dominant land cover	11	39
	Medium density single-unit (MSU)	Located in areas with medium population density, average too large residential buildings and some degree of distinct spatial arrangements along roads, landscape dominated by vegetation cover	9	30
	High density single-unit (HSU)	Small homogenous building units with distinct regular spatial structure and small and fragmented intermediate vegetation patches	19	41
	Multi-unit (MU)	Residential areas with multiple unit or multi-family housing and mixed residential land uses including condos, apartment buildings etc., large building units with regular shape and distinct spatial arrangement, large intermediate vegetated areas	21	34
	Commercial and Industrial (CI)	Large regular commercial and industrial building structures, sometimes in combination residential housing, high degree of imperviousness and only few small fragmented vegetation patches	19	43
	Institution (INST)	Educational and research institutions, churches and other distinct religious buildings, and hospitals, large spatially clumped building structures surrounded by large vegetated areas	11	22

Non-residential	Recreational and open spaces (REC)	Parks, open urban space, vacant lots and other recreational facilities such as golf courses, soccer and baseball fields etc., dominated by vegetation and non-impervious cover types, sporadic isolated buildings	9	23
	Agriculture and rangeland (AgR)	Areas with intensive and extensive agriculture (field crops, orchards, vineyards) and lifestock (cattle), dominated by vegetated surface types with distinct spatial cultivation pattern	11	45
	Forest and wetlands (FW)	Natural or quasi-natural, uncultivated areas including protected areas and riparian zones, dominated by tree and natural vegetation with indistinct spatial pattern	9	28

The output from a texture-measuring method is a vector consisting of texture descriptors. Two classifiers were employed to classify the vectors into land use classes: the minimum distance classifier and the Fisher Linear Discrimination method. Details on the methods can be found in (Liu, 2003). For each test data, it is firstly classified into one of the Level II classes using the above two classifier. The result is then grouped into a binary map according to the level I information in table 2.

RESULTS AND DISCUSSION

Land Use Classification

The GLCM-based classification requires the specification of the lag distance. Since no prior knowledge is available on the optimal lag distance, an isotropic displacement vector ranging from 1 to 9 pixels are examined using both the NDVI and NIR images. It is found that for multiple land use classification, the minimum distance classifier results in higher accuracy than Fisher linear discrimination in all displacements. Overall, the classification accuracy is not high enough to be satisfactory. In the case of minimum distance classifier, the overall accuracy ranges from 50% to 57% and the Kappa coefficient ranges from 44% to 52%. The Fisher linear discrimination performed worse, with an overall accuracy between 39% to 42% and Kappa coefficient between 32% to 34%. Both classifiers display the pattern that higher accuracy is obtained when the displacement is small – less than 4 pixels. These results suggest two things: one is that texture feature alone is not sufficient to differentiate urban land uses, the other is that for GLCM-based classification, the displacement distance should not be too big. This echoes other people's finding (Chen, 2002). For this application, a distance with 3 pixels gives good results for both classifiers. Since NDVI image gave slightly better result than NIR image, its result is presented in Table 3 and Table 4. It can be seen that confusion mainly happens within two clusters: one is among the residential land uses (including low-density, medium-density, high-density, and multi-unit housing area). The other is among land-use classes with lower degree of fragmentation, such as recreational, commercial, agricultural uses and forest. These land uses are usually made up of large contiguous patches and have similar textural characteristics. Although texture-based classification can not separate them well, these classes have significantly different spectral reflectance, thereby if spectral information is combined with textural information, the classification accuracy will be significantly improved.

The GLCM-based analysis involved six texture descriptors including energy, entropy, contrast, homogeneity, dissimilarity, and variance. A question to ask is: which single texture is most efficient in land use classification? How does the displacement distance affect their values? To answer the question, similar tests as that described previously is conducted using each single texture descriptor only. As expected, the overall accuracy is poorer than that obtained using all six textual descriptors. The best Kappa coefficient is below 50%. For all texture descriptors, the minimum distance classifier consistently yields a higher accuracy than Fisher linear discrimination. The accuracy differences between the two classifiers are much more significant compared to the case when all texture descriptors are used. For example, in the case of entropy, the contrast between the two is 41-49% vs. 15-20%. Among the 6 texture measurements, variance is slightly more efficient than dissimilarity, followed by contrast, entropy, energy, and homogeneity. For the purpose of binary classification, the results obtained from contrast and dissimilarity are close to that obtained using all six texture measurements, reaching an overall accuracy over 85% and Kappa coefficient over 70%.

