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Using the Automatic Interaction Detection (AID) Model to Obtain Homogeneous Classifications of Farmland Markets

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Most data on the market value of farm real estate are presented on the basis of national aggregates. Though continuing to serve many useful purposes, such data have limited use when more exacting economic analysis is required. Data are needed that more accurately reflect local market responses. Thus, an automatic interaction detection model was used to group counties on the basis of their similarity across selected farm and nonfarm factors into optimal farm real estate submarket areas. Through use of the model, factors are identified and examined that help to discriminate between both local markets and variations in land values.

Keywords: Farm real estate; market; submarkets; market value; farm and nonfarm factors; automatic interaction detection model.

For purposes of economic analysis, farmland market areas have historically been defined on the basis of contiguous geographic boundaries such as States and selected regions, and for the Nation as a whole. The U.S. Department of Agriculture and other institutions have, using such a base, collected, maintained, and published data on land values and related subjects for over a century (*7*).[1] These data have been used by researchers in many empirical studies of the land market and by private and public agencies in decision-making (*8, 11, 12, 15, 16*). The common assumption has been that such data represent a single and homogeneous market area.

However, farmland market areas seldom, if ever, follow commonly defined aggregate geographic boundaries. Rather, many varied submarkets exist within the "aggregate" market area, as evidenced by the substantial variations in land values across the country, within States, and even within local communities. Barlow (*4*) concludes that what is often referred to as the "real estate market" actually comprises a conglomerate of thousands of smaller markets operating in different geographic areas for different types of property. Focusing exclusively on the farm real estate market, Scofield states: "Instead of a single market or closely integrated markets, land transactions occur in hundreds and possibly thousands, of local markets, with no standardization, little exchange of information and a minimum of competitive bidding" (*18*). Therefore, market data aggregated across diverse areal units can be and often are poor indicators for use in assessing and forecasting local market activity.

In addition, demand for land and its services is influenced by differences in productivity, climate, location, and economic activity. None of these elements is necessarily confined to or contained within specific geographic areas. Thus, the usefulness (validity) of farmland market areas defined on the basis of aggregate geographic areas is limited.

To forecast future land prices in specific areas and to explain local variations in farmland values require the use of specialized models to define homogeneous farmland market areas. Such a market classification system could supplement current procedures for reporting land values and it could serve as a basis for constructing indices that more accurately measure local changes in values.[2]

Classification of homogeneous land markets may be beneficial in other ways besides direct land value analysis. Economic issues of land use, ownership, appraisal, taxation, and financing (capital markets) can be more accurately probed with improved market information. Wealth and equity concerns, such as the level and distribution of capital gains accruing to real estate owners, also require homogeneous market areas for sound economic analysis.

STUDY OBJECTIVES AND DATA

The primary objectives of this study are to: (1) focus briefly on some methodological and theoretical considerations in market classification and (2) explain and illustrate use of the automatic interaction detection (AID) model in defining an alternative system of farm real estate market classification.

No previous effort has been made to specify statistically optimal farm real estate market areas using multivariate criteria. Several researchers (*8, 12, 16*) have attempted to define more homogeneous market areas

[1] The census of agriculture reports county level values and other agricultural data every 5 years. For example, average size of farms, distribution of land among major uses, and tenancy.

[2] The term "market" as used in this study denotes the grouping of homogeneous counties, those with similar characteristic effects on farmland. Counties assigned to a particular group or market area may not necessarily be contiguous.

subjectively. These studies share some common weaknesses, discussed in the section on methodological considerations.

Data used in the current study are county level observations, primarily from the 1959 and 1969 Census of Agriculture and the 1960 and 1970 Census of Population for the Lake States, Corn Belt, and Northern Plains regions.[3] Throughout the analysis, 1959 and 1960 data have been paired, as have 1969 and 1970 figures. Since the county is the primary unit of observation, many needed factors are not available. For example, rents, number of transfers, and capitalization rates are not reported for counties. The absence of such factors certainly affects the results of the study. However, factors that could be included in the analysis—gross sales of farm products, average size of farm, percent of cropland, density of population, and percent of county population urban—appear sufficient to demonstrate the use of the AID model in market classification.

