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8.2 MISREGISTRATION'S EFFECTS ON CLASSIFICATION AND PROPORTION ESTIMATION ACCURACY*

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The estimates of crop type and acreage (proportion estimation) are undertaken in the AgRISTARS program by registering multiple date acquisitions of small subareas of Landsat scenes (termed segments), and applying multispectral analysis to them. An important contribution to errors in classification and acreage estimates is misregistration between multiple acquisitions. The relationship can be expressed as:

$$VAR(\hat{A}) = \sum_i \omega_i \sigma_i^2$$

σ_i^2 = VARIANCE OF ACREAGE ESTIMATE FOR iTH STRATUM

ω_i = WEIGHT WHICH DEPENDS ON STRATUM SIZE

$$\sigma_i^2 = (\omega_i)^2 \sum_j \sigma_{js}^2 + \sigma_{jc}^2 + \sum_{j \neq k} COV(\hat{P}_j \hat{P}_k)$$

σ_{js}^2 = VARIANCE RESULTING FROM SAMPLING

σ_{jc}^2 = VARIANCE RESULTING FROM SAMPLE SEGMENT PROPORTION ESTIMATES

$\hat{P}_i$ = PROPORTION ESTIMATE IN iTH SEGMENT

The particular series of operations applied are shown diagrammatically in Figure 1. The spectral data brought in with ancillary data are transformed into the Kauth-Thomas space, where features are extracted. The Kauth-Thomas greeness is a function of time for multiple acquisitions. It is approximated in functional form with various parameters and the vector of these parameters and its distribution within the segment you are working with is decomposed so that its overall distribution function is approximated a posteriori. The a priori probabilities given class and spectral vector that describe a class are the parameters that give you the estimate of the area and crop type. The ancillary data is the place where you bring in the fact that you are working in a specific area, thereby limiting the variety of possible crop choices.

Figure 2 illustrates the taking of a Landsat feature vector and deriving the brightness and the greeness. A procedure derives certain parameters that describe the time at which a crop begins to green up, and the steepness with respect to which the curve moves off the soil line is a function of time; time being a characteristic difference between some of the crops that we're trying to differentiate. This kind of procedure is sensitive to absolute radiometry to perhaps a larger extent than some researchers maybe are interested in with regard to maintaining radiometric fidelity in the resampling process. Figure 3 illustrates the procedure whereby a scene is broken into various strata. There are distribution functions within each strata for the spectral measurement vectors via a procedure called CLASSY. CLASSY breaks the curve down to

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several distributions which are assumed unimodal and normal. This is the place at which the proportion estimates fall out. In the process of doing this, the mixture pixels along the boundaries of the segments create confusion. Registration error looks something like a mixture pixel. If there is misregistration, and a given address for a pixel jumps across the boundary, it acts as a noise, and in the multitemporal sense will tend to confuse crop discrimination.

Figure 4 presents the expression of pure and mixed pixel contributions to classification error. Knowing full well that we have mixture pixels, and if you can parameterize the problem in terms of your estimate of a crop that has found its truer pixels, the equation can be applied to derive a final proportion estimate. The variance in the estimate of the crop proportion in mixed pixels is typically larger than the variance of the estimate of the crop that is in pure pixels. You would like to have q, which is the proportion of the scene which is in pure pixels, to be a larger number so as to reduce the overall variance. That, of course, is done in one way by going to smaller pixels and in another by having better registration accuracy so that you don't have the multitemporal jumping of pixels. Now the quantity q will approach a number that is limited by the spatial resolution of the system as the registration error declines. There is a point at which you cannot drive q to be a larger number with increasing registration accuracy and that declining gain determines the point at which for any particular analysis technique, it is not practical to expend more effort in trying to get better.

For any given sensor IFOV geometry, you can derive ty al populations of fields and you can plot histograms of the number of fielc against field size and you can draw different histograms for the different k nds of crops that, according to your ground truth, go into making up the population examined. Dave Pitts and Gothem Badhwar have published some results for representative samples in the growing regions of the U.S. that are of significance to us (Figure 5). As a function of the resolution element, the IFOV of the sensor, according to those kinds of histograms in Figure 5, can draw the proportion of pure pixels in a given crop (Figure 6). This is the quantity which you would like to drive up. The TM will have a resolution that is considerably smaller, so the proportion of pixels that are pure in any given area will be larger. You can draw an analogy between the misregistration error as acting much the same as an increased resolution IFOV and expect that things will go in the same direction although we have some doubts that you can draw an exact equivalence there because there is some difference in behavior.

