MODELLING FARMLAND ABANDONMENT IN THE REGIONAL MUNICIPALITY OF OTTAWA-CARLETON

by

HAROLD BRENT DIRSCHL, B.Sc.

A thesis submitted to
the Faculty of Graduate Studies and Research
in partial fulfilment of
the requirements for the degree of

Master of Arts
Department of Geography

Carleton University
Ottawa, Ontario
June 10, 1992

ISBN 0-315-79836-X

ABSTRACT

A probability model, integrated with a geographical information system, has been developed to predict farmland abandonment in the Regional Municipality of Ottawa-Carleton, specifically the census subdivisions of Goulbourn, March (Kanata), Osgoode, Rideau, and West Carleton. A set of 1977 land-use and CLI soil capability maps were used to calculate the abandoned proportion of all farmland parcels for each of several sets of parcel attributes. The attributes examined were soil capability, area-perimeter ratio (shape), and an index of neighbouring land-use.

The model was used to predict abandonment between 1977 and 1992 under the assumption that the proportion of abandoned parcels observed prior to 1977 would be maintained in the future. All farmland parcels active in 1977 were assigned to one of four classes, where the predicted 1992 proportion of abandoned parcels for each class was 0.450, 0.302, 0.127, 0.019, respectively. A random field survey of 20% of all active parcels compared well with model predictions; the observed proportions of abandoned parcels were 0.413, 0.340, 0.100, and 0.063, respectively.

ACKNOWLEDGEMENTS

I am grateful to my Supervisor Dr. Mike Smith for his advice and guidance during this study. Thanks are also extended to Steve Prashker and Danny Patterson for their help in importing the original GIS data. Last, but not least, I wish to thank my wife Kimberly Anne for her assistance with my field work, as well as for her patience and support throughout the writing of this thesis.

TABLE OF CONTENTS

TABLE OF CONTENTS; cont'd

LIST OF FIGURES

LIST OF TABLES

LIST OF TABLES; cont'd

CHAPTER 1: INTRODUCTION

1.1 Sustainable Development and Land-Use Planning

The concept of sustainable development has become an environmental policy objective of all levels of Canadian government since it was defined by the World Commission on Environment and Development (1987) as "...development that meets the needs of the present without compromising the ability of future generations to meet their own needs". The concept is a central theme of the federal government's Green Plan (1990) which further defines it as "... activity in which the environment is fully incorporated into the economic decision-making process as a forethought, not an after-thought". Furthermore, the Regional Municipality of Ottawa-Carleton is also considering sustainable development as a policy objective (Citizen's Greenprint Committee of Ottawa-Carleton, 1990). Thus, it appears that the integration of economic development with environmental values is becoming an important aspect of government policy at all levels.

The difficulty, of course, is in applying principle to practice. Land-use management is a major means of contributing to the achievement of sustainable development because there "... is little in the relationship between society and economy on the one hand and the physical environment on the other that is not mediated by land and the ways in which land is used" (Richardson, 1989). Furthermore, land-use planning with respect to agriculture may be of fundamental importance

because of the large proportion of land which is typically in agriculture. When agriculture in eastern Ontario reached its maximum areal extent by 1941, fully 86% of the total land area was farmland. The maintenance of a sustainable agricultural system is crucial to any sustainable development policy and land-use planning is a means to its achievement.

Richardson (1989) proposes a number of important elements involved in the land-use planning process, including the setting of explicit goals, identifying land-related problems and issues, systematic application, flexibility to deal with changing circumstances, and public participation. Another important element is the requirement to anticipate changing circumstances and future needs. In other words, an ability to predict, to some degree, future land-use conditions. This is the subject matter of this thesis.

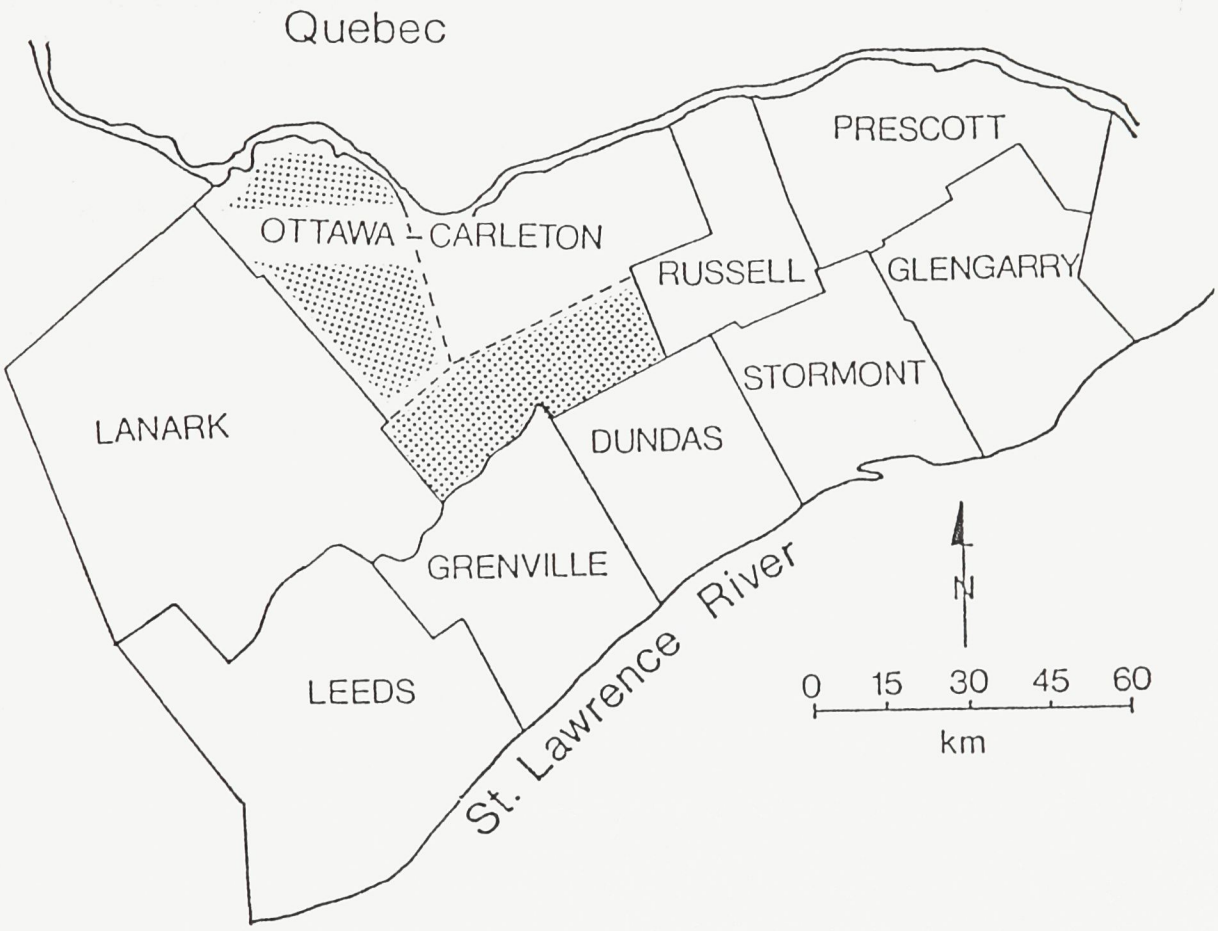
1.2 Thesis Objectives

Land-use change is influenced by a myriad of factors that operate on a number of temporal and spatial scales (e.g. socio-economic factors). Consequently, the prediction of future land-use change by modelling these processes is often time-consuming and difficult to accomplish. However, empirical modelling based on changes observed in the past is often an effective option, particularly with the widespread availability of land-use maps, aerial photography, and remotely-sensed imagery. The objective of this thesis is to

develop such an empirical model. The particular aspect of land-use change examined is the abandonment of agricultural land, a widespread and continuing phenomenon in North America and Europe over the last several decades. The study area is in the Regional Municipality of Ottawa-Carleton, specifically the census sub-divisions of Goulbourn, March (Kanata), Osgoode, Rideau, and West Carleton.

The overall objective of the thesis is to develop an empirical simulation model of farmland abandonment that is integrated with a geographical information system (GIS). In specific terms, the simulation model will be of the Markov-chain type in which the probabilities of change are linked with landscape attributes via a rule-based approach, using input data of land-use and soil capability.

FIGURE 1(a)
LOCATION OF STUDY AREAS IN EASTERN ONTARIO
(Modified From Hoffman and Noble, 1975)



CHAPTER 2: THE ABANDONMENT OF AGRICULTURAL LAND

2.1 Trends

The demand for both agricultural land and timber that accompanied the colonization of North America resulted in the widespread deforestation of much of eastern Canada and the northeastern United States (Cronon, 1983). This deforestation reached its maximum in the early 1900's by which time the major agricultural regions of the American Midwest and Canadian Prairies began to open up (Nyland *et al*, 1986). The resulting shift of agriculture to the west initiated a decline in agriculture in the east that continues to this day (Hart, 1968; Parson, 1979; McCuaig and Manning, 1982; Lamoureux, 1985; Nyland *et al*, 1986).

The decline of agriculture in northeastern North America has resulted in the large-scale abandonment of farmland. McCuaig and Manning (1982) state that in Canada "... the bulk of agricultural land losses are due to abandonment of farmland or its conversion to such non-urban uses as forestry or outdoor recreation and most of these losses have occurred in eastern Canada". This trend has become widespread throughout the northeastern United States and Canada over the last sixty years and is expected to continue (McCuaig and Manning, 1982).

The rate of farmland loss has been remarkable. For example, Parson (1979) showed that in the period between 1921 and 1971 the central Ontario counties of Haliburton, Hastings, Muskoka, Peterborough, and Victoria combined lost almost 50%

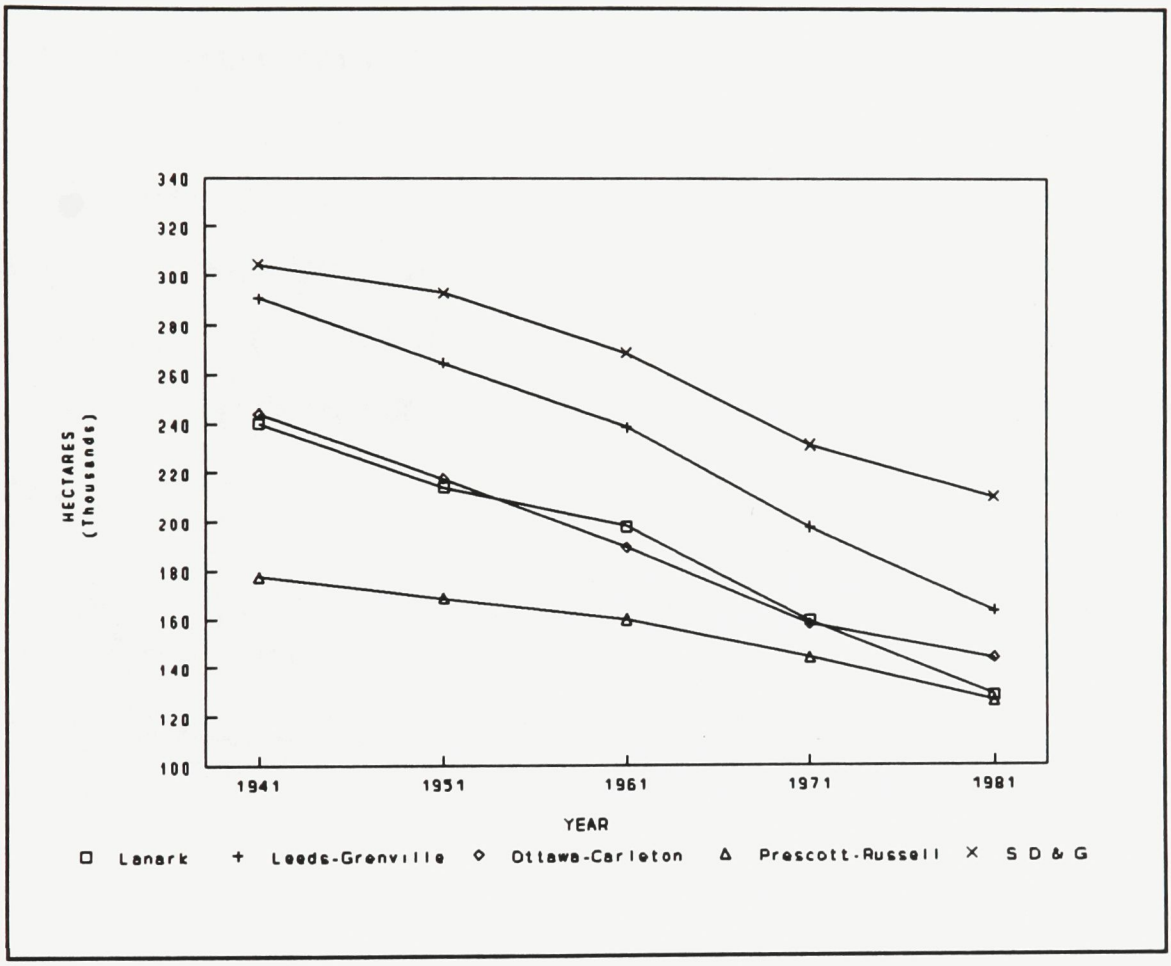
(0.465 million ha) of their agricultural land. Similarly, the Gaspé region of Quebec has demonstrated an almost 50% loss in farmland, but in only twenty years between 1961 and 1981 (Lamoureux, 1985).

Eastern Ontario has also experienced extensive losses in farmland area. Census data for the counties of Lanark, Leeds-Grenville, Ottawa-Carleton, Prescott-Russell, and Stormont-Dundas-Glengarry, reveal that farmland area peaked in 1941 and has declined steadily ever since (Figure 1). In the period between 1941 and 1986, roughly 44.1% or about 0.554 million ha of farmland was lost. Since the total area for the above-named counties is about 1.44 million ha, 38.5% of the total land area has changed from agriculture to some other use in this 45-year period. Clearly eastern Ontario has undergone a period of considerable land-use change.

As a whole, the provinces of Quebec and Ontario lost 37% of their total farmland in the period between 1941 to 1976, amounting to approximately 6.1 million hectares (McCuaig and Manning, 1982). Some of this land was lost to urbanization; however, according to McCuaig and Manning (1982) only 10% of farmland loss can be attributed to urban development in all of Ontario. Furthermore, it may be that the farmland losses due to urbanization in eastern Ontario have been lower than the average because of the larger proportion of urbanization in southwestern Ontario.

Since only a small proportion of farmland loss is due

FIGURE 1(b)
CHANGES IN FARMLAND AREA IN EASTERN ONTARIO, 1941-1981
(From Census of Canada, 1941-1981)



either to urbanization, conversion to recreational use or forestry, most of the lost land must simply have been abandoned and left to natural succession -- a reversal of the earlier historical trend. For example, in central New York State, deforestation was so extensive by the early 1900's that only 8% of the total land area remained as forest. By 1980, however, forest cover had increased back to 40% (Nyland *et al*, 1986).

It should be noted that *farmland* does not necessarily imply cropland and that the rate of farmland abandonment often varies with the type of farmland. For example, the Census of Canada for agriculture classifies farmland under two broad categories as follows:

1) <u>improved farmland</u> including cropland, improved pasture (i.e. cultivated and seeded), and summer fallow; and,

2) <u>unimproved farmland</u> including farm woodland used for fuelwood, timber, and Christmas trees, as well as other unimproved land for natural pasture/hay.

In the case of the eastern Ontario counties discussed above, the 44.1% loss of total farmland between 1941 and 1986 comprised a 36.0% loss in improved land and a 54.6% loss in unimproved land (corresponding to a loss of roughly 0.30 and 0.26 million ha respectively). In the Gaspé, the 50% loss of farmland between 1961 and 1981 consisted almost entirely of unimproved land (Lamoureux, 1985). Thus, it appears that unimproved land may be more susceptible to abandonment than

improved land.

McCuaig and Manning (1982) studied the question of where land abandonment occurs in a case study of land-use change in the Saugeen valley in southwestern Ontario. By overlaying two land-use maps of the area for 1966 and 1976, they found that a minor net loss (0.5%) of agricultural land occurred due to the near balance of losses (27,390 ha) and gains (25,792 ha) to agriculture. Of the land that was lost from agriculture, 54.0% was converted to *forest* and 38.5% to *scrub*. Since a forest cannot grow in 10 years, *forest* likely implies that active maintenance and/or reforestation is undertaken with the expectation of future (economic) benefit. On the other hand, *scrub* likely implies outright abandonment. Since 14.0% of unimproved land and 2.3% of improved land reverted to scrub between 1966 and 1976, it appears that the former showed a much higher rate of abandonment than the latter.

By overlaying the above land-use maps with the Canada Land Inventory (CLI) for Agriculture map of the area, McCuaig and Manning revealed that the area added to agriculture was primarily land of good capability that had been woodland in 1966. Similarly, the losses were located primarily on scattered parcels of poorer land capability. Thus, the land brought into agriculture was generally superior in capability to that leaving agriculture. This regional trend towards the agricultural use of the best capability land reflects a national trend in Canadian agriculture, namely, that over

time, there has been a greater correspondence between land in improved agricultural use and its cropping capability (McCuaig and Manning, 1982).

Parson (1979), using Canada Census data for central Ontario, determined that farmland abandonment was highly correlated with land capability. Using the percentage loss of farmland between 1921 and 1971 as the dependent variable and an index of soil capability as the independent variable (for each census subdivision in the study area) she found that almost 70% of farmland loss could be explained in terms of soil capability. Simply put, subdivisions of low soil capability tended to lose more farmland than areas of high capability.

Similar results were found for eastern Ontario by the present author. An index of soil capability was calculated for each census subdivision using data from Hoffman and Noble (1975). This index was then correlated with various land-use measures including the proportion of subdivision area in farmland, the proportion of farmland in improved condition, and the proportion of farmland in farm woodlots for 1951, 1976, and 1986. The results showed that the above measures were highly correlated with soil capability (r^2 values from 0.58 to 0.80). Unfortunately, analyses of farmland losses over time could not be performed for eastern Ontario, as Parson (1979) did for central Ontario, because of changes to subdivision boundaries. Still, the data appear to support the

contention that farmland abandonment is correlated with land capability.

It should be noted that although the comparison of land-use maps for the Saugeen revealed only a 0.5% net loss of agricultural land between 1966 and 1976, Census of Canada data indicate that a 9.7% loss of farmland occurred. McCuaig and Manning (1982) state that one of the reasons for this discrepancy is the substantial time delay that occurs between the moment of abandonment from active agriculture and the land's change in appearance to a point when it can be classified as non-agricultural. Thus, the appearance of agricultural use during a land-use survey does not necessarily imply that the land is, in fact, being farmed. In other words, land surveys may tend to overestimate the area being actively farmed, whereas census data is a relatively accurate estimate because the data is provided by the farmers, who know exactly how much land they are farming.

Hart (1978) suggests that cleared farmland (i.e. total farmland minus farm woodland) reverts to farm woodland about ten years before going out of agriculture completely. In other words, farmland tends to follow a sequence of improved land to unimproved land to farm woodland before being abandoned. Coleman (1967), in a study of farmland abandonment in Ottawa-Carleton, identified two distinct contexts in which abandonment occurs, the rural-urban fringe and the rural-wilderness fringe. She contends that the dynamics of farmland

abandonment are different within these two zones. For example, rural-wilderness fringe abandonment is characterized by the irregular shape of abandoned parcels, which typically progress through a long drawn-out series of steps as follows:

1) the farmland parcel, although still under active grazing, attains a scrub state with shrubby elms, junipers, and willows;

2) the parcel is abandoned, usually prompted by low return versus maintenace costs or possibly a single bad year;

3) the parcel attains a slashland state where overgrowth has continued long enough to produce complete cover of shrubs and young trees;

4) the parcel attains a woodland or forest state after it has been abandoned long enough to carry a cover of fully grown trees.

There is no distinct moment when "abandonment" occurs because grazing can continue well into the slashland and even woodland state. At the small-scale, encroachment does not necessarily affect the poorest land first, but over the whole of Ottawa-Carleton there is a definite correlation between soil capability and abandonment. Coleman states that the key criterion for identifying the rural-wilderness fringe, and thus areas of likely abandonment, is the presence of active abandonment. The presence of old abandoned areas is not enough because woodland can coexist stably with prosperous farmland. Thus, slashland areas in close proximity to recently abandoned land may be prone to abandonment.