METHODOLOGICAL CONSIDERATIONS

Many methodological problems are encountered in segmenting homogeneous market areas. Foremost, there is no accepted approach to market areal segmentation. Claycamp and Massey (*6*) argue that segmentation (not necessarily of land) must be viewed as an aggregation process, starting with micro-organizations and building up to the desired macro-level unit. Others maintain that segmentation begins with disaggregation, that homogeneous submarkets should be delineated from the aggregate heterogeneous space. Claycamp and Massey's approach has the greater appeal for land market studies. The large amount of data at the county level are readily available to help delineate the aggregate market into submarkets. Disaggregation below the county level would be desirable because land values vary widely within counties but data by township or census tract are not readily available.

Another problem faced by the researcher is which delineating criterion to select. In the studies conducted by Ruttan (*16*), Corty (*8*), and Harrell and Hoover (*12*), a univariate criterion was used. But since a multitude of different factors generate local variations from the aggregate market response, a multivariate criterion appeared to be needed to achieve meaningful market segmentation. Basically, with the AID technique, agricultural, demographic, and economic factors are jointly employed to assign counties in the study to different market areas.

THE DECISION MODEL

The AID model as developed by Sonquist and Morgan (*22*) is a cross-classification or configuration analysis which predicts and classifies by using patterns of independent variables.[4] Up to 63 explanatory independent variables can be entered into the model as interval codes containing fewer than 31 categories (codes). For example, income is entered as 1 equals less than $500, 2 equals $500-$999, 3 equals $1,000-$1,499, and so on. No codes are required for the dependent variable, which is assumed to be continuous.

This analytical technique has been used primarily in nonagricultural marketing research. Assael (*3*) used AID to segment markets by group purchasing behavior. For Newman and Staelin (*13*), it helped them analyze differences in buyer decision time. Support for the use of the AID model in this capacity is rooted in the theory of market segmentation developed by Smith (*27*). Carmen (*5*) and Armstrong and Adresss (*2*) used AID to develop consumer purchasing behavior models. Their use of the technique is analogous to the activity of a researcher investigating a body of data with only a minimal amount of theory concerning what variables are important.

Assumptions and Analytical Procedure

Because the AID technique predicts via pattern variables instead of linear functions, restrictive assumptions of linearity and additivity common to regression analysis pose no problems.[5] The algorithmic procedure used in AID permits the relationship between the dependent variables and the independent variables to be nonlinear. Further, the relation can have multimodal distributions or nominal scaled independent variables. Since each split of the data is conditioned on a prior one, the model is able to detect and handle interaction effects as well as causal priorities.

The logical step using AID is to partition a sample of observations (counties in this study) into "optimal" sets of nonoverlapping submarkets; the intent is to explain the variation present in the dependent variable. The "optimal" partitioning of the set of explanatory independent variables is said to exist when the categories defined explain a larger share of the variation in the dependent variable than is possible with any other set of submarkets.

Stated as a computation strategy, the analysis proceeds according to the following series of decisions:

1. Consider all counties as constituting a single market area.
2. Choose an unsplit market (ith), composed of $j = 1, 2, 3 \ldots N_i$ counties, which account for the largest

[3] The study area includes all counties in the States of: Michigan, Wisconsin, Minnesota, Ohio, Indiana, Illinois, Iowa, South Dakota, North Dakota, and Kansas.

[4] The term pattern denotes a class of recently developed techniques which predict by creating selected dichotomous and trichotomous splits on the data. The splits are chosen so as to minimize the total error sum of squares around the dependent variable. Common among models that fall into this class are AID, THAID (Theta-AID) interaction detection), and MAID-M (monitored automatic interaction detection). For a discussion of these models, see (*10*). Models of the above class are distinct from those such as regression, canonical, discriminant analysis, and other types which predict exclusively by creating linear functions.

