SPATIAL DATA HANDLING
IN DATA-POOR ENVIRONMENTS

by

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ABSTRACT

This study focuses on geographic data handling problems which occur when data are unavailable, unattainable, or qualitative in nature. It examines the potential use of subjective data from expert opinion as a source of spatial information in these situations and develops a method through which this information can be gathered and processed. The approach is called the Strabo method which finds its roots in the widely known Delphi technique. Delphi is a structured communication process designed to form consensus from expert opinion. Strabo uses similar structured communication procedures to form consensus with cognitive representations of space.

The research reviews much of the literature related to using experts as a source of information and how this information can be manipulated. It also examines the previous work dealing with cognitive-spatial representations and with ways of measuring and extracting these. On the basis of these foundations, the study proposes that spatial opinions from experts can be used to derive meaningful geographic information about an area. It asserts that cognitive information from a number of knowledgeable people can be aggregated into a composite result, and that through a structured feedback process, this result will show an increase in the amount and strength of consensus about a spatial problem.

The study develops the Strabo method and demonstrates its spatial data-handling capabilities in an application. It selects an urban social environment in north west Burnaby as a pilot test application. Five spatial variables with increasing levels of subjectivity are studied using two 5 person panels of local experts. The variables used are residential dwelling types, housing quality, income areas, crime rates, and livability. A questionnaire is developed to elicit, from each panel member spatial opinions about each of the variables. Results are then processed to determine composite responses. These responses are evaluated for the amount of consensus produced, and for their reliability in estimating objective reality.

The study concludes that spatial consensus can be significantly increased within a group of experts by the iterative, structured feedback procedures of Strabo, and that the results after several rounds do reflect the real distribution of a variable. It demonstrates that the technique has potential usefulness in situations where data are unavailable and/or subjective in nature, and calls for further research into other types of applications.

To my parents and to Amy

The phrase "more or less" is a fault much in evidence in kings and geographers.

— Strabo

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

Underlying most spatial decision-making processes is an assumption that necessary and relevant data are already available or at least attainable. Attention has been paid to problems of processing and modelling data (*e.g.*, Evans, 1984), to data structures which are most appropriate for storage and analysis (*e.g.*, Peucker and Chrisman, 1975; Peuquet, 1982; Mark and Lauzen, 1984), and to data quality issues (*e.g.*, Chrisman, 1983b), among many others. Much has been written on sampling methods (*e.g.*, Cochran, 1953; Yates, 1960), developing representational indicators (*e.g.*, Haggett, 1965; Berry and Marble, 1968), and inferential analysis of relationships amongst variables (*e.g.*, King, 1969; Abler, *et al.*, 1971). But, what of problems associated with unavailable data or, at best, information which would be expensive to acquire? The understanding of these problems, especially as they relate to geographic phenomena, is poor. The reasons behind the problems are as varied as the data themselves. Some data are extremely subjective defying easy measurement, (for example, quality of life (Dalkey, 1975)), while other variables are more easily measured and quantified but the process may be expensive and time consuming with conventional data gathering approaches. To illustrate this situation, consider doing detailed geological surveys in relatively unknown areas for the purpose of providing data for mineral exploration.

These problems of data availability and data attainability are particularly acute in the world's developing nations (Luscombe and Peucker, 1983). In many, even the rudiments of large scale base-maps do not exist for large areas, and the technical infrastructure for measuring and analysing basic resource information is only in early stages of development (Chatel, 1979). An interest in third world development brings these geographic data problems into focus. The objective of this research is to examine some of these spatial analysis problems and to explore approaches to deal with them.

1.1 Defining the Problem

Borrowing from concepts developed in other fields which are also concerned with subjective data gathering, especially those of futures research and technological forecasting, analogous methods can be developed to deal with information problems uniquely suited for spatial analysis. One such method which has been widely used in forecasting and group decision making problems is called Delphi, developed in the 1940s by the Rand Corporation (Gordon and Helmer, 1964). In its most general sense, it is a set of techniques designed to structure a group communication process to solve complex problems (Linstone and Turnoff, 1975). It derives answers from subjective data gleaned through consensus-reaching amongst a group of "experts". Because of differences between applying such an approach to spatial problems and applying it to the usual Delphi problems, a distinct name has been chosen for the spatial approach -- Strabo (Peucker, 1975). It seeks consensus of opinions as they relate to spatially distributed information.

It is hypothesized that spatial information can be derived from expert sources and that the data can be used reliably in some types of spatial analyses. In developing the method, a number of conceptual issues are explored to place it within a sound research and applications framework. Specifically, four objectives are addressed in this study:

i) To examine spatial data-handling problems in data-poor environments;

ii) To develop a method to provide an alternative Geographic Information System approach to data-poor spatial analysis problems;

iii) To examine the role of "experts" and "expert opinion" in spatial analysis problems; and

iv) To develop the concept of confidence measures on knowledge surfaces. This examines the problems of subjective probabilities and probability aggregations.

1.2 Focus of the Study

Since some concepts and notions employed in this research may not be familiar to many in the geographic community, this section gives a general overview of the study. With this foresight, discussions in the second chapter, which reviews appropriate literature, will fall into context as they are dealt with systematically .

A major concern of this study is for problems of geographical analysis in environments where data are unavailable, subjective, or uncertain in nature. Geographical analysis is a term broadly defined as those activities related to the study of spatially distributed phenomena, from collecting quantitative and qualitative data and handling the information in either a manual or computer-assisted fashion, to techniques for modelling the information and for discovering relationships within and between variables. Others have used narrower and more precise definitions of the term (Tomlinson, 1983), but within the context of this study, the more generic usage is preferred. When a more precise meaning is intended, the text will clearly indicate.

Similarly, the expression Geographic Information System (GIS) is treated in a broad sense to mean the organized collection of information, which is in some manner referenced to geographic location, together with a set of procedures and techniques for storing, retrieving, manipulating, and managing the data. Although GIS has become widely associated with computer-based systems, the usage here is less restrictive and encompasses non-automated capabilities as well. For the most part, the term does not distinguish between specific types of systems or capabilities, for example, image processing systems dealing with various forms of remotely sensed information about the earth (Simonett, 1983), and Land Information Systems (LIS) which are more parcel-oriented (Marble, 1984).

Data environment is defined as the general condition of the quantity, quality, and types of data and information which are available for describing or analysing a problem. To define the context in which "data-poor" is used in this study, it is necessary to examine more closely some of the generic aspects of data and data collection procedures. Data are facts or observations about a particular subject which can be used to describe its behaviour and its relationships with other subjects. The collection of data requires appropriate measurement and classification methods (e.g., nominal, ordinal, interval, and ratio scales) depending on the nature of the subject. In the physical sciences, these methods have a lengthy history and are well understood because the phenomena are usually objective in nature and directly observable, for example, the heights of trees, the weights of chemical compounds, and the wave lengths of light. In the behavioural and social sciences, however, data measurement is more problematic because the phenomena are usually not directly observable (e.g., social class). Most ordinary definitions of such phenomena in the social sciences are theoretical rather than operational (Blalock, 1972). In a theoretical definition, a concept is defined in terms of other concepts which supposedly are already understood. On the other hand, operational definitions prescribe the procedures to be used in measurement. Theoretical definitions of such concepts as social class and livability defy easy operational definitions in that there is no logical way of determining whether a given operational definition really measures the theoretically defined concept or variable. The operational definitions of many concepts in the social sciences use generalizations of related, directly observable, quantifiable variables. Statistical procedures, such as factor analysis (Taylor, 1977), have been developed to help with these generalizations. Social class, for example, may be defined in terms of associated, substitute variables such as education, income, occupation, ethnic origin, among others. Because such descriptions rely on indirect measurements, an element of error and uncertainty in validity is introduced. Other approaches of attempting to measure such variables more directly call upon data which are in the form of opinions or attitudes. Concepts such as social class and livability find meaning in the perceptions and attitudes of individuals. Therefore, by trying to elicit these opinions through devices such as interviews and questionnaires, the researcher tries to establish an operational measure of these subjective variables.

In attempting to develop a data-environment model, several dimensions emerge. First, the nature, or character, of the variable to be measured falls on a continuum ranging from opinion-based speculation with a high degree of subjectivity to directly countable, objective observations. Technological forecasts and social characteristics (e.g., social class, livability, and quality of life) are examples which illustrate subjective variables. These data are represented by opinions, attitudes, and perceptions. Objective variables, as illustrated by census counts (e.g., number of persons, or number of cars), are represented by a more precise metric. They are precise in the sense that the data are exactly replicable and the values are non-fuzzy in a mathematical context.

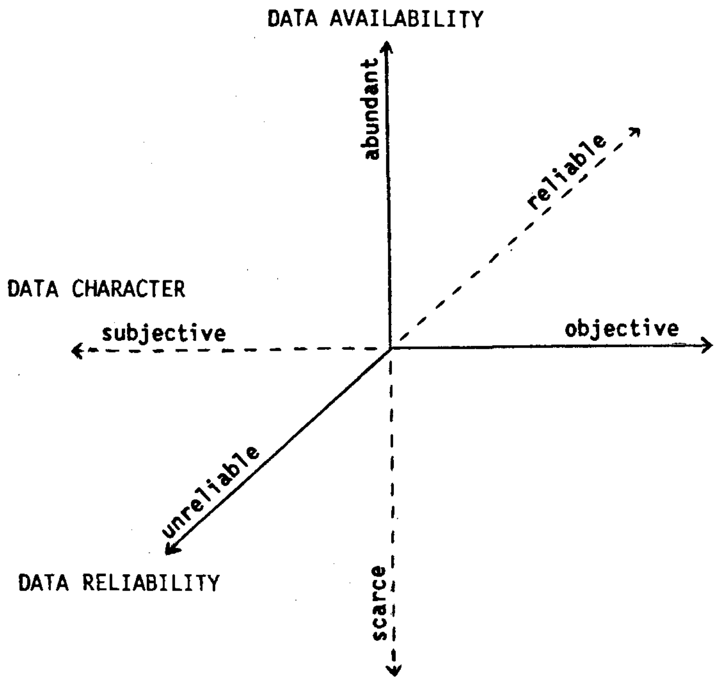
A second dimension to data-environments relates to the quantity or amount of data readily available for analytical or descriptive purposes. Some situations, for example, national censuses, are found to have massive amounts of data, systematically organized and managed for easy retrieval and processing. This however does not assume any quality attributes to the data; if the data, for example, were collected on the basis of non-rigorous statistical sampling procedures, they may contain biases and distortions. These biases can result from an imperfect data collection instrument (e.g., a poorly worded questionnaire, or a poorly calibrated planimeter which systematically records larger area values than expected), as well as from improper applications of the instruments. The classic "next-door neighbour" problem in household surveys describes haphazard substitutions in the sample. The result may produce distortions in the probability distributions and uncertainty in the "goodness" of any derived estimators (Mendenhall, et al., 1971).

At the other end of this dimension are situations void of existing data. This is often typical of problems in developing countries where data about population, agricultural production, or energy consumption in remote areas are not available. Even in situations where massive amounts of information are available, data about a particular issue or variable may not exist. For example, urban data bases in North America often contain information on a variety of subjects such as demographics, housing stock, and utility networks, but do not include data on problems such as "quality of life", "social class", or "livability" because these variables are subjective in nature and are difficult to measure quantifiably.

Availability of data has to be viewed in terms of a particular study or research problem. In some situations the appropriate data exist but are not available to the researcher, for example, detailed topographic information about an area may have been collected by the military, but because of security reasons it may be "classified" and unavailable for non-military applications. Likewise, data may exist in some form but may be prohibitively expensive to access. Petroleum companies frequently maintain data bases of geological and topographical information, but the data may be considered proprietary or, at best, may be very expensive to access through a data subscription. Therefore, one must interpret availability to mean accessible to a particular researcher within his constraints and limitations.

A third dimension of data which defines environments from which they are collected is reliability. The notion of reliability encompasses the associated concepts of data accuracy (about which more is discussed in Chapter 2), replicability, and verifiability. Again, a reputable population census may be considered reliable if acceptable standard statistical procedures were followed in collecting the data. The results can be easily verified and replicated (although possibly at considerable expense). On the other hand, objective data collected by ad hoc survey methods, and subjective data in the form of individual opinions contain a considerable degree of uncertainty in their reliability.

These three dimensions -- data character, data availability, and data reliability -- are useful in building a model of data-environments.



The three dimensional schematic identifies eight quadrants representing the extremes of the data environments. For example, one of the environments is characterized as having massive amounts of objective data with a high degree of reliability, and another as having massive amounts of subjective data with a low degree of reliability. In this model, those environments which have available, reliable data (either subjective or objective) are considered to be rich with data. The term "data-poor", often used informally and defined rather vaguely in discussions about data environments, is taken to mean those situations which lack information or have data (either subjective or objective) of uncertain reliability.

Two of the data environments which are discussed later in this study fall within this definition of "data-poor". The first, an illustration of geologists predicting mineral finds, represents a situation where the data are unavailable and objective in nature, i.e., whether or not oil is located at a site is verifiable by direct measurement. In the absence of existing objective measures, reliabilities of the predictions and estimations of individual geologists are uncertain. In the second example, the situation represents an urban environment in which information about social variables such as income classes and livability are important. This type of information is more subjective in nature and, because it represents perceptions and opinions, is not, with the exceptions noted later, directly measureable or verifiable. It, therefore, is also attributed with an uncertain reliability. These two situations fall in different quadrants of the data model, differentiated primarily by their relative degrees of objectivity or subjectivity. Both contain an element of uncertainty, or unreliability, in the available information which exists in the forms of opinions and perceptions. In the context of this model, they are classified as "data-poor".

How data are measured and collected depends on such factors as resources available (e.g., time, manpower, and relative costs of alternative methods), and on the nature of the variables. Population census data may be collected by doing a 100 percent survey and counting every individual. This would give the most accurate results, however, if time and funds for such a survey were not available, the data could be estimated with a specified degree of statistical accuracy by doing only a partial sample and extrapolating the results. This would still produce an "objective" measure, however, it would include a recognized statistical margin of error.

Other data gathering techniques rely more on subjective interpretations of opinions than on objective measurements. This is typical of group decision-making procedures (e.g., meetings, Delphi-type excercises, and opinion polls) where individual ideas and opinions are input into a decision-making model.

In this study, the underlying premise to developing an approach for dealing with geographic data problems in data-poor environments is that cognitive information residing with "experts" can be used as a source of spatial data. The Strabo approach is developed on the basis of a structured communication process providing feedback to a group of experts in an attempt to derive a consensus of spatial opinions. One aspect of the interpretive nature of the Strabo technique is that the data that are collected directly are the "target variables" of an analysis, and not intermediate substitutes.

Because of the cognitive spatial emphasis, the study examines previous research in this field and looks at ways of recovering "maps" from the "minds" of those with special knowledge about a geographic area. This leads to discussions about how experts can be defined and how to measure their "expertness" (Linstone, 1975; Wallsten and Budescu, 1983). Recognizing that knowledge about a geographic area is itself spatially distributed, the study also examines the concept of "knowledge surfaces" and how these can be determined (Gould, 1975).

Data accuracy issues are an important concern when dealing with subjective data. These issues are examined systematically looking first at an operational definition of accuracy and then at possible sources of error (Chrisman, 1981, 1983a). Data accuracy and reliability can be viewed in terms of subjective and Bayesian probabilities because they relate to opinions based on degrees of belief (De Finetti, 1974a; Hartigan, 1983).

The Strabo method, (named after the early Greek geographer), aggregates cognitive maps representing the spatial opinions of several "expert" individuals. To identify and determine the effects of these aggregations on the reliability of the resulting data, the study examines several approaches to combining subjective probability estimates.

Strabo is a structured communication method finding its roots in the established Delphi technique. In capsule, Delphi utilizes panels of experts to elicit quantitative information about a subject such as futures forecasts (Linstone and Turoff, 1975). These individual responses are "averaged" and this summary information is then fed back to the individual panelists as new information into their decision-making process. The question-answer and subsequent feedback steps are iterated several times with the objective of producing a consensus of opinion within the panel. The premise is that the summary information fed back at the end of each round or iteration adds new common information to the decision-making processes. To establish a foundation for Strabo, the study looks at the development of Delphi techniques since the 1940s and how the process has been altered and modified. It attempts to summarize some of the criticisms which have been leveled against such structured communication procedures and to identify controversial issues (Sackman, 1974, 1975).

Strabo attempts to produce consensus of spatial opinions within groups of experts by using techniques borrowed from Delphi and other structured feedback approaches. It requires participants of an "expert" panel to answer spatial questions by drawing their responses on a map. In addition to the response maps, "confidence maps" representing each individual's knowledge surface, or how sure they were that their answers were correct for any given location in the study area, are derived. These are used to weight the response maps in the aggregation process. The response maps are weighted and aggregated into a composite map which is then summarized in statistical form. These results are examined in terms of levels of consensus and are fed back to the participants prior to their completing subsequent rounds of questions. In this manner, the structured communication process attempts to develop a spatial consensus and to strengthen the amount of agreement within the expert panels.

To demonstrate the method in an application and to examine its assumptions about forming spatial consensuses from panels of experts, the study selected an urban social environment for a test area and chose five variables about which information would be gathered. Panels were formed from local experts who have a specialized knowledge about the area and about the subject matter of the questionnaire. Problems encountered in panel formation and in the administration of the iterative procedures are discussed and limitations and constraints that these problems have on the results are identified. An analysis of the results demonstrated that the Strabo procedures produce a meaningful consensus of opinion and that the structured feedback of results to the panelists improves the "quality" of the consensus. It also makes some observations about the relationships between the consensus and the degree of subjectivity within the variables.

CHAPTER 2: MAPS AND MINDS

The premise explored in the thesis is that "soft information" which is stored in the human mind can be used as a reliable source of spatial data. This chapter reviews prior research pertaining to data accuracy, data reliability, qualitative spatial data, subjective information, cognitive mapping, and subjective probability theory (Coombs, 1964). This body of literature crosses disciplinary boundaries and finds parallel research efforts in the fields of geography/cartography, psychology, statistics, management science, forecasting, among others. Many of the topics are relatively new to the literature and as such remain controversial, for example, fuzzy set information and subjective probability aggregations (Zadeh, et al., 1975; Bordley and Wolff, 1981; Kmietowicz and Pearman, 1981). The review attempts to synthesize the arguments, present various positions, and develop reasoned assumptions upon which to build the Strabo method and its applications.

2.1 Geographic Information in the Cognitive Domain

Geography has always had space and the organization of that space as a central concept. Although philosophies and methods in the discipline have changed, spatial considerations have remained important. Modern geography focuses on the location and distribution of phenomena, as well as on interactions amongst the phenomena and the processes that produce the locations, distributions, and interactions. As geographers sought to explain distributions and relationships between spatial phenomena, they became aware of techniques and concepts developed by other disciplines which could facilitate their theoretical understandings. Biology, physics, economics, and psychology were a few of the more influential fields which have affected the way geographers view the world.

Since the 1960s, some geographers and psychologists have been consciously learning about each other's problems and concerns, and have begun to work together to find solutions (Rushton, 1969; Lowenthal, 1972; Golledge and Rushton, 1973, 1976; Gilmartin, 1981). This is particularly apparent when dealing with subjective data and data reliability. In the late 1950s, many numerical geographic data handling techniques were borrowed from psychology; for example, factor analysis became widely used for nearly a decade by geographers studying "factorial ecologies" of urban areas (e.g., Berry and Rees, 1969). As the two disciplines began to explore common ground, there was a realization that they were interested in many similar problems, however, for different reasons. Golledge (1982, p. xix) explained the prior lack of cross-disciplinary interaction and the subsequent "meeting-of-the-minds":

> "The reasons for lack of interface are obvious. For many years geographers were concerned only with macro environments (in a psychological sense) and cared little about fundamental psychological variables such as learning, preference, choice and decision making, attitudes, images, values, personality, motivation, and so on. Geography was dominated by a form-oriented approach, which took as its fundamental data sets the environment external to humans and the modifications made to the external environment by humans working alone or in groups. In other words, geographers were interested in the spatial manifestations of human existence and searched for explanations in terms of coincidental relationships between overt human activity and structured characteristics of the environment and its resource base. With few exceptions, the field of psychology concentrated on the micro scale, with an emphasis being placed on the process by which sentient beings were able to manifest behavior. Critical variables often were defined on humans or other thinking organisms in experimental situations...The development of process-oriented approaches for

analyzing various aspects of human geography inevitably led to the discipline of psychology.... [D]escription of "man-environment" relations gave way to more extensive searches for explanation of such relations."

Interest has increased among psychologists in the late 1970s and early 80s in psycho-spatial phenomena, particularly in the area of human spatial perception and cognitive spatial models (Golledge and Rayner, 1982; Portegal (ed.), 1982). Because of these common interests, albeit at different scales, a cross-fertilization of ideas, concepts, and methods occurred.

2.1.1 Cognitive Mapping

As geographers concern themselves with organization of space, particularly on the earth's surface, data collection within this domain is often confronted with special and sometimes unique problems (Abler, et al., 1971). One important factor for geographic data collection is scale -- the metric relationship between objective reality and model representation. The integrity, reliability, and validity of spatially oriented information for given scales, whether at, for example, a neighborhood, city, regional, or national level, are of primary concern. Information is sampled at a given scale and then extrapolated and generalized to create a data model of objective reality. These models can frequently be represented by a spatial graphics, or map, at the same scale or smaller. Often, our knowledge and understanding of spatially distributed phenomena are non-homogeneous over a region. This is especially true of subjective or "soft" data, but is also valid for concrete, physical data (such as "head counts", and species identification). Spatial variations in reliability of the knowledge of a region are important considerations which have not received much attention in the literature. The concept of a "knowledge surface" could be used to measure reliability of information and could contribute to explaining spatial decision-making behavior. Allen (1972), for example, used a similar idea to explain patterns of activity during the Lewis-Clark expedition of 1803-1806 as they searched for a water passage to the Pacific. He identified two types of knowledge about a region -- "real knowledge" based on currently accepted geographical reality, and "perceived knowledge" based on how the "real knowledge" was understood by those to whom it was available. The data upon which their knowledge was derived were classified by degree according to reliability. In Allen's case, reliability was determined by the source of information. The most reliable data ("first degree") which Lewis and Clark had to consider in their planning of the expedition were obtained through active commercial, diplomatic, military, political, and scholarly enterprise. Allen classified that information derived from traveler's accounts and from "fairly reliable hearsay" as second degree knowledge, and that acquired only through rumor and conjecture as the least reliable, or third degree (Ibid., p. 14). Although the explorers were likely not conscious of the theoretical model of their "knowledge surface", in retrospect, Allen was able to demonstrate how their decision-making behavior was radically altered on the basis of the changing reliability of their spatial knowledge.

2.1.2 A Review of Spatial-Cognitive Structures

The early and mid 1970s produced a great deal of work concentrating on the cognitive representations of information space (Gould, 1966; Kaplan, 1973; Gould and White, 1974; Gould, 1975; Downs and Stea, 1973, 1977). Much of this early literature examined spatial cognitive structures as they related to people's preferences for geographic space and residential desirability using case studies in a number of countries including Britain, U.S.A., Sweden, Malaysia, Nigeria, Tanzania, and Ghana (Gould and White, 1974). It recognized that behind the cognitive representations and graphic manifestations -- variously called cognitive maps (Downs and Stea, 1977), mental maps (Gould and White, 1974; Tuan, 1975), and perception surfaces (Gould, 1975) -- are "invisible landscapes" of information. These "information surfaces" affect spatial preference and decision-making processes, but it is difficult to get a firm grasp of this amorphous concept called information. Intuitively, an understanding has been developed of what information is, but there are difficulties in trying to operationalize the concept. As Gould (1975, p. 77) noted, it is "one of those fuzzy, will-o'-the-wisp notions like 'accessibility' that appear naively obvious until we try to handle them in any systematic way."

Information is scale and topic dependent. The larger the scale, the more detailed and specific is the information (Gale and Golledge, 1982). For example, at a macro scale an area might be known to be "forested", but at a micro scale the individual forest species, size of trees, and production potential may be known. Similarly, a great deal of information may exist for other locations such as land use, vegetation cover, soil type, precipitation, and land tenure, but to have knowledge of a location or to collect data for a specific area seldom covers all such topics. An urban utilities engineer may have detailed knowledge of the topography, geology, and hydroclimatic conditions of a neighbourhood, but he may have little knowledge of the number of television sets per household or average annual income of the people living in the area. The knowledge surface for a defined area can be thought of as a set of information surfaces dependent on scale and theme.