The irregularity of shape that characterizes rural-

wilderness abandonment is due to the encroachment of the wilderness along an irregular front combined with the maintenance of residual portions of fields as long as possible. On the other hand, abandonment in the rural-urban fringe is characterized by rectangular shapes due to the rapid change from use to disuse. In competition with urban uses the abandoned farmland was clearly marginal but not necessarily in terms of land capability (Coleman, 1967).

In summary, farmland abandonment has been occurring at a relatively rapid rate in eastern North America (including eastern Ontario) for the last several decades. Although all types of farmland are abandoned, it appears that low-intensity (unimproved) farmland on poorer capability land is more prone to abandonment than is high-intensity (improved) farmland on higher capability land.

2.2 Causes and Consequences

The principal reason for the increase of agriculture in western North America and the corresponding decline in the east is likely that the former is more profitable than the latter. This is due in large part to western agriculture having greater potential for expansion through the use of new techniques and the application of capital than does eastern agriculture (McCuaig & Manning, 1982).

Many European countries, particularly members of the European Economic Community (EEC), are also experiencing

reductions in agriculture and anticipate considerable further reductions when the EEC comes into full effect in 1994 (Primdahl, 1991). There are several reasons for this decline but they generally stem from the fact that the EEC countries have a considerable overproduction in agriculture. The high levels of agriculture have been supported in the recent past by ever increasing subsidies such as in the Netherlands where subsidies to farmers currently stand at around $2000/ha/year (Zonneveld, 1991).

However, subsidies are to be eventually dropped as trade barriers are lifted within the EEC, and this is expected to lead to the large-scale abandonment of farmland in Europe. For example, the Netherlands is anticipating a 50% reduction in agriculture and is making major efforts in land-use planning for the large land area expected to be abandoned (Gray Merriam, personal communication). Sweden expects to take approximately one-third of its agricultural land out of production within the next five years (Angelstam, 1991).

Even further changes to agriculture in both Europe and North America are anticipated as a result of the General Agreement on Trade and Tariffs (GATT) talks which aim to reduce trade barriers and subsidies throughout the world. For example, there is a very real possibility of a GATT agreement calling for the abolition of Canada's marketing board approach to agricultural production because marketing boards protect Canadian farmers from international competition. The opening

of a once-closed system to international competition would undoubtedly result in the decline of some sectors of the Canadian agricultural system, such as the dairy industry, and would likely lead to more farmland abandonment. The decline of the dairy industry is of particular concern to Ontario and Quebec.

Economics and agricultural policy in both Europe and North America typically operate at the regional level or higher. However, the impact of these decisions is felt at the level of individual farms. For example, several EEC programmes compensate farmers for converting agricultural land into grass or woodland, which results in a considerable increase in semi-natural areas in many regions (Primdahl, 1991). Consequently, the cumulative effect of decisions by individual farmers to change land-use can have a profound effect at the regional scale. McCuaig and Manning (1982) state that "... the pattern of land-use in Canada today is the legacy of countless decisions made by individual landowners from the time of earliest settlement to the present".

The primary causes of farmland abandonment are manifested in many ways at a smaller scale. Lamoureux (1985) identified several causes for the 50% loss of farmland that occurred in the Gaspé region between 1961 and 1981, including biophysical, policy, and personal factors. For example, economic development programs such as marketing networks encouraged farm specialization and consolidation and consequently caused

small isolated farms located outside of the networks to be under-utilized and eventually abandoned.

The old style of farming had enabled the use of these small plots of land and thus a larger total area devoted to farming small, isolated, and often poorer parcels of land. However, the requirements of commercial farming promoted by the above programs forced the consolidation of small farm units and the abandonment of scattered, isolated plots of land. Furthermore, factors such as increased educational levels and popular aspirations made farm life less attractive. Thus, older farmers were forced to abandon their land because they were unable to pass their farms to the next generation.

McCuaig and Manning (1982) state that changes in land-use tend to occur on the best and worst lands; where the best provide advantage for greater opportunities while the poorest must be altered to remain viable or be eased out of farming. Intermediate quality units probably have neither the degree of opportunity nor the need to change relative to those units on the better or poorer land. Furthermore, rural-urban fringe farms are often left in a state of decline because owners may be reluctant to make major investments because of imminent conversion to urban use. Or land may be held idle specifically in anticipation of urbanization.

In summary, agricultural policy at the national and international level is undergoing considerable change. As a result, many areas of the world are experiencing losses of

agriculture, which is often manifested by the abandonment of agricultural land. It is reasonable to assume that the trend of farmland abandonment demonstrated in eastern Ontario will continue, and perhaps increase, in the future.

The consequences of widespread abandonment of farmland can be significant. The most obvious impact is the loss in regional agricultural production due mainly to the reduction of the agricultural land base, but also to the loss of infrastructure when agricultural activity falls below a critical level. Hence, certain regions could lose much of their economic base and population.

Farmland abandonment can also affect landscape patterns; where a *landscape* is defined as a spatially heterogeneous area, in terms of land-use or habitat, at scales of hectares to many square kilometers (Turner, 1989). This can, in turn, have a positive or negative effect on a variety of ecological phenomena, including animal movements, water runoff and erosion, and the spread of disturbance such as fire or insect infestation (Odum and Turner, 1990). Also, the total area of natural habitat would also increase.

Another positive effect of farmland abandonment is that the area of open space available for outdoor recreation would increase. This is an important consideration in the Regional Municipality of Ottawa-Carleton which aims to protect 12% of its land area as open space (Citizen's Greenprint Committee of Ottawa-Carleton, 1990; Greenspace 2000, 1990).

It is important that these be planned for. As a first step, an effective methodology for predicting land-use change would be invaluable. Census statistics, although useful, may be inadequate for determining the effect of economics or policy on the actual landscape since they are recorded at the census subdivision level or higher. The aim of this thesis is to develop a methodology for predicting land-use change at the landscape scale.

2.3 Modelling Landscape Change

Baker (1989) has divided models of landscape change into two basic types, distributional and spatial. The former predict the distribution (i.e. proportion) of land area in terms of a set of landscape classes or element types, such as if census data were used to predict the future percentage of farmland in improved and unimproved categories. The latter model the spatial location and configuration of these landscape elements, using distributional sub-models for each sub-area of the landscape.

Distributional landscape models have been more popular to date mainly because they are simpler to develop and use. Their value, however, is limited to the extent that they give no indication of spatial location or configuration of landscape elements, which is important in landscape (i.e. land-use) studies and planning. Spatial landscape modelling requires

primary data in the form of aerial photography, satellite imagery, and maps, which are becoming more readily available. Furthermore, the advent of geographical information systems (GIS), which are specifically designed for the rapid utilization and manipulation of data in this form (Burrough, 1986), are enabling spatial landscape modelling to become an effective tool for studies of landscape change.

In many land-use studies, GIS has typically been used only to make comparisons between "snapshots" of an area at different times, with no attempt at modelling the actual process of change (Baker, 1989). An example of the former is McCuaig and Manning's (1982) use of a GIS to quantify the change in area and location of land-usage in the Saugeen Valley between 1966 and 1976. An example of the latter would be a model that predicted the land-usage in the Saugeen Valley in 1986 based on the characteristics of change displayed between 1966 and 1976. There are few cases in which GIS has been used to predict future landscape change (Baker, 1989; Schaller, 1990).

Spatial landscape models generally use distributional sub-models for each sub-area of the landscape. In the following discussion, a sub-area is analogous to a raster cell or a vector polygon in a GIS and can have only one state or class. The sub-model is commonly expressed as a difference equation using discrete state space; i.e. a mathematical equation which determines the change from one state or class

to another within a fixed time-period (Baker, 1989). Furthermore, the difference equations are generally one of the following types:

1) Projection a deterministic model in which the change from one state or class to another is based on transition coefficients;

2) Markov-Chain a stochastic model in which the change from one state or class to another is based on a transition probability.

Given identical input, the former is completely predictable whereas the latter is not.

Projection models usually attempt to describe a change process in terms of physical laws, often incorporating a series of equations with large numbers of variables (Baker, 1989). Examples include general circulation models of the atmosphere and human population models. However, the use of projection models for landscape studies is rare, most likely because the processes causing landscape change are often poorly understood and rarely quantified.

McCuaig and Manning (1982) developed a conceptual model of the decision process that determines rural land-use change. Many of their factors, such as a landowner's *aspirations*, *skills*, or *willingness to innovate*, are almost impossible to quantify or classify. Consequently, the development of a deterministic model of land-use change that incorporates such a decision-making process may be very difficult at best.

On the other hand, Wilkie and Finn (1988) have developed

a deterministic landscape model that predicts the effects of changes in human population density, settlement patterns, cultural land use patterns, and market economy on forest composition in the Ituri forest of northeastern Zaire. The model, using a raster GIS, was designed to simulate how land was selected for clearing, the spatial distribution of the cleared land, and forest regeneration.

The model defined eight land-use categories including road, village, farm, uncultivable land, and four stages of successional forest, where the successional stage for each cell was determined by time since abandonment. The prospect of any cell being cleared for farming depended on the travel time from cell to village and from the cell to the previous year's farm, the maximum travel time, the fallow period since last cultivation, and whether the cell is within the usufruct area. The model was run with different scenarios of population growth, land-tenure, and amounts of uncultivable land. The results revealed that the model, using the simple set of parameters, successfully emulated the spatial patterning of horticultural land-use and vegetation regeneration in the area (Wilkie and Finn, 1988).

Nevertheless, most models of landscape change are empirically-based where the estimates of change are determined by resampling the landscape at discrete intervals (Baker, 1989). For example, the data on changes in farmland area in Figure 1 can be used to estimate the expected farmland area in

1991 with reasonable precision, but this requires no real understanding of the processes that determine how much area is in agricultural use. Markov-chain models are well-suited for the use of empirical data which may be why they have become the more common form of landscape model. Furthermore, Tarrant (1974) states that "... the recognition of the importance of probability in agricultural location and change emphasizes the importance of stochastic methods of analysis where uncertainty and *noise* can be introduced through the operation of random variables". Thus, a stochastic Markov-chain model may be the optimum way to approach the analysis of agricultural land-use change.

Tarrant (1974) further states that "... the state of agriculture at one moment is partly a reflection of what it was previously and partly the result of the outcome of certain probabilities of change". In a Markov-chain model, these *transition* probabilities are represented by P_{ij}, which is the probability of going from state *i* to state *j* in a given time-period. The estimate of P_{ij} is based on the proportion of state *i* that converted to state *j* in the previous time interval. Hence, the major assumption of a Markov-chain model is that a past proportion holds as a future probability. This is called the assumption of stationarity.

When applied to a spatial model, stationarity implies that any sub-area of the landscape having state *i* will have a probability P_{ij} of becoming state *j* in the next time period.

For example, Canada Census data reveals that the 128366 ha of farmland in Lanark county in 1981 was reduced to 117794 ha by 1986, an 8.2% loss of 1981 farmland area. Given that state *i* and *j* represent farmland and non-farmland respectively, the transition probability P_{ij} is 0.082. Note that in a two-state model, P_{ij} and P_{ji} are the only two transition probabilities possible, and in this case P_{ji} is assumed to be zero. Thus, any sub-area of farmland in Lanark will have a probability of 0.082 of becoming non-farmland by 1991.

In practice, the realism of the above is influenced by the number of sub-areas and the manner in which they are segregated. For example, if all the farmland of Lanark was located in one sub-area, the above approach would, in essence, be saying that there is a probability of 0.082 that all 117794 ha of farmland in 1986 will have become non-farmland by 1991. Given 100 model runs, the average would approximate the expected loss of 9659 ha (i.e. 117794 x 0.082) in the period, but this would represent roughly 92 runs of no loss and 8 of total loss of farmland. Hence, the number of sub-areas should be reasonably large so that the result of each model run is relatively close to the average.

Estimates of transition probabilities for spatial models should be derived from spatial data, because aggregate data, such as the Canada Census, may miss important details. For example, the 8.2% overall loss of farmland discussed above may in fact incorporate two-way conversions (i.e. farmland to non-

farmland and vice versa) which would mean that, in truth, P_{ij} is greater than 0.082 and P_{ji} is greater than zero. The point is that a single transition probability for an entire landscape will be a poor representation of the transition probabilities for the sub-areas.

The above is a simple model of land-use change for a two-state landscape; farmland and non-farmland. Accordingly, its simplicity also limits its usefulness. Most land-use studies involve more land-use types, hence increasing the number of states and estimates of transition probabilities. For example, a two-state landscape requires two transition probabilities (P_{ij}, P_{ji}); a three-state landscape requires six (P_{ij}, P_{ji}, P_{jk}, P_{kj}, P_{ik}, P_{ki}).

Generally, the most desired feature of any Markov-chain land-use model is a link between the transition probability of a sub-area and the attributes of the sub-area. Given that the land characteristics of sub-area *x* are symbolized by LQ, then the probability of a sub-area in state *i* with LQ converting to state *j* in the future is based on the proportion of land in state *i* with LQ that converted to state *j* in the past. Burrough (1988) states that for any given sub-area *x*, the value of LQ can be given by one of three functions:

1) when no spatial contiguity is taken into account, then

$$LQ = f(A, B, C, \ldots)$$

where A, B, and C are the values of the land attributes used to estimate LQ;

2) when spatial contiguity is taken into account (i.e. the value of the LQ at sub-area *x* is dependent on spatial associations with the area surrounding *x*), then

$$LQ(x) = f(\ Ax,\ Bx,\ Cx,\ \ldots)$$

3) when the land attributes vary over time, hence LQ also varies with time, then

$$LQ(x,t) = f(Ax,\ Bx,\ Cx, \ldots),\ t$$

In other words, the land characteristics used in the estimate of transition probabilities of sub-areas may be endogeneous and/or exogeneous attributes that can vary over time.

The reason for linking transition probabilities to landscape attributes is simply the expectation that land attributes influence land-use change. In this regard, evidence has been presented (section 2.1) which shows that physical factors (i.e. land capability) do play a major role in determining farmland abandonment. The previously discussed analyses of Parson (1979) and the present author (for central and eastern Ontario) use empirical models, in the form of regression equations, to estimate the proportion of a subdivision that is expected to have a particular land-use based on the subdivision's soil capability index. However, they give no indication of the location or configuration of landscape elements and cannot easily be used to determine a transition probability for future conditions. On the other hand, they do indicate that soil capability is a landscape attribute that should be linked to transition probabilities,

as discussed above.

Iverson (1988) went further by using a GIS to analyze the effect of soil and landscape attributes on patterns of land-use change in the state of Illinois. A series of land-use maps were overlayed on a soil-type map to determine the percentage area of each soil map-unit which changed land-use. For example, of the portion of the Alford-Wellston soil unit which was covered by forest in 1820, 63.4% remained as forest, 34.0% changed to agricultural land, and 0.4% changed to urban land by 1980. Since fifty soil types and up to twenty-three land-use types existed, there were a considerable number of calculations involved. Each of the fifty soil types which occur in Illinois were rated in terms of their particular attributes including percent sand, percent organic matter, a productivity index, permeability, slope, and others. Each soil type was then assigned a single numerical value for each attribute, allowing correlation and regression analyses between the percentage change in land-use and the soil attributes.

The results showed a few moderate strength correlations such as between the *forest to agriculture* conversion and the productivity index (positive) and slope (negative). Similar strength correlations existed between the *prairie to forest* conversion and the productivity index (negative) and slope (positive) reflecting the fact that nearly all arable lands had been converted to agriculture with only highly sloping

and/or infertile lands remaining uncultivated. However, the r^2 values were generally low which Iverson suggests may be due to the following:

1) the inherent variation in natural and managed systems;

2) the omission of important attributes such as topography and historical use of land; and,

3) errors arising from the GIS data and processing, such as those associated with digitizing or overlay procedures.

Iverson's model involves a series of regression equations which determine the expected percentage of conversion from one land-type to another, for each soil type within the given time period. The advantage of his approach over regression models of census data (e.g. Parson, 1979) is that the spatial distribution of the results is given.

This approach can be used to determine the expected conversion of farmland to non-farmland in a sub-area based on the attributes of the sub-area, although higher coefficients of correlation would probably be desired. For example, if a regression equation predicts a 20% conversion of farmland to non-farmland within a particular soil unit, then every sub-area of farmland in that soil unit would have a transition probability of 0.20. This assumes stationarity and a reasonable number of sub-areas within the soil unit (as discussed above). Thus, Iverson's approach can be used to link landscape attributes with transition probabilities in a

predictive model.

The main limiting factor for using regression models in this manner, is that, by definition, they require data in interval or ratio form. However, many landscape attributes which influence farmland abandonment are measured on a nominal or ordinal scale. For example, the CLI measures soil capability on an ordinal scale; many non-physical attributes such as jurisdiction (i.e. marketing boards) are nominal in form. Thus, correlation and regression approaches can often not be used.

An alternative to parametric approaches is to use a rule-based method, where the transition probabilities are linked to the attributes by logical combination. In this way, a whole series of rules-of-combination can be determined in the following format:

> for any sub-area in state *i*, where x and y are measured on nominal or ordinal scales.
>
> IF (attribute A = x) AND (attribute B = y) THEN Pij = z

The transition probability P_{ij} can be estimated by observing the proportion of state *i* land with the above attribute combination that converted to state *j* in a given time period.

A drawback with this approach is that there is the potential for a large number of such rules-of-combination. For example, assuming that there are two states and each attribute has two classes, then eight transition probabilities would need to be defined. Thus, the number of states, attributes,

and attribute classes may be limited by time constraints and calculation costs. Furthermore, as the number of cases increase, the number of observations (from which transition probabilities are determined) per case decreases. Therefore, it is necessary to limit the number of cases to maintain statistical validity; for further discussion of this, see Chapter 3. Nonetheless, the rule-based method facilitates the linkage between transition probabilities and landscape attributes.

Moore *et al* (1991) developed an integrated approach to vegetation mapping using rule-based modelling in a GIS framework. Unlike image analysis and field approaches to mapping, their approach employed a rule-based model that predicted vegetation patterns based on local topography and geology, data for which was available in a geographical data base. The relationship between particular vegetation types and environmental factors (related to geology and topography) were defined from field samples and translated into the model. The model classified the study area into topographic and geologic regions and then mapped the expected vegetation communities. This approach can also be used to model land-use change, whereby a particular landscape is classified into regions or zones based on various attributes.

The rule-based approach to modelling is the basis upon which expert systems are designed, which are computer programs that emulate the thought patterns of a human expert to solve

significant problems in a specific area of knowledge (Sell, 1985). These systems consist of a knowledge-base containing rules typically in the IF/THEN format and a procedure for processing those rules (Rykiel, 1990). The rules are arranged into a hierarchical structure providing the system with an efficient means for sorting observations into classes because at each step alternative paths and/or class assignments are eliminated (Moore *et al*, 1991).

Although the development of an expert system is not within the scope of this thesis, there is the potential for expert system techniques to be used in models of land-use change. Given the myriad of potential attributes or factors that influence land-use change, it is clear that models can become quite complicated. For example, attribute "a" may have no effect on land-use change except in the presence of attributes "b" and "c", in which case its effect is significant. Expert systems provide efficient procedures for sorting rules and would undoubtedly aid in the development of more sophisticated and effective models.

CHAPTER 3: METHODS

3.1 Overview

The main purpose of the modelling exercise was to predict where in the study area farmland abandonment was likely to occur over a given time period. The modelling methodology involved three stages: the estimation of the transition probabilities, the realization of the model, and finally the verification of the model. Emphasis was placed on the use of readily available data to allow the duplication of the methodology for other geographic areas and other aspects of land-use change.

The study was confined to the Regional Municipality of Ottawa-Carleton (RMOC) for a number of reasons, including the fact that digitized versions of land-use and soil capability maps necessary to the project were already available for the region. Furthermore, land-use issues in the region have been frequently studied in the past (Coleman, 1967; Waddell, 1972; Huffman and Dumanski, 1978; Dumanski *et al*, 1979; Marshall *et al*, 1979) which provided a knowledge-base that assisted this study.

The geographical information system used in the study was the Environmental Planning and Programming Language (EPPL7), chosen because of its availability and familiarity to the present author, its simplicity, and its speed. Most of the data manipulation and calculation external to the GIS was carried out in a Lotus 123 spreadsheet, although for special

circumstances new utilities were created in the programming language Turbo Pascal.

3.2 Data Sources

The data used in this study came from three sources: a series of land-use maps, soil capability maps, and census data. The land-use maps utilized were derived from the *Agricultural Land Use Systems of the Regional Municipality of Ottawa-Carleton* (Huffman and Dumanski, 1983) developed by the Land Resource Research Institute (LRRI) of Agriculture Canada. This series of three 1:50,000 maps employs the concept of *land-use systems* whereby farmland areas are identified as belonging to particular cropping systems of varying intensity. For example, the most intensive crop system found in the RMOC is the *monoculture* system in which corn is grown on a continuous rotation on the same fields. The maps also identify two types of idle agricultural land; land idle for 1-10 years and land idle for greater than 10 years. A more complete description of the land-use systems is provided in Table 1.