[5] The problem of linearity can be overcome in regression analysis through dummy variables and transformations. Hence, additivity is the most crucial limitation.

reduction in error sum of squares (TSS_i) for the dependent variable, Y. This decision is satisfied by equation

$$(1.0) \quad TSS_i = \sum_{j=1}^{N_i} X_j^2 - \frac{\left[\sum_{i=1}^{N_i} X_j\right]^2}{N}$$

3. Determine which of the submarkets (n_1 or n_2) has the largest unexplained sum of squares (SS) and is therefore to be investigated next for a further partitioning. Here, the algorithm searches each of the X_j independent variables, determining the partitioning that will provide the largest reduction in SS for the dependent variable. The X_j independent variables and splits between categories of X's are chosen so as to split the sample into two nonoverlapping submarkets. This search procedure is repeated across each submarket formed. The between sum of squares (BSS) of the resulting submarkets is computed using

$$(2.0) \quad BSS_i = (n_1 \bar{x}_1^2 + n_2 \bar{x}_2^2) - N_i \bar{X}_i^2 \quad \text{where}$$

n = size of split submarket
N = size of total sample ($N_i = n_1 + n_2$)
x = mean of the explanatory variable for the split submarket
X = mean value of the explanatory variable for the total sample

The BSS of each explanatory variable is computed and divided by the TSS of the market to be split. The explanatory variable with the largest ratio (BSS_i/TSS_i) is chosen to split the market into additional submarkets unless constrained by one of the following three stopping rules:

(1) Sample size—Each submarket must contain a minimum sample size to be eligible for further splitting. (A minimum sample size of 15 was used in this study.)
(2) Split eligibility criterion—A submarket must contain a minimum percentage of the total original sum of squares if it is to be further partitioned. This criterion prevents submarkets with little variation from being further split. (The split eligibility criterion was set at .02 in this study.)
(3) Split reducibility criterion—This criterion is invoked when none of the explanatory variables sufficiently reduces the unexplained sum of squares. The size of the BSS for the ith market must be a minimum percentage of the TSS. (The split reducibility criterion was set at 1.0 percent in this study.)

Actually, there are two methods of entering a variable in AID models. Explanatory variables are classified either as free or monotonic, depending upon whether the researcher desires to have the coded values of the independent variables maintained or rearranged during the partition process. In monotonic AID, the class value (0, 1, 2, 3 . . . 31) is maintained during the partition scan. This type of AID analysis is intended for use with independent variables which are ordinary scales or which consist of class interval codes. Since it was hypothesized that changes in the independent variable varied directly with changes in the dependent variable, monotonic AID was selected for use in this study. (All references to AID in this study are to the monotonic form, unless otherwise specified.)

The independent variables in free AID are permitted to be rearranged to find that partition which maximizes the error sum of squares between the two subgroups formed. The free AID model is developed for use with nominal scales, or for situations in which the researcher desires not to constrain the classes which are to be placed together in the resulting subgroups. The developers of the model caution that free AID can give idiosyncratic splits because of the large number of possibilities considered during the partition scan.

Limitations

A limitation of the AID technique is that it requires a large sample. The model developers suggest that the sample size be at least 1,000, particularly where prediction is sought. However, Sheth (*20*) has found that a sample size as small as 100 can be used with satisfactory results, providing that the reducibility criterion is properly adjusted.

Another disadvantage of AID is that it focuses exclusively on determining the "importance" and not the "significance" of variables.[6] The likelihood that another sample would give the same results can be estimated by viewing the competitive possibilities at each split, but the probability of replicating the results in full is negligible. Sonquest and Morgan (*22*) indicate that tests of significance are inappropriate in AID. Hence, one must use other multivariate techniques in conjunction with AID to establish the significance of variables.