This is a workshop and not a symposium so I am not presenting a final result. At this point we do have a program underway to come up with quantitative numbers for the results for the effect of the misregistration error. Also, we are tending to work mostly on the multitemporal aspects of misregistration at this point. Band-to-band misregistration has similar effect, but, in our particular application, it's a less dynamic kind of an affect. We built a registration system at JSC to a point when it was clear that the one pixel registration accuracy that the LACIE processor was giving us was only marginally adequate for the LACIE technology, and with AgRISTARS we needed something better. The MDP, being a full-frame system, does not concentrate as heavily its computation power on an individual pixel. We set ou selves a goal of 2/10 pixels as the registration accuracy that we would like to get to. This was based on the arbitrary criteria that what you would like is 50% of the multitemporal energy to come from a common area on the ground. When you do that, it's really amazing how strictly that ties down the registration accuracy that you think you would like to get to. When you begin talking about registration at that accuracy you uncover all sorts of things that you didn't have to think about previously. As Figure 7 illustrates, the difficult problem to determine is the registration accuracy that you want analytically when you overlay one aperture over another. For pixel A and pixel B, the portion of the clear aperture is a function of the position of the pixel B, given pixel A is fairly easy to calculate. But when you begin to add other pixels that complicates your clear aperture upon adding a third aperture, given a position of the first two is some value on the ramp. It is highly nonlinear and this gets worse when you go to two dimensions, and when you get nonsquare IFOVs, and when you have a variation of response within a IFOV. Our plan is to pursue a Monte Carlo approach in assuming a misregistration error and model its distribution through the process.

In conclusion, it should be noted that we do not have a quantification of misregistration's effect on our analysis at levels better than we currently achieve. Synthetic data is one approach; extrapolations obtained by deregistration is another. Registration accuracy requirements are difficult to specify *a priori*. "More is better"; everyone's an expert. Extrapolation to the performance expected from better registration is risky, and highly dependent on analysis techniques. The proper arena for testing is one's own applications analysis.