Some cognitive-spatial researchers have attempted to measure, or at least define, these information surfaces (see for example, Gould, 1975). Since much of the work dealt with location desirability, measurement of information surfaces was operationalized by having respondents record, under the pressure of a time constraint, all towns and cities they could recall. Further exploration revealed that it was possible to predict, or model, information surfaces according to a commonly used analytical procedure -- the gravity model (Ibid.). Information about different places relative to a fixed location (i.e., respondent) is a function of the population and distance separating them, e.g.,

$$\text{Information} = f(\text{Population}, \text{Distance}).$$

This is expected because, as Gould and White (1974, p. 131) suggested, "[a]fter all, people generate information, and we might expect [places] with very large populations to generate very strong informational signals that are gradually attenuated with distance away from the transmitting source."

Information surfaces are typically characterized by "cones", or peaks, located at focal points that are familiar to an individual or a group of individuals (analogous to Lynch's (1960) dominant points, lines, and areas in a city; see also Appleyard, 1969; Carr and Schissler, 1969; Downs, 1970; Golledge, 1975). It is possible to measure information gradients on the surface depending on the strengths of the focal points and the familiarity with surrounding adjacent areas. Such gradients prove useful for interpolating information "strengths" at specific points or over given areas on a surface.

Related to the concept of information surfaces is a loosely complementary notion of an "ignorance surface" (Gould and White, 1974, p. 120), which is affected to some degree by geometric shape, adjacencies, travel fields, and distance (Tobler, 1976, 1979). The ignorance surface reveals weaknesses in information and distortions of the cognitive representations of the objective space. Commonly, errors occur when people confuse areas of relatively the same size or same shape, or when they reverse the identification of adjacent areas. The latter indicates that they have a general idea of where things are but confuse the details.

Another body of research examining psycho-spatial problems has dealt more with cognitive representations of space and how the brain encodes, stores, and retrieves spatial information and relationships (Robinson and Petchenik, 1976; Bartram, 1974; Huttenlocher, 1968; Kuipers, 1982). By attempting to understand better the physiological and psychological factors involved in creating a cognitive spatial image, researchers hope to develop better ways of soliciting, measuring, and understanding mental maps. Spatial information is detected by the human sensory organs, undergoes a transformation, and is stored in memory. Little is known about the way information is actually transformed and stored, but some progress has been made in identifying what types of cues are used to develop a cognitive image and how they are ordered (Rumelhart and Abrahamson, 1973; Louviere, 1976; MacKay, 1976; Stevens and Coupe, 1978; Klein and Cooper, 1982). Golledge, et al. (1982) described a conceptualization involving a hierarchy of image building cues held together by spatial relations such as proximity, dispersion, clustering, separateness, and orientation. These relations are effective among major cues (e.g., primary nodes), among secondary cues (e.g., minor nodes), and between primary and secondary cues. Distortions in the mental map can occur because of incomplete understanding of the spatial relations among sets of the information generating cues. For example, an individual may have a good understanding of the spatial relations among the cues around his residence as well as those around his place of work in the city center. But, because his travel patterns between these higher order cues typically involved underground subway, his orientation and sense of distance may be greatly distorted and thus his mental map may be "accurate" with respect to the relations between major and minor nodes but distorted in the relations between the two major nodes. This would result in whole "patches" (associated with higher level cues) being offset or misplaced in some way.

Pipkin (1982) referred to geographic space cognition as being a "number of schemata linked by transformational processes". The cognitive map actually exists at several levels--as "deep schemata" possessing complex semantic, motor, and other features, and as "surface schemata" which are simple and more imagelike. He also suggested that recovering a cognitive map involves three levels of processing -- deep, deep to surface, and conscious (Ibid., p. 222). Our understanding of these processes (with the possible exception of the conscious manipulation of the image) is extremely poor and remains by and large conjectural.

Kuipers (1982) argued that the mental map can be described not as a single representation of spatial knowledge, but rather as a number of distinct representations including metrical, topological, procedural, and sensorimotor, all of which are implemented as components of a computational model. Such complexity makes it difficult to model the transformations from objective reality to a cognitive representation. One can theorize about the process involved with individual representations (e.g., topological or metrical), but the derivation of a comprehensive model will require more research.

While most spatial-cognitive experimental researchers in the past two decades have concentrated on the decoding stage of the process, (i.e., from the already formed cognitive representation to the recovered spatial image), Lloyd (1982) has suggested that more attention should be paid to the fundamental issues concerning how spatial information is originally coded, transformed, stored, and processed in memory. Both approaches (not that they should or can be completely separated) require further investigation (Pocock, 1979).

2.1.3 Recovering Cognitive Maps

A number of experimental methods have been developed to reconstruct, or recover, metric configurations of cognitive maps. These include the above mentioned approaches of Lynch (1960) and Gould (1975), where individuals are requested to either draw a graphic which represents their understanding of a spatial environment or to add information to an existing, scaled graphic (map). Cromley, et al. (1981) referred to these as "construction maps" and "completion maps" respectively.

Another widely used method in recovering a spatial perception is called Multi-Dimensional Scaling (MDS) and has been used in locational preference analysis (Kruskal, 1964; Young, 1968; Kruskal, et al., 1973, 1977; Deutscher, 1982; Green, 1982; Tobler, 1982; Young, et al., 1982) . Frequently, this procedure involves collecting subjective data by having subjects rate the similarity of all (or in cases of large data sets, a subset of) pairs of "stimuli" (Shephard, et al., 1972; Young and Cliff, 1972). For example, cognitive spatial information about an urban environment can be uncovered by measuring the perception of relationships between objective stimuli, such as distance comparisons between pairs of shopping centers, major routes, and parks (Spector, 1975, 1978; Rivizziano, 1976; Golledge and Spector, 1978; Spector and Rivizzigno, 1982; Clark, 1982a, 1982b). This approach was also used to extract a cognitive representation of an environment for the purposes of comparing it with cartographic representations, or maps (Golledge, et al., 1969, 1982). Although many findings were preliminary, a number of important results were presented. Some experimental evidence was found to support a hypothesis that if the "fit" between cognitive and cartographic representations of space increased over time, this would indicate that learning was occurring and that the cognitive representation was maturing. One of the procedures for comparing these representations was spectral analysis of the two-dimensional surfaces (Rayner, 1971; Rayner and Golledge, 1972). It yielded additional information about mental maps which will undoubtedly have future impact on psycho-spatial research; that is, it was able to recover minimum scales for the generalization in mental maps of individuals and was able to detect distortions in orientation. The recovered scale, below which an individual is unable to reproduce reality, could be useful in assessing reliability of mental maps as a source of spatial information.

Some have questioned the validity of recovering the cognitive representation as a geometric configuration (or map) on a two dimensional piece of paper. Marchand (1982) has suggested that (from some preliminary research on paired distance perceptions) mental representation might best be described in terms of fractional dimensionality, a concept first introduced by Mandelbrot (1975, 1977). This permits a line, for example, to have a dimension other than 1, say 1.5. The argument for fractal dimensions in cognitive representations has been suggested as an explanation for findings that in some cases short distances are overestimated relative to longer ones (e.g., Briggs, 1973).

The work in multi-dimensional scaling for recovering cognitive representations of space is still in its infancy, but it appears to hold potential for a number of practical applications. It is, however, beyond the scope of this research to explore these conceptual issues and applications further.

2.2 Quantification and Quality Issues for Geographic Data Handling

The past several decades have produced a strong interest in the quantification of geographical phenomena, and they have seen new methods borrowed, modified, or otherwise developed to analyze these spatially oriented data (Berry and Marble, 1968; Abler, et al., 1971). Maps, a traditional primary tool-of-the-trade for geographers, took on new dimensions as this quantification era gained momentum (Maling, 1977; Robinson, et al., 1978).

Maps no longer just showed locations which thereby described spatial relationships; they began to show more complex phenomena and more complex relationships between geographical variables. Choropleth maps of representational indices (for example, factor scores and regression residuals) became common (e.g., Berry and Rees, 1969). Questions were soon raised concerning the validity of some data analyses, and results of analyses were tested in various degrees, with statistical procedures. Some of the analytical methods which were developed withstood critical scrutiny, while others, such as factor analysis, faced continuing controversy (Cattell, 1965). Although the mathematical foundations of the analytical tools were tested, there was little accompanying attention to the accuracy of the data which was being processed and to the confidence and reliability of the analyses performed on such data. Quantification seemed to suggest an implicit accuracy and an absolute ordering to a sometimes chaotic reality.

Quantification efforts were fueled by developments in the field of electronic data processing. Vast amounts of numerical data could be manipulated, transformed, summarized, and otherwise processed in short periods of time -- a situation not possible before. Quantification took a monumental leap forward as geographers and cartographers discovered ways of converting entire maps and other graphics tools into numbers (Peucker, 1972). This increased the potential for analyses as it became possible to manipulate map information as well as the usual statistical data. A whole new body of analytical tools, techniques, and methods were developed (Tomlinson, et al., 1976). Some of these grew into much larger entities or systems which have been given generic names such as computer-assisted mapping systems, image processing systems, and geographic information systems (Marble, 1980;

Monmonier, 1982). It has become possible to work with and process very large amounts of geographic data, and commercial companies now offer these analytical services and/or sell systems to individuals or agencies wishing to process their own data. New professional societies (e.g., Auto-Carto) and journals (e.g., Geoprocessing) have developed in response to the need for sharing ideas, information, and research initiatives amongst the members of the geographic information processing community.

Developments in geographic data processing have proceeded more quickly than research efforts in the area of data accuracy and reliability. Data bases of geographic information are often collected from different sources, at different scales, and at different levels of generalization. There may be problems with information accuracy from a single source, and the difficulties increase when assessing reliability of information from several sources. For example, what level of confidence can be placed in the results of a classification system obtained by overlaying maps of soil regimes with maps of vegetation distributions. By and large, these concerns have been neglected until recently (Campbell, 1983; Cook, 1983).

Several researchers have begun to devote attention to these issues, most notably Chrisman with his conceptual work on cartographic error (Frolov and Maling, 1969; Lyord, 1976; Quirk and Scarpace, 1980; Chrisman 1981, 1982a, 1982b, 1982c, 1983a, 1983b). Others have chosen to look at geographic data as something other than definite and precise (e.g., Leung 1982a, 1982b, 1982c; 1983a, 1983b) using a mathematical model of data called "Fuzzy Set Theory" (Zadeh, 1965; Gupta and Sanchez, 1982).

2.2.1 Data Accuracy

Nearly all geographic information has a locational component and the amount of error in this factor alone can be greatly influenced by scale, level of generalization, and calibration of the measuring instruments (Robinson, et al., 1978). Additional errors may be introduced in the processing and storage of information because of numerical rounding procedures, number of significant digits retained, or by addressing limitations of the computer (Chrisman, 1981).

Since error is associated with the data, concerns should focus on the "quality" of the information and the degree to which inaccuracies can be tolerated for a given application of the data. This issue has received considerable attention as a result of the investigation of the National Committee for Digital Cartographic Data Standards which has established a working group on Data Set Quality (Moellering, 1984). A useful definition of quality which has been commonly used is that of "fitness for use" and seems particularly appropriate for cartographic data. Each application can define the standards and "quality" of data required for a given situation (Vonderohe and Chrisman, 1985). Roberts (1980), for example, addressed the issue of data accuracy in a resource information system and established that, for a graphic display only, locational data should be accurate within one metre, but for the location of underground services, it should be within ten cm and for a legal cadastre within one cm. These standards, of course, are not universal but serve to illustrate that for a particular application, an appropriate level of accuracy should be defined. Relative accuracy is but one factor determining how "fit for use" a particular data set is; other considerations are its currency, and its referencing system.

Locational, or positional, accuracy usually receives the greatest amount of attention and scrutiny; it is easy to discern when some known feature appears on a map at a location other than where it should be, or when a feature is missing (Marino, 1979; Feldscher, 1980). But, another source of data error lies with the categorical attributes. Categorical attributes are characteristics associated with geographic phenomena (Jensen, 1978). These may be nominal characteristics (e.g., parcel identifiers, feature names and codes, vegetation types) or interval data (e.g., population densities). The most obvious type of error associated with this component of geographical data is the assignment of an incorrect or false "value" to the attribute; for example, labelling an area as being used for agriculture when it should be correctly labelled as forest. Such errors are detectable, but usually are found only after close data checking (Hay, 1979; Welch and Hsu, 1983). Less apparent, but equally important, is the uniformity of the regions which are being categorized (Ginevan, 1979; Henderson, 1980). This concept of "purity" is of particular concern to soil scientists as soil zones are rarely clearly defined but rather are classified on the basis of the predominant soil type. The U.S. Soil Conservation Service recognizes that regions on large scale soil maps may contain up to 15% of a different soil (more in certain cases), and the Canada Land Inventory specifies the purity of each region to the nearest 10% (MacDougall, 1975). As scales decrease (and generalization increases), "purity" decreases. An estimate by Bie, et al. (1973) indicates that for maps in the 1:25 000 scale range, the purity of soil classification is approximately 75% and at scales of 1:50 000 the purity decreases to about 55%.

Cook (1983, p. 65), interested in geographic data overlay problems, has created a general model which relates data reliability to the factors which are its determinants. Simply stated,

Reliability = f(a,b,c,d)

where a = degree of descriptive generalization

b = degree of spatial generalization

c = accuracy of description in the descriptive scheme

d = accuracy of the spatial delineation of the regions

As in many fields, computers have introduced new ways of looking at and thinking about data processing and storage (Castonguay and Thouez, 1977; Boyle, 1980). Geographic data elements are basically "something" located "somewhere". Two methods have developed with different conceptual approaches to the handling of digital spatial data. These have become known as vector and raster methods (Monmonier, 1982), and for some time controversy existed over the relative merits of each. The debate is not yet over, but each approach has established a degree of reputability. Some attempts have even been made to established hybrid approaches taking concepts from each, most notably an approach called "vasters" (Peuquet, 1982).

2.2.2 Vector Representation of Spatial Data

Each of the approaches used to handle geographic data has predictable and different impacts on the accuracy of the data. The vector approach is most akin to the "natural" way of viewing the geographic environment and to the traditional methods of representing that environment in map form. The basic building blocks of this representation are points and lines. Dependent on scale, features such as landmarks, road intersections, transmisson towers, even towns and cities, are mapped as points with a defined set of coordinate values. Lines represent administrative boundaries, roads, coastlines, and edges between zones of different attribute categories (e.g., soils). Digitally, lines can be conveniently represented as a sequence of points each with its defined set of coordinate values (Marino, 1979). This approach has an elegance which makes it attractive conceptually. From simple "spaghetti" type lines (so called because of their intermingling yet independent nature) to complex topological structures (Corbett, 1979), this approach has been used to build both simple map drafting systems and sophisticated analytical geographic information systems (e.g., ESRI, 1984).

In spite of the conceptual elegance of information manipulated and stored in a vector format, there exists an error component in the underlying data. Chrisman (1981) discussed cartographic error and attempted to build a model of the error in order to understand better the impact it had on spatial analysis. He detailed the sources of error, not all of which were limited to vector information. One of the earliest sources of error to contribute to the overall inaccuracy of geographic data occurs as the ground location is determined. This finds its roots in surveying and geodesy. Fortunately, these fields have devoted a great deal of attention to the accuracy issues of their measurements, and the errors associated with these measurements are well defined within specified tolerances (e.g., Breed and Hosmer, 1928).

2.2.3 Raster Representation of Spatial Data

Errors associated with raster representation of spatial data stem primarily from the difficulties encountered when continuous, irregular surfaces are forced into discrete, regular grids as a model of the surface (Switzer, 1975; Muller, 1977). This approach partitions a surface into a lattice of regularly shaped geometric cells--usually rectangular, however, hexagonal type lattices have also been used (Interactive Systems Corporation, c.1980). These cells form the building blocks of the model; data are then associated with the cells. There is a usual assumption of homogeneity within each cell, but this can be a major source of error. Geographic phenomena are seldom organized into neat, regular units and to represent them thus requires generalization, loss of detail, and potential inaccuracies. This is particularly troublesome in transition areas between categories of data, for example, soils, and vegetation. A cell is usually assigned the value of the category dominating the area covered by the cell, or a value sampled at the midpoint of the cell, (*e.g.*, elevation).

An important factor influencing the accuracy of a cell's representation is its size (Wehde, 1982). Large cells have more generalization and a greater loss of detail. Conversely, small cell sizes represent the surface in greater detail and improve the overall quality of the data in the model (assuming that the calibration of the data gathering processes is consistent at all scales). With infinitely small cell sizes, the amount of generalization tends to zero and the model approaches perfect representation of the data. Although not as conceptually elegant as the vector approach, the raster approach offers tremendous efficiencies in some data processing functions because data are represented essentially in large matrices which can be easily combined, compared, and otherwise manipulated. The primary drawback of raster models lies not with data processing but with data storage. Increasing the amount of detail in a surface area by using smaller cell sizes increases exponentially the number of cells and consequently the storage requirements. Efficient data structures and compaction techniques have been developed to reduce storage requirements, however, this remains a significant problem.

There is a degree of arbitrariness to raster representations of spatial data. This in turn has inspired a number of studies (e.g., Switzer, 1975; Muller, 1977) which have investigated the impact of some of these arbitrary components on data accuracy. Establishing a regular lattice on which the raster representation can be based assumes an "origin" somewhere. This origin is often determined by an arbitrary coordinate system such as the Universal Transverse Mercator (UTM) coordinates (they are arbitrary in the sense that they are not tied to physical features on the surface, but rather are geometric constructs usually based on some feature of the earth's geoid such as the equator and lines of longitude. Muller (1977) has shown that altering the origin, and thus moving the boundaries of the cells, has no significant effect on the overall representativeness of a grid model. Localized error, that is, the accuracy of the model at a given location, may be affected by a shift in the origin, but over a large area the relative error is not changed.

Orientation of the lattice, or grid, is another factor which is usually arbitrarily defined. Often it is oriented north-south, if for no other reason than it conforms to an existing coordinate system such as the UTM. Muller (1977) demonstrated that changing the orientation of the grid has little effect on the results. Of course, if the phenomenon being modeled has an inherent orientation of its own, for example, linear, geological folds, or cultivation practices designed to counteract wind erosion, the altering of the orientation of the grid can change the accuracy of the representation.

The ease of data manipulation is a strong incentive for using a raster representation, however, that is neither the only reason, nor necessarily the main one. Many data collection procedures are efficiently and effectively performed in this manner. Tremendous volumes of information are recorded in raster format by remote sensing systems using aircraft and satellite platforms (Lillesand and Kiefer, 1979). Remote sensing from space has established a wide range of applications, among which are the monitoring of resources such as forest and agriculture, weather forecasting, and military surveillance (Robinove, 1979; Simonett, 1983). The resolution of the sensors is a factor of the application-- meteorological satellites have a wide range of resolutions typically in the tens of kilometres (Allison & Schnapf, 1983), LANDSAT MSS has an 80 m resolution (Simonett, 1983), Thematic Mapper (TM) has a 30 m resolution, the French SPOT satellite has a resolution of 20 m (Ibid.). Sensors with higher resolutions than these can and have been produced, reducing the amount of generalization in the data, but higher resolutions (smaller cell size) create almost prohibitively large data sets which in turn create enormous storage and processing problems.

2.2.4 Other Common Sources of Error

The medium on which graphic representations of spatial data are portrayed can also contribute significantly to the error component of data. Most maps are printed on a paper base, and paper has a tendency to shrink or stretch under varying environmental conditions of temperature and humidity (Robinson, et al., 1978, p. 358). Bending and folding source documents also cause distortions in the planar surface and introduce additional error. These errors appear in digital data bases because printed maps are often sources of locational data for computer-assisted mapping and analysis applications. A 0.1 mm displacement represents a 5 metre error in the horizontal ground location on a 1:50 000 map, and a fifty metre error on a 1:500 000 map.

The actual drafting of linework on a map introduces additional error. Theoretically, a line is a one-dimensional entity with a defined length and a width of zero. However, the actual construction of this geometric abstraction involves tracing an image with a pen or scriber, and this image not only has a length, but also a width -- commonly in the range of 0.1 mm to 1 mm (Robinson, et al., 1978). "Pens create lines of finite width as symbols of features of infinitesimal width" (Chrisman, 1981, p.51). To illustrate the effect of two dimensional lines, a 1 cm long, fine line, 0.1 mm in width, covers 25 hectares (61.75 acres) on a 1:500 000 scale map. The total length of lines on a map can be considerable, as will be the area covered by them. The final representation of a line on a map will be subject not only to the judgement and interpretation of the human draftsman, but also to the precision of his motor-mechanical skills.

Converting map information into digital form has its own sources of error. To date, much of the conversion has been done in a semi-automatic fashion, that is, a human operator selects which features are to be encoded and then an electronic digitizer records the coordinates (Boyle, 1980). When digitizing lines, an operator follows a feature with a cursor either selecting points manually or instructing the digitizer to select, on the basis of distance or time criteria, points from a constant stream of representative points. Just as with the drafting process, following lines on a map is subject to human judgement and motor-mechanical skills. Coastlines, for example, are often generalized as a result of imprecise cursor placement. Digitizing devices also have physical measurement limitations and operate within known tolerances. A digitizer with a known resolution (for example, 0.005 inches) is unable to measure distances smaller than that on the map, and although this induced error is relatively small, it is an important source of dilution in data base accuracy (Thompson, 1981). To put the error in perspective, on a 1:50 000 scale map the resolution of the digitizer corresponds to 6.35 m on the ground. This means that it is not possible, within the constraints of the hardware, to measure distances with a precision greater than this value.

2.2.5 Using Probabilities to Define Accuracy

To recognize the influence of error factors, it is useful to think of and treat geographic data in terms of probability theory. Probability analysis is a method of dealing with uncertainty; and since nearly all geographic data has an uncertain accuracy associated with it, concepts of probability can be meaningfully applied. Unfortunately, little attention has been given to analysis of the probability that individual data items in a set of geographic data are accurate.

Often a high degree of accuracy is suggested by data once they appear in numeric form or are cartographically portrayed. Even when something is known about information reliability (e.g., Ley, 1981), there is a tendency to assume the limitations are not important and to treat the data as though they were accurate. These reliability levels are seldom explicitly stated, but rather require the reader to estimate data accuracy. In some instances stating the source of information implies something about its accuracy. Data provided by a national bureau of statistics is apt to be viewed as being more accurate than that derived by some small agency or company doing a partial, random sample. In these cases, it is difficult to distinguish between accurate and authoritative. Authoritative data, as one obtains from official government agencies, United Nations, and other high profile agencies, are often considered reliable; unfortunately, such assumptions are often unfounded.

Another method of indicating cartographic data reliability is to provide supplemental information in the legend. This may include simply a data history indicating when the data were collected, checked, revised, and printed, but in some cases, especially with maps of more "unknown areas", a reliability diagram in the legend indicates which portions of the map are reliable and which are not (Robinson, et al., 1978, p. 158).

There are many other ways to indicate data reliability, but in general they only serve to determine whether the information is fit to be used or not. If it is deemed fit, then it is often treated as being accurate. Values are defined precisely and locations are given exactly -- even though the likely margin of error would indicate otherwise. A common reason for using such data is that "it's the best that is available" or "it's better than nothing". The argument here is not against using such data because even data with a degree of uncertainty in their accuracy are valuable, but for better methods of handling and processing this type of information. In fact, a major premise of this research is that geographic data with a high degree of uncertainty as may be found with opinion data are useful if properly handled.

The need for understanding data error and data reliability is particularly important now because of the sophistication which has developed in geographic data manipulation and processing. As it becomes easier to combine layers of spatial data (i.e., map overlays), it is crucial to understand what happens to the reliability levels of the derived data; in other words, how are individual reliabilities aggregated into composites? To date, this is not frequently a major consideration when performing spatial analysis (MacDougall, 1975).