Sheth (*19*) argues that, since the AID model relies on a local optimization strategy in which a latter result is conditional upon a prior one, ordered bias is introduced into the analysis. Though introduction of such a bias could be a problem, it is no more of one in AID than in stepwise regression. Andrews, Morgan, and others (*1*) find no evidence to support Sheth's claim.

[6] The model focuses on searching data for an optimal model. Theory is involved in the selection of explanatory variables, their hierarchical rank, and interpretation of the results.

Comparison with Other Classification Techniques[7]

The primary difference between AID and techniques which predict via linear functions has previously been discussed; that these other techniques impose restrictive assumptions. Contrary to popular belief, regression analysis does not provide the same results as AID.[8] How does the AID method differ from cross-classification, cluster, and hierarchical grouping methods?

AID is an extension of cross-classification analysis, which, at best is a bivariable analysis. Yet many situations exist (as in this study) where a multivariable method extending beyond two-variable classification is needed. AID can handle up to 63 variables.

Several differences exist between AID and cluster analysis. The latter method does not seek to determine groups on the basis of their value on a single variable. Instead, it derives groups which simply exist in the dimensionality considered by virtue of their own density in the 'n-space'.

Although many different algorithmic procedures are used in cluster and hierarchical grouping methods, these techniques invariably rely on hueristic algorithms.[9] Hence, these methods contain no sampling theory for statistical inferences or validation procedures to insure that the resulting clusters are, in fact, true invariant. Sheth (*20*) and Lance and Williams (*24*) have labeled such techniques as essentially trial and error methods. For this study, a technique was desired that provided some measure of statistical reliability concerning markets derived.

Variables Used

A multitude of different factors generate local variation divergence from the aggregate market response. Economic theory suggests that expectations of future earnings are important in the valuation of an asset. For farmland, such expectations may be based on soil productivity levels and resulting net rents. However, expected land use changes may be equally important. Thus, both farm and nonfarm factors influence land values. Since these factors are not constant over space, different demands and, hence, different markets emerge for land and its services.

It is hypothesized in this study that many of the factors (farm and nonfarm) previously used to explain variations in farmland values are important in defining alternative market areal units. The following variables were used in the model to search for an optimal market classification:[10]

- X_1 = Average value of farmland and buildings per acre (dependent variable)[11]
- X_2 = gross sales of farm products per acre (dollars), 1969
- X_3 = average size of farm (acres), 1969
- X_4 = percentage change in the number of farms, 1959-69
- X_5 = percentage change in cropland acres, 1959-69
- X_6 = percent of cropland in farms, 1969
- X_7 = percentage change in the number of part-time farms, 1969
- X_8 = percentage of farmers working 100 or more days off-farm, 1969
- X_9 = density of population (per square mile), 1970
- X_{10} = change in population density, 1960-70
- X_{11} = percent of county population urban, 1970
- X_{12} = change in percent of urban population, 1960-1970

EMPIRICAL RESULTS

Results of the AID model appear in the table and the figure. The table shows variables selected by the model as primary discriminators of farm real estate markets. The relative importance of these variables and other related statistics are also presented. The figure provides a more detailed configuration of markets classified than is shown in the table.

Strategy Variables in Classifying Optimal Market Areas

Only four of the explanatory variables were found to be important in defining an overall optimal market classification system. Gross sales of farm products per acre (X_2), average size of farm (X_3), percent of cropland in farms (X_6), and density of population per square mile (X_9) jointly explained 72 percent of the total variation in farmland values (table). They are termed the principal discriminators. As expected, farm-related factors had a dominant role in explaining variation in values since the study area is primarily agriculturally oriented. These factors (X_2, X_3, and X_6) accounted for 61 percent of the total explained variation—56, 2, and 3 percent, respectively. Density of population, a nonfarm variable, explained 11 percent of the total explained variation. Clearly, the nonfarm factor is important in explaining variations in land values, even in a predominantly agricultural area.