The concept of land-use systems was developed to alleviate the problem of earlier surveys where farm crops were identified on a field-by-field basis, requiring long and specific map legends (ARI, 1983). Furthermore, only the crop evident at the time of the survey was identified on the maps, hence the data quickly became out-of-date. Errors arise, for example, when analyzing the extent to which the potential of

TABLE 1
DESCRIPTION OF AGRICULTURAL LAND USE SYSTEMS

a) Agricultural Land (in Descending Order of Intensity)

Monoculture	Corn constitutes 90% of the area in almost continuous rotation (P).
Corn	Corn constitutes 30-90% of the area in greater than a 1 in 4 year rotation but less than continuous (C).
Mixed	Corn constitutes 1-30% of the area; typical rotation is 2 yrs corn to 1 yr cereal grain to 1 yr legume hay (M).
Hay	Composed of cereal grains and good hay which is maintained through regular fertilizer and reseeding (H).
Pasture	Relatively permanent stands of improved grass for hay and pasture, sporadically reseeded at intervals >10 yrs (HG).
Grazing	Uncultivated native grass pasture or poorly maintained (>10yrs) improved pasture (G).

b) Non-Agricultural Land

Idle Farmland	Agricultural land that has remained idle for <10 yrs (A1) or >10 yrs (A2) and is in a state of reversion to natural vegetation.
Forest/Wetland	Natural forest cover with a minimum of 45% crown closure (Z), pastured woodland (Zp), reforestation (Zr), and wetland areas (X).
Built-Up	Urban-related uses (B).
Extraction	Sand/gravel pits (E1), topsoil (E2).
Recreation	Parks, golf courses, campgrounds (R).
Sod farms	Public or commercial sales (T).
Specialty Farms	Orchards, market gardens (SF).

a land-unit is being utilized, because the survey may occur during the low-intensity phase of a rotation (i.e. the hay phase of a corn rotation). The land use-system concept however takes into account climate, soil capability, crop demand, and marketing facilities to distinguish the system of land-use in an area in a way which would remain valid for a number of years (ARI, 1983). The above maps are based on data collected from field surveys and land-owner interviews conducted in 1977, as well as aerial photographs from 1975.

The Ontario Ministry of Agriculture and Food has recently compiled a series of agricultural land-use maps based on the systems approach used above (ARI, 1983). The 1:50,000 scale maps are from surveys conducted in 1983 and are available for each census subdivision in southern Ontario. Thus, the modelling approach used in this study can be duplicated in almost any area of southern Ontario.

As previously mentioned, the land-use systems maps for the RMOC were already available in digitized format from the Land Resource Research Institute. The data, in the form of Digital Line Graph (DLG) code, was converted to EPPL7 raster format in a four-step process as follows:

STEP 1 the DLG format was converted into the DGT format via the EPPL7 IMPORT command;

STEP 2 an attribute file in which each polygon had been assigned the letter attribute code (e.g. H for hay system) had to be manually edited to change the letter code to an integer class code;

STEP 3 the new attribute file was merged to the DGT file with a utility developed by Prashker (1991);

STEP 4 the new DGT file was converted to raster format via the EPPL7 RASTER command.

This procedure was repeated for two of the three maps that comprise the set covering the RMOC; West Carleton-Goulbourn-March and Rideau-Osgoode. The map of Nepean-Gloucester was not used in this study because the corresponding soil capability map was not available.

The soil capability maps used in the project were derived from the *Soils of the Regional Municipality of Ottawa-Carleton* (Schut and Wilson, 1987). These maps were also available in DLG format from the LRRI; however, the conversion process from DLG to raster format required some additional effort to that described above. The original soil survey maps identify each soil map-unit by a rather complex symbol (e.g. N4/R2.3) from which the soil capability can be derived by means of a look-up table. For this study, each map-unit symbol was converted to an integer capability class code during step two of the above process. This was a tedious chore given that there were over a thousand polygons.

In many cases, a soil polygon was identified by a compound map-unit symbol (i.e. two soil ratings) where the dominant type occupies more than 40% of the area and a second type occupies 20-40% of the area. Thus, two different soil capability ratings were possible for one map-unit (although

frequently the capability ratings were the same for both units). It was decided, however, that in these cases the capability rating of the dominant unit would be assigned to the entire unit. This enabled the number of capability classes to be kept to nine, including the organic and disturbed soil classes. A more complete description of the soil capability classes is provided in Table 2.

The soil maps, like the land-use maps, are separated into three sections, West Carleton-Goulbourn-March, Rideau-Osgoode, and Cumberland, but do not cover Nepean-Gloucester. In this study, however, only the first two sections were examined. Both sets of maps, being the same scale (1:50000) and projection (UTM), were digitized by LRRI with the intention of being overlayed. Thus, they were immediately ready for overlay procedures upon import into EPPL7.

The third data source used in this study was the Canada Census for Agriculture for the years 1941 to 1986. The Census records data for such things as total farm area, improved farmland, and farm woodland for each of the eight census sub-divisions of the RMOC. The data reported herein were adjusted to account for changes in sub-division boundaries over the years. For example, the sub-divisions of Fitzroy, Huntley, and Torbolton were aggregated after 1966 to form West Carleton. Similarly, North Gower and Marlborough were aggregated to form the sub-division of Rideau. The census data was not used in the model but was used for comparison with model output.

TABLE 2
DESCRIPTION OF CLI SOIL CAPABILITY CLASSES

Class 1	Soils in this class have no significant limitations to use for common field crops.
Class 2	Soils in this class have moderate limitations or a combination of minor limitations which restrict the range of crops or require special conservation practices.
Class 3	Soils in this class have moderate limitations or a combination of lesser limitations which restrict the range of crops or require special conservation practices, or both.
Class 4	Soils in this class have a severe limitation or combination of lesser limitations which restrict the range of crops or require special conservation practices, or both.
Class 5	Soils in this class have a very severe limitation or combination of lesser limitations which restrict their capability to producing perennial forage crops. Improvement practices are feasible.
Class 6	Soils in this class are capable of producing only perennial forage crops. Improvement practices are not feasible.
Class 7	Soils in this class have no capability for arable culture or permanent pasture.
Organic	Organic soils which cannot be classified as above due to their unique characteristics; it is assumed that substantial costs are associated with the reclamation of these soils and that high return crops will have to be grown.
Disturbed	Land altered by humans including urban land, landfill sites, sewage lagoons, and topsoil removal sites.

3.3 Estimation of Transition Probabilities

As discussed in Chapter 2, the estimation of transition probabilities for future land-use change is based on the past record of change for land with particular attributes. Thus, in this study, the proportion of abandoned-to-total farmland with specific attributes must be determined for a given time-period. Note that *total* farmland includes active and idle farmland. A difficulty arises, however, in deciding what "proportion" to examine.

Initially, it might be assumed that the proportion be based on relative areas of abandoned and total farmland. For example, in a given area, if 10000 ha of total farmland were located on land of class one capability and 1000 ha of this land was idle farmland, then the proportion is 0.100. In this way the proportions can be easily determined by a GIS using functions such as COUNT in EPPL7. In a raster-GIS like EPPL7, the proportions determined in this manner would be assigned to each cell as a probability of future change, such that any cell with a particular combination of attributes would be assigned a particular transition probability.

The main drawback with the above approach is due to the fact that farmland abandonment is generally a field-by-field phenomenon, where farmers tend to abandon entire fields rather than just poor sections of a field. Note that the smallest land unit on the land-use maps is the *parcel* which may comprise several fields. In this study, cell size (0.25 ha) is

much smaller than the average farmland parcel size (80.5 ha). It is unlikely that there will be perfect correspondence between land-use and soil capability (i.e. all parcels are not likely to have uniform soil capability throughout). Thus, a cell-based probability model would result in a single parcel having a range of transition probabilities. This would, therefore, require that parcel-based transition probabilities be determined from cell-based probabilities -- a possibly difficult procedure.

The best way to avoid this problem is to derive parcel-based transition probabilities directly; i.e. to determine proportions and attributes at the "parcel" scale as opposed to the cell scale. The procedure used in this study involved such an approach by first determining the attributes of each individual parcel and then the proportion of idle-to-total farmland parcels for each set of attributes.

The determination of the parcel attributes which affect farmland abandonment is probably the most important stage of the modelling process. It amounts to uncovering the rules which govern where farmland is abandoned. A major problem arises from the fact that most land-use change is driven by human responses to socio-economic regimes, as discussed in Section 2.2. This study, however, does not involve the modelling of the human decision-making process. Rather, the focus is on identifying large-scale spatial and physical attributes that can be derived from original map data. It is

hoped that these attributes will serve as proxy for the smaller-scale and more complex factors that ultimately influence farmland abandonment.

Before the analysis was begun, the original land-use maps were reclassified to reduce the number of classes from thirteen to nine in order to simplify the analysis. In the reclassified maps, the built-up (B), recreation (R), sod farm (T), extraction (E1/E2), and specialty farm (SF) classes were combined into one class called "other". Also, the two classes of idle farmland (A1/A2) were combined into one class. The resulting land-use maps for West Carleton-Goulbourn-March (Figure 2) and Rideau-Osgoode (Figure 3) were designated as LAND1.EPP and LAND2.EPP, respectively (where the suffix "EPP" denotes an EPPL7 map). Similarly, the soil capability maps for the two areas were designated as SOIL1.EPP (Figure 4) and SOIL2.EPP (Figure 5), respectively.

3.3.1 Soil Capability Analysis

The first attribute to be examined was soil capability since there is considerable evidence that it is correlated with farmland abandonment (Parson, 1979; McCuaig & Manning, 1982). Both the soil capability and land-use maps were used in the GIS to determine the soil capability of each farmland parcel. The procedure involved a series of steps described below which were repeated for each farmland type and for both study areas; a diagrammatic representation of the steps is