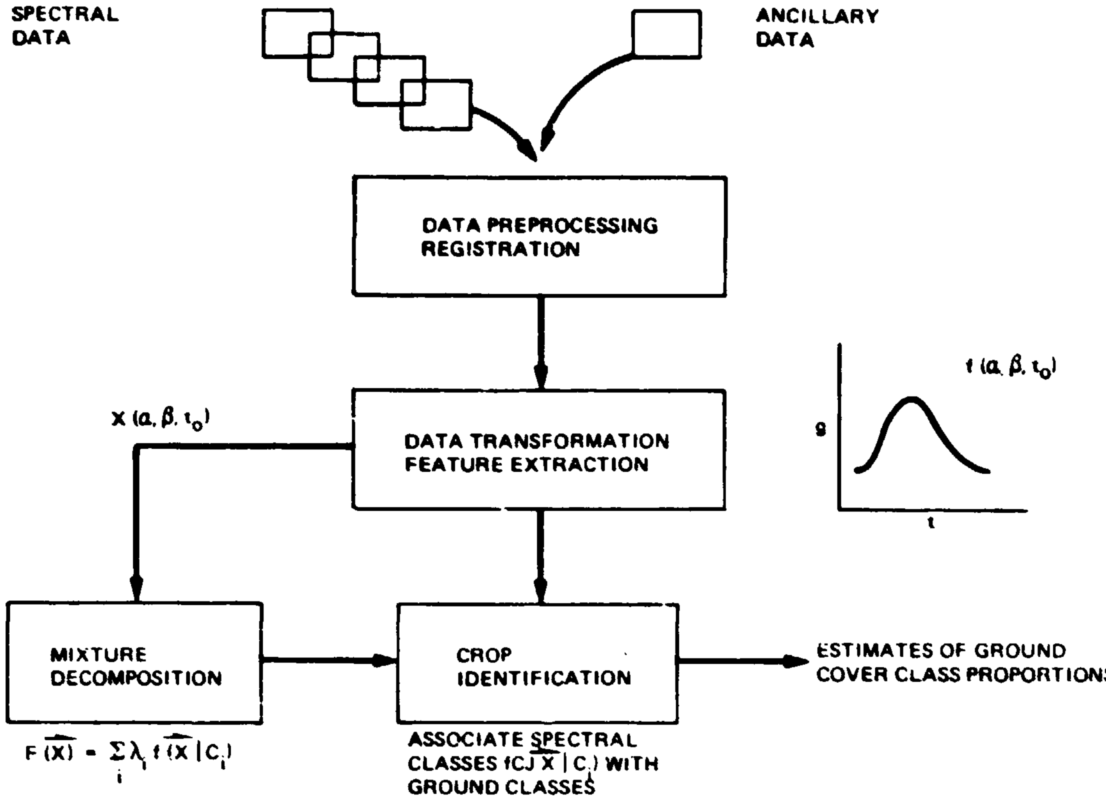

Figure 1. Crop ID/Proportion Est.