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[7] The following discussion is not intended to suggest that AID surpasses all other available techniques. Obviously, the relative usefulness of any technique is influenced by the objective of the researcher. However, for the purpose of this study, AID appears to be more useful than other techniques that attempt similar tasks.

[8] The reader who is interested in the difference between AID and regression should see (*2, 9*).

[9] For a discussion of cluster and hierarchical methods, see (*22, 23*).

[10] The economic rationale for including these variables are determinants of farmland values is presented in (*8, 11, 12, 15, 16, 17*).

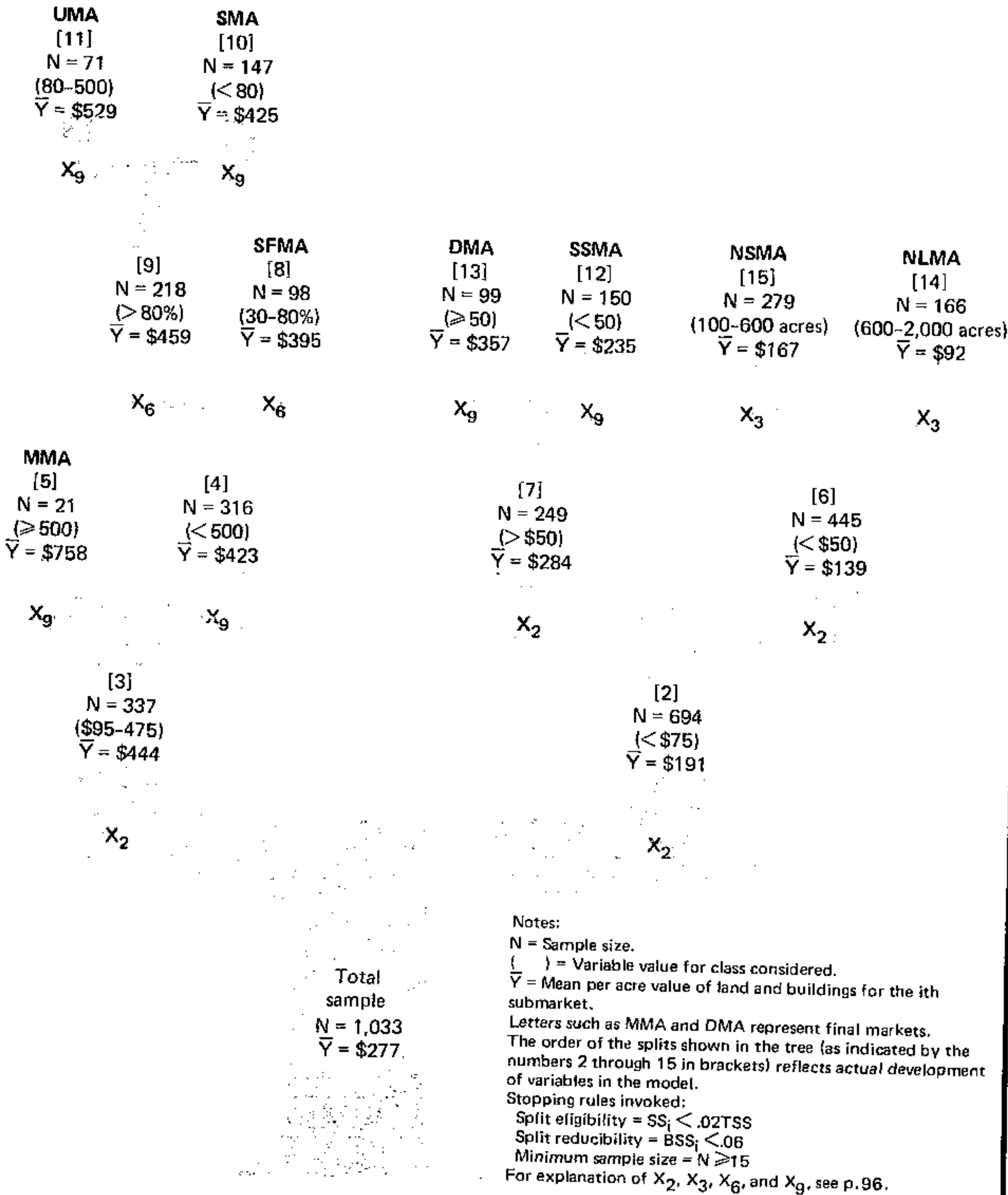
[11] Variables X_2-X_{12} were used as explanatory independent variables. All variables are measured on a county basis.