FIGURE 2: LAND-USE SYSTEMS, WEST CARLETON-GOULBOURN-MARCH

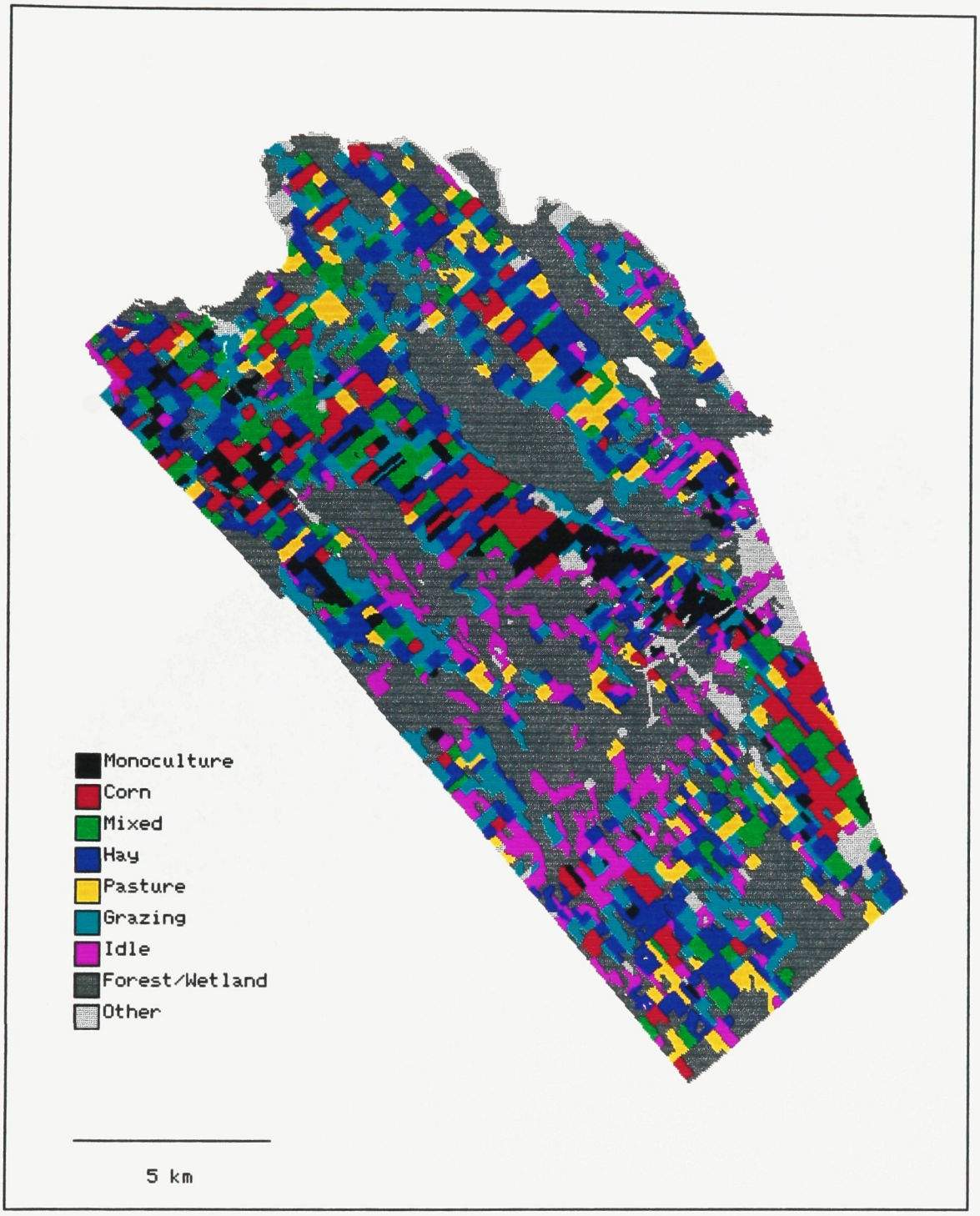


FIGURE 3: LAND-USE SYSTEMS, RIDEAU-OSGOODE

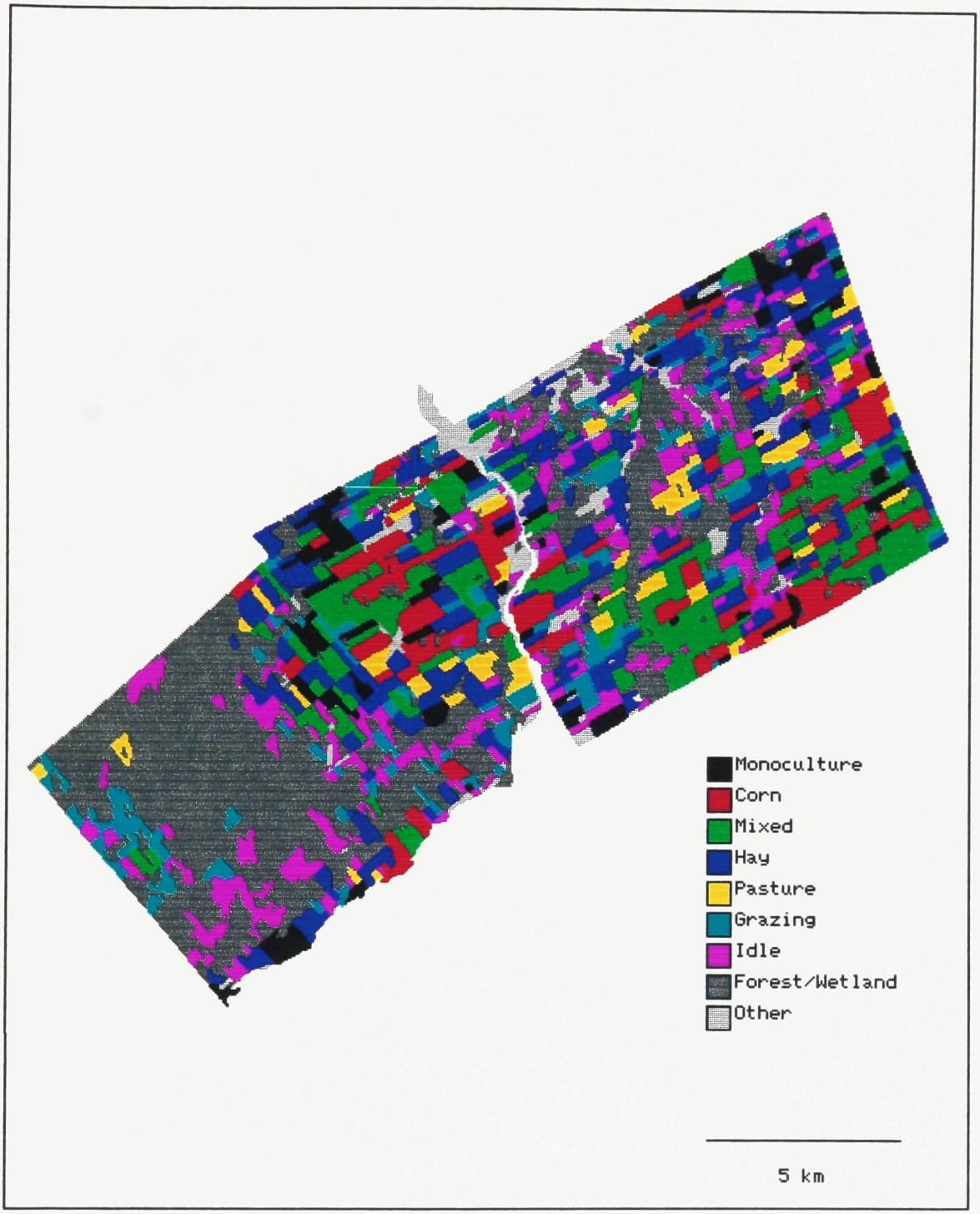


FIGURE 4: SOIL CAPABILITY, WEST CARLETON-GOULBOURN-MARCH

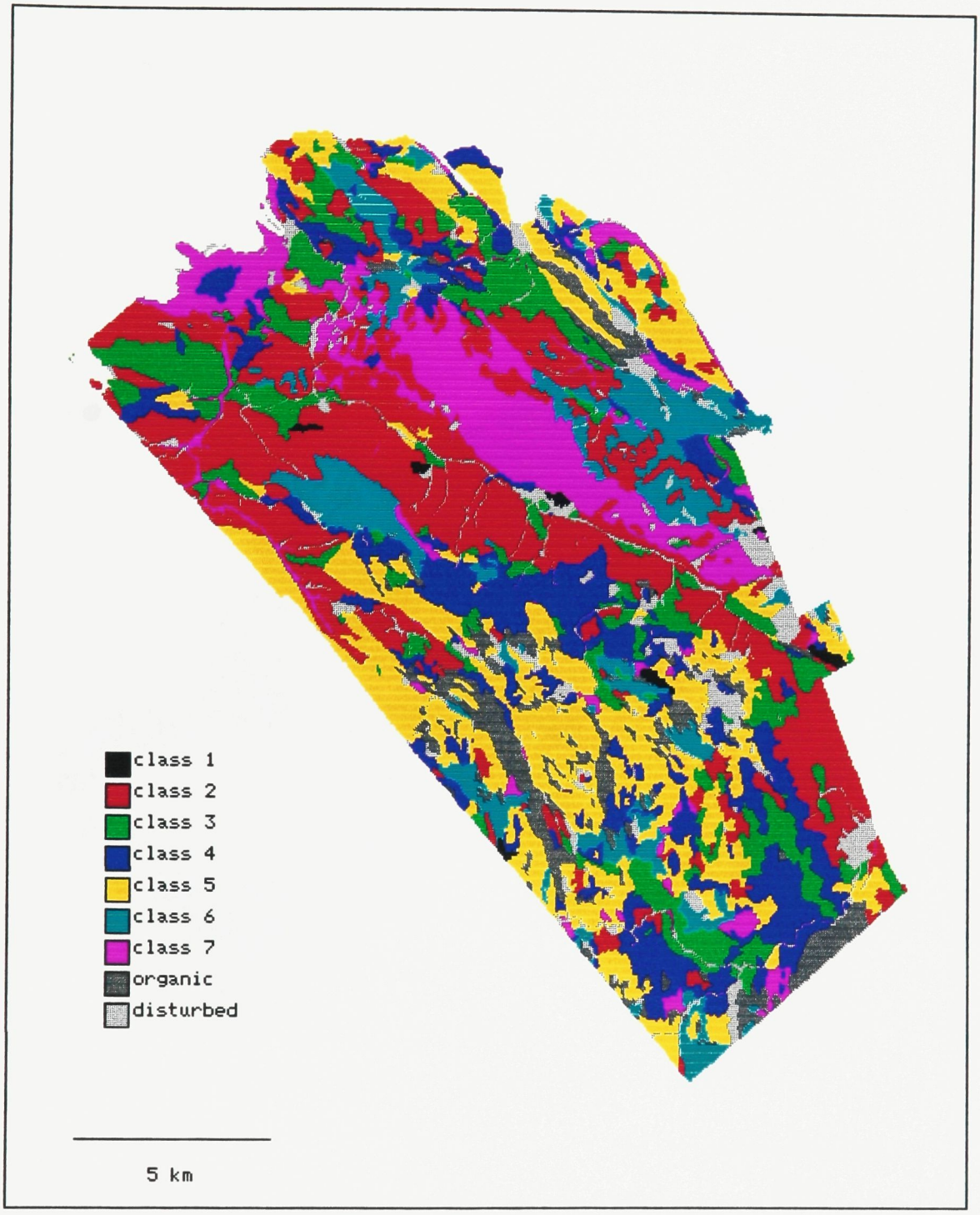
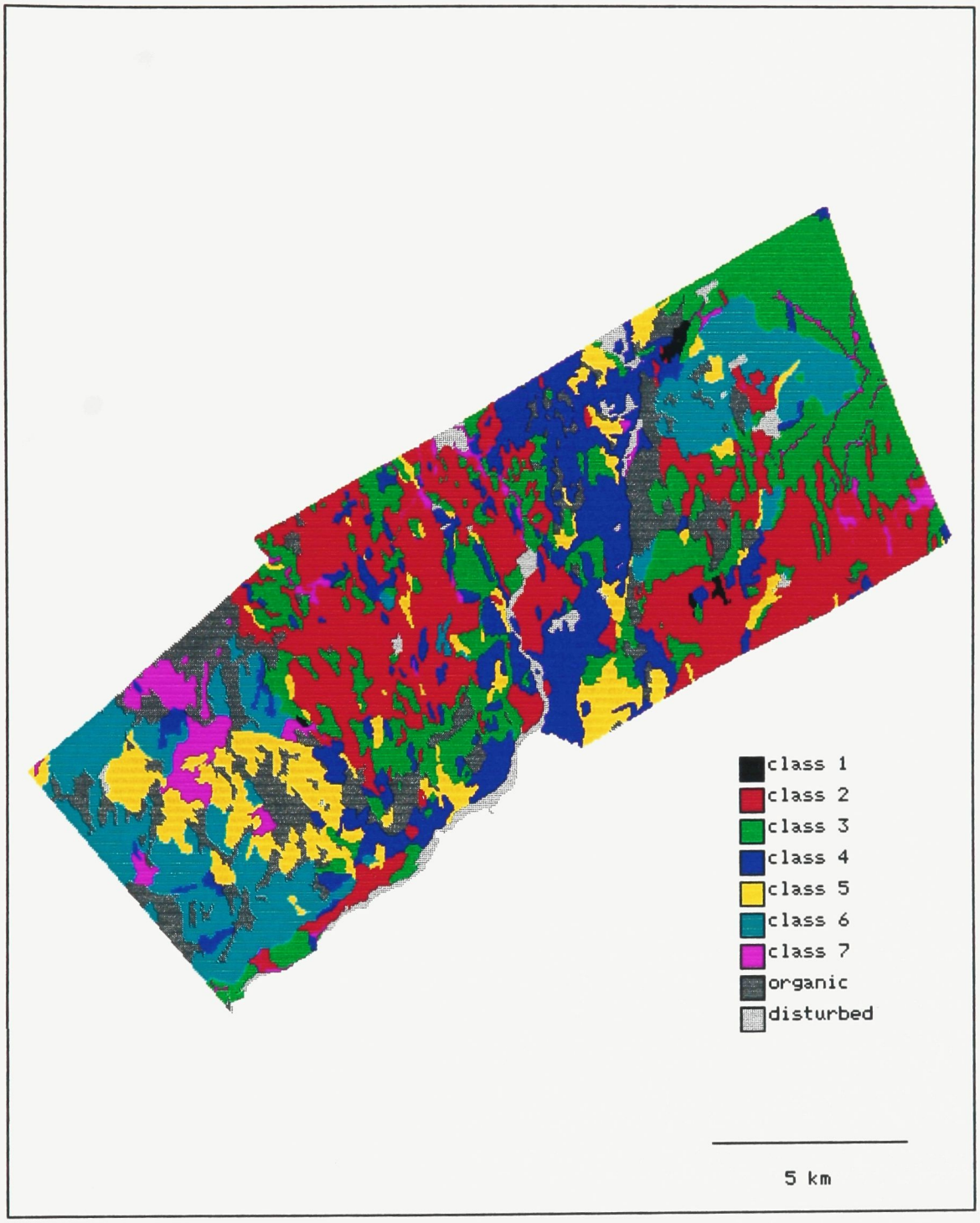


FIGURE 5: SOIL CAPABILITY, RIDEAU-OSGOODE



presented in Figure 6. Note that EPPL7 commands used in the procedure have been capitalized and a full description of these commands is provided in the glossary in Appendix 1.

STEP 1 RECLASS was used on LAND*.EPP so that the chosen farmland type (e.g. mixed, pasture) was re-assigned to class 1; this is because the next step requires the cells of interest to be class 1. The resulting map was designated as LANDTYPE.EPP (Fig. 6b).

STEP 2 CLUSTER was used on LANDTYPE.EPP so that each and every contiguous grouping of class 1 cells (i.e. parcels) was re-assigned to a different class. Since no land-use class had more than 255 parcels (the maximum number of classes allowed in EPPL7) each *parcel* was assigned a unique class. The new map was designated as CLUST.EPP (Fig. 6c).

STEP 3 OUTTABLE was used with the above cluster map and the soil capability map to determine the dominant soil capability (mode option) of each parcel; the first column of the table file is the cluster class and the second column is the dominant soil capability class (Fig. 6d).

As stated above, the procedure was repeated for every farmland type and for both study areas, resulting in a total of fourteen table files (7 farmland classes x 2 study areas). The format of the table file enables analysis at the "parcel" level because each uniquely identified parcel (first column) is linked to a single attribute value (second column). For example, the table file in Fig. 6d shows that one parcel has a dominant soil capability of six, and four parcels have a

FIGURE 6

RASTER REPRESENTATION OF SOIL CAPABILITY ANALYSIS

a) Original land-use map with four classes.

LAND*.EPP

4	4	3	3	4	4
4	4	3	3	3	3
1	1	2	2	4	4
1	1	2	2	4	4
4	4	4	2	2	2
4	4	4	2	4	4

b) RECLASSed map to examine "type A" farmland (class 4).

LANDTYPE.EPP

1	1	0	0	1	1
1	1	0	0	0	0
0	0	0	0	1	1
0	0	0	0	1	1
1	1	1	0	0	0
1	1	1	0	1	1

c) CLUSTERed map to uniquely identify parcels.

CLUST.EPP

1	1	0	0	2	2
1	1	0	0	0	0
0	0	0	0	3	3
0	0	0	0	3	3
4	4	4	0	0	0
4	4	4	0	5	5

d) OUTTABLE of CLUST.EPP and SOIL*.EPP (where first column is cluster class number and second column is dominant soil capability class).

CLUST.EPP

1	1	0	0	2	2
1	1	0	0	0	0
0	0	0	0	3	3
0	0	0	0	3	3
4	4	4	0	0	0
4	4	4	0	5	5

+

SOIL*.EPP

6	6	7	7	7	7
6	6	7	7	7	7
6	6	6	6	7	7
6	6	6	6	7	7
6	7	7	7	7	7
6	7	7	7	7	7

=

Table File

1	6
2	7
3	7
4	7
5	7

dominant capability of seven. Thus, in this example, 80% of the parcels are found on class seven capability soil, which suggests an association between soil capability and "type A" farmland. In order to test for such a relationship, the data in the fourteen table files were counted and summarized in contingency table format and then tested for statistical significance using the chi-square method.

3.3.2 Parcel Shape Analysis

As discussed in Chapter 2, Coleman (1967) stated that rural-wilderness fringe abandonment was characterized by its irregularity of shape, suggesting a relationship between parcel shape and farmland abandonment. Also, Odum and Turner (1990) used the fractal dimension of parcel perimeter to find that abandoned land in Georgia was more convoluted in shape than cropland or woodland. It is probable that shape itself is not a cause of abandonment; however, it may serve as an indicator of other factors that influence abandonment, such as lack of maintenance in poor sections of parcels. Since parcel shape is a spatial characteristic that can be derived from the map data, it was chosen as an attribute for investigation.

In order to facilitate simple analysis, a numerical measure for parcel shape needed to be chosen. Although several such measures exist, including fractal dimension, the area-to-perimeter ratio (A/P) was chosen because it is relatively easy to calculate and it is commonly used in landscape studies

(Forman and Godron, 1986; Iverson, 1988). The A/P ratio is influenced by both parcel shape and size, such that large rectangular parcels tend to have higher A/P ratios and small irregular parcels have lower A/P ratios.

In this analysis, only the land-use maps (LAND1.EPP and LAND2.EPP) were required and, again, the following steps were repeated for each farmland type and both study areas:

STEP 1 RECLASS was used on LAND*.EPP so that the chosen farmland type was re-assigned to class 1 and the others to class 0. The new map was designated as LANDTYPE.EPP (Fig. 7a).

STEP 2 CLUSTER was used on LANDTYPE.EPP so that each and every contiguous grouping of class 1 cells (i.e. parcels) was re-assigned to a different class. The new map was designated as CLUST.EPP (Fig. 7b).

STEP 3 EDGE was also used on LANDTYPE.EPP so that cells on the perimeter of each class 1 cluster were re-assigned to class 2. The new map was designated as EDGE.EPP (Fig. 7b).

STEP 4 OUTTABLE was used with CLUST.EPP and EDGE.EPP with two options; the first summed all the cells in each cluster, the second summed the cells of the highest class in each cluster; i.e. the perimeter cells (Fig. 7c).

The format of the resulting table file is such that the first column is the cluster class (i.e. parcel label), the second is the number of cells per cluster (i.e. area), and the third is the number of perimeter cells per cluster (i.e. perimeter). In truth, this is not a true perimeter because it

FIGURE 7
RASTER REPRESENTATION OF AREA/PERIMETER ANALYSIS

a) RECLASSed map for farmland type of interest.

LANDTYPE.EPP

0	0	0	0	0	0	0	0	0	0
0	1	1	1	1	1	0	0	0	0
0	1	1	1	1	1	0	0	0	0
0	1	1	1	1	1	0	1	1	0
0	1	1	1	1	1	0	1	1	0
0	0	0	0	0	0	0	1	1	0
0	1	1	1	0	0	0	1	1	0
0	1	1	1	0	0	0	1	1	0
0	1	1	1	0	0	0	1	1	0
0	0	0	0	0	0	0	0	0	0

b) CLUSTERed map uniquely identifies parcels and EDGEd map identifies perimeter cells (class 2).

CLUST.EPP

0	0	0	0	0	0	0	0	0	0
0	1	1	1	1	1	0	0	0	0
0	1	1	1	1	1	0	0	0	0
0	1	1	1	1	1	0	2	2	0
0	1	1	1	1	1	0	2	2	0
0	0	0	0	0	0	0	2	2	0
0	3	3	3	0	0	0	2	2	0
0	3	3	3	0	0	0	2	2	0
0	3	3	3	0	0	0	2	2	0
0	0	0	0	0	0	0	0	0	0

EDGE.EPP

0	0	0	0	0	0	0	0	0	0
0	2	2	2	2	2	0	0	0	0
0	2	1	1	1	2	0	0	0	0
0	2	1	1	1	2	0	2	2	0
0	2	2	2	2	2	0	2	2	0
0	0	0	0	0	0	0	2	2	0
0	2	2	2	0	0	0	2	2	0
0	2	1	2	0	0	0	2	2	0
0	2	2	2	0	0	0	2	2	0
0	0	0	0	0	0	0	0	0	0

c) OUTTABLE of CLUST.EPP and EDGE.EPP where the first column is cluster class number, the second column is the total number of cells per cluster, and the third column is the number of perimeter cells.

1	20	14
2	12	12
3	9	8

encompasses area. However, determining true perimeter with a raster GIS is difficult because it requires finding the number of "exposed" sides of each border cell. Thus, it was decided that the above "perimeter" was a reasonable approximation for purposes of this study. The fourteen table files were then imported into Lotus 123 where the A/P ratio was calculated and then exported into new A/P table files. For the example in Figure 7(c), the following table file would result (where the first column is the cluster number and the second column is the A/P ratio):

1	1.43
2	1.00
3	1.13

The data in the A/P table files was then summarized into contingency table format for chi-square analysis. Unlike soil capability, however, the A/P ratio is a continuous variable, ranging from 1.00 to 10.32 here. Therefore, to enable a frequency count of the data, the A/P ratio data was divided into discrete classes (i.e. attribute classes).

3.3.3 Adjacency Analysis

Huffman and Dumanski (1983) discuss how the above land-use systems maps can be used for assessing the underuse, misuse, and potential use of the land base as well as for predicting and monitoring land-use change. They state that a parcel can be seen as being under-utilized if the surrounding

area is of predominantly higher intensity. Similarly, a parcel can be considered as being over-utilized if the surrounding area is of low-intensity or non-usage. Coleman (1967) stated that low-intensity farmland was more prone to being abandoned if it was in close proximity to active abandonment. It may be that low-intensity agricultural land (e.g. grazing) surrounded by idle or forested land has a higher probability of being abandoned than a similar parcel surrounded by land of higher-intensity use. Therefore, the land-use of neighbouring parcels was chosen as an attribute for investigation.

However, in order to use neighbouring land-use as an attribute, a numerical measure of "neighbour" needed to be chosen. It was decided that a measure based on the land-use of parcels immediately adjacent (i.e. bordering) to each parcel was most suitable, because it could be readily determined in EPPL7. Initially, *dominant neighbour* was used whereby the class of the land-use that shared the largest proportion of border with the given parcel was assigned. For example, if a particular parcel had ten perimeter cells adjacent to forest, nine cells adjacent to mixed land, and four cells adjacent to idle land, that parcel would have "forest" designated as its dominant neighbour.

The drawback with the *dominant neighbour* measure is that the association with non-dominant neighbours is lost. For this reason, a new measure called the *adjacency index* was developed. The adjacency index, modified from an index of soil

capability used by Parson (1979), involves multiplying the proportion of border shared with a particular neighbour by the class number of the neighbour. In the example above, 44% (10/23) of the perimeter cells are adjacent to forest, 39% (9/23) are adjacent to mixed land, and 17% (4/23) are adjacent to idle land. Since, forest, mixed, and idle land are represented by classes eight, three, and seven, respectively, the adjacency index for that parcel is calculated as follows:

$$(44 \times 8) + (39 \times 3) + (17 \times 7) = 588$$

The adjacency index ranges from a minimum of 100 (where 100% of border is adjacent to class one) to a maximum of 900 (where 100% of border is adjacent to class nine). Thus, lower values of the index indicate neighbours of higher-intensity farmland (monoculture, corn, mixed) whereas higher index values indicate lower-intensity neighbours (grazing, idle, forest, other). Caution should be exercised interpreting mid-range index values because these can be derived from neighbours of either medium-intensity farmland or an even split of high and low-intensity neighbours.

The EPPL7 procedure for determining the adjacency index was somewhat more complicated than for the soil capability or parcel shape analyses. Only the land-use maps (LAND1.EPP and LAND2.EPP) were required and the following series of steps were repeated for each farmland type and for both study areas:

STEP 1 RECLASS was used on LAND*.EPP so that the chosen farmland type was re-assigned to class 1 and the others to classes 2 through 9. The resulting map was called LANDTYPE.EPP (Fig. 8a).

STEP 2 CLUSTER was used on LANDTYPE.EPP so that each and every contiguous grouping of class 1 cells (i.e. parcels) were re-assigned to a different class. The new map was designated as CLUST.EPP (Fig. 8b).

STEP 3 EDGE was also used on LANDTYPE.EPP so that cells on the perimeter of each class 1 cluster were re-assigned to the class that they were adjacent to. The new map was designated as EDGE.EPP.

STEP 4 EVALUATE was used with CLUST.EPP and EDGE.EPP so that only the perimeter cells of each cluster were onsite (offsite being 0). The resulting map was designated as EDGEONLY.EPP (Fig. 8b).

STEP 5 COUNT was used on CLUST.EPP and EDGEONLY.EPP so that the number and proportion of perimeter cells per cluster was calculated. The COUNT file is shown in Fig. 8c.

Note that in Figure 8(c), the numbers offset to the left in the "class" column are the cluster class while the numbers offset to the right are for the perimeter cells which were re-assigned to the class of the adjacent land-use.

The resulting fourteen count files were imported into Lotus 123 and edited so that only the class columns and percent columns of the count files remained. A third column was then created by multiplying each value in the class column by its corresponding value in the percent column, as in the example below:

FIGURE 8
RASTER REPRESENTATION OF ADJACENCY INDEX ANALYSIS

a) RECLASSed map for farmland type of interest.

LANDTYPE.EPP

2	2	2	2	2	3	3	3	3	3
2	1	1	1	1	1	3	3	3	3
2	1	1	1	1	1	3	3	3	3
2	1	1	1	1	1	3	1	1	3
2	1	1	1	1	1	3	1	1	3
2	2	2	2	3	3	3	1	1	4
5	1	1	1	3	3	3	1	1	4
5	1	1	1	5	5	5	1	1	4
5	1	1	1	5	5	5	1	1	4
5	5	5	5	5	5	5	5	4	4

b) CLUSTERed map uniquely identifies parcels and EDGEd map reclasses perimeter cells to class of neighbour.

CLUST.EPP

0	0	0	0	0	0	0	0	0	0
0	1	1	1	1	1	0	0	0	0
0	1	1	1	1	1	0	0	0	0
0	1	1	1	1	1	0	2	2	0
0	1	1	1	1	1	0	2	2	0
0	0	0	0	0	0	0	2	2	0
0	3	3	3	0	0	0	2	2	0
0	3	3	3	0	0	0	2	2	0
0	3	3	3	0	0	0	2	2	0
0	0	0	0	0	0	0	0	0	0

EDGEONLY.EPP

0	0	0	0	0	0	0	0	0	0
0	2	2	2	2	3	0	0	0	0
0	2	0	0	0	3	0	0	0	0
0	2	0	0	0	3	0	3	3	0
0	2	2	2	3	3	0	3	3	0
0	0	0	0	0	0	0	3	4	0
0	5	2	3	0	0	0	3	4	0
0	5	0	5	0	0	0	5	4	0
0	5	5	5	0	0	0	5	4	0
0	0	0	0	0	0	0	0	0	0

c) COUNT file of CLUST.EPP and EDGEONLY.EPP.

Class	Count	Percent
1	14	100.00
2	9	64.29
3	5	35.71
2	12	100.00
3	6	50.00
4	4	33.33
5	2	16.67
3	8	100.00
2	1	12.50
3	1	12.50
5	6	75.00

Class	Percent	Class x Percent
1	100.00	100.00
2	64.29	128.58
3	35.71	107.13
2	100.00	200.00
3	50.00	150.00
4	33.33	133.32
5	16.67	83.35
3	100.00	300.00
2	12.50	25.00
3	12.50	37.50
5	75.00	375.00

A Turbo Pascal utility was written which used these new files to calculate the adjacency index for each cluster (i.e. parcel). The results were then output into table files similar to those for the soil capability and parcel shape analyses. Following the above example, the resulting table file would appear as follows (where the first column is the cluster number and the second column is the adjacency index):

1	235.71
2	366.67
3	437.50

The data in the adjacency index table files were then compiled into contingency tables as was done for both the soil capability and parcel shape analyses. Similar to the A/P ratio, the adjacency index is a continuous variable ranging from 100 to 900. Therefore, to enable frequency counts, the adjacency index was divided into (attribute) classes. This will be discussed further in the next chapter.

3.3.4 Combined Attributes

With the data summarized in contingency table format, the transition probabilities can be easily calculated by dividing the number of idle parcels by the total parcels per attribute class. However, the transition probability for any given parcel will be different for each attribute considered. For example, depending on how the A/P ratio and adjacency index are classified, a parcel with a soil capability of five, an A/P ratio of 2.75, and an adjacency index value of 720.01, might have transition probabilities of 0.40 (62/155), 0.46 (154/338), and 0.34 (153/449), respectively. It would be difficult, if not impossible, to combine the separately derived probabilities into a valid single probability.