In other fields there has been a keen interest in these types of problems and, as with many new approaches to problems, the solutions have been followed by controversy. The larger generic field of decision theory centres around uncertainty and risk analysis, for which concepts of probability are particularly suited (Pitz, 1970; Wise, 1970). Many of the traditional concepts of probability have proved to be limited in their abilities to deal with uncertainties particularly as they relate to cognitive structures. This has led to the development of a more cognitive oriented theory of probability which has become known as "subjective probability" (de Finetti, 1937, 1974a, 1974b, 1974c). The foundation for this approach lies in the early work of Thomas Bayes who espoused the idea that probability could be defined as a "degree of belief" (Wise and Mockovak, 1973). The body of theory which subsequently developed, and has become known as Bayesian Statistics, has had a marked effect on our understandings of uncertainties and probabilities. Probably one of the most important contributions was the definition of conditional probabilities which describes the relationship between an outcome and its a priori dependent events.

2.2.6 Different Approaches to Assessing Probabilities

Hartigan (1983) defines three types of probability theories, namely, logical, empirical, and subjective. It is beyond the scope of this study to analyze each of these in detail; it is sufficient to describe in general terms the first two types, and concentrate more on the third since this has potential applications to the area of cognitive representations of spatial data. In logical theories, probabilities are defined in terms of rational degrees of belief in an event relative to known evidence, for example, knowing that a die is fair and has six faces, the probability of any face being thrown is 1/6. Most introductions to probabilities begin with the logical theories, but often the known evidence upon which the probabilities are based does not exist and some other criteria must be used to determine the probabilities. One such criterion is based on repetition of experiments, which are assumed to be independent. For example, to determine the probability of a fuse being defective would require experimenting with a large number of fuses to determine a proportion of defective fuses in the sample. This is an "empirical" observation of sequences and leads to frequency distributions. Using again the example of rolling a die, the probability of throwing a one would be determined by counting the number of ones thrown in a sequence of tries, and then determining the ratio. Assuming the die is fair, the limiting ratio should approach 1:6 as the number of experiments becomes large. Statisticians build frequency models to describe probability distributions, and these are commonly used to test the significance of an event. Some standard frequency models are the normal, t, F, and Chi squared distributions (Blalock, 1972).

The third type of probability theory is "subjective" where probability is viewed as an individual's degree of belief. This view is often described in terms of an individual's predisposition to "bet" on an event (de Finetti, 1937). It is the amount you are <u>willing</u> to bet rather than the amount you <u>ought</u> to bet, assuming that you are "coherent" in your betting. Bunn (1979a, p. 40) defines the coherence principle of rational belief and action in terms of requiring a decision maker "to use all the available evidence and hypothesis in a self-consistent way" (<u>i.e.</u>, no contradictions in the decision maker's opinions). Subjective probabilities have also been called "personal" probabilities (Savage, 1954; Lindley, 1982) because they are associated with individuals, that is, the probability that an individual would assign to an event.

Some have found it useful to distinguish between "objective" or "true" probabilities (as defining logical and empirical types) and "subjective" probabilities. However, the subjectivists would contend that all probabilities can be considered subjective (Phillips, 1970). De Finetti (1974b, p. 16) described the objective-subjective distinction as illusory. He asserted that

> "...every evaluation of a probability is based on all the available information including objective data, but only our subjective judgement can guide our selection of what information to consider as relevant for our purposes and how to let it influence our belief. Even in the cases where one accepts the so-called objective probabilities (e.g., the ratio of white to colored balls or the observed frequency of their occurrence in drawings), the subjective decision to admit only such information as relevant and to make use of it in the ordinary ways is what transforms objective data into a probability. Therefore, the probability itself is subjective".

The determination of subjective probabilities has inherent difficulties (Gustafson, et al., 1973; De Zeeuw and Wagenaar, 1974). It is easy to ask a person for his subjective probability regarding some event, but how can one know if he has given his true probability. It is frequently difficult for a person to translate his "degree of belief" into a numeric representation of his probability. Various techniques have been developed to elicit the true probability and to ensure that the probabilities are coherent (Mitchell, 1980; Moskowitz and Sarin, 1983). One such mechanism is the use of "scoring rules", or incentive schemes which might, for example, assign a pay-off to the assessment of probabilities on the basis of the "true" value, if it subsequently becomes known (Winkler, 1967; Winkler and Murphy, 1968; Murphy and Winkler, 1970; Staël von Holstein, 1970; Friedman, 1983). A great deal of research has been devoted to the cognitive processes of formulating subjective probabilities and to the factors which influence individuals (Manz, 1970). "Probabilities do not exist as characteristics of the physical world; they are a person's statement about his degrees of the belief" (Phillips, 1970, p. 254). Therefore, a number of factors and variables may have differing impacts on the probability decision. The extent to which one pays attention to one's environment, one's ability to remember relevant information, and the logical processes by which one assimilates information are examples of parameters influencing the final decision (Bunn, 1979b; 1979c). Others such as prior experience and information, cultural and social factors, and personality also have potential to affect the assessment of a probability for an event to occur.

Decisions based on the analysis of spatial data must take into consideration probabilities that the information contained therein is correct. Since it is a human belief based on a number of the factors mentioned above, the decision maker/analyst is weighting the decision by an internal representation of an assigned subjective probability. He is not likely to think of the probability in a formal sense, but rather in terms of a qualitative representation. For example, a motorist attempting to navigate a route between two locations may feel that he is very likely to succeed without getting lost, rather than to think of it in formal probability terms as the chance of successfully navigating a route between points A and B is 0.87.

Probabilities associated with complex events are usually composites of the probabilities of a number of simple events. The probability that one's car will break down is a function of the probabilities that individual components of the car will fail. Aggregations of probabilities have interested statisticians for centuries and are of particular importance to the field of automated geographic information processing today. As layers or themes of geographic data are analyzed and combined, the reliability of the results must be defined in terms of a composite probability of individual a priori probabilities (MacDougall, 1975; Cook, 1983). A simple, but illustrative, example of overlaying a map of land use onto a map of land suitability, each with its own distinct surface of probabilities that the information is correct, produces a new map of combined information. The new map also has a surface of derived probabilities, different from either of its constituents. Although the user of "raw" information may be aware of its particular reliability, it is rarely the case that the "derived" probabilities are determined or reported, and thus users of composite data or results of analysis have little or no idea about the confidence they can place in their accuracy. In the field of geography, little attention has been paid to these problems; but as computer-assisted capabilities of handling and analysing spatial data continue to develop at a rapid rate, they must be considered.

2.2.7 Conditional Probabilities

The conceptual basis for combining probabilities exists in the field of statistics, and could be applied to geography and cartography. Bayesian statistics, developed in the 18th century, forms the basis for much of modern statistical analysis (Hartigan, 1983). It defines the behavior of conditional probabilities taking into consideration dependencies amongst events. Probabilities of independent events occurring simultaneously are usually calculated as the product of the individual probabilities. In other words, $P(A \cap B) = P(A) \cdot P(B)$. Applying this to an analytical map, one could conclude that following an overlay of land use data for which the probability of having a correct classification is 0.9, onto a map of land suitability with a corresponding probability of 0.8, the resultant map has a probability of 0.72 (i.e., 0.9 x 0.8) that both classifications are correct. The same map however, has a probability that either of the classifications is correct of

0.98, *i.e.*, $P(A \cup B) = P(A) + P(B) - P(A \cap B)$. The probability that either or both of the classifications is correct is 0.9954 - $P(A \cup B \cup (A \cap B)) = P(A \cup B) + P(A \cap B) - P((A \cup B) \cap (A \cap B))$. This of course is based on the assumption that the events, *i.e.*, occurrences of land use and land suitability classifications, are not mutually exclusive.

The problem of combining, or aggregating, subjective probabilities, however, is considerably more complex than that illustrated in the previous paragraph. It is relevant to most decision-making processes as decision-makers weigh information provided by others who might be considered experts (Brichacek, 1970; Kadane and Larkey, 1982). The uncertainty associated with this information may be of two types. First, experts may be providing information directly as a probability, for example, the weatherman predicts likelihoods of precipitation or freezing temperatures in terms of a probability, or percent chance (Murphy and Winkler, 1974a, 1974b; Winkler and Murphy, 1979). Similarly, forecasting the market performance of a new product can be described as probabilities for success. With this type of information, decision-makers are confronted with problems of how to update their own probability judgements on the basis of additional information provided by one or more experts.

The second type of uncertainty, which may be dealt with in terms of probabilities, is the confidence one has towards data. Probabilities can express how certain one is that the data are correct. This is often applied to statistical data and forms the basis for much inferential decision-making. It is also important in forecasting, as prediction data are weighted by a confidence factor represented in terms of a probability that the data are correct. This latter case is of primary concern to this study. Experts provide spatial data from their cognitive domain which are then weighted by a measure of confidence. The decision-maker not only has to contend with aggregating responses of individual experts, but also with compositing their individual confidence ratings.

Little can be found in the geographic literature regarding the treatment of such aggregations; however, the concept of subjective probabilities is not new. Curry (1966) employed "degrees of belief" as a framework for trying to explain the decisions made by man with respect to spatial problems. He was dealing specifically with meteorological situations and probabilities assigned to weather forecasts. For example, farmers commit themselves to a production program on assumptions that weather conditions, such a rainfall and frost, have an acceptable probability of being marginally favorable (Ibid., p. 135). Much of the interest in subjective probabilities has come from meteorological applications because of the concern for forecasting events (Winkler and Murphy, 1973a, 1976, 1979). Whenever a forecast, i.e., a decision about some future event, is made there is always some uncertainty about the truth value of the prediction. Confidence in the prediction can only be described as a degree of belief that the event(s) will occur.

2.2.8 Incorporating Information from Experts

Wallston and Budescu (1983, p. 157) suggested that "[t]he term 'expert' is flexible and in most cases refers to a person who has some degree of training, experience or knowledge significantly greater than that in the general population. Morris (1977, p. 679) offered a more general definition calling "anyone with special knowledge about an uncertain quantity or event" an expert. For some investigations into how experts encode their beliefs and how reliable their information is, it has been useful to divide the experts into two categories - substantive and normative (Staël von Holstein, 1970). Substantive experts are those who have a specialized knowledge in a given field and are able to assess events within their domain of expertise, for example, electrical engineers, meterologists, medical doctors. Normative experts, such as statisticians, economists, and decision analysts, are those with a knowledge about probability theory who are therefore able to structure their opinions in a coherent fashion, i.e., consistent with rules of probability. Beyond these rather qualitative definitions of expert, there is no rigorous approach to identifying measurable criteria for the determination of expertise.

A number of methods have been devised to elicit an individual's degree of belief in an event (Stäel von Holstein, 1970; Lieber, 1976). The simplest is to ask directly for a probability value, but individuals, with the possible exception of normative experts, do not formally think in terms of probabilities as numbers. Therefore, attempts have been made to infer probabilities on the basis of behavior. Wyer (1975) asked subjects to make direct judgements on a scale from 0 to 100. This is a rather direct measurement of the probability, but it provides subjects with a useful scale to which they can relate the strength of their belief. Similar tangible scales have been used, for example, Beach (1966) obtained subjective probabilities by having the participants slide markers along a metallic bar of fixed length. Other approaches include analyzing the results from a number of pair-wise comparisons, and inferring probabilities from the betting behavior of individuals (Tuersky, 1967: cited by Wallsten and Budescu, 1983). Considerable interest has been given to such approaches for encoding subjective probabilities and results of controlled experiments have not always been in agreement (Wallsten and Budescu, 1983). Frequently, encodings by different methods do not yield identical results. The literature also suggests that encoding approaches often produce results in violation of basic probability axioms (Phillips, et al., 1966). For example, a number of subjects given a set of mutually exclusive and exhaustive events may produce probabilities summing to greater or less than unity.

Much of the literature in this field concentrates on integrity of information obtained by encoding subjective probabilities (Lindley, 1983; Wallsten and Budescu, 1983). Two important considerations when dealing with subjective data are their reliability and validity. Reliability, in this sense, refers to encodings which are relatively free from random error and are repeatable and consistent. Validity is somewhat more difficult to evaluate as it measures how accurately encoding represents opinions of the person from whom they were elicited. A thorough and recent review of the literature dealing with reliability and validity aspects of subjective probability encodings can be found in Wallsten and Budescu (1983). They draw important comparisons in the similarities and differences between expert and non-expert groups. Although not conclusive, existing evidence indicates that (generally) subjective probability encoding techniques provide a moderately high degree of reliability or consistency with both expert and non-expert groups.

2.2.9 Calibrating Information Sources

The technique of calibrating individuals depends on the degree of reliability and validity of the encoding approach. Calibration is a process of accounting for systematic error in the expert's opinion. It can be considered as applying a transformation to data obtained from an expert to produce adjusted data which more closely fits reality. This might be done by observing the relationship between expected/predicted values and the observed/actual values of a number of events and determining a transformation model. A simple, but illustrative example described in Winkler (1981, p. 486) uses the case of a "bookie" from the Chicago Daily News who, over a 91 game professional football season, consistently underestimated point spreads by an average of 1.07 points. To calibrate the "bookie", one could simply add 1.07 points to his future predictions assuming that no other information concerning over or underestimation is available.

It was suggested from the literature that experts could be calibrated successfully, whereas non-experts do not calibrate accurately (Wallsten and Budescu, 1983). Non-experts, however, did show rapid but limited improvement in calibration with training and feedback. Also, experts were less accurately calibrated when dealing with less familiar events. There are several reasons why experts tend to be better calibrated than non-experts. Their training usually extends over a period of years rather than days or weeks as with non-experts. They gain extensive experience with specific events in question and with general factors that affect the events; in fact, some events might even be routine or repetitive for the expert.

A number of studies on subjective probabilities indicated that subjects tend to be "conservative" in their estimates (e.g., Phillips, et al., 1966). Conservative refers to the phenomenon that although the probabilities are related in a consistent manner to the expected ones, high probabilities are usually underestimated and low probabilities are over-estimated. This has been of particular interest for studies on how individuals revise their opinions on the basis of new information. There appears to be a bias towards original a priori probabilities or estimates indicating a conservative revision of their opinion. This is an important consideration when decision-makers aggregate or combine subjective probabilities to arrive at a composite value. It is also important to consider when using iterative feedback as a mechanism to reach a consensus. However, evidence for conservatism, as for many of the factors involved in subjective probabilities, is inconsistent and inconclusive. Phillips (1970, p. 259) pointed to evidence indicating that conservatism might not exist:

> "Conservatism is always found in bookbag-and-pokerchip experiments; for these tasks most subjects have had very little prior experience with the binomial data-generators. But in a task using normal data-generators DuCharme and Peterson (1968) found little conservation. Possibly subjects' considerable experience with the normal distributions of heights of men and women leads them to be too certain, and this just balances out the conservatism associated with revision in the light of the data".

Even a cursory overview of literature dealing with subjective probabilities in decision theory suggests that there are still a lot of questions and few conclusive answers. Some issues which have received little attention are those relating to the effect of social parameters, such as culture, social class, age, social roles, among others, on judgements of probabilities and revision of opinions. Phillips (1970) suggested the possible importance of some of these, citing, for example, the more prominent role that chance factors play in the future in some eastern cultures than they do in the west. These problems, although significant and requiring additional research, do not lessen the contribution to be made by subjective judgements measuring the likelihood of events.

2.2.10 Aggregating Probabilities

In recent years, a great deal of attention has been devoted to the problem of combining probabilities, much of it drawing on Bayesian theory. As with the handling of subjective probabilities, it is still too early to find a consistent and coherent treatment of the topic. However, there have been some useful approaches which provide insights to the problem and suggest partial solutions. Much of the interest in this field comes from management science and decision theory as they try to determine the effect of integrating the opinions of a number of experts on a decision. It has become common for companies and agencies to use experts (consultants, as well as internal specialists) to provide opinions and information for the decision-maker.

The problem of combining different advice, forecasts, or estimates from individuals is referred to as the "aggregation problem" (Bordley and Wolff, 1981). There are several distinct situations for which aggregation of opinions is important. First, there is the decision-maker who, as a single individual, wants to use information from others in the decision process. The simplest case involves only one opinion other than that of the decision-maker. He may then opt to revise his opinion on the basis of information provided by the expert. A less trivial case involves a group of experts for which a number of individual opinions must be combined in some manner. In the decision-making process, Morris (1977, p. 687) suggested that "[a] collection of experts should be treated exactly like one 'composite expert' whose prior represents all the relevant information of the entire set of expert priors". This information is likely to form only part of the total information going into the decision process as other data, e.g., historical information and empirical models, may also be considered. The problem then expands to aggregating information across various information sources (Winkler, 1981). In an earlier article, Morris (1974, p. 1235) described the consultation with experts as being conceptually similar to performing an experiment where observed data is a function rather than a number. It is described as a function because subjective information is really a probability distribution. Clearly, this type of situation is one where a decision-maker makes a choice as an individual taking into consideration information provided by other sources. This is in contrast to the group decision-making situation where the group as an entity decides.

The distinction between these two basic situations lies more in the process of soliciting information from experts than in the methods of handling its aggregation. Individual decision-making usually treats information from experts as being from independent sources (Collins and Guetzkow, 1970). However, group decision-making usually implies more interaction amongst experts.

There are several formal approaches to handling data from experts in a decision-making or information gathering problem (Morris, 1977). One approach to aggregation of expert probability assessments is by weighting schemes in which the decision-maker, or whoever evaluates the expert, combines the probabilities with subjective weights. This has the advantage of being simple and easy to apply, but at the same time it is often "ad hoc". A second approach to using expert information in decision-making is by calibration which applies a systematic adjustment to the expert's raw information in order to improve its correspondence with objective reality. A subject is asked to provide probability assignments on a number of variables. These are used to measure his assessment performance which then leads to a calibration rule to be applied to subsequent probability assignments. This is only useful when dealing with one expert because there is an apparent contradiction if two or more calibrated experts disagree. A third approach involves more interaction amongst the experts. It attempts to reach a group consensus on an uncertain quantity. The Delphi method is one of the best known and widely used techniques which would fall into this category. In order to reach a consensus, there must be an iterative feedback process so that individual experts can reevaluate their position and revise their opinions if warranted. Conceptually, Morris (Ibid.) has noted two problems with this approach, first, there is no general rule of what to do if there is no consensus, and second, there seems to be no rationale for why consensus should be the right answer.

A number of procedures have been proposed for the aggregation of experts' probability distributions (e.g., Winkler and Murphy, 1973b; Morris, 1977; Bordley, 1982). These range from simple averaging methods to more complex conditional probability calculations based on formal Bayesian theory. A very important consideration in most statistical treatments of the experts' probability assessments is the problem of "independence" amongst the individual assessments. Individuals are considered to be experts because of a specialized knowledge within a certain domain. This knowledge is generally acquired through training (Wallsten and Budescu, 1983). It is probable that in this training they have been exposed to the same information and to the same theories and models. Experts need not associate with each other to be dependent in the probabilistic sense (Morris, 1977). An example to demonstrate this is in weather forecasting. Several studies have shown that weather forecasters are quite accurate and well "calibrated" in predicting probabilities of precipitation and high and low daily temperatures (Murphy and Winkler, 1974; Winkler and Murphy, 1979; Peterson, et al., 1972). Their consistant forecasting is at least partly attributable to having available common climatological data on which to anchor their initial judgments. Also, they receive continuous, and often almost immediate, feedback. Since individual assessments are being made on the basis of common background information, i.e., current weather conditions, past weather patterns, and climatological models, they are highly dependent in a statistical sense.

Little attention has been paid to the problem of dependence in the consensus literature, although most studies acknowledge that it exists (Winkler, 1974, 1981). Morris (1977, p. 687) developed a Bayesian approach for combining expert judgments which dealt with issues of dependence but admitted that "it is not at all clear...[that the approach used] is the best structure within which to model dependence among a group of experts". More recently, Winkler (1981, p. 480) set out to "develop a consensus model which allows formally for dependence among experts while still being reasonably tractable...." His results showed that posterior distributions, taking into consideration the information from experts, may be quite sensitive to the degree of dependence. This is obviously an area requiring more attention as interest in analyzing the contribution of experts in the decision-making process increases.

Any approach to aggregating individual probability estimates should fit a general model which considers: individual estimates, dependence assumptions about these estimates, and qualifications of the individuals (experts) (Bordley and Wolff, 1981). In general terms, the aggregate probability that some event A will occur is $P(A) = f(p_1,\ldots,p_n)$ where f is some function of the individual estimates, p_i.

The simplest approach to deriving an aggregate measure is to select one individual estimate to reflect the information obtainable from the group. This might be the estimate which has a relative maximum value (i.e., $p_k \geq P_i$ for $i=1,\ldots,n$), as in a case where a decision-maker wants to be ultra conservative in his judgment. For example, if the event that it will rain tomorrow is highly critical on the successful outcome of another event, say the launching of a space craft, the decision-maker may wish to plan on the basis of the worst case scenario. Alternatively, some situations may call for the use of the minimum individual probability estimate (i.e., $p_k \leq P_i$ for $i=1,\ldots,n$). This approach, in comparison with the model described in the previous paragraph, considers all estimates in order to determine a maximum or minimum estimate. Dependency issues are not significant to the statistical manipulation, and all individuals are assessed equally in terms of their qualifications, (i.e., all of the individuals are equally qualified to have provided the relative minimum or maximum values).

The aggregate measure might also be represented simply as an arithmetic average, $P(A) = \sum p_i/n$. This has the advantage of reflecting each individual's estimate in the final assessment. Again, this assumes that each individual is equally qualified. A slight modification to this approach can produce a weighted average which recognizes that some individual estimates are more reliable than others. This may be done by having participants assign themselves a weighting value based on how confident they are in their probability estimate, or by the decision-maker assessing the qualifications of individuals and assigning each a subjective weight. This can be represented as $P(A) = \sum w_i p_i / \sum w_i$ (Ibid., p. 960).

Oller (1978) used a modified version of a weighted average approach to pool estimates. It partly bridges the gap between straight numerical averaging methods and those employing subjective probabilities and Bayesian theory to derive a joint forecast. Its attraction is that it "is very easy to apply and presumes no knowledge of statistical theory, but the probabilities which it uses will inevitably be rather approximate" (Ibid., p. 55). It requires that experts rate their own forecasts according to the confidence that they have in them. Each expert is given a "total influence" score based on his qualifications to respond to the forecasting problem, which he then has to distribute over all of his forecasts. Oller used, as an example to illustrate, a case of four economists who were asked to forecast growth rates in total production for three OECD countries. Each expert was given a "total influence" score of 6, except one of the economists, considered to be more experienced, who was given a score of 8, to distribute over their three estimates. This produced a pair of matrices, one of forecasts f_{ik}, and one of corresponding weights w_{ik}, i.e., Forecast Matrix: (f_{ik})

	E_1	E_2	E_3	E_4
C_1	1.0	1.0	1.0	1.0
C_2	6.0	4.5	5.5	4.0
C_3	3.5	2.0	4.0	4.0

and

Weight Matrix (w_{ik})

	E_1	E_2	E_3	E_4
C_1	3.0	1.5	2.0	1.0
C_2	2.0	2.0	2.0	2.0
C_3	1.0	2.5	4.0	3.0
t_i	6.0	6.0	8.0	6.0

where E_i represents economist i, i=1,...,4; C_k represents country k, k=1,...,3 and t_i represent "total influence" weight assigned to E_i, i=1,...,4.

The weight matrix was transformed into a probability matrix with a total sum of all elements (v_{ij}) equal to unity, i.e., $v_{ik}=w_{ik}/\sum t_i$

Probability Matrix: (v_{ik})

	E_1	E_2	E_3	E_4	P_i
C_1	0.1154	0.0577	0.0769	0.0385	0.2885
C_2	0.0769	0.0769	0.0769	0.0769	0.3076
C_3	0.0385	0.0962	0.1538	0.1154	0.4039

Total 1.0

One last transformation of this matrix produced what Oller called a conditional probability matrix with each element u_{ik} of the row represented as a proportion of the row total, <u>i.e.</u>, $u_{ik}=v_{ik}/p_i$

Conditional Probability Matrix: (u_{ik})

	E_1	E_2	E_3	E_4	Total
C_1	0.4	0.2	0.27	0.13	1.0
C_2	0.25	0.25	0.25	0.25	1.0
C_3	0.095	0.238	0.381	0.286	1.0

To pool the estimates into a combined forecast for, say, country 3 (C_3), the rule becomes

$$\sum u_{i3} \cdot f_{i3}$$

or, (0.095 x 3.5 + 0.238 x 2.0 + 0.381 x 4.0 + 0.286 x 4.0) = 3.48

By forcing the expert to distribute his "total influence" weight over all his forecasts, the approach is better able to distinguish differing degrees of confidence in individual forecasts.