Table 3. Accuracy assessment of GLCM-based land use classification of NDVI data

Displacement	1	2	3	4	5	6	7	8	9
Minimum distance classifier				Binary land use classification					
Overall	87.17	86.84	86.84	87.83	85.20	85.53	84.21	83.55	82.51
Kappa	74.24	73.68	73.65	75.65	70.38	71.05	68.40	67.08	64.96
				Multiple land use classification					
Overall	57.24	54.61	56.91	55.26	54.28	50.99	52.30	50.99	50.50
Kappa	51.61	48.71	51.32	49.39	48.18	44.54	46.02	44.55	43.98
Fisher linear discrimination				Binary land use classification					
Overall	83.22	83.88	83.22	82.89	83.55	83.55	83.55	82.89	82.51
Kappa	66.67	68.08	66.80	66.14	67.44	67.42	67.42	66.12	65.33
				Multiple land use classification					
Overall	41.78	44.74	45.07	43.75	42.76	42.76	42.76	42.76	39.27
Kappa	34.40	37.67	38.02	36.55	35.50	35.54	35.51	35.54	31.59

Table 4 Confusion matrix of the accuracy assessment of GLCM-based classification (displacement distance = 3 pixels, image = NDVI)

Class		*Producer Accuracy*	*# of Samples*	*Low_d* 1	*med_d* 2	*High_d* 3	*multi* 4	*institut* 5	*recreat* 6	*com* 7	*agri* 8	*forest* 9
Low_res	1	51.3	39	20	3	4	1	--	6	5	--	--
Med_res	2	43.3	30	4	13	3	6	--	--	4	--	--
High_res	3	70.7	41	1	--	29	11	--	--	--	--	--
Multi_ res	4	70.6	34	1	2	4	24	1	1	1	--	--
Institution	5	63.6	22	1	2	3	1	14	--	1	--	--
Recreation	6	63.6	22	--	--	--	--	--	14	4	3	1
Commercial	7	56.8	44	--	4	2	4	3	4	25	1	1
Agriculture	8	45.5	44	1	--	3	--	1	10	6	20	3
Forest	9	50.0	28	--	--	1	--	--	8	3	2	14
Total			304	28	24	49	47	19	43	49	26	19
User Accuracy				71.4	54.2	59.2	51.1	73.7	32.6	51.0	76.9	73.7

Overall Accuracy = 56.9% **Kappa = 51.3 %**

The value of texture measurements varies with the displacement distance and form a curve. For different land use classes, there could be a characteristic texture associated with it. To examine the behavior of the six texture measurements, the mean value of the texture measurements of the training samples are plotted against the displacement distance and is shown in Figure 2.