In order to have a single transition probability based on all three attributes, it is necessary to combine the attributes before the frequency count for the contingency table. To accomplish this, a Turbo Pascal utility was written which imported the original table files for each attribute, classified the data, and then combined the data into a new output table file. The resulting "combined" table file looks similar to the following example, where the first column is the parcel number and second column is the combined class:

1	212
2	131
3	243
4	222

In the combined class number, the first digit is the soil capability class (one of two), the second digit is the A/P ratio class (one of four), and the third digit is the adjacency index class (one of three). With the combined table files in the above format it was easy to do the frequency count for the combined attribute contingency tables.

The EPPL7 INTABLE function and the combined table files were then used to create a new combined attribute map by reclassing each parcel of the land-use maps to their corresponding combined attribute. For example, using the combined table file shown above would result in parcels 1,2,3, and 4 being reclassed to 212, 131, 243, and 222, respectively. Thus, the combined attribute could be read directly from the combined attribute maps. These combined attribute maps were the working maps used in the remainder of the modelling process.

3.4 Realization of Model

With the combined attribute data in contingency table format, the calculation of the transition probabilities is simple (dividing idle parcels by total parcels). These transition probabilities, however, correspond to a period of abandonment represented by the land-use maps; i.e. a period beginning the year the first parcel was left idle, until 1977. This represents roughly twenty to thirty years of abandonment (an estimate which will be discussed in detail in Chapter 4).

Therefore, if a time-period of a different length is to be simulated, then the transition probabilities must be adjusted to correspond with the new time-period.

For example, the land-use maps reveal that when no consideration is given to parcel attributes, 312 of all 1347 farmland parcels are idle, representing a 23.2% abandonment of parcels between roughly 1947-1957 and 1977. Assuming stationarity, it is expected that 23.2%, or 240, of the remaining 1035 parcels will be abandoned over this same period in the future; i.e. between 1977 and 1997-2007. Clearly, if only the ten-year period between 1977 and 1987 were being simulated, then the abandonment of much fewer than 240 parcels would be expected. Therefore, the initial transition probabilities representing a twenty-to-thirty year period on the maps must be corrected to correspond with a simulation period of different length.

The simulation period chosen for this study was between 1977 and 1992; a period which allowed field verification to be conducted. Thus, the initial transition probabilities were multiplied by a correction factor, to correspond to a fifteen-year simulation period. The details of this adjustment will be discussed in Chapter 4.

Once the adjusted transition probabilities were calculated for each combined attribute class, the combined attribute maps could be reclassed (via EPPL7's RECLASS function) to create the final probability maps. These maps

identified each parcel by its probability of being abandoned (rather than by land-use or attributes). However, for display purposes and for the field investigation, it was decided that the full range of probabilities be aggregated into just four probability classes, where class one has the highest probability of being abandoned and class four the lowest. This procedure is discussed in the next chapter.

3.5 Field Investigation

The final stage of the analysis was field verification of the model predictions, to correspond with a simulation period ending in 1992. Field inspection of approximately 20% of the 1035 active farmland parcels was decided upon as an adequate sample size, and a Turbo Pascal utility was written which used table files to randomly select parcels for field inspection. As mentioned above, the range of transition probabilities was aggregated into four classes, hence, 20% of the parcels in each probability class were randomly selected.

The chosen parcels were then labelled with numbered, removable, "dots" on the hardcopy versions of the land-use maps, which also displayed needed information on roads, towns, railroads, and other landmarks. Almost all of the sample parcels were accessible by road which allowed for roadside visual inspection from an automobile.

In most cases, map parcels comprised several fields, and thus a fractional estimate of abandonment was recorded (e.g.

1/3 abandoned, 0/1 abandoned, 1/1 abandoned). For practical purposes, parcels that showed less than one-fifth abandonment were recorded as having no abandonment. Inaccesible parcels, parcels for which a clear determination of abandonment could not be made, and parcels which had changed active use (i.e. to urban use) were so recorded, and eventually taken out of the sample.

The results of the field investigation were then compiled into contingency table format for chi-square testing, as was done for the above analyses. Thus, the contingency table of field data yielded a proportion of idle-to-total farmland for the period 1977 to 1992. This proportion was then compared to the predicted proportion (i.e. transition probabilities) of the model for the same period.

CHAPTER 4: RESULTS

4.1 Contingency Table Analyses

As discussed in the previous chapter, the raw data for each of the three attribute analyses were compiled into contingency tables for both study areas (West Carleton-Goulbourn-March and Rideau-Osgoode) for a total of six tables. In these tables, the column totals denote the number of parcels of a particular farmland type, while the row totals denote the number of parcels in a given attribute class. Thus, the contingency table format enabled the calculation of transition probabilities by simply dividing the number of idle parcels per attribute class by their corresponding row total. Recall that a preliminary model of farmland abandonment for both study areas, which makes no consideration of parcel attributes, would assign a transition probability of 0.232 to every active farmland parcel because 312 of 1347 farmland parcels (23.2%) were idle in 1977. However, by considering parcel attributes, a range of transition probabilities is developed which provides a better picture of reality.

4.1.1 Soil Capability Data

The contingency tables from the soil capability analysis are provided in Tables 3(a) and 3(b) for West Carleton-Goulbourn-March and Rideau-Osgoode, respectively. Initial inspection of the tables suggests that parcels of high-intensity land-use (i.e. monoculture, corn, mixed) occur

TABLE 3
CONTINGENCY TABLES OF FARMLAND TYPE VS. SOIL CAPABILITY

(a) West Carleton-Goulbourn-March

CLI Capability Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
Class 1	0	1	0	1	2	1	0	5
Class 2	41	42	45	89	27	50	21	315
Class 3	8	20	20	27	15	17	20	127
Class 4	8	4	9	22	24	28	33	128
Class 5	2	3	2	16	10	42	48	123
Class 6	1	1	2	4	2	21	23	54
Class 7	0	0	1	4	1	13	8	27
Organic	0	0	1	1	0	1	1	4
Disturbed	2	0	1	3	1	5	9	21
Total	62	71	81	167	82	178	163	804

(b) Rideau-Osgoode

CLI Capability Class	Farmland Type							
	Mono.	Corn	Mix.	Hay	Past.	Graz.	Idle	Total
Class 1	0	1	0	1	0	0	0	2
Class 2	20	30	26	43	17	16	17	169
Class 3	16	13	18	33	10	35	36	161
Class 4	8	4	6	17	7	24	47	113
Class 5	2	0	1	6	4	5	14	32
Class 6	1	1	1	6	4	14	31	58
Class 7	0	0	1	0	0	1	1	3
Organic	0	0	0	0	0	2	3	5
Disturbed	0	0	0	0	0	0	0	0
Total	47	49	53	106	42	97	149	543

Note that the frequency is in terms of the number of parcels of each farmland type for which the given soil capability class is dominant.

on higher-capability land (i.e. CLI classes one, two, or three), and conversely, low-intensity land-use is located on low-capability land. For example, in both study areas, more than three-quarters of monoculture, corn, and mixed parcels, but less than one-third of idle parcels, occur on CLI class one, two, or three land. Furthermore, in Table 3(a), farmland parcels with soil capability of two have a transition probability of 0.07 (21/315), while parcels of capability six have a transition probability of 0.34 (122/357). Similarly, the respective probabilities in Table 3(b) are 0.10 (17/169) and 0.53 (31/58). Thus, the data appear to support the contention that higher rates of abandonment are expected on land of poorer capability (Parson, 1979; McCuaig & Manning, 1982).

As stated previously, the chi-square statistic was used to test the significance of the association between land-use and soil capability. One of the main assumptions of the chi-square test is that none of the expected frequencies should be too small; i.e. less than five. Everitt (1977), however, states that this requirement may be too stringent and suggests that if fewer than one-fifth of the cells are less than five, then a minimum expected frequency of one is acceptable. Nevertheless, this assumption would be violated if Tables 3(a) or 3(b) were used for the chi-square test, since the former would have fourteen cells with expected frequencies less than one and the latter would have twenty-eight. Therefore, to meet

this requirement, the classes in the above tables were pooled.

The original CLI capability classes were pooled into two classes, with one including the first three CLI classes, and the other comprising the remaining CLI classes. The resulting contingency tables, shown in Tables 4(a) and 4(b), have no expected frequencies of less than five. The chi-square tests reveal that, for both study areas, the association between soil capability class and land-use type is significant.

The data in Tables 4(a) and 4(b) also show that, within either attribute class, the proportions of parcels by land-use type are very similar for both study areas. For example, the percentage of monoculture parcels in capability class one is approximately 11% in both study areas (49/447 in West Carleton-Goulbourn-March, 36/332 in Rideau-Osgoode). Thus, by dividing each cell entry in Tables 4(a) and 4(b) by their corresponding row totals, Tables 5(a) and 5(b) were created where each cell entry represents the percentage of parcels in the given land-use. With the data in this form, it is clearly evident that the association between land-use and soil capability is similar in both study areas.

Since the corresponding proportions in both study areas are so alike, Everitt (1977) states that the raw data from the two sample areas may be safely aggregated for an overall analysis (Table 6). The main advantage of this is that the sample size on which the transition probabilities are based is larger, and hence, more statistically reliable. This became a

TABLE 4(a)
CHI-SQUARE ANALYSIS OF SOIL CAPABILITY DATA

West Carleton-Goulbourn-March

Soil Capab. Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
Class 1 ≤3(CLI)	49 (34.5)	63 (39.5)	65 (45.0)	117 (92.8)	44 (45.6)	68 (99.0)	41 (90.6)	447
Class 2 ≥4(CLI)	13 (27.5)	8 (31.5)	16 (36.0)	50 (74.2)	38 (36.4)	110 (79.0)	122 (72.4)	357
Total	62	71	81	167	82	178	163	804

Note that the numbers in brackets are the expected frequencies.

$$\sum \frac{(o-e)^2}{e}$$

$$= 6.12 + 14.02 + 8.85 + 6.28 + 0.06 + 9.69 + 27.17 + 7.67 + 17.55 + 11.08 + 7.87 + 0.07 + 12.12 + 34.02$$

$$\chi^2 = 162.50$$

The requisite value of chi-square with six degress of freedom at the 0.01 significance level is 16.812. Since the value of chi-square derived from the above contingency table is far greater than this value, the association between land-use and the given soil capability classes is deemed to be significant.

TABLE 4(b)
CHI-SQUARE ANALYSIS OF SOIL CAPABILITY DATA

Rideau-Osgoode

Soil Capab. Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
Class 1 ≤3(CLI)	36 (34.5)	44 (39.5)	44 (45.0)	77 (92.8)	27 (45.6)	51 (99.0)	53 (90.6)	332
Class 2 ≥4(CLI)	11 (27.5)	5 (31.5)	9 (36.0)	29 (74.2)	15 (36.4)	46 (79.0)	96 (72.4)	211
Total	47	49	53	106	42	97	149	543

Note that the numbers in brackets are the expected frequencies.

$$\sum \frac{(o-e)^2}{e}$$

$$= 1.84 + 6.58 + 4.14 + 2.29 + 0.07 + 1.16 + 15.93 + 2.89 + 10.35 + 6.53 + 3.61 + 0.11 + 1.83 + 25.07$$

$$\chi^2 = 82.41$$

The requisite value of chi-square with six degress of freedom at the 0.01 significance level is 16.812. Since the value of chi-square derived from the above contingency table is far greater than this value, the association between land-use and the given soil capability classes is deemed to be significant.

TABLE 5
PERCENTAGE OF PARCELS PER ATTRIBUTE CLASS
FOR DIFFERENT LAND-USE CLASSES

a) West Carleton-Goulbourn-March

Soil Capab. Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
Class 1	11.0	14.1	14.5	26.2	9.8	15.2	9.2	100%
Class 2	3.6	2.2	4.5	14.0	10.6	30.8	34.3	100%

b) Rideau-Osgoode

Soil Capab. Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
Class 1	10.8	13.3	13.3	23.2	8.0	15.4	16.0	100%
Class 2	5.2	2.4	4.3	13.7	7.1	21.3	45.5	100%

TABLE 6
CHI-SQUARE ANALYSIS OF AGGREGATED SOIL CAPABILITY DATA

Combination of Tables 4(a) and 4(b)

Soil Capab. Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
Class 1 ≤3(CLI)	85 (63.0)	107 (69.4)	109 (77.5)	194 (158)	71 (71.7)	119 (159)	94 (180)	779
Class 2 ≥4(CLI)	24 (46.0)	13 (50.6)	25 (56.5)	79 (115)	53 (52.3)	156 (116)	218 (132)	568
Total	109	120	134	273	124	275	312	1347

Note that the numbers in brackets are the expected frequencies.

$$\sum \frac{(o-e)^2}{e}$$

$$= 7.65 + 20.37 + 12.80 + 8.26 + 0.01 + 10.07 + 41.40 + 10.49 + 27.94 + 17.56 + 11.33 + 0.01 + 13.82 + 56.78$$

$$\chi^2 = 238.50$$

The requisite value of chi-square with six degress of freedom at the 0.01 significance level is 16.812. Since the value of chi-square derived from the above contingency table is far greater than this value, the association between land-use and the given soil capability classes is deemed to be significant.

concern when the attributes were combined, which increased the number of attribute classes, and accordingly, reduced the number of observations per attribute class. Therefore, aggregating the data into a single table for both study areas permitted a larger number of combined attribute classes (see below).

4.1.2 Area-Perimeter Ratio Data

The data from the parcel shape analysis was also compiled into contingency table format (Tables 7a, 7b). However, the A/P ratio, being a continuous variable ranging from 1.00 to 10.32, required division into discrete attribute classes to permit a frequency count of the data. The data in Tables 7(a) and 7(b) were divided into only two classes, both to meet statistical conditions of minimum expected frequency, as well as to allow comparison with the other attribute analyses. Since no natural breaks on which to establish class intervals were apparent in the data set, intervals were chosen so that each class (in the aggregated contingency table) had a relatively equal number of observations.

Visual inspection of the data in Tables 7(a) and 7(b) suggests that there is a relationship between A/P ratio and land-use. For example, in both tables, roughly three-quarters of all idle parcels are in the first A/P ratio class (1.00 to 3.70). Since lower A/P ratios are related to irregular parcel shapes, the data appear to support the observation of Coleman

TABLE 7(a)
CHI-SQUARE ANALYSIS OF AREA-PERIMETER RATIO DATA

West Carleton-Goulbourn-March

A/P Ratio Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
Class 1 ≤3.70	30 (30.5)	17 (35.0)	28 (39.9)	77 (82.3)	29 (40.4)	89 (87.7)	126 (80.3)	396
Class 2 ≥3.71	32 (31.5)	54 (36.0)	53 (41.1)	90 (84.7)	53 (41.6)	89 (90.3)	37 (82.7)	408
Total	62	71	81	167	82	178	163	804

Note that the numbers in brackets are the expected frequencies.

$$\sum \frac{(o-e)^2}{e}$$

$$= 0.01 + 9.23 + 3.55 + 0.34 + 3.21 + 0.02 + 26.03 + 0.01 + 8.96 + 3.44 + 0.33 + 3.12 + 0.02 + 25.27$$

$$\chi^2 = 83.53$$

The requisite value of chi-square with six degrees of freedom at the 0.01 significance level is 16.812. Since the value of chi-square derived from the above contingency table is far greater than this value, the association between land-use and the given A/P ratio classes is deemed to be significant.

TABLE 7(b)
CHI-SQUARE ANALYSIS OF AREA-PERIMETER RATIO DATA

Rideau-Osgoode

A/P Ratio Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
Class 1 ≤3.70	22 (24.1)	12 (25.2)	12 (27.2)	45 (54.5)	20 (21.6)	61 (49.8)	107 (76.6)	279
Class 2 ≥3.71	25 (22.9)	37 (23.8)	41 (25.8)	61 (51.5)	22 (20.4)	36 (47.2)	42 (72.4)	264
Total	47	49	53	106	42	97	149	543

Note that the numbers in brackets are the expected frequencies.

$$\sum \frac{(o-e)^2}{e} = 0.19 + 6.90 + 8.52 + 1.64 + 0.12 + 2.50 + 12.10 + 0.20 + 7.29 + 9.00 + 1.74 + 0.12 + 2.64 + 12.79$$

$$\chi^2 = 65.75$$

The requisite value of chi-square with six degrees of freedom at the 0.01 significance level is 16.812. Since the value of chi-square derived from the above contingency table is far greater than this value, the association between land-use and the given A/P ratio classes is deemed to be significant.

(1969) and Odum and Turner (1990) that abandoned land is often irregularly-shaped. There is a tendency in the data for higher intensity land-uses to have higher A/P ratios.

Chi-square analysis of the data reveals that the association between land-use and A/P ratio is significant in both study areas. Furthermore, as was found in the soil capability analysis, the proportions of parcels by land-use type are very similar for both study areas. The data in Tables 7(a) and 7(b) were converted to percentages by dividing each cell entry by its corresponding row total. With the data as percentages in Tables 8(a) and 8(b), it is evident that the proportion of parcels in each land-use type is again similar for both study areas. Therefore, by the same reasoning used in the soil capability analysis, the data from both study areas was aggregated into a single contingency table (Table 9).

4.1.3 Adjacency Index Data

The data from the adjacency index analysis were placed into contingency Tables 10(a) and 10(b). However, as with the A/P ratio, the adjacency index is a continuous variable ranging from 100 to 900. Thus, the data required division into discrete classes to permit a frequency count. The data was again divided into two classes to meet the statistical conditions of minimum expected frequency per cell, as well as for comparison with the other attribute analyses. As was done in the A/P ratio analysis, class intervals were chosen so that

TABLE 8
PERCENTAGE OF PARCELS PER ATTRIBUTE CLASS
FOR DIFFERENT LAND-USE CLASSES

a) West Carleton-Goulbourn-March

A/P Ratio Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
Class 1	7.6	4.3	7.1	19.4	7.3	22.5	31.8	100%
Class 2	7.8	13.2	13.0	22.1	13.0	21.8	9.1	100%

b) Rideau-Osgoode

A/P Ratio Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
Class 1	7.9	4.3	4.3	16.1	7.2	21.9	38.4	100%
Class 2	9.5	14.0	15.5	23.1	8.3	13.6	16.0	100%

TABLE 9
CHI-SQUARE ANALYSIS OF AGGREGATED A/P RATIO DATA

Combination of Tables 7(a) and 7(b)

A/P Ratio Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
Class 1 ≤3.70	52 (54.6)	29 (60.1)	40 (67.1)	122 (137)	49 (62.1)	150 (138)	233 (156)	675
Class 2 ≥3.71	57 (54.4)	91 (59.9)	94 (66.9)	151 (136)	75 (61.9)	125 (137)	79 (156)	672
Total	109	120	134	273	124	275	312	1347

Note that the numbers in brackets are the expected frequencies.

$$\sum \frac{(o-e)^2}{e}$$

$$= 0.13 + 16.12 + 10.98 + 1.60 + 2.78 + 1.08 + 37.58 + 0.13 + 16.19 + 11.03 + 1.61 + 2.79 + 1.08 + 37.75$$

$$\chi^2 = 140.80$$

The requisite value of chi-square with six degrees of freedom at the 0.01 significance level is 16.812. Since the value of chi-square derived from the above contingency table is far greater than this value, the association between land-use and the given A/P ratio classes is deemed to be significant.

TABLE 10(a)
CHI-SQUARE ANALYSIS OF ADJACENCY INDEX DATA

West Carleton-Goulbourn-March

Adjac. Index Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
Class 1 ≤579.32	41 (30.5)	53 (34.9)	54 (39.8)	75 (82.0)	39 (40.3)	78 (87.5)	55 (80.1)	395
Class 2 >579.32	21 (31.5)	18 (36.1)	27 (41.2)	92 (85.0)	43 (41.7)	100 (90.5)	108 (82.9)	409
Total	62	71	81	167	82	178	163	804

Note that the numbers in brackets are the expected frequencies.

$$\sum \frac{(o-e)^2}{e}$$

$$= 3.65 + 9.41 + 5.07 + 0.61 + 0.04 + 1.02 + 7.86 + 3.52 + 9.09 + 4.90 + 0.58 + 0.04 + 0.99 + 7.59$$

$$\chi^2 = 54.35$$

The requisite value of chi-square with six degrees of freedom at the 0.01 significance level is 16.812. Since the value of chi-square derived from the above contingency table is greater than this value, the association between land-use and the given adjacency index classes is deemed to be significant.