Table—Monotonic AID analysis of homogeneous farm real estate market areas, 1970

Market split on	Market number split into	Sample size	Explanatory variables	Mean value	Standard devia- tion	Total sum of squares	Variable value	Between sum of squares	Percentage of variance explained
				Dollars	*Dollars*	*1,000*		*1,000*	*Percent*
	Total sample:	1,033		277	178	32,860			
1	2	694	Gross sales of farm products per acre, dollars, 1969	191	107	8,030	95-475	15,174	46.2
	3	337		444	155	8,063	<95		
3	4	316	Density of population per square mile, 1970	423	123	4,811	>500	2,216	6.7
	5*	21		758	227	1,035	<500		
2	6	445	Gross sales of farm products per acre, dollars, 1969	139	63	1,799	>50	3,339	10.2
	7	249		284	107	2,892	<50		
4	8*	98	Percent of cropland in farm, 1969	385	92	835	>80	901	2.7
	9	218		459	119	3,076	30-80		
9	10*	147	Density of population per square mile	425	99	1,455	80-500	521	1.6
	11*	71		529	125	1,099	<80		
7	12*	150	Density of population per square mile	235	76	855	>50	886	2.7
	13*	99		357	108	1,150	<50		
6	14*	166	Average size of farm, acres, 1969	92	101	168	100-600	582	1.8
	15*	279		167	61	1,049	600-2000		
								25,213	71.9
								F = 422**	

* Final markets.
** Significant at .01 level.

MONOTONIC AID TREE



Notes:
N = Sample size.
( ) = Variable value for class considered.
$\overline{Y}$ = Mean per acre value of land and buildings for the ith submarket.
Letters such as MMA and DMA represent final markets.
The order of the splits shown in the tree (as indicated by the numbers 2 through 15 in brackets) *reflects actual development* of variables in the model.
Stopping rules invoked:
Split eligibility = $SS_i < .02TSS$
Split reducibility = $BSS_i < .06$
Minimum sample size = $N \geqslant 15$
For explanation of X_2, X_3, X_6, and X_9, see p. 96.

Market Areas Classified by the Monotonic AID Method

The principal discriminators of farm real estate markets (X_2, X_3, X_6, and X_9) were used as criteria for assigning each county to a particular market area. Eight different market areas resulted from the cross-classification (see figure). Labeled on the basis of their relative position in the urban hierarchy, these market areas are arbitrarily designated as: (1) metropolitan (MMA), (2) urban (UMA), (3) semiurban (SMA), (4) surburban-rural fringe (SFMA), (5) densely settled rural (DSMA), (6) sparsely settled rural (SSMA), (7) noncommercial small farm (NSMA), and (8) noncommercial large farm (NLMA) real estate market areas. Two questions can now be addressed. What are the intrinsic or inherent characteristics of these market areas? Are farm factors important in classifying market areas near urban areas?

At the uppermost branch of the AID tree (see figure), the MMA's comprise those counties that averaged between \$95 and \$475 in per acre gross sales of farm products in 1969 with a population density of at least 500 per square mile in 1970. Population density was the primary discriminator for the MMA, reflecting the strong nonfarm demand for land in urban areas. About 2 percent of all counties fell in the MMA category. These were primarily counties with the large cities and with less than 25 percent of their area classified as land in farms. The mean per acre value of farmland in the MMA's was \$758—\$481 per acre higher than the overall average value in the study area.