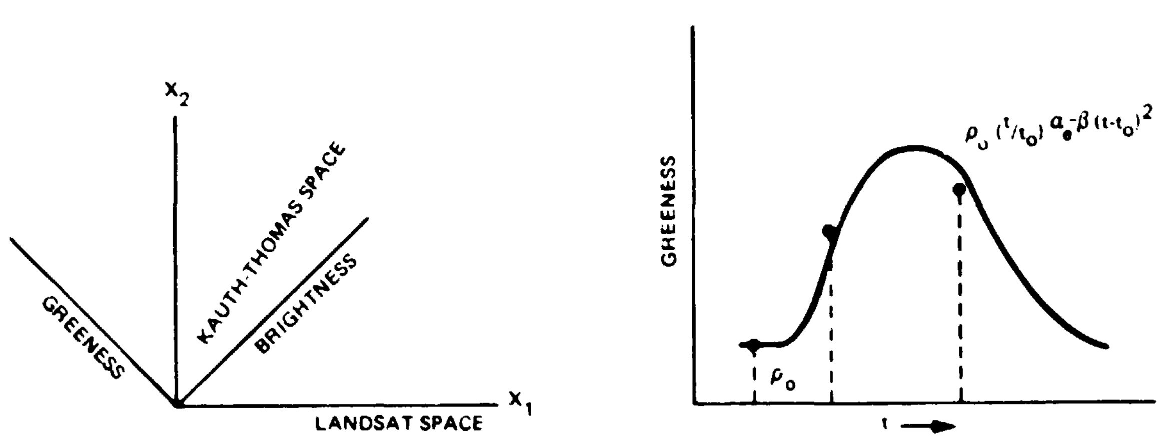

Figure 2. Data Transformation/Feature Extraction

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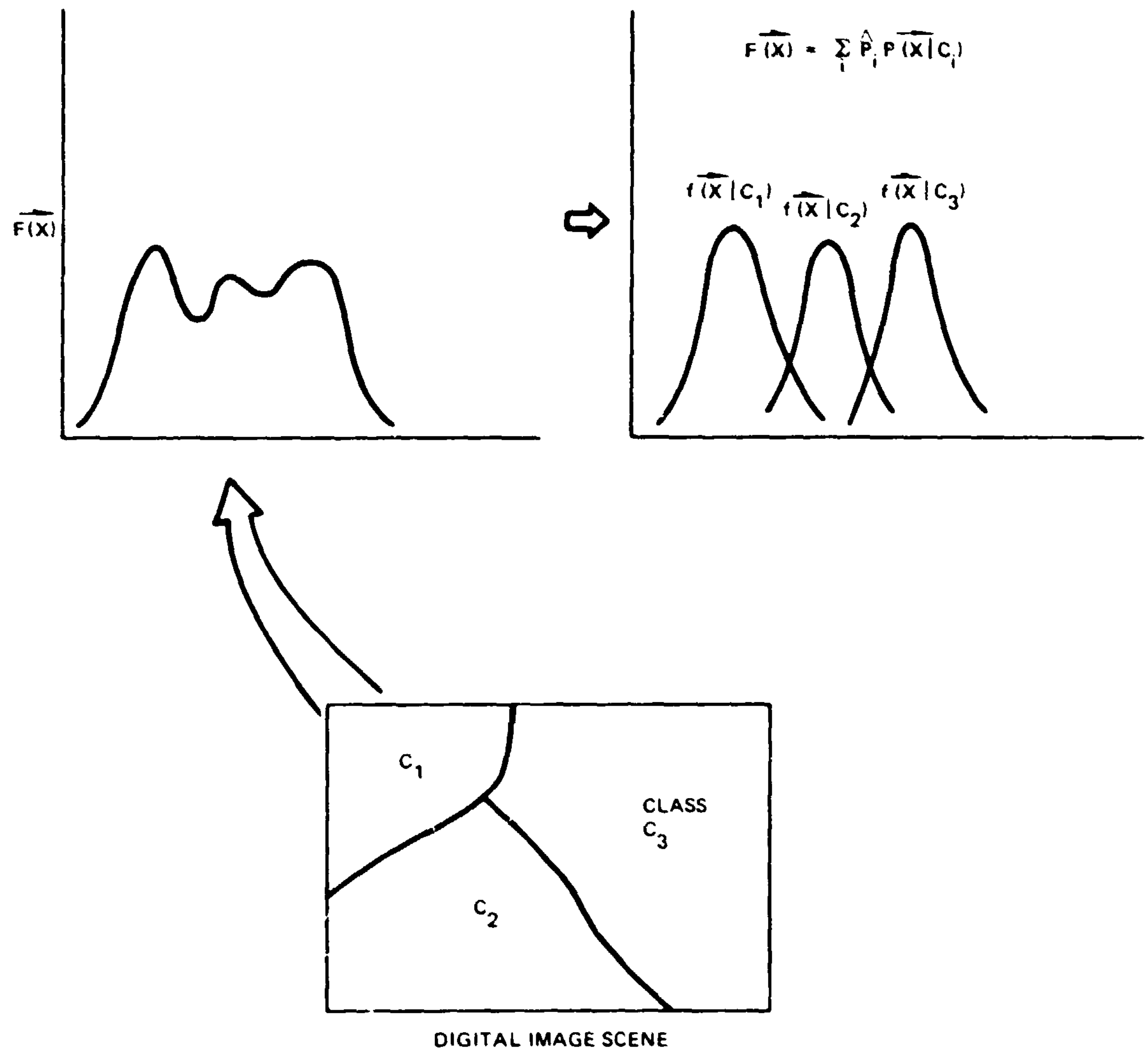