TABLE 10(b)
CHI-SQUARE ANALYSIS OF AGGREGATED ADJACENCY INDEX DATA

Rideau-Osgoode

Adjac. Index Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
Class 1 ≤579.32	31 (24.1)	38 (25.1)	34 (27.1)	54 (54.3)	26 (21.5)	46 (49.7)	49 (76.3)	278
Class 2 >579.32	16 (22.9)	11 (23.9)	19 (25.9)	52 (51.7)	16 (20.5)	51 (47.3)	100 (72.7)	265
Total	47	49	53	106	42	97	149	543

Note that the numbers in brackets are the expected frequencies.

$$\sum \frac{(o-e)^2}{e}$$

$$= 2.00 + 6.65 + 1.74 + 0.00 + 0.94 + 0.27 + 9.76 + 2.10 + 6.97 + 1.82 + 0.00 + 0.99 + 0.28 + 10.24$$

$$\chi^2 = 43.75$$

The requisite value of chi-square with six degrees of freedom at the 0.01 significance level is 16.812. Since the value of chi-square derived from the above contingency table is greater than this value, the association between land-use and the given adjacency index classes is deemed to be significant.

the classes had almost an equal number of observations, based on an aggregate table of both study areas.

Initial inspection of the data in Tables 10(a) and 10(b) suggests an association between parcel land-use and adjacency index. Since low adjacency index values suggest adjacent parcels of monoculture, corn, and/or mixed use, it appears that high-intensity parcels tend to be adjacent to high-intensity farmland. Similarly, low-intensity parcels (including idle) tend to be located adjacent to low-intensity farmland, forest, and "other". For example, in both tables, two-thirds of all monoculture parcels but only one-third of all idle parcels belong to the first index class.

Chi-square analysis shows that the association between land-use and adjacency index is significant in both study areas. Furthermore, as seen in both the soil capability and the A/P ratio analyses, the proportion of parcels by land-use type is very similar in both study areas. The data in Tables 10(a) and 10(b) were again converted to percentages. With the data in percentage form in Tables 11(a) and 11(b), the similarity in proportions between the two study areas is clearly evident. Therefore, by the same reasoning used previously, the raw data from the two sample areas were aggregated into a single contingency table for adjacency index (Table 12).

In summary, the chi-square analyses for all three of the aggregated contingency tables reveal a significant association

TABLE 11
PERCENTAGE OF PARCELS PER ATTRIBUTE CLASS
FOR DIFFERENT LAND-USE CLASSES

a) West Carleton-Goulbourn-March

Adjac. Index Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
Class 1	10.4	13.4	13.7	19.0	9.9	19.8	13.9	100%
Class 2	5.1	4.4	6.6	22.5	10.5	24.5	26.4	100%

b) Rideau-Osgoode

Adjac. Index Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
Class 1	11.2	13.7	12.2	19.4	9.4	16.6	17.6	100%
Class 2	6.0	4.2	7.2	19.6	6.0	19.2	37.7	100%

TABLE 12
CHI-SQUARE ANALYSIS OF ADJACENCY INDEX DATA

Combination of Tables 10(a) and 10(b)

Adjac. Index Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
Class 1 ≤579.32	72 (54.5)	91 (60.0)	88 (67.0)	129 (136)	65 (62.0)	124 (137)	104 (156)	673
Class 2 >579.32	37 (54.5)	29 (60.0)	46 (67.0)	144 (137)	59 (62.0)	151 (138)	208 (156)	674
Total	109	120	134	273	124	275	312	1347

Note that the numbers in brackets are the expected frequencies.

$$\sum \frac{(o-e)^2}{e}$$

$$= 5.65 + 16.07 + 6.62 + 0.40 + 0.15 + 1.31 + 17.27 + 5.64 + 16.05 + 6.61 + 0.40 + 0.15 + 1.30 + 17.24$$

$$\chi^2 = 94.86$$

The requisite value of chi-square with six degrees of freedom at the 0.01 significance level is 16.812. Since the value of chi-square derived from the above contingency table is far greater than this value, the association between land-use and the given adjacency index classes is deemed to be significant.

between land-use and parcel attributes. Also, the association appears strongest for soil capability (chi-square = 238.5), followed by A/P ratio (chi-square = 140.8), and then adjacency index (chi-square = 94.9). Therefore, as a result of the significant association between the chosen attributes and land-use, all three attributes were used in combined attribute classes to determine the overall transition probabilities for each parcel of active farmland.

4.1.4 Combined Attribute Data

The next stage involved the development of combined attribute classes so that each parcel could be described by a single transition probability based on all three attributes. The attribute data as classified in the above contingency tables resulted in eight combined attribute classes (2 soil capability classes x 2 A/P ratio classes x 2 adjacency index classes), the frequency count for which is compiled in Tables 13(a) and 13(b). Obviously the number of combined attribute classes depends upon the number of classes assigned to each individual attribute. Note that the minimum number of combined attribute classes is eight because each individual attribute has a minimum of two classes.

More classes, however, result in fewer observations per class, and consequently, statistical limitations are quickly reached. This is seen in Table 13(b), where chi-square analysis could not be done because seventeen of the fifty-six

TABLE 13(a)
CONTINGENCY TABLE OF COMBINED ATTRIBUTE CLASS DATA

West Carleton-Goulbourn-March

Combined Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
111	15	10	9	24	5	22	27	112
112	5	6	11	21	8	12	9	72
121	20	37	37	41	21	21	3	180
122	9	10	8	31	10	13	2	83
211	4	0	4	3	4	15	20	50
212	6	1	4	29	12	40	70	162
221	2	6	4	7	9	20	5	53
222	1	1	4	11	13	35	27	92
Total	62	71	81	167	82	178	163	804

Note that:

(1) the first digit of the combined class is the soil capability class where,
1 = CLI classes 1, 2, and 3;
2 = CLI classes 4, 5, 6, 7, organic, and disturbed.

(2) the second digit of the combined class is the A/P ratio class where,
1 = 1.00 to 3.70;
2 = 3.71 to 10.32.

(3) the third digit of the combined class is the adjacency index class where,
1 = 100.00 to 579.32;
2 = 579.33 to 900.00.

TABLE 13(b)
CONTINGENCY TABLE OF COMBINED ATTRIBUTE CLASS DATA

Rideau-Osgoode

Combined Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
111	10	8	4	19	10	20	22	93
112	4	4	4	10	3	10	18	53
121	20	29	29	31	11	13	6	139
122	2	3	7	17	3	8	7	47
211	1	0	0	2	2	8	17	30
212	7	0	4	14	5	23	50	103
221	0	1	1	2	3	5	4	16
222	3	4	4	11	5	10	25	62
Total	47	49	53	106	42	97	149	543

Note that:

(1) the first digit of the combined class is the soil capability class where,
1 = CLI classes 1, 2, and 3;
2 = CLI classes 4, 5, 6, 7, organic, and disturbed.

(2) the second digit of the combined class is the A/P ratio class where,
1 = 1.00 to 3.70;
2 = 3.71 to 10.32.

(3) the third digit of the combined class is the adjacency index class where,
1 = 100.00 to 579.32;
2 = 579.33 to 900.00.

cells (30%) had expected frequencies below five. This problem was overcome by aggregating Tables 13(a) and 13(b) into a single contingency table (Table 14) for both study areas, so that no cell in the aggregated table had an expected frequency below five. Table 14 shows a significant association between land-use and the combined attribute classes, since the chi-square value of 403.50 is far greater than the requisite value of 66.18 for forty-two degrees of freedom at the 0.01 level.

It is clear, though, that larger contingency tables with more than eight attribute classes will likely require the pooling of classes due to statistical limitations. One way of doing this is by pooling the column data into *active* and *idle* categories, an acceptable approach since the transition probabilities require no distinction to be made between active farmland types. The data in Table 14 was pooled in this manner to form Table 15; note that the transition probabilities have been ranked in descending order. Similarly, Table 16 is an aggregated table of twenty-four combined attribute classes (2 soil capability x 4 A/P ratio and 3 adjacency index classes). Despite having twenty-four classes, only four of the forty-eight (8%) cells have expected frequencies of less than five. Thus, the association between land-use and the attribute classes is again shown to be significant, where the calculated chi-square of 242.19 is greater than the requisite value of 41.638 (for twenty-three degrees of freedom at the 0.01 level). In this way, many more attribute classes are possible,

TABLE 14
AGGREGATED CONTINGENCY TABLE OF COMBINED ATTRIBUTE CLASS DATA

Combination of Tables 13(a) and 13(b)

Combined Class	Farmland Type							
	Mono.	Corn	Mix	Hay	Past.	Graz.	Idle	Total
111	25	18	13	43	15	42	49	205
112	9	10	15	31	11	22	27	125
121	40	66	66	72	32	34	9	319
122	11	13	15	48	13	21	9	130
211	5	0	4	5	6	23	37	80
212	13	1	8	43	17	63	120	265
221	2	7	5	9	12	25	9	69
222	4	5	8	22	18	45	52	154
Total	109	120	134	273	124	275	312	1347

Note that:

(1) the first digit of the combined class is the soil capability class where,
1 = CLI classes 1, 2, and 3;
2 = CLI classes 4,5,6,7, organic, and disturbed.

(2) the second digit of the combined class is the A/P ratio class where,
1 = 1.00 to 3.70;
2 = 3.71 to 10.32.

(3) the third digit of the combined class is the adjacency index class where,
1 = 100.00 to 579.32;
2 = 579.33 to 900.00.

TABLE 15
EIGHT-CLASS PROBABILITY TABLE

West Carleton-Goulbourn-March
and Rideau-Osgoode

Combined Attribute Class	Farmland Type			p
	Active	Idle	Total	
211	43	37	80	0.463
212	145	120	265	0.453
222	102	52	154	0.338
111	156	49	205	0.239
112	98	27	125	0.216
221	60	9	69	0.130
122	121	9	130	0.069
121	310	9	319	0.028
Total	1035	312	1347	0.232

Note that:

(1) the first digit of the combined class is the soil capability class where,
1 = CLI classes 1, 2, and 3;
2 = CLI classes 4, 5, 6, 7, organic, and disturbed.

(2) the second digit of the combined class is the A/P ratio class where,
1 = 1.00 to 3.70;
2 = 3.71 to 10.32.

(3) the third digit of the combined class is the adjacency index class where,
1 = 100.00 to 579.32;
2 = 579.33 to 900.00.

TABLE 16
TWENTY-FOUR CLASS PROBABILITY TABLE

West Carleton-Goulbourn-March and Rideau-Osgoode

Combined Attribute Class	Farmland Type			p
	Active	Idle	Total	
212	22	28	50	0.560
213	55	63	118	0.534
211	10	11	21	0.524
111	39	26	65	0.400
233	37	24	61	0.393
222	34	21	55	0.382
112	28	16	44	0.364
223	55	28	83	0.337
221	12	6	18	0.333
232	35	15	50	0.300
243	32	12	44	0.273
113	30	10	40	0.250
242	26	9	35	0.257
123	33	9	42	0.214
133	31	5	36	0.139
122	48	6	54	0.111
121	76	9	85	0.106
132	62	6	68	0.088
143	23	2	25	0.080
241	19	1	20	0.050
131	104	3	107	0.028
141	117	2	119	0.017
142	94	0	94	0.000
231	13	0	13	0.000
Total	1035	312	1347	0.232

Note that the:

(1) first digit of combined class is soil capability class where,
1 = CLI classes 1,2, and 3;
2 = CLI classes 4,5,6,7, organic, and disturbed.

(2) second digit of the combined class is A/P ratio class where,
1 = 1.00 to 2.90; 2 = 2.91 to 3.70;
3 = 3.71 to 4.70; 4 = 4.71 to 10.32.

(3) third digit of combined class is adjacency index class where,
1 = 100.00 to 500.01;
2 = 500.02 to 647.06;
3 = 647.07 to 900.00.

while still meeting statistical requirements.

The argument for having a larger number of combined attribute classes is that, with more cases, a greater range of transition probabilities is derived, each of which relates to a more homogeneous set of parcels. However, there are upper limits to the number of combined attribute classes that can be used. First of all, with the present data set, statistical limitations (i.e. minimum expected frequency) resulting from too few observations per cell are reached at about thirty combined classes. Secondly, the value of making minor distinctions between the transition probabilities of small sets of parcels may be limited in practical terms. For example, with a small number of classes, one large set of parcels could have a probability of 0.300. However, the same set could be segregated into several small sets if a larger number of classes were used, each with probabilities in the order of, say, 0.291, 0.311, and 0.305. In practice, fine distinctions such as these may be of little additional value. This will be discussed in more detail in the next chapter.

4.2 Transition Probabilities

Several contingency tables with different combinations of attribute classes (e.g. 2x2x2, 2x3x3, 2x4x3) were made, each of which showed a significant association between land-use and parcel attributes. From the contingency tables, the transition probabilities were calculated by dividing the number of idle

parcels per attribute class by the corresponding marginal row total. The table rows were then sorted in descending order, as in Tables 15 and 16. In Table 15, an eight-class model, the highest probability for abandonment (0.463) belongs to parcels with soil capability class two, A/P ratio class one, and adjacency index class one (i.e. class 211). In Table 16, a twenty-four class model, the highest probability (0.560) belongs to parcels with soil capability class two, A/P ratio class one, and adjacency index class two. The reasons for the difference between the two models will be discussed in the next chapter.

As discussed in Chapter 3, the initial transition probabilities required adjustment to conform with the fifteen-year period of the simulation. Recall that the land-use maps, from which the initial transition probabilities were determined, represent a period of farmland abandonment in the order of twenty-to-thirty years. From this rough estimate, however, it is difficult to determine how many parcels of farmland should be abandoned in only fifteen years.

The imprecision of the estimate is due to the definition of one of the two original types of idle farmland (Table 1). The definition of A2 idle farmland as having been abandoned for *more than ten years* precludes the determination of a precise date of abandonment. Note that A2 farmland must have been idle for less time than is needed to reach the *woodland* state (as defined in Table 1) or else it would have been

classified as such in the original field surveys. Therefore, a maximum age on the order of twenty to thirty years can be used for A2 farmland, because this is roughly the time required for old-field succession to attain a *woodland* state (Brunton, 1988; Kricher & Morrison, 1988). However, this time varies considerably and many areas may remain "scrubby" for a much longer period.

It would be difficult to avoid error if a rough estimate of A2 age were used to predict the number of parcels abandoned between 1977 and 1992. Thus, it was decided that only A1 land would be used to calculate an annual rate of abandonment, since it is precisely defined as land left idle for *one to ten years*. Using the EPPL7 count function, it was determined that 13095 ha of A1 land existed over both study areas, representing abandonment between 1967 and 1977. This corresponds to a compounded annual loss of 1.332% of the area of active farmland during this period. Assuming this rate is maintained, then 16626 ha of active farmland would have been abandoned between 1977 and 1992. Dividing this area (16626 ha) by the average area of active farmland parcels (88.1 ha) gives an estimated loss of 188 parcels of active farmland between 1977 and 1992. Thus, the initial transition probabilities must be corrected so that, in aggregate, they predict the loss of the same number of parcels.

In order to determine the correction factor, the number of abandoned parcels predicted by the initial probability

tables for the 1977-1992 period were calculated. This was done by multiplying the number of active farmland parcels by their corresponding transition probabilities. For example, the eight class model described above (Table 15) predicts that 19.9 (43 x 0.463) parcels of active farmland in combined class 211 would be abandoned. Repeating this for all eight attribute class leads to a sum total of 203.35 parcels. Therefore, the initial transition probabilities for the eight class model predict the abandonment of 203 parcels, over the twenty-to-thirty year period following 1977. Since, 203 must be multiplied by a factor of 0.925 to get 188 parcels, then the final transition probability table is derived by multiplying every probability in the initial table by this factor (Table 17).

As discussed in the previous chapter, working maps were created in which each parcel was identified by its combined attribute class. Once the final transition probabilities were calculated, each combined class of the working maps was re-assigned (via EPPL7's reclass function) to its corresponding transition probability. This resulted in the final maps where every active farmland parcel was identified by its probability of abandonment in the period 1977 to 1992.

Given the potentially large range of probabilities that could be shown on the final maps, however, it was decided that the full range of probabilities should be aggregated into only four classes. There were two reasons for doing this. First,

TABLE 17
ADJUSTED EIGHT-CLASS PROBABILITY TABLE

West Carleton-Goulbourn-March
and Rideau-Osgoode

Combined Attribute Class	Farmland Type			Adjusted p	Active x Adj. p
	Active	Idle	Total		
211	43	37	80	0.428	18.4
212	145	120	265	0.419	60.8
222	102	52	154	0.312	31.8
111	156	49	205	0.221	34.5
112	98	27	125	0.200	19.6
221	60	9	69	0.120	7.2
122	121	9	130	0.064	7.7
121	310	9	319	0.026	8.1
Total	1035	312	1347	----	188.1

Note that:

(1) the first digit of the combined class is the soil capability class where,
1 = CLI classes 1, 2, and 3;
2 = CLI classes 4, 5, 6, 7, organic, and disturbed.

(2) the second digit of the combined class is the A/P ratio class where,
1 = 1.00 to 3.70;
2 = 3.71 to 10.32.

(3) the third digit of the combined class is the adjacency index class where,
1 = 100.00 to 579.32;
2 = 579.33 to 900.00.

it simplified the visual interpretation of the maps because it is easier to distinguish between four classes on a map than eight (or twenty-four).

The second reason was that a contingency table of field results with eight or more attribute classes had the potential to violate the requirement of minimum expected frequency. This is because the sample size of 20% translates into far fewer observations per cell than in the tables previously shown. A comparison between the model predictions and the field results is most easily accomplished if their respective contingency tables are of the same format. Therefore, it was decided that a four-class probability table would likely meet the statistical requirements for both.

It was decided that the twenty-four class model shown in Table 16 would be tested through field sampling. A four-class probability table was created from this table, by aggregating the six highest probability classes into class one, the next six into class two, and so on (Table 18). This format of aggregation was chosen so that it could be repeated for the eight-class model or any other combination of attributes whose total combined classes were divisible by four. The final four-class probability maps for West-Carleton-Goulbourn-March and Rideau-Osgoode are shown in Figures 9 and 10, respectively.

TABLE 18
FOUR-CLASS AGGREGATED PROBABILITY TABLE

West Carleton-Goulbourn-March and Rideau-Osgoode

Trans. Probability Class	Farmland Type			Adjusted p	Active x Adj.p
	Active	Idle	Total		
Class 1	197	173	370	0.450	88.7
Class 2	188	86	274	0.302	56.8
Class 3	280	45	325	0.127	35.6
Class 4	370	18	378	0.019	7.0
Total	1035	312	1347	-----	188.1

Note that the above table is derived from the twenty-four class probability model in Table 16, where:

Class 1 = 212, 213, 211, 111, 233, and 222;
Class 2 = 112, 223, 221, 232, 243, and 242;
Class 3 = 113, 123, 133, 122, 121, and 132;
Class 4 = 143, 241, 131, 141, 231, and 142.