Morris (1983) used a somewhat similar approach, however, he tackled the problem from a more mathematically rigorous stand. He proposed a set of axioms for combining expert probability assessments. Many non-Bayesian approaches to pooling expert opinions treat the problem of defining the "decision-maker's" role in the process rather loosely. His opinions, if indeed he is considered an expert, are handled in exactly the same way as those of the rest of the experts. Or, his opinion may be defined as the result of the pooling exercise and he becomes basically a non-active participant in the joint forecasting process. However, the Bayesian approach is to view experts' priors as information and to update the decision-maker's probabilities taking into consideration his own prior probabilities as well as those of the experts and, importantly, the relative expertise of each. Simply stated, the decision-maker's posterior probability is:

$$p^* = \sum_{i=0}^{N} w_i \, p_i$$

where p_0 and p_i are the decision-maker's and the ith expert's prior probabilities and w_0 and w_i are the relative expertise of the decision-maker and his experts; $\sum w_i = 1$ (Ibid., p. 29)

In an earlier paper, Morris (1977) described a set of assumptions for combining expert priors which resulted in a multiplicative rule. For example, he defined a composite prior for a pair of experts as $h(x)=k.f_1(x).f_2(x)$

where h is the composite prior of event x occurring, f_1 and f_2 are the individual priors of the experts, and k is a normalizing factor (Ibid., p. 682).

A limitation to the multiplicative rule described by Morris (1977, 1983) is that it should not be applied when experts are assigning probabilities to occurrences of discrete events such as the likelihood of it raining on a given day. He showed, for example, that if the decision-maker's prior (p) for an event was 0.55 and an expert's prior (q) was also 0.55, the revised probability (p*), by the multiplicative rule

$$p^* = \frac{pq}{pq+(1-p)(1-q)}$$

was 0.6. Such a conclusion is tempting if two individuals agree that the probability for an event (e.g., it will rain tomorrow) to occur is 0.55, it slightly increases the joint confidence in the event. But, if 10 experts held a 0.55 probability view, the joint probability by such a multiplicative rule would be greater than 0.9 which is "counter-intuitive, since learning that a large group of experts are quite uncertain... shouldn't make you confident that it will [occur]" (Morris, 1983, p. 25). After all, 0.55 indicates only a very slight confidence that an event will occur as opposed to it not occurring (i.e., slightly better than a 50-50 chance). If in fact, both individuals are equally ignorant of the event occurring (p=p'; q=q'; p=q') the decision-maker should not change his beliefs. French (1980, p. 47) amusingly summarized the theory as "Bayesian fools are not so stupid as to listen to each other".

Not all, however, agree that there exists any mathematical formula for aggregating individual probability assessments which is consistent with the rules of probability. Dalkey (1972), for example, developed what has become known as an Impossibility Theorem which attempted to prove that no such formula exists. The Impossibility Theorem and the existence of Bayesian models seem to be contradictory. Bordley and Wolff (1981) examined this contradiction in terms of the underlying assumptions in Dalkey's approach and concluded that one of his assumptions is unreasonably restrictive. They therefore rejected the notion that individual probabilities cannot be mathematically aggregated in accordance with the rules of probability.

An examination of many of the ideas, concepts, and contentious issues regarding aggregating individual probability assessments shows that there are still differing views and approaches to the subject. There does not exist a uniform, coherent theory as yet, but this does not imply that there is no validity to the approach nor that it should not be applied.

2.3 The Delphi Approach

One method which has received considerable attention and has been widely applied is what is now commonly referred to as the Delphi method. Although it appears in a variety of forms, one of its basic tenets which runs consistently throughout is the reliance on information obtained from a group of "experts" and the formation of consensus through structured feedback.

2.3.1 Delphi's Early Development

Delphi developed from some early work done for the American military, although Adams (1980, p. 51) reported that the first known use of the Delphi process was in 1948 to "predict the results of horse races". In the early 1950s the Air Force sponsored a Rand Corporation study under the code name "Project Delphi" which was concerned with using expert opinion to forecast strategic information. Its objective was to "obtain the most reliable consensus of opinion of a group of experts...by a series of intensive questionnaires interspersed with controlled opinion feedback" (Dalkey and Helmer, 1963, p. 458). The subject of this pioneering study was strategic locations of U.S. industrial targets as seen from the viewpoint of a Soviet military planner. The alternative would have been a lengthy and costly data collection activity for which processing and analysis by computer would have been a major undertaking considering the state of computer development at that time. As Linstone and Turoff (1975, p. 10) pointed out,

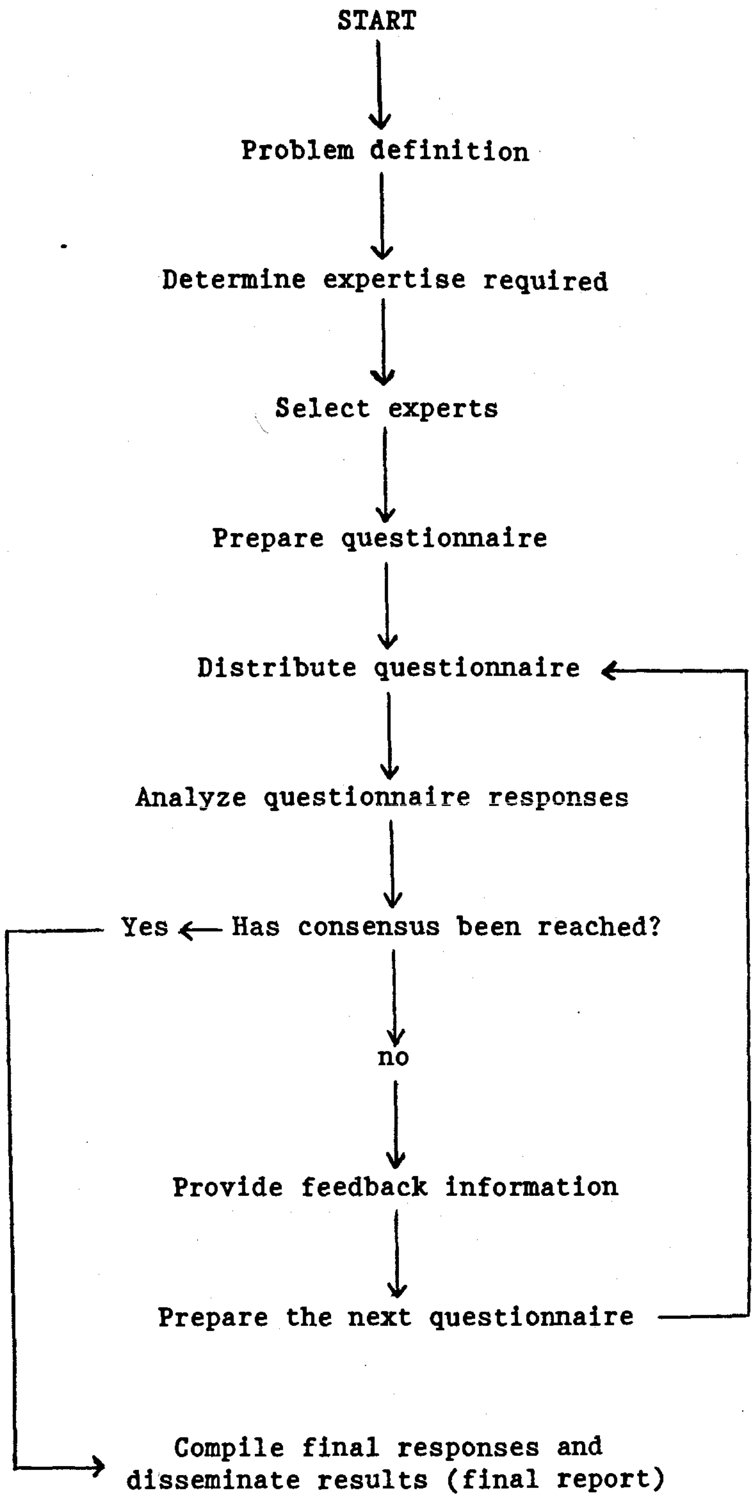
> "[e]ven if...[an] alternative approach had been taken, a great many subjective estimates on Soviet intelligence and policies would still have dominated the results of the model. Therefore, the original justifications for this first Delphi study are still valid for many Delphi applications today, when accurate information is unavailable or expensive to obtain, or evaluation models require subjective inputs to the point where they become the dominating parameters".

Because of the sensitive nature of this first serious application, it was over a decade before the approach received much exposure beyond the military. In 1964, Gordon and Helmer published a milestone report in the Rand paper series on using Delphi for long-range forecasting which attracted a great deal of attention. Their study concentrated on forecasting significant events in six different fields - scientific discoveries, population control, automation technology, space exploration, war prevention, and weapon systems. Shortly, thereafter, numerous articles began to appear in the literature reporting on applications of the method in a wide range of fields (e.g., Gunther and Vallery, 1971; Bawander, 1976; Kennington, 1977; Singg and Webb, 1979), from regional and urban planning (e.g., Schneider, 1972; Gordon and MacReynolds, 1974) to predicting educational requirements in academic and technical training institutions (e.g., Berghofer, 1970). Several journals were the primary conduit for reporting Delphi applications in the early years, primarily, the newly formed Technological Forecasting and Social Change, FUTURES, Long Range Planning, and Management Science.

It wasn't until the 1970s that Delphi began to make an impact. Linstone and Turoff (1975, p. 591) reported that prior to 1970 there were only 134 references in the literature to Delphi studies, of which a very large number were to be found in the Rand papers. As interest increased in technological forecasting, a parallel increase in Delphi applications occurred. The method spread from the U.S. to Canada (e.g., Bell-Canada's Business Planning Group -- Goodwill, 1971)), to Europe, and the Far East (Linstone and Turoff, 1975, p. 11). The use of Delphi saw dramatic increases in the 1970s and with its increased use, a number of modifications, changes, and spinoffs developed (e.g., Turoff, 1970; Rauch, 1979).

2.3.2 Conventional Delphi

Regardless of their form, Delphi studies fall generally into one of two categories, which for the convenience of taxonomy, have been labelled in the literature as "conventional or classical Delphi" and "Policy Delphi" (Turoff, 1970, 1975; Linstone and Turoff, 1975). Conventional Delphi is the term applied to those studies which use a panel of experts to gather information about an unknown or uncertain event through an iterative administration of a questionnaire to each panel member. Frequently, the questionnaire is administered through the mail. Responses to the questionnaire are summarized and analyzed, then panelists receive structured feedback regarding their individual responses and how they compare with the group's averages or summaries. Panelists are again asked to update their beliefs or opinions and the process of summarizing, analyzing, and structuring a feedback goes through another iteration. Each of these iterations is called a round. A significant characteristic of conventional Delphi is the conscious effort to maintain anonymity amongst panel members. Anonymity is seen to be important to avoid the "bandwagon" effect and to reduce possible impacts of socially or politically dominant individuals in the group. The aim of most conventional Delphi studies is to reach a consensus amongst experts which is expressed as measures of central tendency and dispersion. A consensus is defined within the context of individual studies; i.e., identifying the level of dispersion about a central measure which can be tolerated in a consensus. Through the iterative response-feedback-response process, individual assessments of events are expected to migrate toward a central value as opinions are updated in a Bayesian fashion with new information (Sahal and Yee, 1975). Normally, the iterative process stops when there is no more significant movement of opinions or when the dispersion falls within an acceptable range. Riggs (1983, p. 90) diagramed the typical Delphi process as:


START
Problem definition
Determine expertise required
Select experts
Prepare questionnaire
Distribute questionnaire
Analyze questionnaire responses
Yes
Has consensus been reached?
no
Provide feedback information
Prepare the next questionnaire
Compile final responses and
disseminate results (final report)

2.3.3 Policy Delphi

The second major type of Delphi application, Policy Delphi, was first described by Turoff in 1970. Its objectives are often different from those of conventional Delphi in that it is not intended to forecast or predict objective data, but rather to analyze issues, many of which are often value laden. Rauch (1979) suggested that conventional Delphi is more useful in natural science and engineering applications while Policy Delphi is more suitable in the social sciences. Turoff (1975, p. 84) described the foundations of Policy Delphi as:

> "It represented a significant departure from the understanding and application of the Delphi technique...Delphi as it originally was introduced and practiced tended to deal with technical topics and seek a consensus among homogeneous groups of experts. The Policy Delphi on the other hand, seeks to generate the strongest possible opposing views on the potential resolutions of a major policy issue. ...[A] policy issue is one for which there are no experts, only informed advocates and referees. An expert or analyst may contribute a quantifiable or analytical estimation of some effect resulting from a particular resolution of a policy issue, but it is unlikely that a clear-cut...resolution of a policy issue will result from such an analysis.... The Policy Delphi also rests on the premise that the decision-maker is not interested in having a group generate his decision; but rather, have an informed group present all the options and supporting evidence for his consideration. The Policy Delphi is therefore a tool for the analysis of policy issues and not a mechanism for making a decision. Generating a consensus is not the prime objective, and the structure of the communication process as well as the choice of the respondent group may be such as to make consensus on a particular resolution very unlikely. In fact, in some cases the sponsor may even request a design which inhibits consensus formulation."

Policy Delphis are not meant to replace or usurp the roles of committees in the decision-making process, but rather to function as their precursors. They are used to gather information and to identify important issues which can then be dealt with by more conventional methods. They ensure that all possible options have been raised for consideration and that impacts and consequences of each option are identified and weighed. The decision-maker can also use the tool to evaluate the acceptability of various options or courses of action (Ibid.).

Although objectives and reasons for using a Policy Delphi differ from those for using a conventional Delphi, the steps are basically similar. They both rely on soliciting information from individuals participating in a response group, and they both provide structured feedback to individuals through several iterations of the information gathering process.

2.3.4 Decision Delphi

A more recent variant of the process, which is different enough to warrant special consideration, was developed in Austria by Rauch (1979). The process, called "Decision Delphi", uses the general Delphi approach to prepare decisions and to influence social developments. The composition of the panel differs from that of either conventional Delphi or Policy Delphi. With these, panelists are experts and "lobbyists" respectively, but in a Decision Delphi, panelists are decision-makers and are recruited only with regard to their actual position in the decision-making structure. The process is not so concerned with whether or not they understand a particular situation or how accurately they can describe and predict it, but with the determination of a course of action. It is a mechanism for structuring communication and feedback from a group of decision-makers to arrive at a decision. "In a decision Delphi reality is not predicted or described; it is made" (Ibid., p. 163).

Panelists explore broad ranges of ideas and evaluate various alternatives. Delphi feedback provides additional information for consideration as the decision-makers update their positions. The emphasis on anonymity which characterizes many Delphis, especially those of the conventional mold, is relaxed intentionally. Panelists are identified so that each participant knows who else will be contributing in the process. Responses to the questionnaires, however, remain anonymous. A distinct advantage of this quasi-anonymity is that panelists are more likely to take interest and actively participate in each round. Rauch found that the prestige of some of the panelists was a motivation for other members to take a more keen interest in the process, while others took an active role because they feared that the views of their "antagonists" may have an undesirable influence on the final outcome.

Motivation of panelists in a Decision Delphi is somewhat more complicated than in classical or policy Delphis. Because they are "well-placed" in a decision-making hierarchy, they are less apt to be enticed by a monetary reward, or if so, rewards may have to be so excessive as to make the cost of the exercise prohibitive. Also, such panelists usually have tight limitations on their time and are accustomed to delegating letter-answering, fact-finding, and committee-sitting to trusted subordinates. The director of the study must rely on other enticements to involve individuals. Some of these enticements as already mentioned, include subtly impressing them with the prestige of other panelists and even the reputation of the institution or agency carrying out the Delphi. Public relations activities, such as personal contact, "arm-twisting", and playing on each individual's sense of professionalism have proved to be effective motivators.

2.3.5 Other Delphi Spin-offs

Other variants to the Delphi approach abound in the literature on decision theory, forecasting, and futures research (see, for example, Nelms and Porter, 1985). In fact, Delphi has come to connote rather loosely all those approaches which employ panels of experts, knowledgeable individuals, and decision-makers, and are characterized by an iterative feedback component. Such a generalization is for convenience only; often the methodological underpinnings of these approaches do not adhere strictly to the doctrines of Delphi. Jillson (1975), concerned about the proliferation of studies "masquerading as Delphi", suggested that guidelines should be established to prevent the "denigration" of the method and to ensure high standards in its utilization.

A Delphi-type approach developed by Press et al. (1979) concentrated on qualitative information rather than quantitative as is frequently the application for a conventional Delphi. The approach, called "Qualitative Controlled Feedback" (QCF), was developed "to help policy makers order priorities by assessing reasoned individual judgments after the individuals have benefited from group interactions" (Ibid.). It stressed anonymity of participants and, similar to Delphi, avoided face-to-face interaction amongst group members to counteract the effects of peer intimidation and bandwagoning. However, it did not require members of the group to reach a consensus. No quantitative measures were fed back to the group. Individuals were asked to provide justifications for their responses; these were aggregated and the composite reason was fed back to the individuals. The approach was first tested in a study of community attitudes towards the construction of an indoor aquatic centre at the University of British Columbia. It was found that judgments provided by participants in a QCF group were quite different from those of a control group which was established as a reference (Ibid.).

Delphi-type methods have also been applied to problems with a major spatial component. Farkas and Wheeler (1980) demonstrated the use of a Delphi technique as a method to forecast land use change in the Appalachian region of Georgia. The study selected thirty five counties. The panelists were drawn from knowledgeable residents from banking, planning, real estate, and government occupations. The questionnaire contained two major questions for each county - "by what percentage will population and employment grow between 1970 and 1985, and what specific areas would be the locations of future residential, commercial, and manufacturing growth to 1985..." (Ibid., p. 221). These same questions were repeated during each of the three iterations that it required to reach a "consensus". A particularly interesting facet of this study was the approach used to measure the reliability of each response. Each panelist was asked to indicate on a self-rating scale the amount of confidence he or she had in the response given to a particular question. If a panelist indicated no confidence in his/her response, the answer was not included in the statistical summary which was prepared at the end of each round. The study also found that, consistent with a Bayesian approach, the levels of confidence generally increased as individual opinions were updated on the basis of additional information provided by the round summaries. A common, yet significant, problem faced by this study, as with many such experiments, was the loss of participant interest after the initial round. In any Delphi application, this problem must be anticipated and appropriate measures taken to minimize its affect. Panelists, who are not well acquainted with the significance of the Delphi iterations, may not see the need or reason for answering the same questions over and over. It is here that skillful use of public relation techniques, monetary compensation, among other incentives have to be considered to maintain and encourage panel participation.

A number of spatially oriented studies have used Delphi approaches. Irvin (1977, p. 58) used the technique to predict the "spatial pattern and mix of future industrial land uses" in eastern Tennessee. Dames and Moore (Halpern, et al., 1975) had a Delphi component in an environmental analysis project conducted in the DelMarVa area (Delaware, Maryland, and Virginia). Environment Systems Research Institute (ESRI) has used Delphi type approaches in urban planning and environmental impact applications (Dangermond, 1984, personal communication). The usual procedure is to have a panel respond with quantitative answers or evaluations of different scenarios which have been presented to the panelists in map form. Information is taken from each of these rounds, and the study team updates the statistical summaries and prepares new graphic representations (i.e., maps) before going through the next iteration. It is important to note that panelists do not respond with graphic answers, but graphics are part of the questionnaires requiring evaluations or judgements.

2.3.6 Delphi Critiques

A considerable amount of attention has been devoted to the philosophical under-pinnings of the Delphi method. It has come under criticism (see, for example, Sackman, 1974), but in spite of its critics, it has seen rapid growth, especially in the mid and late 1970s. Although some studies have had as their primary objective an examination of the basic foundations of the approach (e.g., Welty, 1972), most evaluations of the technique have been a secondary consequence of a specific application (Dajani, et al., 1979; Brockhaus and Mickelsen, 1977; Hill and Fowles, 1975).

Sackman's criticism went so far as to suggest that the technique should not be used "until its principles, methods, and fundamental applications can be experimentally established as scientifically tenable". He used as a basis for his evaluation the Standards for Educational and Psychological Tests and Manuals of the American Psychological Association which deal with sampling, experiment controls, criteria validity, and measurement reliability. This review will not explore in detail all of his concerns or criticisms; however, it will focus on some of the major issues. The criteria of anonymity amongst respondents in a Conventional Delphi was of particular concern. While attempting to minimise the "bandwagon effect" and authority relations which often appear in normal committee discussions, anonymity tends to confound the problem of differences of interpretation amongst participants. Often these differences can only be revealed by direct discussions and argumentation. He also pointed out that experts may be using different sets of premises and assumptions on which to base their responses. Without a mechanism for identifying these differences, averaging individual responses might be meaningless. Even the anti "bandwagoning effect", hoped for by anonymity, was questioned in light of experiments which showed that opinions could be altered simply by the way information was presented. Sherif (1936), for example, demonstrated that he could alter the estimates of experts concerning current size of the Communist Party of the U.S.A. by approximately ten times by altering the presentation of data concerning its previous size. What is the real significance of this to Delphi? Suppose individuals of a Delphi panel respond to a question, but have different interpretations of it during the first round. Responses are likely to be quite different, and averaging these will produce a misleading measure of central tendency. Based on the summary presentation, a strong likelihood exists that subsequent rounds will tend to gravitate in the direction of the previous average. Thus, a biased consensus may be reached, but it would be misleading because of problems which were inherent in the process. The consensus is not authentic, for, as Sackman wrote,

> "[a]uthentic consensus refers to group agreement reached as a result of mutual education through increased information and adversary process, which leads to improved understanding and insight into the issues; it does not refer to changes of opinion associated primarily or exclusively with bandwagon statistical feedback" (Sackman, 1974, p. 45).

Martino (1972) found an additional problem with assuming that the iterative process would produce an authentic consensus. Although a proponent of the technique, he conceded that evidence existed from a number of studies indicating that if panelists were not really interested in responding to the questionnaires, or if they felt that they had insufficient time to give adequate thought to the problems, "they will agree with the majority simply to avoid having to explain the difference" (Ibid., p. 62). When this occurs, the "bandwagon effect" is actually facilitated rather than reduced as is suggested by the method. Consensus may be reached in the interest of harmony rather than in the interest of accuracy.

Sackman, in his critique, did not dismiss the value of iterative feedback if conducted properly. He proposed it as an "heuristic exercise" (Sackman, 1974, p. 71) to be used within groups of committees to gain a better understanding of the areas of agreement and disagreement. His concerns were more with the idea of achieving authentic consensus and with negative impacts on problem solving by maintaining anonymity amongst participants, than with iterative feedback characteristics of the approach. He summarized his position as

> "it would be highly advisable to mix iterative polling with varying forms of quantitative and qualitative feedback, person confrontation where feasible, cultivated development of adversary positions as opposed to consensus, and controlled variations in the types and level of anonymity" (Ibid.).

Jillson (1975, p. 222) concerned that skeptics were too eager to jump on the bandwagon of critics following Sackman's paper, argued that we cannot assume "that the technique is worthless because there have been poorly developed applications of the technique". She asked in comparison "[w]ould one rescind the process of democratic elections after it had been learned that an inadequate public official had been elected?" Delphi's name has been somewhat tarnished by inappropriate uses of the method. Jillson amusingly described some less prudent Delphi applications:

> "The bureaucrat who is in a tenuous position, and is looking for a catching idea to sell to the Division Director: ergo Delphi.
> The consultant who doesn't know how to do the job required, and doesn't know a Delphi from an overhead rate, but thinks it might serve as a smokescreen: ergo Delphi.
> The graduate student who worries that his thesis proposal seems a bit dull, and believes that there is no dissertation like a spiffy dissertation: ergo Delphi." (Ibid., p. 221).