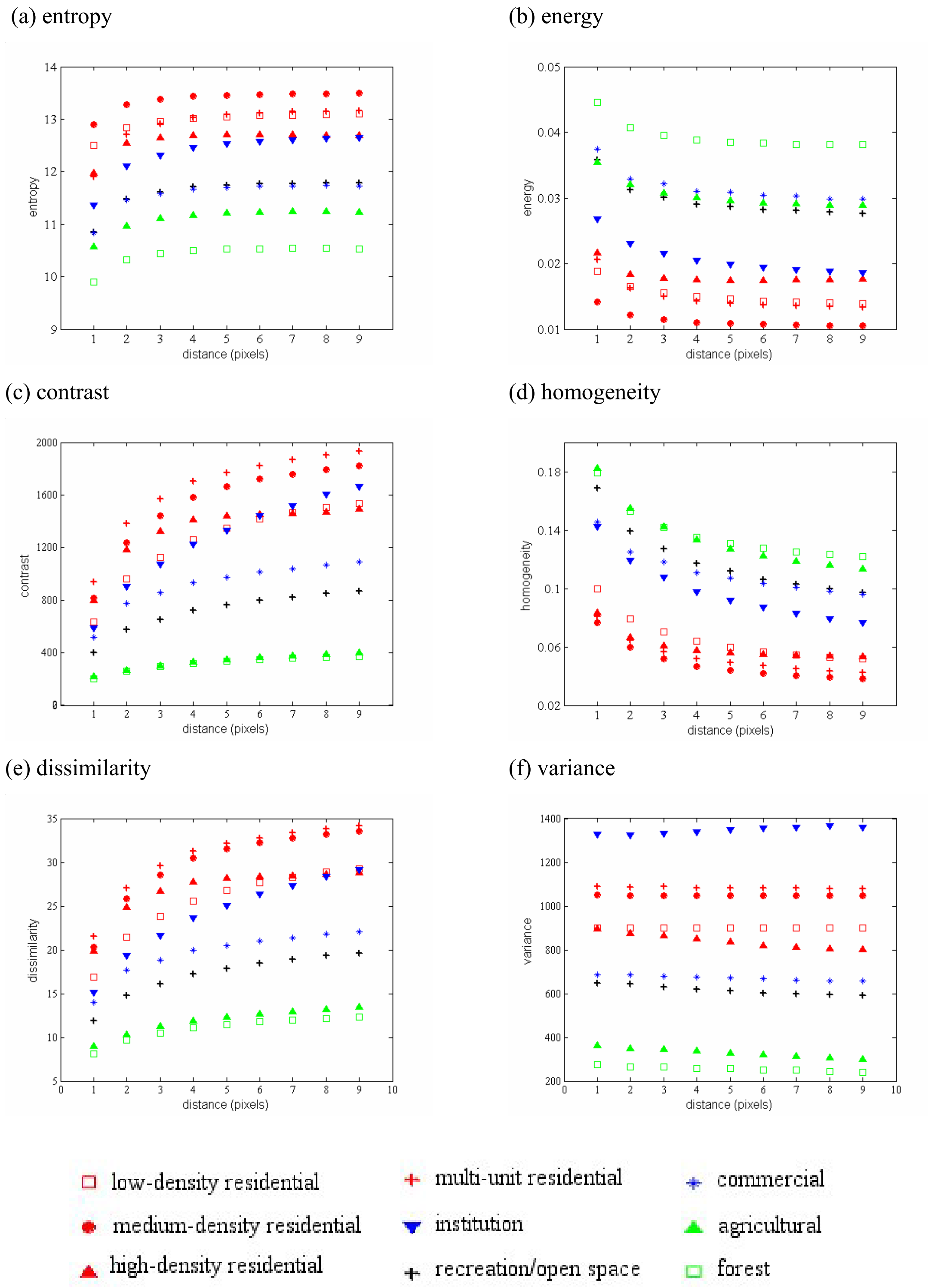

Figure 4.6. Change of texture measurements with varying displacement measurement

To facilitate visualization, residential land use classes are marked in red color, vegetation (forest and agriculture) in green, the others in blue and black. The plots shows clearly the texture of the four residential classes are very close to each other and even overlap in some cases, but very differentiable from vegetation classes. Variance seems to differentiate all 9 classes well. This explains why variance-based classification gives higher accuracy than the other texture measurements. The plots also show that residential classes have a higher entropy, lower homogeneity, and higher dissimilarity than non-residential areas. This is understandable since residential areas are usually fragmented by houses, vegetation, drive-ways, etc. In contrast, forest and agricultural HUPs are much less fragmented. Institution and commercial areas also consist of built-up and vegetation areas, but these patches are more contiguous than that of residential areas and less than non-residential areas. This explains why their texture measurements is somewhere between the residential and non-residential land uses.

Comparison between image texture and residential population density

Having examined the utility of texture to differentiate residential from non-residential land-use class, the next step is to examine whether correlation exists between image texture and residential population density. To do this, some training samples must be collected. 1578 census block groups which fall completely into a HUP were used as training samples. Their textures were calculated and the population was obtained from Census.

For GLCM, both NIR and NDVI images were used. Since previous studies suggest that different texture descriptors describe different aspects of texture, a combination of them were examined as well as single texture descriptors. A linear relationship was found to exist between $\ln(population\ \ density)$ and texture measurements after considerable experimentation. Various displacement distances were experimented with different texture descriptors in the linear regression. In particular, $entropy_{1,2}$ denotes that there are two independent variables -- $entropy_1$ and $entropy_2$, which corresponds to the entropy values calculated using displacement distance of 1 and 2 pixels respectively. This denotation applies to other variables also.

For the same texture descriptors, NDVI seems to result in slightly higher R-square than NIR. Energy and variance does not seem to correlate with population density much, yielding an R-square of nearly 0. In contrast, correlation and dissimilarity are significantly more correlated and the R-square reaches 0.28-0.29. The combination of these variables, i.e. using $entropy_{1,2}$, $energy_{1,2}$, $contrast_{1,2}$, $correlation_{1,2}$, $homogeneity_{1,2,3,4}$, $dissimilarity_{1,2}$, lifted the R-square to 0.45. The use of the more displacement distances or texture measurements does not seem to contribute to improving the correlation. Therefore, the R-square of 0.45 is considered as the highest correlation between GLCM texture and population density.

SUMMARY

As the first step to develop a dasymetric mapping method using IKONOS image, this paper examined the utility of GLCM-based texture analysis to differentiate land use classes and its correlation with population density. To differentiate land use classes, two classifiers were tested: the minimum distance classifier, and the fisher linear discrimination. Results show that minimum distance classifier consistently produces higher accuracy than fisher linear discrimination, with the overall accuracies and the Kappa coefficients around 55%. The texture descriptors were then examined to see whether they are correlated with population density. It is found that the natural logarithmic of population density is linearly correlated with texture measurements. Using six GLCM descriptors: entropy, energy, contrast, homogeneity, dissimilarity, and variance, a correlation coefficient of 0.45 was obtained. Although the correlation is not strong, it does suggest that the some correlation exists between image texture and population density. In the future, other texture measurements such as semi-variograms and spatial metrics may need to be explored.

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