FIGURE 9: PROBABILITY OF ABANDONMENT, WEST CARLETON-GOULBOURN-MARCH

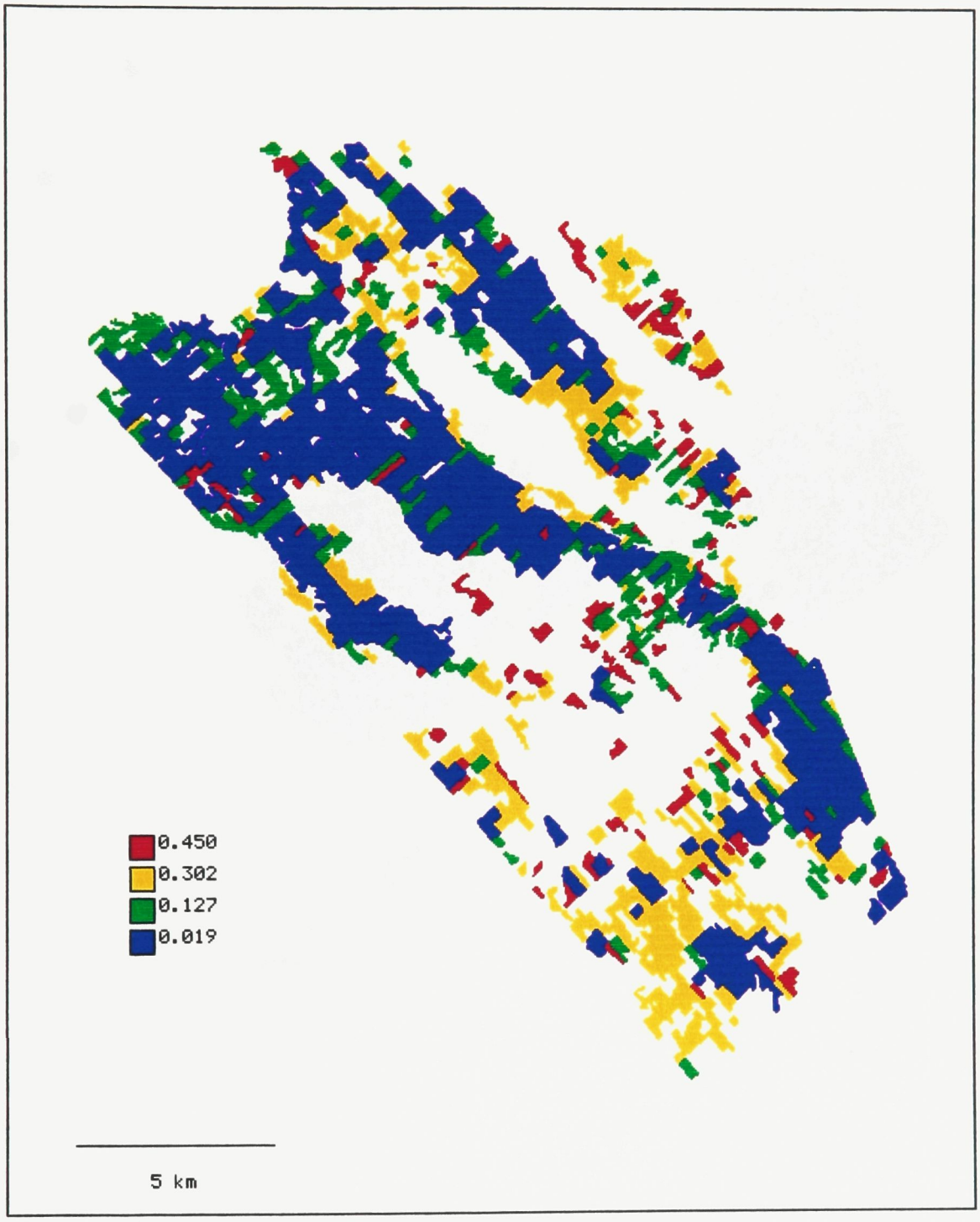
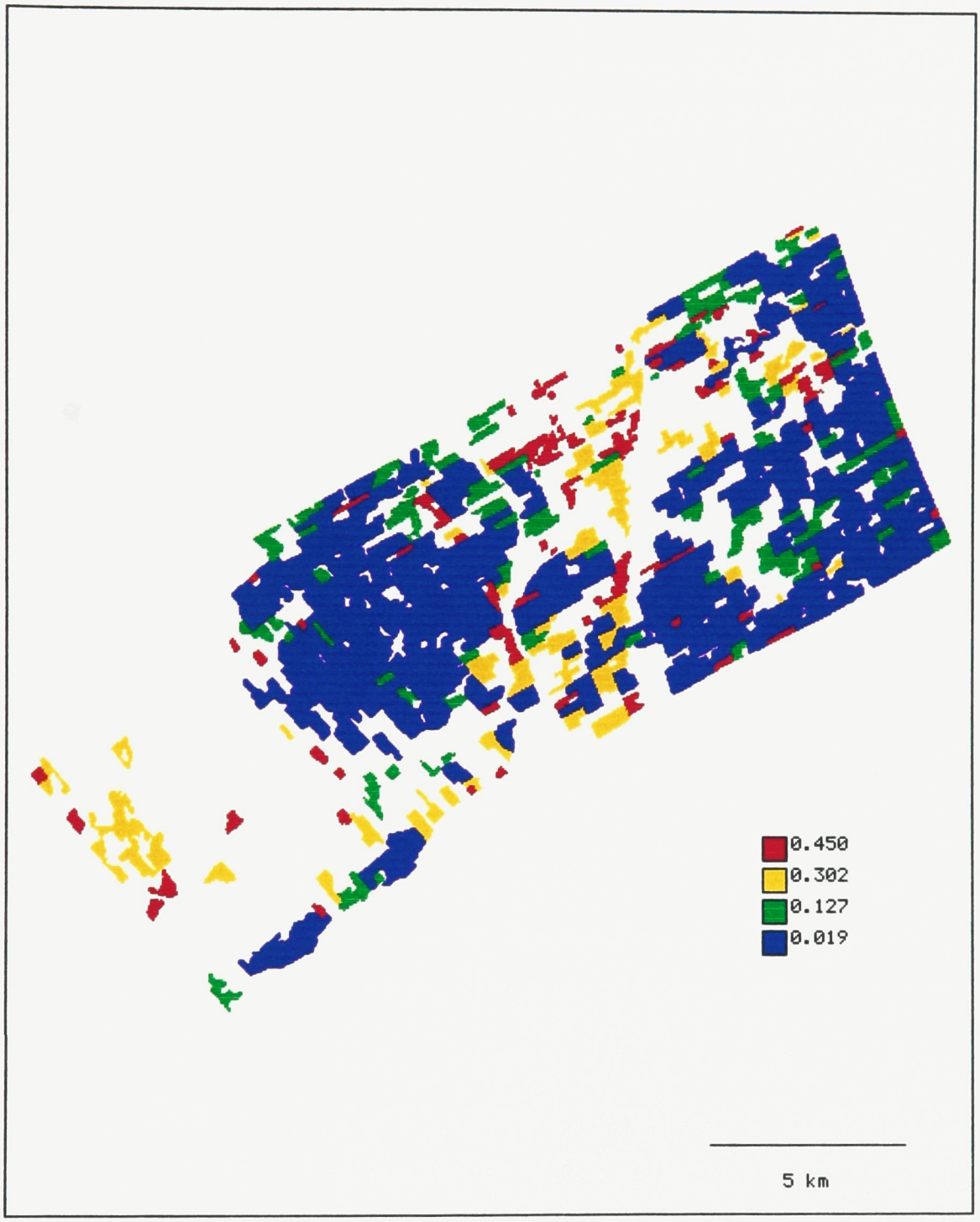


FIGURE 10: PROBABILITY OF ABANDONMENT, RIDEAU-OSGOODE



4.3 Field Results

As discussed in the Chapter 3, a random sample of active farmland parcels was selected for inspection. A sample size of 203 parcels represented 19.6% of the total number of active parcels. As each parcel was inspected, the proportion of abandonment that was evident was recorded. A field was judged to have been abandoned if there was a considerable amount of shrubby growth present and there was no evidence of grazing (i.e. closely cropped grass, trampled ground, maintained fences, and livestock droppings). In cases where no clear determination could be made, the parcel was removed from the sample. Furthermore, inaccesible parcels and parcels which had changed active use (i.e. from farmland to urban or extraction usage) were also removed from the sample. Hence, the final sample size worked out to 184 parcels or 17.8% of the total population of parcels which were active farmland in 1977.

The results from the field survey were compiled into the same contingency table format as Table 18 to allow comparison. However, the frequency count was done in two different ways to reflect the frequent observation that only portions of parcels were being abandoned. The cells in Table 19(a) record the number of parcels which show at least some abandonment; e.g. 18 of 31 parcels in probability class one show some abandonment. These results are significant, meeting all statistical assumptions. However, this approach clearly overestimates the area of farmland, in terms of the number of

parcels, that is abandoned.

A better approach involves a "count" of the actual area abandoned per probability class (Table 19b). This is done by adding the fractional estimates of abandonment for every parcel in the probability class (e.g. 1/3 + 0/1 + 1/1). In this way, it can be seen that a total of 12.8 of the 31 parcels in probability class one have been abandoned. Although the values in Table 19(b) are fractional values, the numbers were rounded to the nearest integer for the chi-square test, as required (Everitt, 1977); the association between land-use and parcel attributes is significant. Note, however, that the observed proportions (*p*) were calculated from the fractional values.

The field results in Table 19(b) compare very well with the model predictions in Table 18. In other words, the proportions of idle-to-total farmland parcels seen in the field sample are very similar to the transition probabilities (i.e. expected proportions) given by the model. For probability classes one through four, the model predicts proportions of 0.450, 0.302, 0.127, and 0.019, whereas the field results indicate proportions of 0.413, 0.340, 0.100, and 0.063, respectively. Thus, it appears that the field results agree rather closely with model predictions.

TABLE 19(a)
FOUR-CLASS TABLE OF FIELD RESULTS

West Carleton-Goulbourn-March
and Rideau-Osgoode

Probability Class	Farmland Type			p
	Active	Idle	Total	
Class 1	13 (23.1)	18 (7.9)	31	0.581
Class 2	18 (22.3)	12 (7.7)	30	0.400
Class 3	37 (32.0)	6 (11.0)	43	0.140
Class 4	69 (59.6)	11 (20.4)	80	0.138
Total	137	47	184	0.255

Note that:

(1) the numbers in brackets are the expected frequencies;
(2) the frequency is in terms of the number of parcels which show at least some abandonment.

$$\sum \frac{(o-e)^2}{e}$$

$$= 4.40 + 12.84 + 0.84 + 2.45 + 0.78 + 2.26 + 1.49 + 4.36$$

$$\chi^2 = 29.43$$

The requisite value of chi-square with three degrees of freedom at the 0.01 significance level is 11.345. Since the value of chi-square derived from the above contingency table is greater than this value, the association between land-use and the given probability classes is deemed to be significant.

TABLE 19(b)
FOUR-CLASS TABLE OF FIELD RESULTS

West Carleton-Goulbourn-March
and Rideau-Osgoode

Probability Class	Farmland Type			p
	Active	Idle	Total	
Class 1	18.2 (25.6)	12.8 (5.4)	31	0.413
Class 2	19.8 (24.8)	10.2 (5.2)	30	0.340
Class 3	38.7 (35.5)	4.3 (7.5)	43	0.100
Class 4	75.0 (66.1)	5.0 (13.9)	80	0.063
Total	151.7	32.3	184	0.176

Note that:

(1) the numbers in brackets are the expected frequencies;
(2) the frequency is in terms of the actual area of parcels which have been abandoned;
(3) the numbers were rounded to the nearest integer before chi-square analysis was done.

$$\sum \frac{(o-e)^2}{e}$$

$$= 2.26 + 10.74 + 0.92 + 0.70 + 0.34 + 1.62 + 1.20 + 5.71$$

$$\chi^2 = 23.49$$

The requisite value of chi-square with three degrees of freedom at the 0.01 significance level is 11.345. Since the value of chi-square derived from the above contingency table is greater than this value, the association between land-use and the given probability classes is deemed to be significant.

CHAPTER 5: DISCUSSION

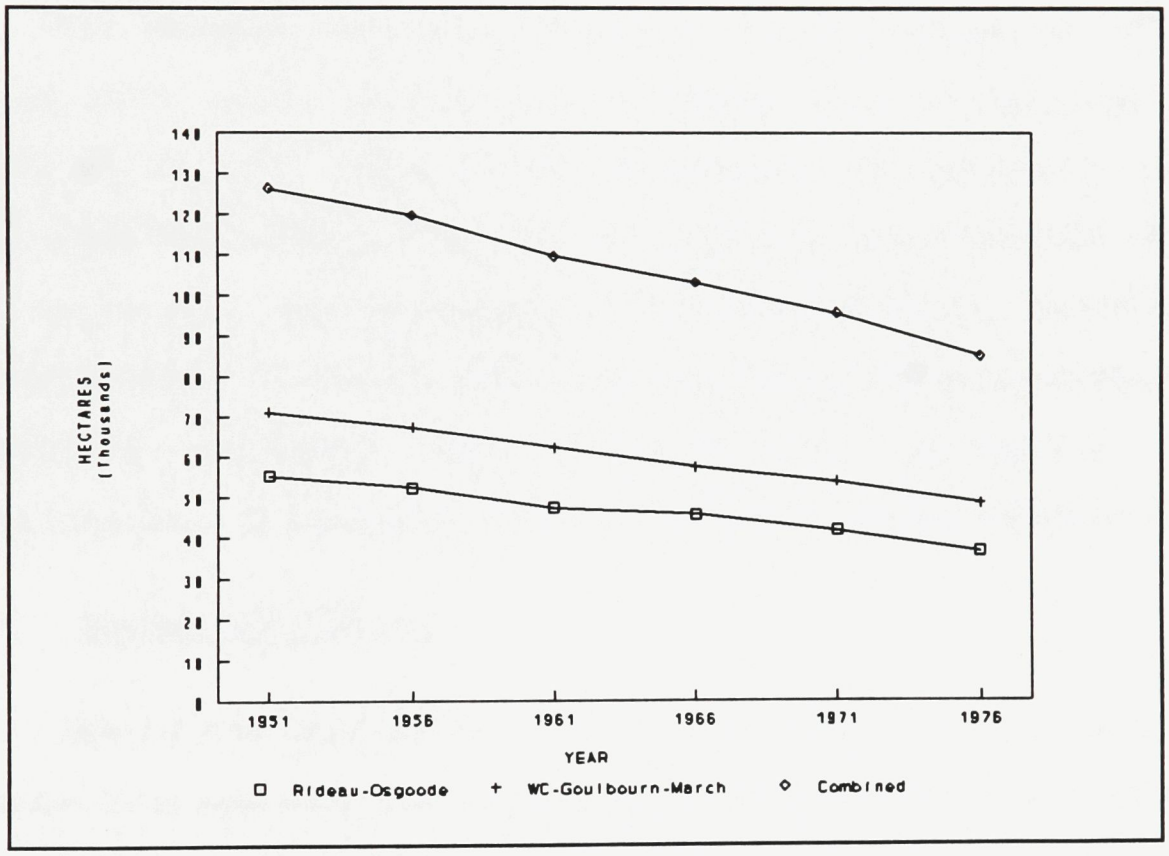
5.1 Assumption of Stationarity

The main assumption of the modelling approach used in this thesis is stationarity; that the pre-1977 proportion of idle-to-total farmland has been maintained in the post-1977 time-period. Hence, it is assumed the regime of physical and socio-economic factors that caused farmland abandonment in the past will continue into the future. This is a major assumption because the time-periods examined in this model are in the order of decades. Before using such a model, it would be prudent to examine this assumption.

Although physical factors may change little over such a period, socio-economic factors (e.g. farm profitability or the attractiveness of farming as an occupation) may change rapidly. Furthermore, examining the socio-economic factors themselves for evidence of change is difficult at best. One option is to examine census data for evidence that the rate of farmland loss is changing, which could indicate that the forces that cause farmland change are themselves changing.

The change in extent of cleared farmland for the study area between 1951 and 1976 is shown in Figure 11; the record only extends as far as 1976 because data for individual census subdivisions (e.g. Rideau, Goulbourn, West Carleton) was not published after this year. The graph in Figure 11 shows no increase or levelling off in the rate of farmland loss over the period and no indication of a significant change in trend.

FIGURE 11
CHANGES IN CLEARED FARMLAND AREA FOR STUDY SITES, 1951-1976



Note that the area of cleared farmland lost is not analogous to abandoned farmland because the former includes farmland that changed to other active uses such as urban, extraction, and recreation. The census category of *cleared* farmland (total farmland minus farm woodlots) probably corresponds most closely with the active farmland of the land-use map data.

For example, map data estimates active farmland at 50531 ha in 1976, while census data estimates cleared farmland at 48391 ha in 1977. Some of the discrepancy may be due to the fact that the land-use maps do not identify woodlots less than 2.5 ha in area, and may tend to overestimate actual farmland. Nevertheless, it can be said that the census data provides no immediate evidence that disputes the assumption of stationarity, although neither is it proof of the assumption.

5.2 Parcel Attributes

One of the main objectives of this thesis was to develop a modelling approach for predicting farmland abandonment which utilized available data, specifically, the existing maps of land-use systems (ARI, 1983) and soil capability (CLI, 1967). This was to enable replication of the approach in all areas covered by such maps; i.e. most of southern Ontario. Consequently, all attributes, and the transition probabilities themselves, were derived directly from the map data.

The three parcel attributes chosen in this study, namely soil capability, A/P ratio, and adjacency index, were used

because they all showed statistically significant associations with agricultural land-use. The attributes were initially tested because of suggestions in the literature of their significance. There were few other attributes, aside from variations of the above three, which could have been derived from the maps.

One attribute not used in the study, which could be expected to influence farmland abandonment, is the existing land-use, and there is evidence for this. Both Hart (1968) and Coleman (1967) mention that parcels often undergo low-intensity grazing just before they are completely abandoned (which can continue as the parcel attains a shrubby or even woodland state). Thus, parcels used for grazing may be one step away from being abandoned. In Table 18, of the active farmland parcels in the "extreme" probability classes one and four, 46.2% (91/197) and 14.1% (52/370) are grazing land, respectively. In other words, grazing land comprises the largest proportion of parcels which have the highest probability of being abandoned but only a small proportion of the land with the least probability for abandonment. Thus, low-intensity land-use (i.e. grazing) may be a good indicator of potential abandonment.

Current land-use, however, could not be incorporated into this study, simply because the 1977 land-use systems maps give no indication of the land-use of idle parcels prior to abandonment. Since the past proportion of idle-to-total land

takes no account of prior land-use, then the expected future proportion (i.e. transition probabilities) cannot either. However, consideration was given to utilizing an earlier land-use map to find the pre-abandonment use of idle parcels.

Coleman's (1967) land-use map of the Ottawa-Carleton region showed areas of abandoned land, active farmland, productive woodland, and unproductive woodland. However, the *active* farmland category did not distinguish between the types of farmland as do the land-use systems maps. Thus, the 1967 land-use map only reveals if the idle parcels on the 1977 land-use systems maps were active in 1967. This information was already known from the A1 and A2 definitions of the 1977 land-use systems maps.

It was also thought that Coleman's (1967) map might be used to approximate the time necessary for abandoned land to become woodland; i.e. by showing if abandoned land on the 1967 map had become woodland on the 1977 maps. However, the 1967 map gives no indication of the time-period that abandoned land had been in that state (as the 1977 land-use maps do), so an approximation could not be made. Therefore, the 1967 land-use map offered no additional information that could be used in this model. Furthermore, not many areas in southern Ontario have land-use map coverage. Therefore, a modelling approach that utilizes a series of land-use maps over time could not be replicated in many places.

Another attribute which could influence abandonment and

was considered for inclusion was the distance of farmland parcels from an urban area. Coleman (1967) suggested that rural-urban fringe abandonment was due to farmland being marginal compared with urban uses, but not necessarily in terms of land capability. The problem with using urban distance as an "attribute", arises from the difficulty in defining what constitutes an "urban" area. For example, could a threshold population density be defined or could an effect be scaled to the population size? Furthermore, it would have been difficult to define a precise measure of distance; e.g. edge to edge, centroid to centroid? Because of these problems, and since there was no readily apparent relationship between the two in visual inspection of the maps, it was decided that distance from an urban area would not be included.

The distance of fields from farmsteads was also considered as an attribute. Tarrant (1974) states that "...the intensity of land-use changes inversely with distance, even in circumstances where the quality of the land improves at greater distance". This was observed during the field survey, in that land near farmsteads rarely, if ever, showed signs of idleness. The problem with using this attribute is that the smallest land unit shown on the maps is the parcel, which often comprises several fields of the same use. Farmsteads are not distinguished on the maps either. Therefore, a measure of distance from farmstead to fields cannot be derived from the maps and would entail considerable field work -- something

this modelling approach is intended to avoid.

The results of the chi-square analyses for the individual attributes (Tables 6, 9, and 12) reveal the strongest association between land-use and soil capability, followed by A/P ratio, and then adjacency index. However, this gives no direct indication of cause-and-effect, and the attributes are not likely to be independent. Only soil capability can be said to be a cause of farmland abandonment, since it affects the type of agriculture that any given area of land can support (Table 2). Conversely, A/P ratio and adjacency index are likely not causes of abandonment, and may themselves be affected by soil capability. For example, most large, high-intensity, farms would likely be clustered in areas of good soil capability which, in turn, would result in parcels having low adjacency index values and high A/P ratios (due to regular shapes of well-maintained fields).

However, A/P ratio and adjacency index may also serve as indicators of other underlying physical or socio-economic factors that cause abandonment. For example, Lamoureux (1985) attributed some of the abandonment of small, isolated, farms in the Gaspé to the rationalization of marketing networks. Furthermore, Girt (1975) states that "...large farms may be more [economically] robust than smaller ones, and as a consequence, areas typified by small farms will show more change than areas of larger farms". Also, the irregular shape of abandoned parcels may reflect a lack of maintenance in

sections of a parcel prior to the abandonment of the entire parcel (Coleman, 1967).

It would be expected, then, that a set of parcels with a low A/P ratio (i.e. small, irregular) and a high adjacency index (i.e. isolated, surrounded by *forest* or *other*) would tend to show more abandonment. This was observed in the study. Thus, these attributes may serve as an indication of socio-economic factors such as the above.