Many reviews of the method have raised similar concerns and criticisms. Shortly following Sackman's milestone review, Hill and Fowles (1975) examined the approach in terms of general issues of reliability and validity. Their article is an excellent discussion of specific failings common to many Delphi applications. Many of the "failings", however, are not specific to Delphi, but apply to a number of scientific research methods. For example, Delphi, like many information seeking approaches, depends upon formal questionnaires to elicit responses from subjects in the study. Reliability of results can be seriously affected by a poorly designed or executed questionnaire. Another common problem mentioned is that of selecting study participants. Although presumptions are made that a sample of respondents can be selected which have certain qualifications in relation to the area of study, selection processes are often less than rigorous. In the case of Delphi, how does one define "expertness" and select individual experts? Hill and Fowles (1975, p. 180) described how groups may be typically created from "respondents who are readily available (associates of the research group conducting the experiment, ... professional associates of the principal researcher, ... other respondents whose reputation is informally known ..., or those who meet some minimal formal criteria of involvement ... such as membership in relevant professional associations". This too is typical of other types of experiments. Consider the large number of studies conducted in academic environments where researchers select their study sample of respondents from their undergraduate and graduate classes of students.

Hill and Fowles (1975, p. 185) concluded cautiously from their review of previous studies and experimental design that Delphi results are of questionable accuracy and doubtful utility, and as a forecasting method it is "inherently wanting". They did not take their argument to the extreme that Sackman did by advocating rejection of the technique, rather they recognized Delphi's many strengths and suggested salvaging the positive aspects. They also recommended modifications to avoid some of the pitfalls. In this vein they suggested that Delphi's restrictive iterative procedures be relaxed to accommodate informally guided sessions that permit face-to-face interactions. This type of structured communication helps ensure that all ideas, reasons, and arguments are fully discussed and explored. This makes better use of panelists as it unbridles their expertise and allows more divergent thinking than is possible within the confines of a questionnaire format where anonymity is stressed.

A different approach to assessing Delphi's success was used by Brockhaus and Mickelsen (1977) in a major study of Delphi applications. The geographic breadth of applications was international in scope, spanning ten countries. Approximately 800 individuals, who were in some way directly involved with a prior Delphi application, were questioned regarding how Delphis have been used, what degrees of success have been attained, how Delphi should be used in conjunction with other techniques, and their assessment of how significant a development the Delphi method has been. The study indicated how successful Delphi is perceived to be on the basis of "user satisfaction". Contrary to what other critical reviews found, this study found that "[b]y far, the Delphi method has proven to be most successful when used for forecasting and planning purposes" (Ibid., p. 106). Nearly all respondents indicated a belief that Delphi consensuses had improved the state of information for which the study was conducted -- 70% felt that improvement was considerable. There is also general agreement amongst prior Delphi associates that Delphi should be used in conjunction with other formal methods of information analysis. Interestingly, although there is agreement that Delphi should not be used in isolation from other methods, the investigation found that one-third of the studies did not, in fact, use any other method in conjunction.

A more recent evaluation used a controlled experiment to compare the accuracy of Delphi with the "conference method" in making long range forecasts (Riggs, 1983). Using analysis-of-variance to test significance in the differences produced by the two techniques, Riggs found evidence to support the contention that Delphi is superior to the "conference method" for long-range forecasting in both high and low information environments.

These are a few of the numerous evaluations of the technique (see also Wagner and Ortolano, 1975; Francis, 1977; Lee, 1977; Ortolano and Wagner, 1977); however, the definitive evaluation, of Delphi's accuracy, validity, and reliability, is yet to be written. The utility of the technique is still controversial with proponents claiming success on the basis of successful applications and opponents leveling criticism at weaknesses in methodological underpinnings. In any event, there is little argument that the approach has found a broad acceptance, especially in the public sector as a multipurpose tool used by government planners and policy makers. Many applications have tailored the approach to their particular situation by making appropriate modifications which have by and large, proved satisfactory to the study designers (Preble, 1983).

CHAPTER 3:

THE DEVELOPMENT OF A SPATIAL DATA HANDLING METHOD FOR DATA-POOR ENVIRONMENTS

Many decision-making situations lack appropriate information, or have information of a subjective or uncertain nature. Within the context of this study, these are referred to as data-poor environments. These are typical of forecasting and prediction problems, where the result of complex interactions amongst many variables cannot be defined. Forecasting has become a recent focus of interest, especially in areas of technology development as countries strive for economic and military superiority. Not only is the future uncertain, but the present is also often undefinable because requisite data are unavailable or unattainable. For example, detailed resource information about a region may not be available without an extensive survey. Similarly, defining urban areas on the basis of "quality of life" requires data which are unattainable other than as subjective opinions (Dalkey, 1975). Although these problems are universal, they are particularly relevant in developing countries where information, especially that related to spatial, or geographic, phenomena is often scarce.

Addressing some of these problems, an idea for a spatial application of a Delphi method grew from a discussion in 1975 between Professor T.K. Poiker and Mr. Alejandro Villanueva about a study on planning activities in Caracas (Poiker, personnal communication). A short, informal discussion paper (Peucker, 1975) was prepared which outlined several issues relating to the spatial extension of Delphi. Because this approach is significantly different from the classic Delphi technique, it has been given a new name - Strabo, after the early Greek geographer. The name suggests an analogy between this technique, with its geographic application, and the Delphi method so named for the soothsaying ability of the oracle from that ancient city.

Some preliminary work was carried out at Simon Fraser University resulting in a first definition of the technique and a simple computer program to combine maps (Edelson, et al., 1979; Luscombe and Peucker, 1979). The potential of the technique was identified (Luscombe, 1979; Luscombe and Peucker, 1983), and development of the spatial Delphi became the focus for this Ph.D. dissertation. Some fundamental questions which required in-depth examination were outlined by Luscombe (1979), however, no conceptual framework for the method had yet been developed. The purpose of this study was to develop the conceptual framework for Strabo as a spatial data handling method and to demonstrate its utility in environments where data are lacking, subjective, or uncertain in nature.

3.1 Spatial Data Handling

"The problem of measurement and scaling is the most fundamental one faced by geography and other factual sciences" (Abler, et al., 1971, p. 93). Measurement is a process of using an unambiguous rule to assign a value to something; however, these rules can be defined in different ways (Stevens, 1946). For example, the population of a city can be measured by a rule of simple counting, or by a rule of assigning a rank value according to its relative size with other cities.

As there are different rules which apply to the measurement of phenomena, so too are there different ways of applying these rules. For example, measuring distance between two locations can be accomplished by various methods -- by actually traversing the space between them and recording the number of defined units (_e.g._, footsteps, rotations of a wheel, or elapsed time on a clock); by using land surveying technologies to derive distances from measured angles; or by computing the distance from a photograph or map of known scale. The method of applying the rules of measurement is often determined by requirements for accuracy, time available to do the measuring, the relative costs of various methods, and simplicity of the approach.

Once measured, characteristics of a spatial phenomenon can be processed in a number of ways. They can be used as simple numbers in a decision-making model (_e.g._, if rent is more than a specified amount, the area is not a candidate for a commercial establishment), or in association with other measurements of the variable to develop spatial models of statistical surfaces (such as digital elevation models, central place models, and temporal diffusion models). The processing function may only involve submitting the information to the brain for an immediate mental decision, _e.g._, a perceived bend in the road triggers a mental decision on the part of a traveller to take corrective action. Or, it may involve complex computer analysis and manipulation of the information to develop the intrinsic relationships between and within the variables (for example, regression analysis (Taylor, 1977)).

This suggests a generalized information processing paradigm:

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measurement/------> processing------> response/
  scaling                             decision
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Within this paradigm, "spatial data handling" encompasses the activities associated with the first two functions -- measurement and processing. In this framework, Strabo is developed as a set of procedures designed specifically to measure spatial phenomena and to process spatial data in a decision-making context. The rules which Strabo uses for assigning values to spatially organized variables are defined at the outset of an application. For example, income areas may be measured by the rule of "high", "middle", or "low" (an ordinal scale), and land use may be assigned to categories according to the rule of "agricultural", "urban", "industrial", "recreational", and "barren" (a nominal scale). Strabo is distinguished from most other data handling techniques by the way the "rules" are applied, i.e., how the data are measured and processed. Data are gathered, not from direct observation of a phenomenon, but from cognitive stores of knowledgeable experts. Experts represent their beliefs about spatial distributions by applying rules for classifying variables and drawing data on a map. These data are processed by aggregating them into composite "values" and through iterative feedback-response procedures, the composite values tend towards a consensus of opinion about the spatial nature of the variable. This makes Strabo particularly suited for handling data which are normally difficult to gather using more traditional methods and for dealing with subjective spatial information. It provides an alternative procedure to work in data-poor environments by facilitating spatial data measurement and data processing.

3.2 Developing The STRABO Technique

Techniques and methods are well developed for collecting, and processing easily attainable spatial data. Sophisticated technology such as satellite sensors and high altitude aerial cameras, are able to sense detailed information from great distances (Lillesand and Kiefer, 1979; Simonett, 1983). Modern computers are able to store, retrieve, and process vast amounts of data quickly (Boyle, 1980), and intelligent software packages can perform complex spatial analysis on maps and other geographic data which have been transformed into digital form (Marble, 1980 Monmonier, 1982; Carter, 1984). But, when there is a lack of available or easily attainable data, methods based around these high technology data collectors and processors have few solutions to offer.

The Strabo approach proposes that human cognition is a reliable source of spatial information. The problem is to measure the information and its degree of reliability. In developing such an approach, a number of issues are raised - who are the individuals to be used as sources of data; what kinds of data can be measured; and how can the data be collected; among others.

3.2.1 The Strabo Data Sources

If spatial information is to be derived from cognitive sources, the process used requires a broad information base. An initial consideration would be to use information from a single source; this would be appropriate if the individual had complete knowledge of issues at hand and if the issues were objective in nature. For example, the landscape architect who has designed a park would be most knowledgeable about the spatial layout of its facilities. However, a single individual seldom has all the information necessary to describe a problem accurately, especially if the problem involves subjective issues. Common decision making practices try to expand the knowledge base by involving more than one individual (Collins and Guetzkow, 1970; Allison, 1971; Fincher, 1976), as found in such devices as meetings, committees, panels, "think tanks", groups, and boards.

The development of Strabo as a spatially-oriented group communication method draws heavily on Delphic research and its underlying concepts. A central principle of Delphi is to have panels composed of "experts" -- a concept difficult to define. Most Delphi applications make general assumptions about the expertise of their participants, but as Hill and Fowles (1975, p. 80) noted "no reported Delphi has directly addressed this issue". Panel selection techniques usually place heavy reliance on subjective definitions of the universe of experts, and extending that, subjectively assess which individuals are experts (Adelman and Mumpower, 1979). This has a tendency to bias the selection because of the likelihood of forming a panel that is not completely representative of the universe of people who are experts in the matter of study. This can restrict the breadth of divergent thinking about an issue and prevent a panel from considering all aspects as it attempts to reach consensus. For example, a panel of experts comprising only professional economists is apt to view the impacts of an urban commercial development project from a different stand point than one containing sociologists or civic leaders.

Attempting to understand the meaning of expert is not new. The question "what is an expert?" was asked nearly two and a half millenia ago of Socrates. This was a fundamental problem for him given his insistence on knowledge in the Socratic argument (Santas, 1971). In an investigation of the meaning of "courage", he defined an expert as a man who has knowledge of the matter at hand; however, he then ran into difficulty with the problem of how to determine whether or not one has knowledge. Like other of his investigations, he could not accept examples of a phenomenon as its definition. Examples of courageous acts do not define courage; examples of pious acts do not define piety; and examples of expert actions do not define the meaning of expert.

Wallston and Budescu (1983, p. 157) have suggested a practical, operational definition of "expert" which serves Delphi well and can be equally applied to Strabo -- "a person who has some degree of training, experience or knowledge significantly greater than that in the general population". However, someone who might be judged "expert" with regard to one set of circumstances may not be an expert with regard to others. Linstone (1975, p. 581) warns that "illusory expertise" can be a pitfall to the process, and reminds that "...a group of experts, each knowledgeable about one aspect of a complex system, does not necessarily comprise expertise about the total system." The question of whether or not it is necessary to use experts at all must be asked. Some authors have suggested that there is little to distinguish between predictions of experts and non-experts (Sackman, 1974, p. 40). Others, however, report evidence that the more expert the panelists, the better the predictions (Dalkey, et al., 1970). Comparing specifically performances of experts and non-experts (or novices), Larkin, et al., (1980) explored why experts are able to solve complex problems faster and more accurately than novices can. They examined a number of components of the expert's skill including perpetual knowledge, recognition capabilities, and the way in which information is represented in long-term memory. They concluded that:

> "...considerable knowledge [is] an essential prerequisite to expert skill. The expert is not merely an unindexed compendium of facts, however. Instead, large numbers of patterns serve as an index to guide the expert in a fraction of a second to relevant parts of the knowledge store. This knowledge includes sets of rich schemata that can guide a problem's interpretation and solution and add crucial pieces of information. This capacity to use pattern-indexed schemata is probably a large part of what we call physical intuition" (Ibid., p. 1342).

Although previous studies are not in complete agreement about the relationship between expertise and Delphi performance, it can be argued that experts (i.e., those with special knowledge of an area) should be used in Strabo panels because of the proposed face-to-face communication which occurs between rounds. The purpose of interround feedback, in the form of response summaries and discussions of individual positions, is to provide new and additional information to the decision-making process. The quality of the information which would be added to the process at these stages would be better if it came from someone who knows about what he speaks (expert) rather than from a novice or non-expert who could offer only uninformed speculation.

In the context of futures research and subjective probability studies, several approaches have been developed for identifying suitable participants for group communication activities. The positional approach identifies individuals on the basis of their official position in social, economic, political, or intellectual structures of a community (Nix, 1969). For example, participants might include mayors, company executive officers, senior scientists, and police chiefs. A second approach is based on the reputation of individuals. It identifies those persons in a community reputed to be most influential or knowledgeable about issues at hand (see, for example, D'Antonio and Erickson, 1962; Sanders, 1966). This usually involves creating a long list of potential participants and then having them ranked according to their perceived degree of "informedness" about particular issues. In this way, it is possible to identify those who are perceived by others to be most qualified to answer questions and discuss problems knowledgeably.

Farkas and Wheeler (1980) used a primarily positional approach to select a panel to forecast land use in several counties of Georgia. Area planning and development commissions were asked to identify several prospective panelists from occupations normally familiar with land development issues, e.g., bankers, planners, real estate developers, and government officials. On the basis of additional background information about each potential participant, the study coordinators, in collaboration with the planning and development commissions, narrowed the selection to a final panel. In a study of how Policy Delphi could be used effectively in public involvement programs, particularly water resource planning, Baumann, et al., (1982) demonstrated how a panel of respondents could be selected using a combination of the two approaches. First, they prepared a list of informants based on their position in the community. In subsequent personal interviews, informants were asked to identify individuals that they thought were most informed and knowledgeable about specific issues. Based on several criteria, one of which was reputation (i.e., how often an individual was mentioned by the informants), a final panel of respondents was selected. Thus, the process derived a first list of informants based on position who then identified potential panel members based on reputations.

Within the broadest definition of community, these approaches have considerable merit for identifying knowledgeable panelists. As Sanders (1966, p. 398) indicated, "those with a community orientation are more apt to be integral parts of the informal patterns of communication that transmit information about local affairs". A person's exposure to information within a community is often related to his position in the formal and informal social, economic and political structures which develop (Blair, 1960). Therefore, selecting a panelist on the basis of his position or reputation within a community, be it at a local level or at an international level, is a good technique for at least the "first cut" at panel formation.

Panel size is another important consideration. Very small panels (e.g., 2-3 members) greatly reduce the effectiveness of an iterative, controlled feedback process such as Delphi (Brockhoff, 1975). With small numbers of respondents, the anonymity of individual responses is compromised and summary statistics such as standard deviations and inter quartile ranges have limited meaning. Large panels on the other hand can be more difficult to manage as it is troublesome to convene large panels at one time and even more difficult to convene the same panel for several sessions as the process goes through its iterations. The response-feedback iterations of a Delphi-type procedure depend on continuity of the panelists from one session to the next. The frequent problem of high attrition in subsequent rounds seriously affects the consensus forming process (Bedford, 1972). Also, with larger groups where face-to-face discussion is required, there is a tendency for some members to be inactive in the discussion and thus not to influence the group judgement (Brockhoff, 1975). In a study of Delphi and face-to-face discussion panels, Brockhoff (1975) found no significant relationship between group size and group performance. The study examined small groups containing from four to eleven members. The justification for deliberately concentrating on groups of this size was that many small and medium-sized organizations are using Delphi and Delphi-type procedures and can call in only small groups of experts. Others, however, have found relationships between group size and performance (see, for example, Steiner, 1966, 1972; Dalkey, 1969; Frank and Anderson, 1971). These studies suggest that the group mean error decreases with increasing group size.

Based on Brockhoff's (1975) study of panel size and considering the minimum requirements for some statistical measures, it can be argued that Strabo panels may be as small as four participants. Considering limitations with setting up and operating Delphi and group discussion panels and recognizing the magnitude of data collection and processing activities involved with running a single Strabo session, seven participants is a practical upper limit for the panels. Even at this, a Strabo application involving six issues/questions would produce 42 response maps for each round - a total of 126 maps for a three round session. Each of these maps, as will be seen in a later section, would require interpretation, digitizing, error checking, processing in a statistical model, comparison with the composite or "average" map, and comparisons with other individual response maps in that round as well as with the corresponding maps of previous rounds. Obviously, larger panels would be expensive to operate, encourage some participants to be less active in discussion sessions (Brockhoff, 1975), and would require considerable time between rounds to process the map data. Small panels, however, will be more seriously impacted if one or more participants drop out of the process.

3.2.2 The Strabo Questionnaire

Strabo's goal is to derive spatial information about an area from the knowledge base of a group of individuals by using appropriate techniques for reconstructing mental impressions of space. Chapter 2 reviewed the research devoted to spatial-cognitive structures and the recovery of mental maps. Many of these studies are of particular relevance to the Strabo approach as they lay foundations for deriving and processing the respondent's spatial-cognitive information. Research has by and large concentrated on two aspects of cognitive spatial representation: the structural elements and the metrics of spatial relationships (Downs and Stea, 1977).

There are several ways of extracting cognitive representations of space which can be used in the Strabo method. First, respondents can be asked to draw their perception of space on a blank sheet. Cromley et al. (1981) refer to these as "construction maps". Such sketching was used by Lynch (1960) in his pioneering work on cognitive mapping. He suggested that contents of cognitive images could be grouped into five classes of elements: paths, edges, landmarks, nodes, and districts. With sketches, cognitive distances, or metrics, between these structural elements often reveal great distortions of reality. A second method is to have a respondent add information to an existing outline map, which contains enough information for the participant to orient himself. These have been referred to as "completion maps" (Crowley et al., 1981); to some extent they reduce the amount of distortion in the metrics. A third approach is to derive the spatial structure by having respondents rate pairs of stimuli according to some criteria, e.g., distance, size, direction, or preference, and then to reconstruct the spatial image by techniques such as Multi-Dimensional Scaling (Golledge, et al., 1982). This approach is also sensitive to distortions in the spatial metrics, and is more complicated to calculate and interpret.

Maps produced in a Strabo exercise should be relatively easy to produce, interpret, and analyze because many participants may not be totally "map literate". Since the proposed process attempts to create an "average", or composite, spatial response, it is desirable to have spatial data represented at a common scale and orientation. For these reasons, a "completion map" technique to elicit spatial responses is preferred. Base maps of the study areas can be provided to the panelists, and each member can be requested to respond by drawing their answers on the map, for example, "where are the blighted areas of the city?".

A separate "attribute" map can be completed for each set of questions relating to a common attribute, e.g., areas of poverty, livable regions, and social classes. Research on information surfaces, discussed in chapter 2 (see, for example, Gould and White, 1974; Gould, 1975) is particularly relevant to the notion of respondents representing their spatial knowledge in map form. Respondents, although considered to be experts with respect to a given spatial issue, are not apt to have a uniform knowledge of the entire study area. The strength of their information may be greater in some areas than in others, for example, along frequently traveled routes, in areas where they live, and around areas where they work. The variable strengths of their individual knowledge surfaces, then, should be taken into consideration when attempting to aggregate the maps into a composite.

Measuring reliability of the knowledge surface is a difficult task. It is often not possible to compare cognitive representations with objective reality, either because the reality is not known or because the objective reality is itself subjective, such as quality of life, social class, or livable areas (Dalkey, 1975). How then can the surface be weighted to reflect the spatial heterogeneity of their knowledge? One approach is to use the concept of a "confidence" map as a weighting procedure. Respondents can be asked to differentiate on common base maps areas of different degrees of certainty about their knowledge. As research on spatial cognitive structures has demonstrated, information is a function of familiarity (Lynch, 1960; Gould, 1975). Therefore, asking respondents to indicate areas with which they are familiar, somewhat familiar, or unfamiliar, can provide an indicator of how confident they are in their spatial answers. It is then up to the study director to determine how he wishes to use these weights.

Having individuals rate themselves or estimate their own probability of correct response is the basis of some recent studies in the field of subjective probabilities discussed earlier (Dalkey, et al., 1970). Farkas and Wheeler (1980) used the "self-rating" approach with a group of experts in a Delphi session to determine weightings for questionnaire responses. In this way, unreliable responses can be controlled in the consensus forming process. In the Strabo process, this can be achieved by overlaying each Attribute map with the respondent's Confidence map and selecting only those categories in areas which the respondent feels certain are correct. These weighted Attribute maps for all respondents can then be aggregated into one Composite map by a process which will be discussed in a subsequent section.

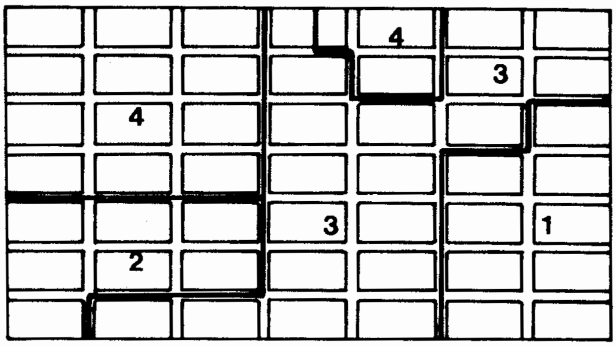
The types of attribute data displayed by respondents will usually be of a nominal or ordinal level of measurement (for example, land use categories, areas of high, medium, or low population densities, and ethnic concentrations). To represent aerial distributions, respondents can draw boundaries around the portions of the map which they believe are characterized by a given attribute (see, for example, Figure 3.1). Likewise, Confidence maps can be produced by drawing boundaries between areas of differing levels of certainty that responses are correct.

In addition to the blank maps provided for each Strabo question, a written statement of the problem can be provided. Salancik, et al. (1971) found a direct relation between the number of words used in a statement and the amount of information obtained from the question. They found that low and high numbers of words resulted in low consensus while medium numbers produced the highest consensus. Twenty to twenty-five words seemed to be an optimum length for a statement. The required length of a statement, however, was also shown to be a factor of how familiar respondents were with particular issues. Familiar items required fewer words to attain agreement than those which were less familiar. Individual Strabo statements, therefore, should be formulated carefully because, as with Delphi statements, those which are too lengthy may require the assimilation of too many elements (Linstone and Turoff, 1975).

3.2.3 The Composite Map

One objective of a Strabo analysis is to search for consensus in the spatial distribution of an attribute. With Delphi, consensus is usually

LAND USE STATUS IN A SAMPLE AREA



Legend:
Land Use Status

Label		Description
1	--	Residential
2	--	Industrial
3	--	Commercial
4	--	Park

Figure 3.1: Example of How a Respondent Should Represent Attribute Data on a Map.

obtained by summarizing responses according to the mean, together with a measure of dispersion about the mean. The type of data dealt with is frequently numeric, measured along an interval or ratio scale. Strabo information, however, is predominantly nominal or ordinal. It is therefore not possible to use the same types of summary statistics. One cannot, for example, sum five categories of soil types and produce an average soil type. Instead, an alternate measure of "central tendency" should be used -- for example, a limited frequency mode. In other words, an area can be summarily categorized as a class of the attribute if more than a predefined percent of the respondents are in agreement. If four out of five respondents identify an area as "residential", and if the level of agreement is 80%, then in the summary map, the area would be classified as "residential". If less than the predefined percent of respondents agree on a classification for an area, it would be identified as an area of disagreement, and flagged for discussion in the feedback sessions.