It is frequently hypothesized that economic activity (nonfarm) drives the price of farmland above its farm use or agricultural productivity value. Thus, in areas with less nonfarm economic activity, the market value of farmland should tend to progressively diverge toward its farm value. The characteristics of the UMA's and SFMA's identified in the study provide some support for such a hypothesis. That is, these two market areas are identical except for differences in level of economic activity. Further, it is assumed that density of population is a close proxy for level of economic activity.

Both market areas—UMA's and SFMA's— have per acre gross sales of farm products ranging from \$95 to \$475, and more than 80 percent of their farmland in cropland. Population density ranged from 80 to 500 per square mile in the UMA counties and it reached less than 50 per square mile in the SFMA counties. The average per acre value of farmland was \$102 higher in the UMA than in the SFMA counties. Based on mean market values, these findings support the hypothesis that increasing economic activity in an area generally results in a widening divergence between the farm use value and current market price of land in farms. An analogous observation was made for the DSMA's and SSMA's.

Population density, the nonfarm factor, is therefore suggested as an important variable influencing the market value of farmland. Deriving suitable elasticity estimates for such a parameter may be one fruitful area for future research.

About half (43 percent) of the counties in the study were classified in the two lowest valued market areas (NSMA and NLMA). Because "average size" of farm was the prime discriminator variable for these markets, the nonfarm variable "density of population" was not important. Counties classified in the NSMA's had per acre sales of farm products averaging less than \$50 and an average farm size ranging from 100 to 600 acres. Counties in the NLMA's had identical characteristics to NSMA counties except that the size of farms ranged from 600 to 2,000 acres. For both types of market areas, farm size is negatively related to the average value of land per acre, although the locational aspect may also be important. The computed F-statistic for these market areas was 422, significant at the .01 level.

CONCLUSIONS

The AID model was useful both in demonstrating the interaction between variables and in identifying the principal discriminators of each market area. Certain factors were not important in discriminating: percentage change in number of farms (X_4), percentage change in acres of cropland (X_5), percentage change in number of part-time farms (X_7), percentage of operators that worked 100 or more days off-farm (X_8), change in population density (X_{10}), percent of county population urban (X_{11}) and change in percent of urban population (X_{12}). An untested hypothesis is that these factors are also not important in explaining variations in the level of farmland values.

Substantial improvements could be made in the model if more adequate data were available. Specifically, statistics on agricultural rents, numbers of transfers, and capitalization rates are needed. These variables tend not to be available below the State level. While density of population is a composite measure of economic activity, this variable may not be the only or most appropriate proxy. Retail sales density could be a more appropriate choice for local economic activity, and numerous other variables might also be considered.

The tree diagram of the AID technique output permits visual perception and understanding of the intermediate processing of the data. Researchers and other decisionmakers can identify from the AID tree the prime discriminating factors of the markets defined. They can also identify variables that interact with these discriminators. Assuming that the stopping rules used in the model were properly set, the discriminators identified can be used with assurance of statistical significance to aid in developing regression and other multivariate techniques which might further highlight the rational functioning of local land markets.

However, additional factors (farm and nonfarm) are needed to improve the overall specification of the AID model because of the rather large (28 percent) unexplained error variance in the study. Since counties can be and often are as heterogeneous as States and larger areas, a unit of observation smaller than the county might lead to a more efficient system of market classification. Currently, the possibility of using the "farm unit" as a criterion variable is being considered. That is, individual farms instead of counties would be classified to specific market areas. Data available from the 1970 Special Agriculture Finance Survey offer some possibilities. The primary drawback, however, is that access is lost to the nonfarm factor, density of population. Whether a suitable proxy or proxies for economic activity can be extracted from the survey is not clear at this time.

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