Furthermore, the relationship between land-use and A/P ratio or adjacency index has been shown to be very similar in both study areas. This suggests that the attributes may indeed represent underlying socio-economic or physical factors because these factors would likely have an equivalent effect on both areas; i.e. the same "rules" appear to apply to both areas. Regardless of what they are indicators of, both attributes show a significant relationship with agricultural land-use and, therefore, are included in the empirical model.

5.3 Final Transition Probabilities

The highest transition probabilities in the individual contingency tables (Tables 6, 9, and 12) belong to soil capability class two, A/P ratio class one, and adjacency index class two; i.e. 0.383 (218/568), 0.345 (233/675), and 0.309 (208/674), respectively. Thus, it would be expected that the combined attribute class with the highest probability, in the eight-class model, would be 212 (where the first, second, and

third digits are soil capability class, A/P ratio class, and adjacency index class, respectively). Similarly, the combined class with the lowest expected probability would be 121. The latter is found to be so (Table 15). However, the highest probability actually belongs to combined class 211 (although class 212 is in second-place with three-times as many observations). On the whole, though, it appears the ranking of the combined attribute classes is close to what would be expected from the individual contingency tables.

The reason that there are differences between the expected and observed rankings (in terms of probabilities) of combined attribute classes is probably because the dominant factor influencing the abandonment of any particular parcel may vary. In aggregate, soil capability appears to have the strongest effect, as expected from the chi-square analyses. However, for many parcels the factors portrayed by A/P ratio or adjacency index may have a stronger effect. Furthermore, the way factors interact to cause abandonment may not be predictable from the individual contingency tables. Thus, it is necessary to combine the attributes as in Tables 15 and 16.

It is clear from the results that when the attributes are combined, the range of transition probabilities increases. For example, the highest probability of abandonment from the individual attribute tables is for soil capability where its class one has a probability of 0.383 (218/568). However, the highest probability in the eight-class combined table (Table

15) is 0.463 (37/80), which is considerably higher. Similarly, the lowest probability in the individual tables is for A/P ratio class one (Table 9) with 0.118 (79/672), while the lowest probability in the eight-class model is 0.028 (9/319). Hence, the range of probabilities increases as the number of classes increase; in this case by combining attribute tables.

This reveals that by combining attributes, each class represents a more homogeneous set of parcels. For example, in the eight-class model, there are so few abandoned parcels in class 121 (9/319) that it is clear that there are factors at work which have prevented the abandonment of farmland; i.e. soil capability and socio-economic factors which maintain agricultural activity. Thus, the few attributes used in this study have been somewhat effective at defining relatively "pure" groupings of farmland; i.e. all active or all idle. Therefore, if the same overall socio-economic regime that existed before 1977 exists after, then a predictive probability model may be succesful.

Note that the model appears to be a better predictor of those parcels which will not be abandoned rather than of those which will. This is because the lowest transition probabilities approach 0% whereas the highest probabilities approach 50%. For example, in Table 15, the lowest (121) and highest (211) probability classes show 9/319 and 37/80 idle parcels, respectively. In other words, any parcel of the former has a 3% chance of being abandoned whereas a parcel of

the latter has a 46% chance. Hence, the former has an almost perfect chance of remaining active whereas the latter has an even chance of remaining active or being abandoned.

The range of probabilities can also be increased by expanding the number of classes into which each attribute is divided. In Table 16, the same three attributes have been divided into more classes (with 2 soil capability classes, 4 A/P ratio classes, and 3 adjacency index classes). It can be seen that the highest probability class (212) has a transition probability of 0.560 (28/50), a marked increase from the eight-class model. Furthermore, two classes (142, 231) show probabilities of 0.00 (0/94 and 0/13, respectively), which is perfect predictability in model terms. Therefore, again, more classes define more homogeneous sets of parcels.

The main problem with this is that more classes means fewer observations per class and, eventually, statistical limitations are reached. Furthermore, there may be little reason in practical terms for having mid-range probability classes which differ by only a few percentage points. For example, in Table 16, classes 223, 221, and 232 have respective transition probabilities of 0.337, 0.333, and 0.300. It is unlikely that anyone would need to predict proportions of abandonment to two or three decimal places, and even less likely that this type of model will have that degree of accuracy. It may be more useful to define fewer classes, each with a distinctly different transition probability. This

is particularly true when the emphasis is more on defining zones where abandonment is likely to occur rather than the precise probability of any given parcel being abandoned.

The above discussion outlines why the probabilities were re-aggregated into four probability classes. Note that the four-class probability table derived from the twenty-four class model (Table 18) has probabilities 0.450, 0.302, 0.127, and 0.019, for classes one through four, respectively. If the four-class probability table had been derived from the eight-class model (Table 15) the respective probabilities would be 0.435, 0.269, 0.128, and 0.038. Therefore, it can can be seen that the probabilities derived from the former have a greater range than those derived from the latter. In other words, the highest and lowest probability classes of the former four-class probability table (i.e. derived from the twenty-four class model) are more homogeneous.

It appears, then, that the optimum model would be one derived from a large number of attributes, each of which has many classes. Again there are practical limits to this, however, including the number of observations per class and the availability of statistically significant attributes. Note that the 2x4x3 combination of soil capability, A/P ratio, and adjacency index classes was used because it resulted in a table with a large number classes (24) which met statistical assumptions. It also allowed re-aggregation into a four-class table to enable comparison with the eight-class model.

Regardless of the model used (e.g. eight or twenty-four class), the final four-class probability tables define distinct categories of abandonment. For example, the highest and lowest probability classes in Table 18 predict abandonment in the order of 44-45% and 2-4%, respectively, between 1977 and 1992. In this way, parcels of active agricultural land can be easily distinguished in terms of their probability of abandonment (see Figures 9 and 10).

5.4 Field Results

As discussed in Chapter 4, the model predicts that the proportion of idle-to-total farmland parcels for classes one through four will be 0.450, 0.302, 0.127, 0.019 (Table 18). In other words, for the respective classes, approximately 89/197, 57/188, 36/280, and 7/370 of parcels active in 1977 should have become idle by 1992. Altogether, 188 out of the 1035 active parcels present in 1977 were predicted to become idle by 1992.

The field results in Table 19(b) compare favourably with the model predictions. For probability classes one through four, the observed proportions were 0.413, 0.340, 0.100, and 0.063, respectively. Note that the model was initially viewed as a predictor of parcel abandonment, such that, in aggregate, a certain proportion of whole parcels in each (probability) class would become idle. However, it appears that the model can also be viewed as predicting the proportion of parcel

units which will be abandoned. For example, the above proportions represent a sum total of 12.8/31, 10.2/30, 4.3/43, and 5.0/80 respectively, of the parcels sampled; an aggregate total of 32.3 out of 184 parcels. This is probably a better perspective because much of the abandonment observed during the field sampling involved portions of parcels (i.e. individual fields).

The above aggregate total (32.3/184) should not be used to estimate the actual area of farmland abandoned because the average parcel area of 88.1 ha comprises different averages for each land-use type. For example, mixed and grazing parcels average 121 and 69 ha, respectively. Furthermore, the road-side estimates of the proportion of abandoned parcels are clearly prone to error. Thus, the observed proportions (and area of farmland) should only be looked at as rough estimates. Nevertheless, the observed proportions are close to those predicted by the model and appear to support the modelling approach used in this thesis.

5.5 Summary and Conclusion

Given the similarity between model predictions and field observations, it seems that the probability model is effective at predicting farmland abandonment in the RMOC between 1977 and 1992. In this study, the simulation period was chosen to end in 1992 to allow field verification, although the model could easily be used to model a longer period (Section 4.2).

Longer periods of abandonment (> 20 years), however, might be better modelled using several iterations to incorporate feedback. This *feedback* results from the fact that parcel attributes, primarily the adjacency index, are continuously changing. For example, an active parcel's adjacency index becomes progressively higher as more of its neighbours become idle. Or the A/P ratio decreases as fields within a parcel are abandoned (resulting in a more irregular shape). Thus, the tendency is for the remaining active parcels in areas undergoing continuous abandonment to become more prone to abandonment (Coleman, 1967).

Modelling several successive, but shorter, time-periods would likely provide better approximations of transition probabilities than would a single, long, modelling period. This is because the probabilities of the former would be derived from several "samples" of parcel attributes over the simulation period, while the latter is derived from a single "sample" taken at the beginning of the period. In the case of the RMOC, the region could be re-surveyed in 1992, from which new transition probabilities for the 1992 to 2007 period, say, could be derived.

The value of the model developed in this thesis is its utility as both a heuristic and predictive tool. The model is strictly empirical, giving little direct indication of the processes which cause farmland abandonment. However, the model is heuristic in that it highlights important factors which are

related to abandonment, such as soil capability, field/parcel shape, and adjacent land-use. Investigation of these attributes could lead to the identification of the main processes which cause abandonment.

One factor not included in the model is the influence of urban areas on farmland abandonment; i.e. farmland-urban distance. In Von Thünen's theory (McCuaig and Manning, 1982), three concentric zones surround an urban area. The first where urban-related returns exceed others; the second where agricultural returns exceed others and farmer's expectations are met; and the third where agricultural returns do not meet farmer's expectations. Note that *returns* can include farm and off-farm incomes and *expectations* can be related to education levels. Farmland abandonment is most likely to occur in the last zone.

On initial inspection, however, there appeared to be no relationship between distance from urban areas and abandonment (see Section 5.2). In other words, abandonment did not appear to be radially distributed around the Nepean-Ottawa core, and so urban-farmland distance was not included as an attribute in the model. However, this may be because the two study areas are relatively equidistant from the core urban area. Study areas chosen at different distances from the core may, in fact, reveal such a radial pattern of abandonment.

Farmland abandonment in the RMOC is almost certainly influenced by its proximity to the Nepean-Ottawa core, because

distance can affect land prices, transportation costs, off-farm employment opportunities, etc (Coleman, 1967). The main limitation of using these factors in the model developed here is that this data is often not recorded at the farm or parcel level; and if it is recorded it is usually confidential. Nevertheless, the model would probably be improved if a way were developed to include these factors.

The model appears to be effective for predicting the location of farmland abandonment in the RMOC. Furthermore, its simplicity and its replicability to most areas of southern Ontario give it potential as a cost-effective tool for agricultural land-use planning. The model could be used to identify areas for development or non-development. For example, the RMOC is considering the purchase of private (agricultural) land to enlarge the current system of open-spaces (Greenspace 2000, 1991). However, the initial plan has met much resistance due to the high land-prices demanded by some farmers (who could otherwise sell to developers).

The model can identify areas for purchase based on their potential for continued agricultural activity, limiting purchases to areas where abandonment potential is high, such as the Marlborough forest region in Rideau Township, because prices may be correspondingly low. Similarly, areas of low abandonment potential can be protected from development, to limit the urbanization of productive agricultural land. At the very least, the modelling approach can give an indication of

the potential for change in the agricultural activity of any region. This type of knowledge is invaluable to any planning process.

REFERENCES

Agricultural Resource Inventory (ARI) (1983) Soil and Water Management Branch, Ontario Ministry of Agriculture and Food.

Angelstam, P.K. (1991) Conservation of natural processes in Fennoscandinavian boreal forest landscapes. World Congress of Landscape Ecology, Ottawa.

Baker, W.L. (1989) A review of models of landscape change. Landscape Ecology. Vol 2(2): 111-133.

Brunton, D.F. (1988) Nature and Natural Areas in Canada's Capital. The Ottawa Citizen. Ottawa.

Burrough, P.A. (1986) Principles of Geographical Information Systems for Land Resource Assessment. Clarendon Press, Oxford.

Burrough, P.A. (1988) Modelling land qualities in space and time: the role of geographical information systems. In Land Qualities in Space and Time. (Eds.) J. Bouma and A.K. Bregt. Pudoc Wageningen.

Canada Land Inventory (1967) Soil Capability for Agriculture, Maps 31G (Ottawa) and 31F (Pembroke). Environment Canada, Ottawa.

Canada, Government of (1990) Canada's Green Plan. Supply and Services, Ottawa.

Citizen's Greenprint Committee of Ottawa-Carleton (1990) The Ottawa-Carleton Greenprint. Regional Municipality of Ottawa-Carleton.

Coleman, A. (1967) The Planning Challenge of the Ottawa Area. Geographical Paper No. 42. Geographical Branch, Department of Energy, Mines and Resources. Ottawa.

Cronon, W. (1983) Changes in the Land: Indians, Colonists, and the Ecology of New England. Hill and Wang, New York.

Dumanski, J., Marshall, I.B. and Huffman E.C. (1979) Soil capability analysis for regional land use planning: a study of the Ottawa urban fringe. Can. J. Soil Sci. 59: 363-379.

Forman, R.T.T. & M. Godron (1986) Landscape Ecology. Wiley, New York.

Girt, J.L. (1975) The Spatial/Temporal Dynamics of Farmland Changes in Southern Ontario: Trends and Projections. Studies in Rural Adjustment, Report No. 1. Centre for Resources Development, University of Guelph.

Greenspace 2000 (1990) Regional Municipality of Ottawa-Carleton, Planning Department.

Hart, J.F. (1968) Loss and abandonment of cleared farmland in eastern United States. Annals, Association of American Geographers. 58: 417-440.

Hoffman, D.W. and Noble, H.F. (1975) Acreages of Soil Capability Classes for Agriculture in Ontario. ARDA Report No. 8. Rural Development Branch, Ontario Ministry of Agriculture and Food, Toronto.

Huffman, E.C. and Dumanski, J. (1978) Land Use of Nepean and Gloucester Townships, Regional Municipality of Ottawa-Carleton, Ontario. Land Resource Research Institute, Research Branch, Agriculture Canada, Ottawa.

Huffman, E.C. and Dumanski, J. (1983) Agricultural Land Use Systems of the Regional Municipality of Ottawa-Carleton. Land Resource Research Institute, Research Branch, Agriculture Canada, Ottawa.

Iverson, L.R. (1988) Land-use changes in Illinois, USA: the influence of landscape attributes on current and historic land use. Landscape Ecology. 2(1): 45-61.

Kricher, J.C. and G. Morrison (1988) A Field Guide to Eastern Forests of North America. The Peterson Field Guide Series. Houghton Mifflin Company. Boston.

Lamoureux, D. (1985) The Abandonment of Agricultural Land in Gaspe, Quebec: The Causes and the Impact on Land Use. Working Paper No. 29, Ottawa: Lands Directorate, Environment Canada.

Marshall, I.B., J. Dumanski, E.C. Huffman, P.G. Lajoie (1979) Soils, Capability, and Land-Use in the Ottawa Urban Fringe. Report No. 47, Ontario Soil Survey. Ottawa: Land Resource Research Institute, Research Branch, Agriculture Canada.

McCuaig, J.D. & E.W. Manning (1982) Agricultural Land Use Change in Canada: Process and Consequences. Land Use in Canada Series, No. 21. Ottawa: Lands Directorate, Environment Canada.

Moore, D.M., B.G. Lees & S.M. Davey (1991) A new method for predicting vegetation distributions using decision tree analysis in a geographic information system. Environmental Management. Vol. 15 (1): 59-71.

Nyland, R.D., W.C. Zipperer & D.B. Hill (1986) The development of forest islands in exurban New York State. Landscape and Urban Planning. Vol 13: 111-123.

Odum, E.P. and Turner, M.G. (1990) The Georgia Landscape: A Changing Resource. In Changing Landscapes: An Ecological Perspective. Eds. I.S. Zonneveld and R.T.T. Forman. Springer-Verlag. New York.

Parson, H.E. (1979) An analysis of farmland abandonment trends: a study of central Ontario. Ontario Geographer. Vol. 14: 41-57.

Prashker, S. (1991) A utility to reclass polytags in DGT files. Unpublished. Geography Department. Carleton University, Ottawa.

Primdahl, J. (1991) Agricultural and landscape change in Denmark: centralized policy making and local effects. World Congress of Landscape Ecology, Ottawa.

Richardson, N. (1989) Land Use Planning and Sustainable Development in Canada. Canadian Environmental Advisory Council. Supply and Services, Canada.

Rykiel, E.J. (1989) Artificial intelligence and expert systems in ecology and natural resource management. Ecological Modelling. Vol. 46(1/2): 3-8.

Schaller, J. (1990) GIS applications in environmental planning and assessment. Proceedings of the Geographic Information Systems seminar, September 1990. Ontario Ministry of Natural Resources. Toronto.

Schut, L.W. and Wilson, E.A. (1987) The Soils of the Regional Municipality of Ottawa-Carleton. Report No. 58. The Ontario Ministry of Agriculture and Food and the Land Resource Research Institute, Research Branch, Agriculture Canada. Ottawa.

Sell, P.S. (1985) Expert Systems: A Practical Introduction. Macmillan Publishers Ltd., London.

Starfield, A.M. (1990) Qualitative, rule-based modelling. Bioscience. Vol. 40(8): 601-604.

Statistics Canada (1941) Census of Canada, Volume 8, Agriculture, Ontario. Ottawa.

Statistics Canada (1951) Census of Canada, Volume 6, Agriculture, Ontario. Ottawa.

Statistics Canada (1961) Census of Canada, Volume 5, Agriculture, Ontario. Catalogue 96-535, Ottawa.

Statistics Canada (1966) Census of Canada, Volume 4, Agriculture, Ontario. Catalogue 96-607, Ottawa.

Statistics Canada (1971) Census of Canada, Volume 8, Agriculture, Ontario. Catalogue 96-707, Ottawa.

Statistics Canada (1976) Census of Canada, Volume 12, Agriculture, Ontario. Catalogue 96-807, Ottawa.

Statistics Canada (1981) Census of Canada, Volume 12, Agriculture, Ontario. Catalogue 96-907, Ottawa.

Tarrant, J.R. (1974) Agricultural Geography. Problems in Modern Geography Series. David & Charles : Newton Abbott.

Turner, M.G. (1989) Landscape ecology: the effect of pattern on process. Annu. Rev. Ecol. Syst. 20: 171-197.

Waddell, D.J. (1972) Agricultural changes in Carleton County, 1940-1970. B.A. Thesis, Carleton University.

Wilkie, D.S. & J.T. Finn (1988) A spatial model of land use and forest regeneration in the Ituri forest of northeastern Zaire. Ecological Modelling, 41: 307-323.

World Commission on Environment and Development (1987) Our Common Future. Oxford University Press, Oxford.

Zonneveld, I.S. (1991) Land abandonment and the chance of obtaining new nature in the Netherlands. World Congress of Landscape Ecology, Ottawa.

APPENDIX 1: GLOSSARY OF EPPL7 COMMANDS

CLUSTER

This command identifies groupings or "clusters" of contiguous data cells possessing a class number of one. Clusters can help identify contiguous areas of specific data, such as various land uses or ownership types.

The search for clusters is done around core cells (all cells of class number one). A minimum size requirement may be specified. If a minimum cluster size of one is specified, the individual clusters of that size or larger are found and then numbered from 1 to 254. However, if more than 254 clusters are found, the numbering of clusters will wrap around, beginning agaon at one. The clusters are not ranked by size.

COUNT

This command counts the number of cells within each class of a file, and displays this information as a frequency count listing. Frequency listings are useful for preparing plots of data files, as well as for analyzing the relative content of various data levels. The format of the frequency count is:

Class Count Percent Cumulative Area Legend

where the class is the class in the data file; count is the number of cells with that class value; percent and cumulative (percent) are calculated by COUNT in relation to all of the cells in the file; area equals the number of cells (count) multiplied by the cell area; and legend is the description stored in the legend file for each class.

EDGE

This command performs edge analysis. It examines the cells that are adjacent to "core" celss of a specified class or class range to see whether they meet the requirements of the edge directives.

Edge directives specify a class (or class range) exhibited by neighbour cells, and a direction from the core cell. A new class number will be assigned to the core cell if edge directives are found to be true. The new file created by this command contains the classes assigned to the core cells.

EVALUATE This command allows a user to perform specialized operations for the purpose of analyzing data. Up to nine old files may be manipulated, using arithmetic and/or logical operations to produce up to four new files. The user supplies directives in a Pascal-like syntax, which are then executed for each cell in the file.

OUTTABLE This command creates an ASCII-formatted, fixed column table file (".TBL" file) from 2 or more EPPL7 data files. The table file can be loaded into a data base or used directly at DOS level.

Each line of the table file contains a minimum of "n" columns, where "n" represents the number of OLD files being considered in the analysis. The number of columns used in the table file to store a class value for each column is separated from the next column by one space. The option selected will determine the appearance of the table file created.