Subsequent iterations can attempt to reduce the amount of disagreement within the panel, or if disagreement persists, strengthen the polarization of opinions and explore the basis for the differences. Consensus in the aggregate map may be "patchy", that is, for a particular issue, respondents may be in agreement only in certain areas. This is unlike Delphi, where the consensus problem can be considered "one-dimensional".

3.2.4 The Iterations

Experts base their opinions on acquired information and a set of rules or heuristics which determine how they interpret, process and derive conclusions (Larkin, et al., 1980). By structuring a communication process such that information is produced at the end of each session and then fed back into the process as new information, opinions of the experts can be up-dated. Strabo experts can receive several kinds of information to up-date their opinions. First, a summary map of the area can show the results of compositing individual responses. It can show areas of agreement (within the tolerance of the exercise, e.g., 80%) and agreed upon attributes within the areas. Each respondent can also be given a copy of his own response map against which he can compare the composite. To assist with the interpretation of how closely his individual response corresponds with the composite map, an index of correspondence can also be provided at the end of a round.

Information obtained in discussions about results of the previous round will be important to the revision of opinion. This will provide each participant an opportunity to bring to the attention of the others information and insights into issues which he feels are important to formulate an opinion.

The sharing of background information and individual insights into the issues at hand can be accomplished effectively and efficiently by direct communication amongst the participants. This raises a concern about anonymity of the respondents. Classical Delphi uses the principle of anonymity to avoid the bandwagoning effect and to eliminate intimidation by a few aggressive participants. However, this anonymity assumption has been widely questioned by some critics and it has been suggested that anonymity may be more hindering to consensus formation than assisting (Sackman, 1974). Variants of the Delphi approach have relaxed this constraint because they found that anonymity tended to confound the problem of differences of interpretation amongst participants (see, for example, Rauch, 1979). Although these recent approaches place less emphasis on maintaining anonymity, there is still a concern that individual answers and comparisons with the aggregate remain confidential. Confidentiality is important so as not to intimidate an individual's honest representation of his beliefs and opinions. To permit an exchange of information and ideas through face-to-face discussion, it is necessary for Strabo to relax the anonymity criteria of conventional Delphi; however, it should maintain confidentiality in individual responses.

The number of iterations through which a Strabo exercise should be taken is an important consideration for introducing closure to the procedure. A review of similar types of techniques, particularly Delphi, revealed some problems in using an iterative procedure. An important problem was the tendency for participants to drop out of the exercise between rounds (Bedford, 1972). In a study of community health needs, Schoeman and Mahajan (1977) reported that only 48.5% of the first round participants continued through to the third round. Similarly, Smith (1978) indicated that, in a Delphi exercise applied to rural development problems, 65% of the first round respondents had dropped out by the fourth round.

Several factors contributed to the drop-out problem. First, some panelists were not available to participate in subsequent rounds. More serious was the problem that some panelists were less motivated initially and more critical of the method's utility (Bedford, 1972; Sackman, 1975; Bardecki, 1984). It became increasingly difficult with each round to convince the participants to answer the same basic questions over and over again, especially if they were somewhat indifferent to the subject matter and/or the procedure.

Addressing the problem of group performance versus number of rounds in Delphi exercises, Brockhoff (1975, p. 315) concluded that the "results seem to indicate that it is not reasonable to extend the number of rounds in Delphi groups beyond the third round". He also suggested on the basis of experimental findings that further rounds may impair the results of the Delphi application (Ibid., p. 320). In fact, a close examination of his study's results indicates that most inter-round changes occur between rounds one and two, and those which occur between rounds two and three are less marked and resemble a fine tuning of responses.

Strabo's similarities to Delphi in the iterative procedures require that like processes and results be obtained. Therefore, three rounds would be sufficient for most applications; extending beyond this would be at the discretion of the study director if third round results did not yet show a stability in aggregations.

To ameliorate the drop-out problem, logistical consideration should be given to completing all the iterations during the course of a one or two day meeting. This continuous approach would ensure that issues remain fresh in the minds of participants, and it would sustain a high level of interest. Drop-out in subsequent rounds would be reduced because all panelists would have committed themselves to a block of time to complete all rounds of the exercise. A common problem with conventional Delphi studies is that they rely on mailed questionnaires; this often requires months to complete even a single round, contributing to participants losing interest and dropping out of the exercise.

Processing Strabo information can not be done easily by hand, and would be handled best in a computer-assisted environment. An optimum scenario would be to have a graphics terminal in front of each participant who could then draw his information on a map provided by the computer. It would be geometrically registered, aggregated with maps from the other participants according to a set of rules provided by the study director, and the summary information provided almost immediately. At present, such a scenario is optomistic because the computer-assisting system would need to be very sophisticated in its user-friendliness to accommodate neophyte mappers who are apt to have inconsistencies in their maps (e.g., overlapping areas) and who want to make changes and modifications.

A more likely scenario would consist of panelists producing their cognitive information on a hard copy, paper map which would be given to a system operator. The operator would assist by handling the technical aspect of converting the map into computer-readable form, processing the information, and generating summary statistics. While results from one question are being processed, panelists would be busy dealing with issues of the next question, thus the process would be continuous, avoiding long delays between activities.

If adequate resources are not available to the study director, or if it is not possible to convene a panel for a sufficient block of time, the process could be conducted over a period of several sessions. During each round, respondents would review the summary information and generate new maps. At the end of each session, the study director would process the information and prepare feedback materials for the next session, several days or weeks later. This scenario may, in fact, be more common, at least in the near future. Recalling that a primary objective for developing such a method is to assist with spatial data problems in data-poor environments, particularly in developing countries, one can expect that technical and skilled resources may be less than optimum. Developed in this fashion, Strabo is an approach that deals with spatial data problems and is not an information system which is hardware or software dependent. A number of existing geographic information systems and software packages are able to perform the functions required to process the Strabo spatial data (e.g., ARC/INFO (ESRI, 1984), MAP (Tomlin, 1984).

3.3 Potential STRABO Applications

A review of Delphi applications finds a number of variations on the basic process. Most notable are Policy Delphi (Turoff, 1975) and Decision Delphi (Rauch, 1979), which represent modifications to accommodate specific applications. Likewise, the basic Strabo technique can be tailored for different types of applications. This section describes some of the potential uses of the basic method.

A fundamental application would be to derive information about an area which would otherwise be extremely difficult to obtain. The iterative feedback approach would be used to formulate a consensus of opinion regarding the current state of some attribute. Particularly appropriate are data collection problems where variables are subjective in nature; for example, identifying urban blighted areas, transition areas, and neighbourhoods. These three examples illustrate different levels of subjectiveness in identifying spatial attributes. Blighted areas will be recognized by general characteristics of housing conditions, population densities, service standards, and economic welfare. Subjectivity lies in each individual's perception of the relative seriousness of conditions. What might be considered blighted in a North American context might be acceptable by the standards of cities in the world's poorest countries.

The second example, identifying transition areas, involves a greater degree of subjectivity. Transition implies change over time rather than a steady state. Therefore, to classify an area as transitional requires a knowledge of its history, development, and rate of change. Characteristics of these areas may be more subtle and may have varying influences on individual perceptions.

The third example, identifying neighbourhoods, is very relevant for many urban social planning applications. Of the three examples, this involves the most subjectivity. The concept of neighbourhood goes beyond mere physical boundaries. It encompasses feelings of belonging and identification with an area, its people, its institutions, and its environment. Neighbourhoods develop over time; their character and composition change in response to internal and external forces. For example, as population ages, demands on the social institutions change, and as transportation patterns evolve, neighbourhoods expand, contract, divide, and dissolve. In the recent Residential Neighbourhood Environment Study (NRES), the municipality of

Burnaby identified 37 distinct neighbourhoods (Burnaby Planning Department, 1984). The process used was entirely subjective; several planners faced a large municipal map and, on the basis of their knowledge of the region, drew boundaries around areas which they felt had distinct neighbourhood characteristics. They assigned names to these neighbourhoods -- many of which would be easily recognized by their inhabitants. These qualitative considerations are important as information for social planning problems.

Another application of the technique would be to forecast the spatial distributions of variables (e.g., projecting urban growth patterns, forecasting changes in regional economic development, and predicting location of hidden mineral and natural resources). Experts in the appropriate fields would provide their individual estimates which would then be combined into a composite estimate of some future occurence. Using the method of providing feedback, discussing the results, and going through a subsequent round, the process would attempt to arrive at a consensus on what the future might look like. The "experts" in this type of application would be individuals with a great depth of knowledge and understanding of the issues involved, for example, economists, urban planners, and geologists.

A third type of application would be in decision-making situations. For example, given a problem of identifying priority areas for urban redevelopment, a group of expert panelists made up of planners, knowledgeable local residents, sociologists, or other appropriately informed individuals, could use the structured communication of Strabo to form a group decision. Of course, this would probably be only one of several methods used to plan and produce decisions. In these applications, the participants would not be merely describing or forecasting spatial distributions, but creating them.

3.4 An Illustration

The application of Strabo may be described best by a simple example, designed to illustrate the procedures and to show how the results can be interpreted. The hypothetical problem is to identify areas which have a high probability of producing oil. Using the combined information from a group of expert geologists, one can narrow the search significantly, which would focus subsequent exploration and seismic activity into those areas agreed to be mineral rich.

Subjective probability assessments and "geological opinion" have previously been used in mineral exploration studies (Barry and Freyman, 1970; Fuda, 1971; Harris et al., 1971). In a mineral resource appraisal of northern British Columbia and the Yukon Territory, Harris et al. (Ibid.) measured the geologic opinion of twenty geologists with first-hand experience in the area by having them "estimate" amount and grade of various mineral ores at specific locations in the study area. This was not a Delphi type exercise, but it did use aggregate "opinions" as a data element in assessing mineral endowments.

For the sake of simplicity, and ignoring the concerns of sample size and data validity, the illustrative example here assumes a panel of four expert petroleum geologists and a single issue questionnaire. The four geologists bring with them to the exercise a thorough knowledge and understanding of the various parameters underlying the development of oil resources, including historical geology, sub-surface geologic structures, among others. In preparation for the exercise, the geologists review available relevant information. This might include, inter alia, geologic maps, aerial photography, satellite imagery, results of previous seismic surveys, and field surveys - assuming that at least some of these exist for the area with which they are dealing.

As the exercise enters its first round of consensus forming activities, each geologist is given blank outline maps of the area. Each is asked to indicate on one map those portions of the area with which he is very familiar and about which he feels confident in his ability to evaluate their resource potentials. This map represents the individual knowledge surface and serves to weight the other response maps in the aggregation process. Participants are also asked individually to identify those portions of the area which would be most likely to produce oil. These are the so called "attribute maps".

To process this first-round information, the maps are converted into digital form. Again, for the sake of clarity and simplicity, the approach to be used converts the maps into a dense grid of small rectangular areas. This is analogous to overlaying graph paper on the map and assigning to each grid cell a value corresponding to the attribute class dominating its area. It is then easy to see that by comparing corresponding cells from each map, an aggregate response can be determined (see Figure 3.2).

For this hypothetical example, the four geologists are of one mind -- that oil can be found in the northeastern and southwestern parts of the region -- but there is some disagreement about its exact location. There is also considerable agreement over those areas where they feel oil will not be found. The aggregate map in Figure 3.2 shows those areas in which they agreed and disagreed. It is produced by counting the number of times each part of the region was believed capable of producing a sustainable yield of oil. The blank portions represent areas of total agreement that oil will not be found, while the darkest shaded areas represent total agreement of a high likelihood of finding oil. The "grey" areas represent differences of opinion and are targets for discussion in subsequent rounds. In this hypothetical example, there was total agreement over 78% of the area. Depending on the specific application, the criteria for deciding whether agreement has been reached may vary. In some situations, the study director may be satisfied that a simple majority in the number of respondents selecting a category is sufficient, while in others, nothing less than total agreement may do. Again, for illustrative purposes, a high level of agreement is assumed only if all four geologists agree that oil may be found in an area. This produces the composite map as found in Figure 3.2.

After aggregating the weighted response maps and producing a composite map, a second round of discussion begins. The panel is assembled in one place, and their initial responses are returned to them together with the composite map and summary statistics. The summary statistics include measures of the correspondence between the individual maps and the composite map, and the amount of agreement over the area, as defined by the criteria -- in this case, agreement by all four experts. With this criterion, there is general agreement that oil can be found in about 4% of the area.

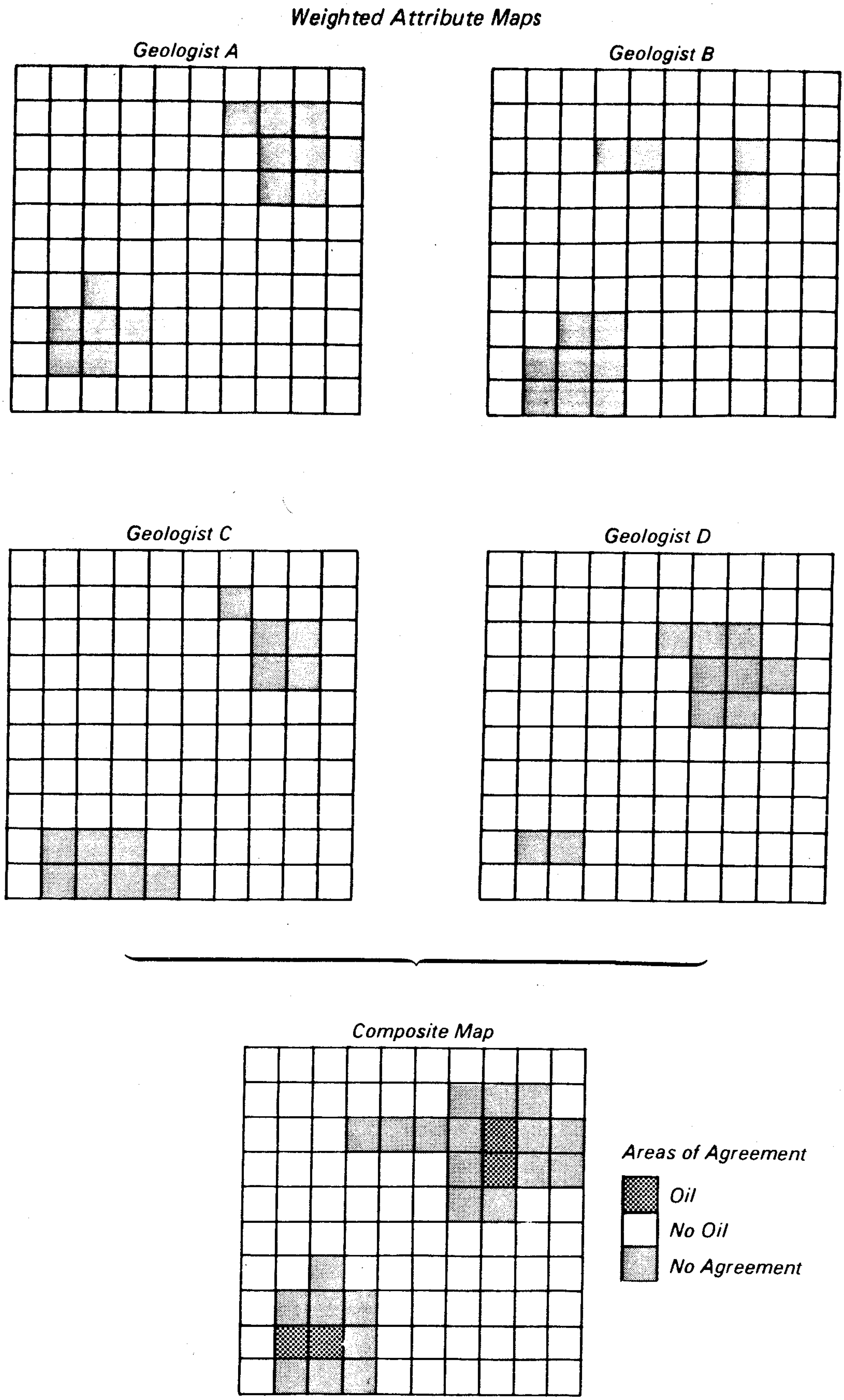


Figure 3.2: First Round Results from a Hypothetical Strabo Exercise.

With this information in hand, the geologists discuss the results of the first round and contribute their ideas about where and why the composite map does not reflect their individual opinions. This injects new information into the base of knowledge about the issue under discussion. Anonymity is not required, in fact, it is discouraged; however, confidentiality in the individual responses is assured. The study coordinator directs the discussion amongst the panelists drawing out all relevant information, yet avoiding "brow beating" and intimidation by more aggressive panelists. When he feels that post session discussion has thoroughly examined areas of disagreement or contention, panelists are again presented with a blank map of the area and asked the same question -- In what areas would they predict a high probability of finding oil. One issue which should be discussed, of course, is how they would individually define "high probability". This mechanism can clarify differences in how certain issues are perceived. The example here is the concept of "high probability", but in other contexts it might be such differing concepts as "poverty", "social class", and "drought".

Each expert completes his map as in the first round. The study director again aggregates the responses and creates a composite map (Figure 3.3). The process of returning summary information to the panel and discussing the results is repeated in each iterative round until the director is satisfied that no further significant "movement" in individual responses will lead to an improved consensus.

Carrying the hypothetical example through a second round, the effects of the first-round discussions can be seen. Suppose geologist C brought to light

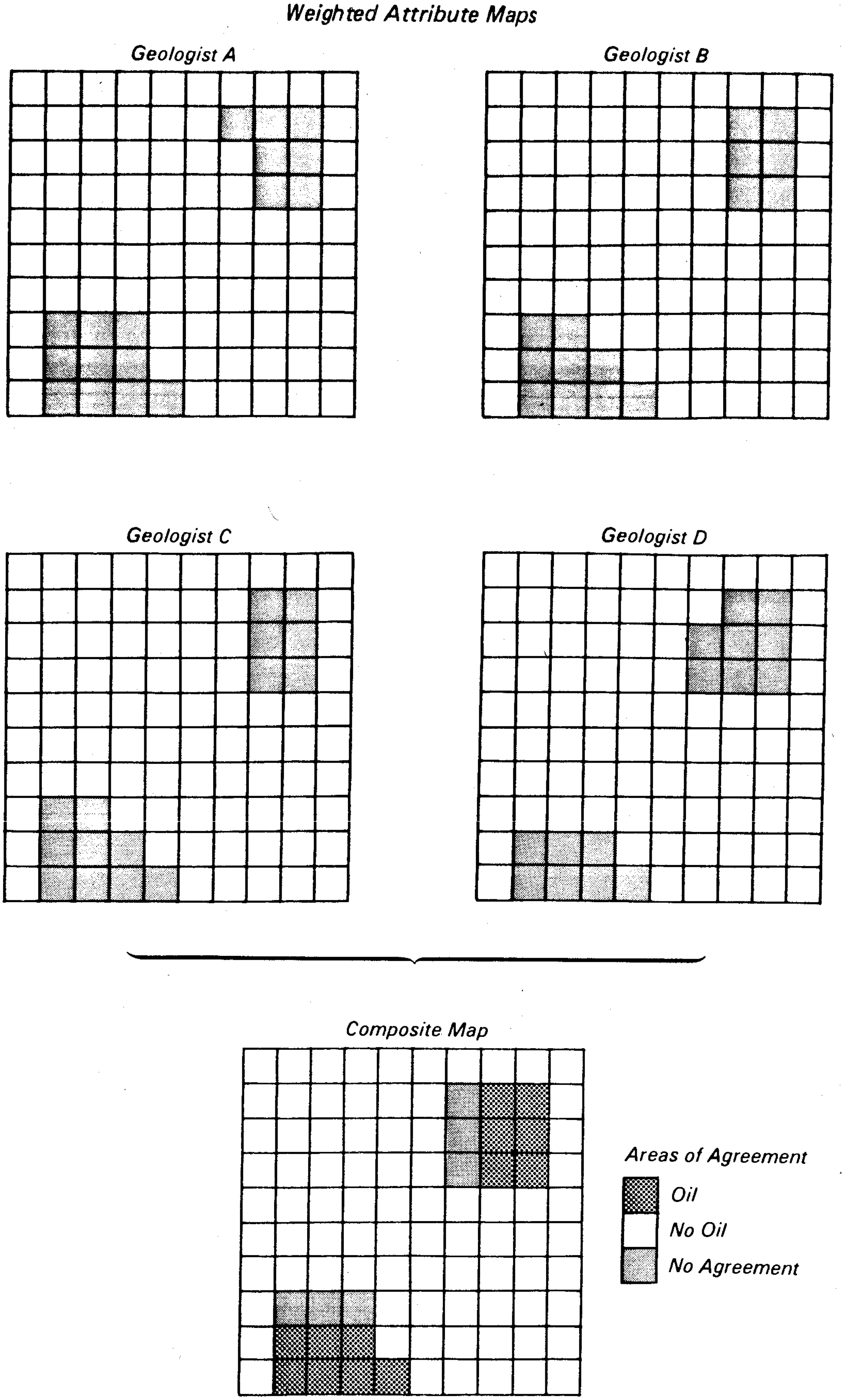


Figure 3.3: Second Round Results from a Hypothetical Strabo Exercise.

two additional pieces of information about the region in the southwest. He reminded the panel that sub-surface geologic folding, in which oil pockets are likely to be trapped in the domes, occurs only in the extreme southwest, and that prior exploration in the region immediately to the south of the study area had reported marginally substainable yields. With this new information in mind, together with other points from the discussion, the geologists revised their opinions and produced their individual attribute maps as in Figure 3.3. There is now total agreement over 94% of the area, and, using the "total agreement" criteria for deciding on agreement, the geologists now believe that there is a high likelihood of discovering oil in 13% of the area.

Although this example is simple, it suffices to illustrate how the information can be collected, processed, and analyzed. It serves as a prelude to the application described in chapter 4.

CHAPTER 4: A STRABO DEMONSTRATION

This chapter demonstrates an application of the Strabo method and explores some assumptions underlying the approach. The application is demonstrative with the focus on the method rather than on a particular problem for which the technique was used to develop a solution. Because of this and because the approach is "expert people oriented", a number of organizational and logistical encumbrances were faced. These are discussed in a later section in terms of their impact on the results of the application.

4.1 Objectives of the Application

This application serves several purposes. It demonstrates in considerable detail the procedures to be followed in conducting a Strabo exercise. It illustrates the preparatory work necessary for each iteration, types of responses produced by participants, methods of processing spatial data, and typical problems encountered. The application also attemptes to demonstrate how structured communication procedures may generate a consensus of spatial opinions, and to show that data thus gathered from the cognitive domains of experts are representative of objective reality. In addition to determining ability of the approach to define existing "hard data" such as urban land use, the application examined its effectiveness in estimating the spatial distribution of more subjective data, *e.g.*, livability.

4.2 Demonstration Design

An application in an urban environment was selected for several reasons. The study area selected offered immediate access which facilitated group contact procedures. It was necessary to meet with individuals of the group to explain the process, and during each round to convene the entire group; therefore, being close to the study area and the panel experts was advantageous. The demonstration was developed such that measureable data were available for some of the variables in the study area which could be later used for validating the Strabo results. Because reliable, objective data existed from other sources for some of the variables (i.e., municipal records of dwelling types and housing quality), the situation cannot technically be considered data-poor in these cases; however, these data were not readily known or available to the panelists. The panelists, therefore, were required to rely on their opinions, attitudes and mental perceptions. This available census data provided a control or a "ground truth" against which the panelists' responses could be validated.