Figure 3. Mixture Decomposition Estimation

$$P = qP_o + (1-q)P_m$$

P = PROPORTION ESTIMATE FOR SCENE FOR CROP

P_o = ESTIMATE OF CROP PROPORTION IN PURE PIXEL AREA

P_m = ESTIMATE OF CROP PROPORTION IN MIXED PIXEL AREA

q = PROPORTION OF SCENE IN PURE PIXELS

$$\text{VAR } P = q^2\sigma_o + (1-q)^2\sigma_m^2 + 2q(1-q)\sigma_{om}$$

$\sigma_o^2 = \text{VAR } (P_o)$

$\sigma_m^2 = \text{VAR } (P_m)$

$\sigma_{om} = \text{COV } (P_oP_m)$

Figure 4. Pure and Mixed Pixel Error Contributions

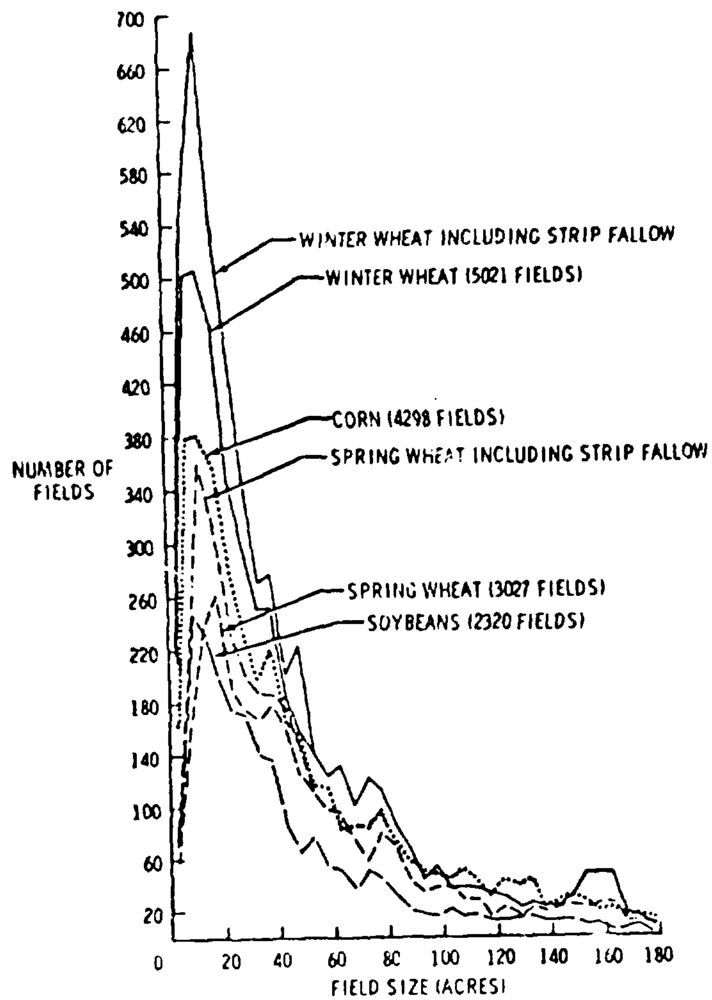


FIGURE 5 Field size distribution for winter wheat, corn, soybeans, spring wheat, winter wheat including strip fallow, and spring wheat including strip fallow.

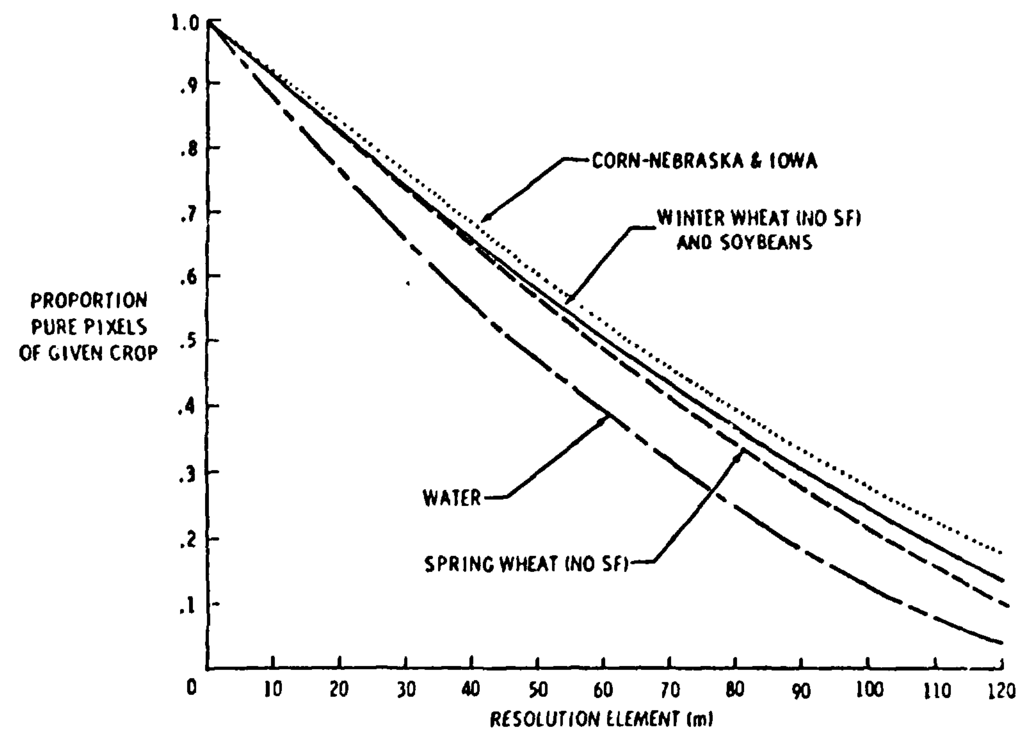


FIGURE 6 Proportion of a crop in pure pixels as a function of sensor resolution.

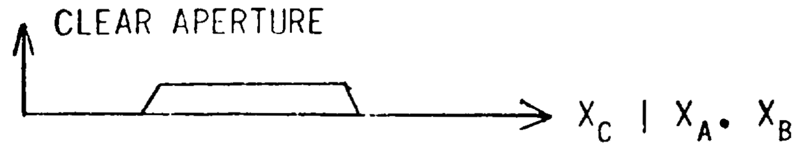
0 ANALYTIC METHOD IS TOUGH

CONVOLUTION OF TWO APERTURES:

|--------| A

|--------| B

ADD A THIRD:



NON-LINEAR EVEN FOR IDEAL APERTURES.

COMPLICATES WITH Z-D, NON-SQUARE IFOV's

0 PLAN TO PURSUE MONTE CARLO

Figure 7. Effects of Resampling Upon Multiple Overlays