4.2.1 The Study Area

The area selected for the application was in the northwest corner of the municipality of Burnaby, British Columbia. The area was bounded on the west by Boundary Road, on the north by Burrard Inlet, on the east by Sperling Avenue, and on the south by Lougheed Highway (see Figure 4.1). The area covered approximately 10 km^2 and was heterogeneous with regard to

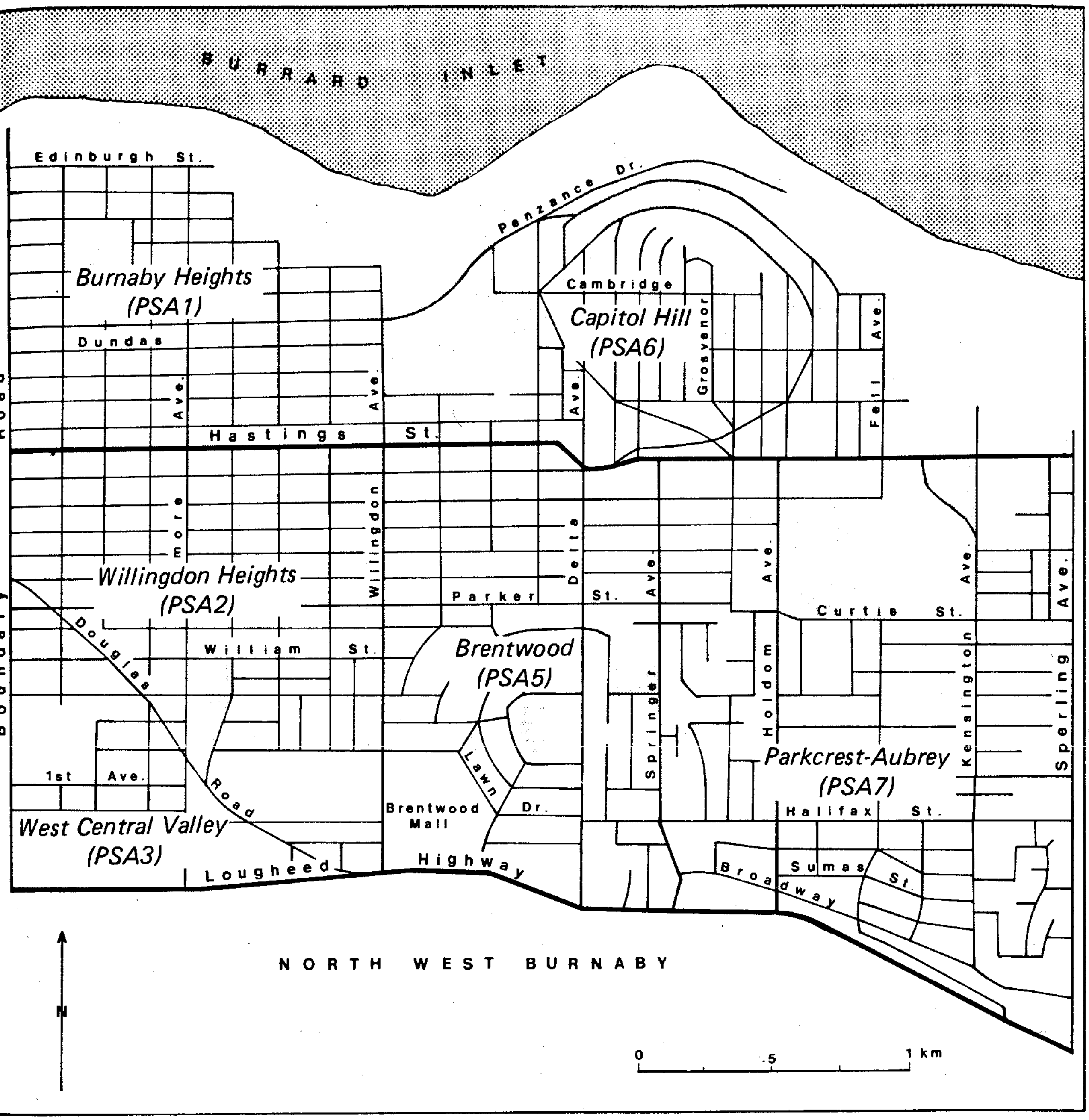


Figure 4.1: The Study Area.

topography, land use, and social fabric. The land use was predominantly residential with some industrial activities in the northern and the southwestern parts of the area and some commercial activities along major arterial routes. There were also institutional uses (e.g., schools, churches, cemeteries) and recreational areas in the form of parks and playgrounds, accounting for a small proportion of the total area. The residential uses were predominantly single family dwellings; however, there were some multi-family areas, characterized by high rises and walk-up apartments. Development of the area has taken place over a period of time (from the 1930s to the present), thus some parts were characterized by older dwellings with narrow (33 feet) lots and others by relatively modern structures on expanded lots.

Recent planning activities in Burnaby have divided the municipality into 37 planning study areas. This was part of the methodology for the Residential Neighbourhood Environment Study (RNES) which reviewed Burnaby's neighbourhoods in terms of opportunities for residential compaction and neighbourhood preservation (Burnaby Planning Department, 1984). Data collected and analyzed for the neighbourhood study were useful in the preparation and execution of the Strabo exercise. The planning study areas (PSAs) covered by the Strabo study included 1 through 7, excluding PSA4 and the portion of PSA3 south of Lougheed Highway. For reference purposes, these neighbourhoods/study areas were called Burnaby Heights (PSA1), Willingdon Heights (PSA2), West Central Valley (PSA3), Brentwood (PSA5), Capitol Hill (PSA6), and Parkcrest-Aubrey (PSA7).

The Burnaby Heights area generally sloped north providing many locations with an attractive view of the mountains across Burrard Inlet. Residences were old, many built prior to 1930. To the south, Willingdon Heights was also an area of higher elevations with views of the Vancouver skyline. It contained primarily older type housing and had in general an aging population. It was mainly a blue collar area with a dual English/Italian ethnic mix. The Brentwood area had primarily intermediate and newer residential dwellings and had a large commercial centre (Brentwood Mall) in its territory. Capitol Hill was one of the older areas of Burnaby, and, as its name suggests, was dominated by elevated topography providing excellent views of Vancouver to the west and mountains to the north. The east slope, however, faced oil refineries and other industrial activities which are often blamed for unpleasant odour emissions. The Parkcrest-Aubrey area sloped from north to south producing aesthetic views of the South Burnaby skyline. Much of the residential housing stock was of the 1950s vintage with little new development. It was characterized by a relatively high concentration of ethnic Chinese and an aging population.

4.2.2 The Questionnaire Design

A set of questions was developed with which the Strabo procedure could be demonstrated and tested. The exercise was contrived to meet this study's specific objectives and should not be viewed as typical. The number of questions requiring spatial answers was kept to a minimum in order to lessen the imposition on the group of experts who had volunteered time from their schedules. Since the process requires several sessions, each requiring a block of time, the study was designed to be completed in a series of 45 minute blocks.

The questionnaire addressed five topics requiring spatial answers (Appendix I). These, together with a question designed to elicit information about the spatial reliability of their responses, constituted six completion maps to be prepared by the participants. To facilitate answering individual questions, all materials and information pertaining to a particular question were presented on one 11 inch by 17 inch sheet of paper.

Each question was accompanied by a blank base map of the study area at a scale of approximately 1:17 000. The base maps contained only basic reference information. All streets were drawn, but only major ones named. Unnamed shaded areas representing parks were also portrayed to assist respondents in orienting themselves in the study area. Burrard Inlet, bounding on the north, was clearly represented and named.

The questionnaire was designed to be administered in person by the study director; to this end, background explanations and question definitions were kept concise and specific. This attempted to ensure that all participants responded on the basis of common information and instructions. When questionnaire items become "wordy", there is a tendency for respondents not to read the information carefully, or in its entirety (Salancik, <u>et al.</u>, 1971).

The questionnaire was tested by administering it to four senior students at Simon Fraser University. Based on this pilot test, modifications were made to the design of the instrument and to the wordings of statements.

The first questionnaire item elicited information about how well each participant knew the study area. This was measured by asking each participant to complete a blank map classifying all areas as being "very familiar", "somewhat familiar", or "unfamiliar" to him. Respondents were instructed to complete the maps by drawing lines between areas which they felt were different according to the topic being considered. For example, they were to draw lines between two areas if one was "very familiar" to them and the other was "unfamiliar". They were also reminded that all areas must be classified according to one and only one of the categories since the categories are exhaustive and mutually exclusive. Familiarity with an area was used to assess the confidence that each participant had in being able to respond to spatial questions. In this way, the demonstation used a self-rating technique to evaluate the reliability of the responses (Dalkey, <u>et al.</u>, 1970). Obviously, if an individual is not familiar with an area, he is unlikely to be confident in his knowledge of it, and his responses cannot be treated as reliable. This spatial familiarity assessment was used to weight the individual responses in the aggregation process.

The second questionnaire item addressed the more objective concept of residential dwelling types. Again, respondents were presented with three clearly distinct categories of the variable. The categories -- single family, multiple family, and non-residential -- are spatially exhaustive within the area. The respondents were instructed to draw lines around areas which they felt were homogeneous in terms of residential type, and to label each area with a simple label, either a 1, 2, or 3, corresponding to categories in the legend.

The third questionnaire item dealt with a slightly more abstract and interpretive concept of housing quality (Peterson, 1965). Categories were defined in ordinal, but subjective terms: poor, moderate, and good quality. By design, questionnaire items became more subjective and abstract with each successive question. This allowed the participants to gain familiarity and to become comfortable with the procedures in the early stages of the exercise.

The fourth item requested that participants identify areas according to low, middle, and high income status. A supplemental question was asked of each respondent to describe in words how he would recognize an area as being either low, middle, or high income. This attempted not only to look for consensus in spatial distributions, but to examine the basis for individual decisions. Also, through iterative discussion of the individual interpretations, it was posited that differences could be resolved and agreement reached. This should then improve the consensus process as it relates to the spatial answers.

The fifth questionnaire item addressed the issue of crime areas. Participants were asked to identify areas of high, moderate, and low crime occurrences -- these categories being defined in relation to an "average" for the study area, that is, areas above average were defined as "high" and areas below average were defined as "low".

The last questionnaire item dealt with the most subjective issue -- "livability". It encompasses many of the qualities of an urban environment which make some areas residentially more desirable than others (Appleyard and Lintell, 1972). It is a concept of interest to some urban planners as they develop regional growth models within cities (see, for example, the Vancouver Livable Regions Study (Greater Vancouver Regional District, 1972; 1975)). The question asked participants to identify areas on the basis of their "desirability" in which to live. The categories were defined in terms of "highly", "moderately", and "less" desirable areas in which to live. Similar to the question on income areas, this question attempted to get at the roots of how individuals interpreted "livability". A supplemental question asked them to define, in words, how they would determine the "degree of livability" of an area. The iterative discussions were designed to examine these definitions, and to attempt to reach agreement on how the group defined the concept. By reducing the divergence in individual definitions, it was hoped to increase the correspondence in the spatial responses.

4.2.3 The Panels

The test application employed two panels of experts who were very knowledgeable about the study area. Based on Delphi findings regarding panel size (Dalkey, 1969; Dalkey, et al., 1970; Brockoff, 1975) and considering the problems of convening large groups, panels composed of five participants each were formed. It proved difficult to assemble a panel of five people at one time, in one place, for the first round and it was even more difficult to assemble the same group at one time for subsequent rounds. Panel formation was affected by vacation schedules, job-related commitments, and shift-work schedules. The complexity of scheduling iterative panel sessions for such an exercise increases with the number of iterations and with the number of participants. Keeping the panels to a membership of five helped avoid participant dropout.

The next step in panel formation was to identify prospective participants. "Experts" in this case, were individuals who had specific and extensive knowledge of the area. Because of the focus of the questionnaire, the type of knowledge required by the experts was of residential and neighbourhood characteristics. Participants had to know both the physical infrastructure of the area and the social fabric. The approach taken was to identify target groups which would satisfy the selection criteria. A number of such groups were identified on the basis of their relation to the study area. These included urban planners from the municipal planning department, the police department with jurisdiction for that area, the fire department, the real estate industry, and others. Following discussions with individuals in these groups and being confronted with the problems of convening a panel from a diverse constituency, a decision was made to create a panel from each of two target groups. A large real estate office, located and conducting business in the study area, agreed to participate. Five individuals from the agency, including the branch manager, were selected on the basis of their activity in the area, the length of time they had worked and lived in the area, and their availability to participate.

A second panel was formed from the Burnaby Royal Canadian Mounted Police (RCMP) detachment. Similar criteria were used to identify participants. By and large, initial selection of possible participants was made at the recommendation of the Commanding Officer who had been briefed on the purpose and procedures of the study. The responses from this panel were useful in the analysis; however, particular difficulties were confronted in following the panel-convening procedures as shift-work timetables and vacation schedules had to be considered. This caused some fundamental changes to the process as it applied to this group.

The real estate panel (hereafter referred to as Panel I) comprised four men and one woman. All had been associated with the study area for periods ranging from 3 to 12 years (average 6.6 years). Their formal education was at least high school level with 2 members having post secondary training (see Table 4.1).

TABLE 4.1

PANEL PROFILES

Profile of Real Estate Panel (Panel I)

Panelist*	Length of time familiar with area	Highest level of educational attainment
R_1	7	Post Secondary
R_2	7	High School
R_3	3	Post Secondary
R_4	12	High School
R_5	4	High School

Profile of RCMP Panel (Panel II)

Panelist*	Length of time familiar with area	Highest level of educational attainment
P_1	5	Post Secondary
P_2	13	Post Secondary
P_3	17	Post Secondary
P_4	18	High School
P_5	20	High School

*For the sake of anonymity, panelist's real names have not been used.

RCMP panel (Panel II) members had worked in the area from 5 to 20 years (average 14.6 years). Three had post secondary training and all had special police training in being observant of the community in which they worked.

4.2.4 Data Processing

Strabo, as described, represents an approach to problem solving in data-poor environments, and as such is not a specific hardware/software device for data processing (Institute for the Future, 1973; Rouse and Sheridan, 1975). It is not a software package such as SPSS, SAS, or ODESSEY, but does, in fact, use programs of this type which have capabilities to process data in a Strabo fashion. Since a number of systems are capable of performing the generic functions such as map overlays, data reclassification, and statistical report generation, it is possible to use the method in many existing data processing environments.

For the application in this study, several data processing alternatives were considered. Small software packages had been developed as part of research programs at Simon Fraser University and had some of the required capabilities (Edelson, et al., 1979). A commercially distributed package called MAP (Tomlin, 1980) was also available on the computer system at SFU. MAP was developed as a spatial analysis tool in a graduate research program at Yale School of Forestry. The decision was made to use this program because it had well developed and flexible capabilities, and was easy to use and manipulate. Another consideration was to use, if possible, existing capabilities within the study environment, or at least those which were readily available and inexpensive, to demonstrate that the process can be used without acquiring a great deal of additional computing capabilities.

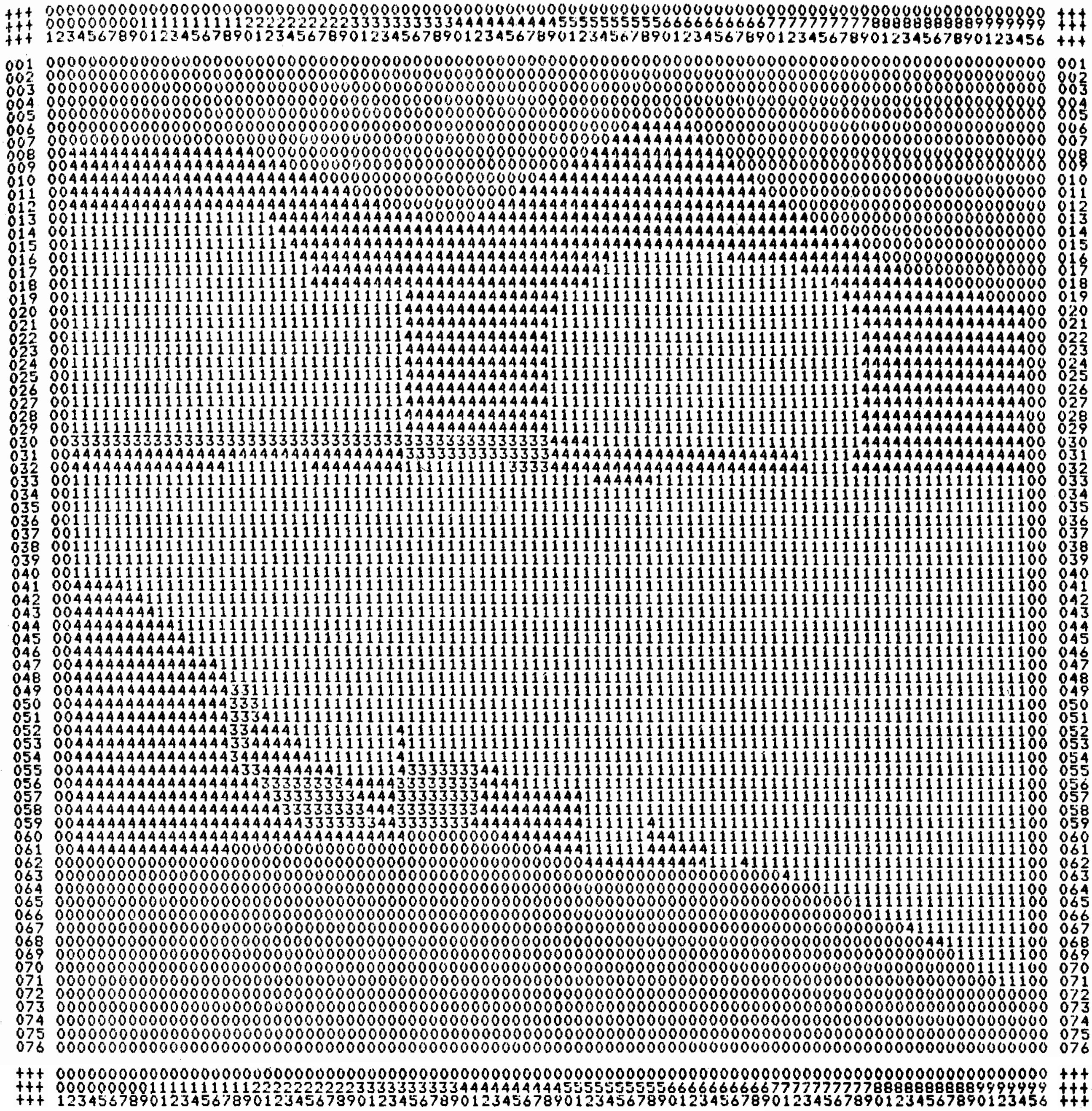
MAP is a command-driven program which employs a basic map algebra, allowing the user to manipulate individual maps or groups of maps as one manipulates variables in an algebraic equation (Ibid.). The program operates in either a batch or an interactive mode. It also permits the building of pseudo "macro" functions, i.e., a sequence of several basic commands strung together to perform a higher level task, which may be used repeatedly. This was particularly convenient in the map aggregation procedures of the exercise.

Before processing the spatial answers with the MAP software program, they were converted to digital form. A digitizing program was used to convert the analog lines into digital X, Y coordinates. The MAP program requires input data in a gridded form, therefore, a preprocessing program was written for this study to take the digitized information from the source maps, convert the lines into raster images, and create the gridded representation of the data (a FORTRAN listing of the routines appears in Appendix II). In essence, the map was converted into a large matrix of values. Each element of the matrix corresponded to a small rectangular area defined by a given coordinate system, and received a value corresponding to the variable class found at that location. The resolution of the gridded spatial data in this exercise was approximately 45 m.

Some topology was added to the originally digitized lines, in as much as the area categories on the left and on the right of each line were tagged to them. The preprocessing program used this topologic information to "fill" the map grid, or matrix. The gridding procedures treated the digitized lines as entities unto themselves and did not attempt to use the topologic information to link the lines together into polygons.

Data processing during each round of the exercise involved three separate steps - i) digitizing the original response maps, ii) preprocessing the digitized information into a gridded format, and iii) processing the gridded information with MAP. The results of the processing were written to a file; this included maps in grid form as well as summary statistical information. The maps thus produced were then displayed by copying them to a line printer (Figure 4.2) or by "post processing" them with a routine to draw them on a graphics plotter (Figure 4.3). In this application, both outputs were produced. Line printer maps were used for quick proof-checks but higher quality displays of the spatial information were produced on a vector plotter. Plotting was performed using the GIMMS software package (Waugh, 1984) after the map information had been processed by a FORTRAN program written for this study to convert MAP output into GIMMS formatted input (a FORTRAN listing of the routine appears in Appendix III).

Following the processing and analysis of the information at the end of each round, a composite map was produced for each variable on the same base that participants used for their answers. This facilitated comparison of individuals earlier round responses with the summary. On each summary map a statistic was included indicating the amount of agreement which occurred



COMP2

0000000000	0	....	2533 CELLS	34.7%
1111111111	1	....	3174 CELLS	43.5%
3333333333	3	....	148 CELLS	2.0%
4444444444	4	....	1441 CELLS	19.8%

Figure 4.2: An Example of a Processed Map Produced on a Line Printer.

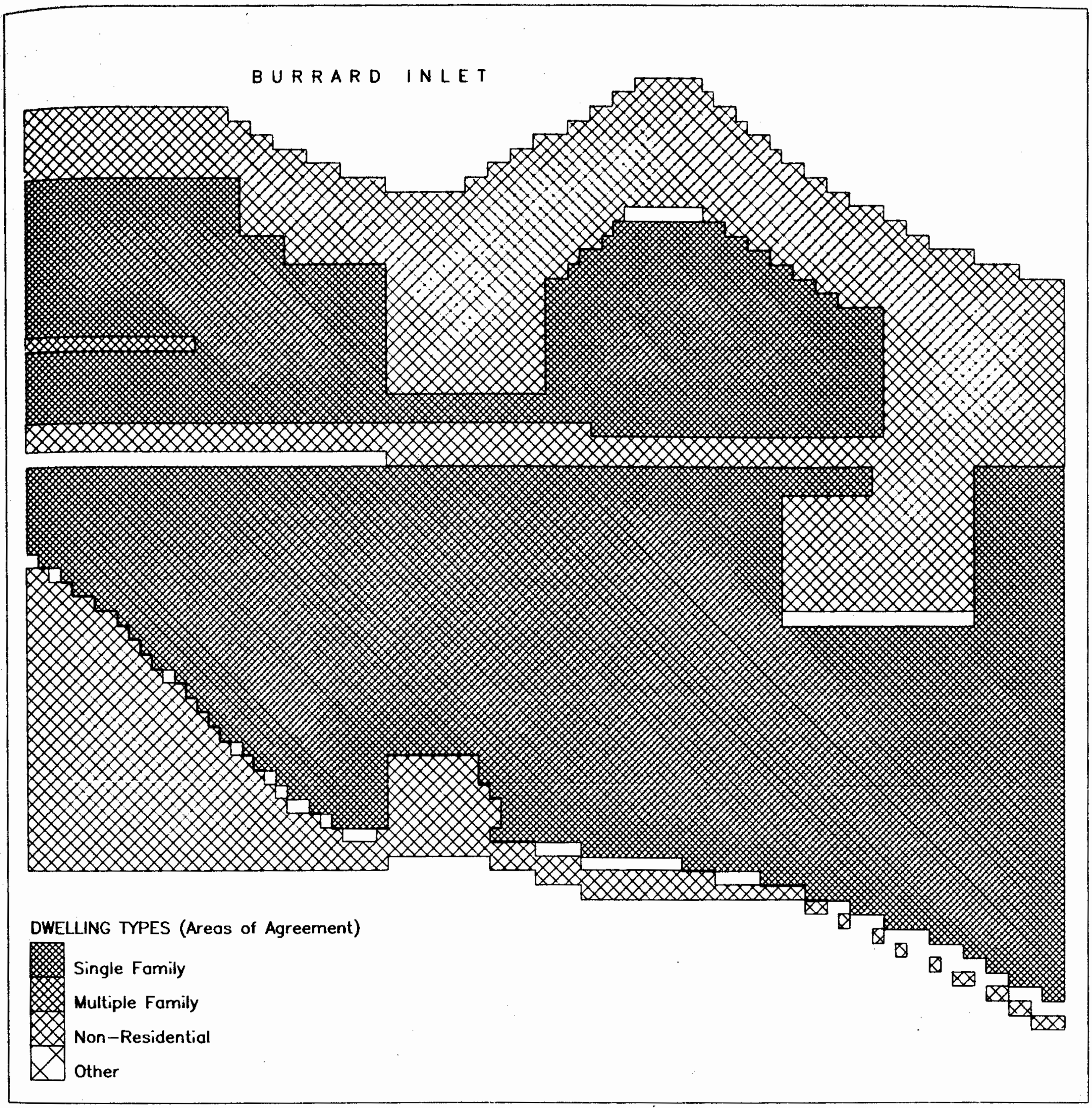


Figure 4.3: An Example of a Processed Map Produced on a Graphics Plotter.

over the entire map. This was represented as a percentage of the total area. Also included was a statistic measuring the correspondence between the individual's response map and the summary, or composite, map. This was shown as a percentage of the summary area of agreement on the composite map with which each individual response map concurred.

Table 4.2 summarizes the series of steps involved in the Strabo process as they were applied to the Burnaby case study. They outline the activities required for gathering, processing, analyzing, and reporting the spatial information.

4.3 Constraints

Participants had little trouble in understanding the intention of the exercise; in fact, most were enthusiastic about the potentials of the Strabo method. They were familiar with maps and were able to identify the area well. However, on the first round with Panel I, there were some difficulties with the way some participants completed the maps. Although instructed to draw boundaries between areas of different values, such as demonstrated in the example on the questionnaire, there was a tendency to identify a particular area as belonging to a certain class and then to indicate it by drawing either very general "swooping circles" around the entire area or by circling the category value in the centre of the area (see for example Figure 4.4). The results of this, of course, meant that two adjoining areas might be separated by two boundaries rather than just one, or might overlap by at least several city blocks. In some situations, where

TABLE 4.2

STEPS IN THE STRABO PROCESS FOR THE DEMONSTRATION

Step 1: DATA INPUT	1.1:	Digitize Attribute Maps for each Respondent (Total number of Attribute Maps for each round equals number of Attributes x number of Respondents, i.e., 25)
	1.2:	Digitize Confidence Maps for each Respondent (Total number of Confidence Maps = number of Respondents, i.e., 5)
	1.3:	Checkplot each Digitized Map from steps 1.1 and 1.2 to verify input data
	1.4:	Convert each of the Digitized Maps (i.e., 30) from vector to raster format (see Appendix II)
	1.5:	Include each of the Raster Maps from step 4 into the MAP data base
Step 2: DATA PROCESSING (this sequence of steps is repeated for each of the Attributes in turn i.e., 5 times)	2.1:	For each Respondent, weight the Attribute Map by the corresponding Confidence Map
	2.2:	Aggregate the weighted Attribute Maps
	2.3:	Create Composite Maps showing areas of at least 60% agreement and areas of at least 80% agreement (see Appendix IV)
	2.4:	Cross-tabulate each individual Attribute Map with the 60% agreement Composite Map and with the 80% agreement Composite Map (see Appendix V)

(Table 4.2 continued)

Step 3: PREPARE RESULTS OF IN-ROUND ANALYSIS	3.1:	Generate statistics of the cross-tabulations in step 2.4 for each Respondent
	3.2:	Generate hard copy Raster Maps for the Composite Maps in step 2.3
	3.3:	Convert the Raster Maps in step 3.2 to a vector format data file to be used by GIMMS (see Appendix III)
	3.4:	Generate Line-plotter Maps with GIMMS showing areas of agreement
Step 4: COMPARE RESULTS WITH PREVIOUS ROUNDS (skip step 4 on first round)	4.1:	Cross-tabulate Composite Map at 60% level with Composite Map at 60% level of previous round and generate statistics
	4.2:	Cross-tabulate Composite Map at 80% level with Composite Map at 80% level of previous round and generate statistics
	4.3:	Test significance of changes between rounds
Step 5: FEEDBACK SUMMARY INFORMATION TO RESPONDENTS	5.1:	Provide each Respondent with a set of Composite Maps for each variable and his individual correspondences with these maps
	5.2:	Discuss results
Step 6: REPEAT STEPS 1 THROUGH 5 FOR NEXT ITERATION		

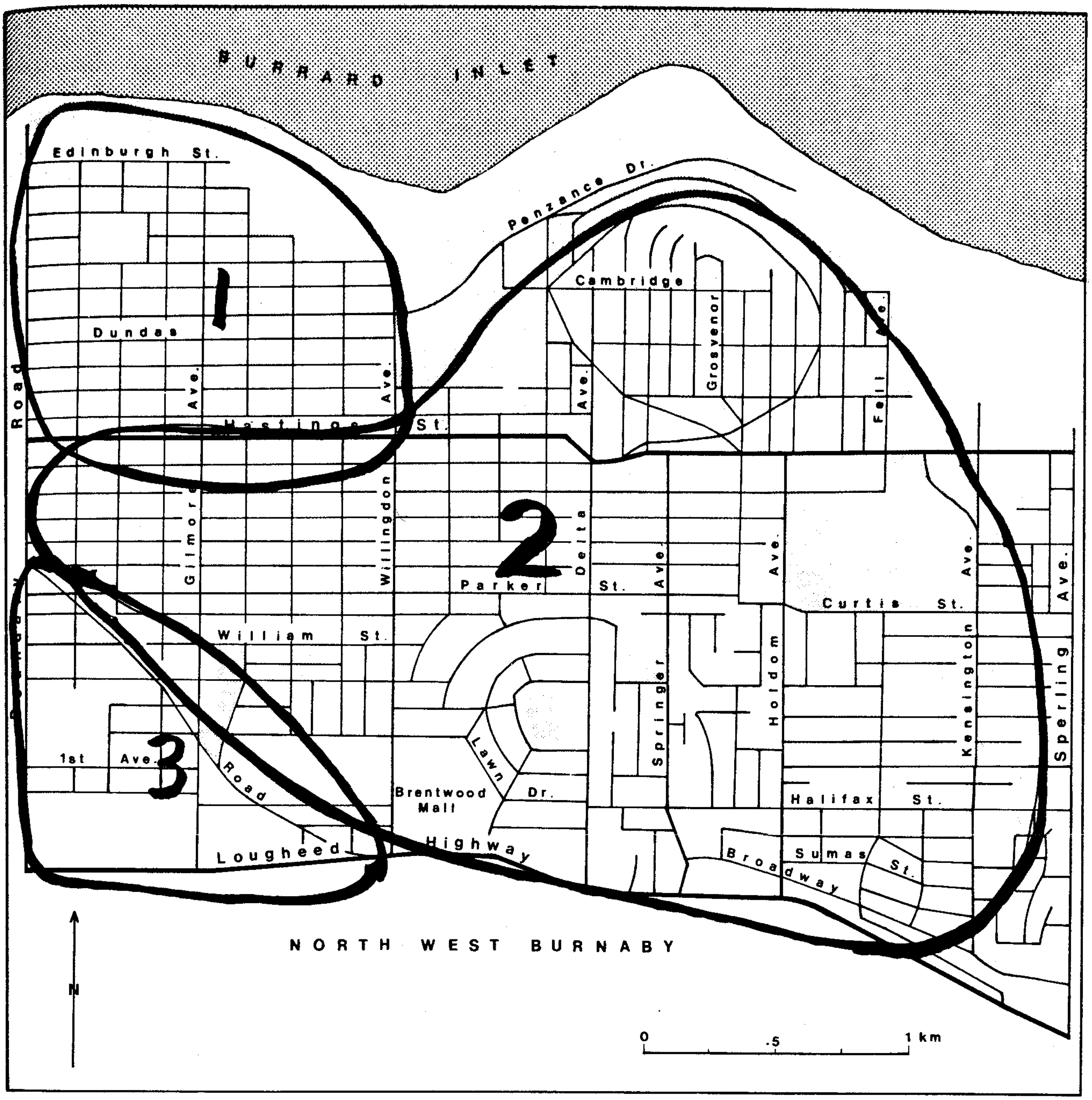


Figure 4.4: An Example of a Respondent's Completion Map Showing Overlapping Boundaries.

the two boundaries did not overlap, there were large areas which appeared to be uncategorized. Also, when participants focussed on individual areas, it was frequently the case that separately identified, but adjoining, areas were given the same classification value (see Figure 4.5).

The indistinct and often overlapping boundaries which were drawn on the maps might tempt one to attribute the phenomenon to "fuzzy" reasoning or to "fuzzy" classifications of the categories; but, while not discounting these possibilities, it is more likely that participants were just unsure of how best to represent their thoughts in graphic form. Subsequent discussions with individuals about this issue revealed that they meant rather specific lines. For example, when lines were roughly drawn along a street, possibly deviating from it by as much as a centimeter or more on the map, they thought the interpretation was obvious that they really meant the street. It is analogous to asking someone to locate a building, say a post office, on a large scale map -- they are likely to draw a circle around the area in which the building is located, assuming that the reader will know they meant the straight lines representing the outline of the building. Of course, humans are attuned to making such interpretations, but to give this general information to a computer means that it will interpret it literally. Only a system with artificial intelligence would be able to make such "educated guesses" as to what the author of the map really meant. Therefore, before digitizing, some lines had to be "interpreted". Because of the underlying street patterns on the map, such interpretations and "straightening" of lines were relatively easy. Any confusions which could not be resolved were clarified with the participants before the maps were used in the analysis.

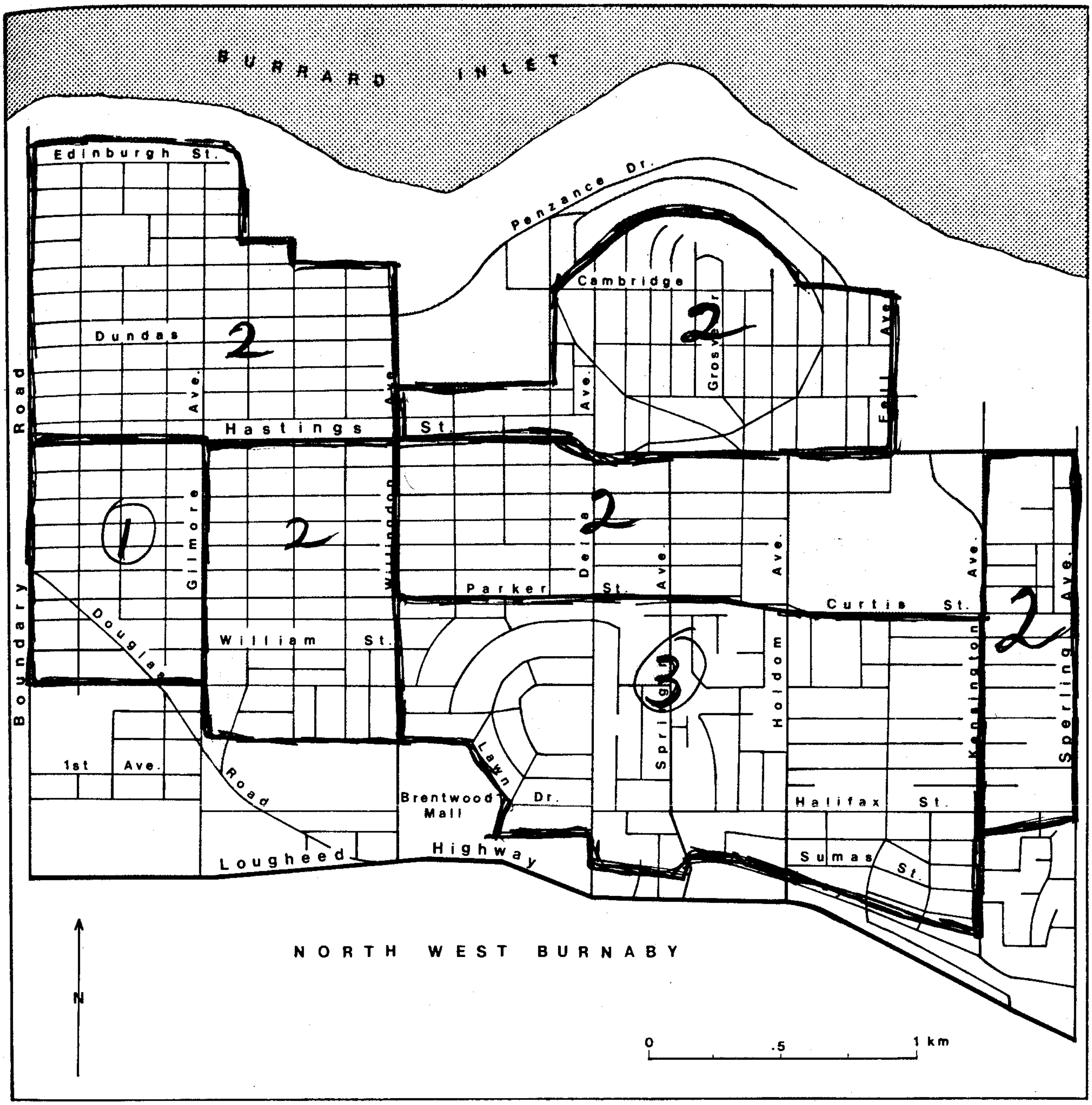


Figure 4.5: An Example of a Respondent's Completion Map Showing 'False' Boundaries.

These problems were not as common with Panel II. Two apparent reasons are suggested. First, during the discussion before the participants completed their response maps, the importance of being accurate with their drawing was emphasized to them. Secondly, because of the nature of their work, there appeared to be more attention paid to the actual street patterns (linear features), i.e., they spend a considerable amount of time patrolling or traveling through the area at all times of the day and night. Therefore, they tended to draw their "dividing lines" more closely to existing street patterns (see Figure 4.6). Still, hand drawn lines had to be "straightened" and made to conform to street patterns when it was obvious that that was the intention.

A second difficulty was with convening the panels. Panel I was convened ensemble for the first round with only minor difficulties. The round preceded a regular staff meeting which all participants were expected to attend. The second round was more of a problem. A mutually convenient time could not be arranged for the five participants to meet. It was anticipated that the second round could be completed within one week of the first, but it was not until three weeks later that at least four of the five panelists were available. Even then, one panelist interrupted his holiday schedule to attend the panel meeting. The fifth panelist was vacationing away from the study area and was not available for the second round ensemble. The questionnaire was administered to the fifth panelist when he returned. He was provided with the information stemming from the discussion of the second round ensemble, therefore, he was able to base his second round decisions on the same information as the rest of the panelists. The drawback was that his input to the discussion was not available for the rest of the panelists.

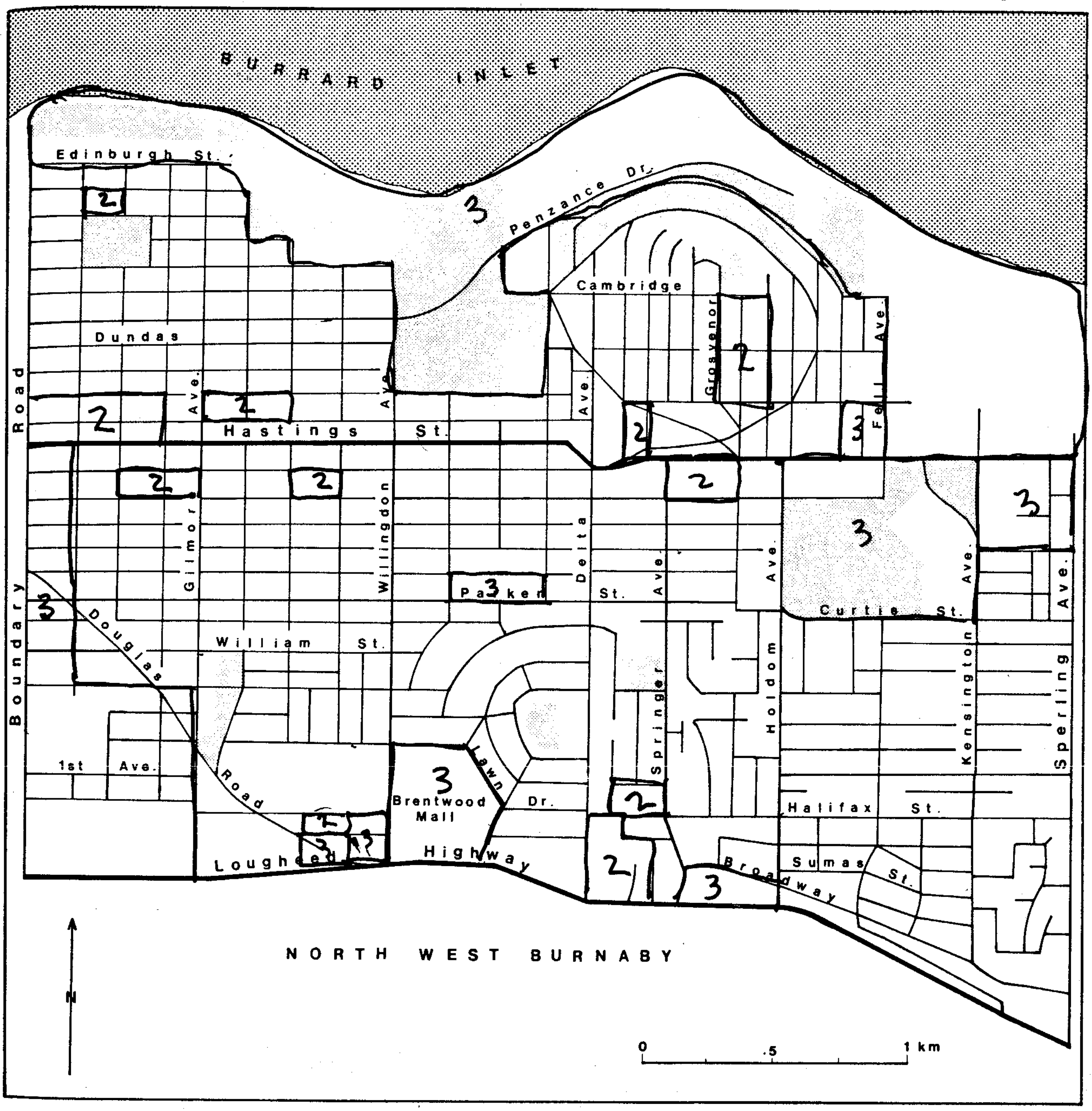


Figure 4.6: An Example of a Completion Map from Panel II Showing Precision in the Representation of the Boundaries.

Other difficulties were encountered with Panel II, composed of RCMP officers. It was impossible to convene all members at one time because of conflicting shift duty rosters, work assignments, and vacation schedules. The first round questionnaire was, therefore, administered on an individual basis as their schedules permitted. For some, this meant during the late evenings and on Sundays. The results from the first round of Panel II were, as will be seen in Chapter 5, in high agreement on a number of the variables. Conducting a second round of the questionnaire became impossible within the time available because two of the participants went on four week vacations shortly after the first round was completed. The results of the first round were useful in the analysis as a comparison with those of Panel I, but no analysis regarding consensus formation can be made.

4.4 Comparing Test Results with Reality

The results of the Strabo process were examined to determine whether or not the structured communication produced higher levels of agreement in the individual perceptions of spatial phenomena. This was done by analyzing the within and between rounds results. The aggregate maps were compared to determine if the amount of disagreement had been reduced by updating individual opinions with the results of the previous round. The results of the Strabo exercise were also examined to determine how well they reflected reality. This was not possible for some of the variables (e.g., livability), because the variables themselves were very subjective in nature. Any operational definition of the concepts, against which the

Strabo results might be compared, would be derived by a subjective weighting of a number of measurable factors (e.g., housing quality and access to amenities). These definitions become indirect measures and the problem would reduce to the comparison of two indirect measures, rather than comparing an experimental measure with reality.

The variables housing type, housing quality, and income levels permitted a more direct comparison between Strabo results and reality. Information on existing housing types was gleaned from several sources. First, the latest zoning maps of the study area from Burnaby municipality were consulted and an initial map of housing types was drafted on the base map used in the Strabo exercise. This draft was then checked against 1:2000 aerial photography of the area. Final verification was accomplished by several field visits to areas which could not be identified with certainty from the two previous approaches, and to areas which had changed since the air photos had been taken. This produced a map of existing housing types to which the Strabo results could be compared.

Information on existing housing quality was obtained from the computer based geographic data files in the Burnaby Planning Department. Every dwelling in the study area was given a "quality" value ranging from poor to excellent based on values assigned by the British Columbia Assessment Authority (1983). These were extracted on a dwelling by dwelling basis and a map produced against which the Strabo results could be compared.

Unfortunately, the same level of detail was not available for "income" data. The comparison had to rely on income data aggregated to the enumeration area level. Census data from 1981 was used; the study area was covered by a total of 42 enumeration areas as defined by Statistics Canada. These covered, in whole or in part, census tracts 238 to 242 of the Vancouver Census Metropolitan Area (CMA). The variable used to determine income levels was "Average Income of Private Households" (Statistics Canada, 1981). Although the census data was for an earlier time than the Strabo data (in fact, 3 years prior), this was not a problem because the focus was on the relative ranking, i.e., high, middle, and low, rather than specific income values. Even though the actual average household incomes would have increased from 1981 to 1984 simply as a matter of inflation, it was assumed that the relative increases would be more or less consistent over the entire study area. Therefore, while the actual incomes would have increased marginally, the relative rankings would not have changed.

Using enumeration areas as the basis for the "real world" income levels was justified because they were small in area and, by definition, relatively homogeneous in terms of population characteristic. At the scale of the study, enumeration areas provided a representative statistical surface against which the Strabo produced surface of income distributions could be compared.

CHAPTER 5: AN ANALYSIS OF THE STRABO RESULTS

The previous chapter described the design and application of the Strabo method for purposes of illustrating the approach, determining cognitive behaviour resulting from a structured communication process, and determining whether the process can reflect reality. This chapter examines the results of the application.

5.1 The Application in Summary

The technique was applied to an urban data problem in northwest Burnaby. The area was primarily residential with some commercial, industrial, and recreational land uses. The area was bounded on the north by Burrard inlet and on the west by the city of Vancouver. The area covered approximately 10 square kilometers and was roughly rectangular in shape.

Two panels were struck -- one composed of five experts from the real estate industry and the other of five experts from the local police department. The first panel participated in two rounds of the exercise, while the second panel participated only in the initial round. The questionnaire instrument consisted of six questions requiring map answers. One completion map measured individual familiarities of the study area. This was used to determine individual confidence in providing spatial answers to the questions. The questions ranged from objective variables like housing type to highly subjective variables such as livability. Respondents were requested to define their conception of the subjective variables, to discover differences in their cognitive structures which might explain variations between their spatial responses.

Individual response maps were aggregated into composite maps at the end of each round and the amount of agreement was tallied according to a criterion established for determining whether a consensus existed for a particular area. This summary information was fed back to the panelists as input to their decision process in the next round. Within and between round analyses were performed to determine the effectiveness of the methodology.

5.2 Strabo's Ability to Form Consensus

This section examines the results of the demonstration in terms of the method's ability to steer individual opinion towards a group consensus. For this, only the Panel I results from the five different questions were used; Panel II did not complete the second round of the exercise, therefore it was not possible to measure any shift with that group.

After the first round interviews, the spatial answers were aggregated into composite maps showing areas of high levels of agreement. Two different criteria were used to measure the strength of the aggregations. The first defined agreement as having occurred if at least three of the panel members indicated with confidence the same category of a variable for an area. This amounted to a 60% criterion. A second level of agreement was defined as at least four respondents (at least 80%) agreeing on a category.

In the aggregation process, individual response maps were weighted by corresponding confidence maps. Only those areas with which individuals were familiar were considered. Weightings were accomplished by using capabilities of the MAP program to multiply two maps together (Tomlin, 1980). The confidence map was recategorized so that all areas with which a respondent felt familiar were given a value of "1"; the rest of the areas were given a value of "0". When any of the attribute maps were multiplied by the "1-0" confidence map, 0 effectively masked out those areas which were less than completely familiar to the individual, while 1 left untouched those categories in areas which were familiar. This assured that only areas for which each respondent was confident that his answers were correct would be considered in the aggregation process (see Appendix IV for a listing of MAP commands used to produce the composite maps).

The results of aggregating weighted attribute maps were influenced by the composite map of individual confidences. For example, if an area was unfamiliar to at least 60% of the respondents, then it would be impossible to reach a consensus about an attribute in that area. Figure 5.0 represents the aggregates of the individual confidences.

The MAP program, which was used to analyse the results of the application, is based on a grid representation of the surface. An appropriate grid size was selected and the maps were converted to a raster image composed of 4763 elements within the study area. In looking for meaningful agreement amongst respondents, it was necessary to show that agreement which did occur was better than that which could be expected from a purely random process. Combinatorial statistics were used to derive maps aggregated from random

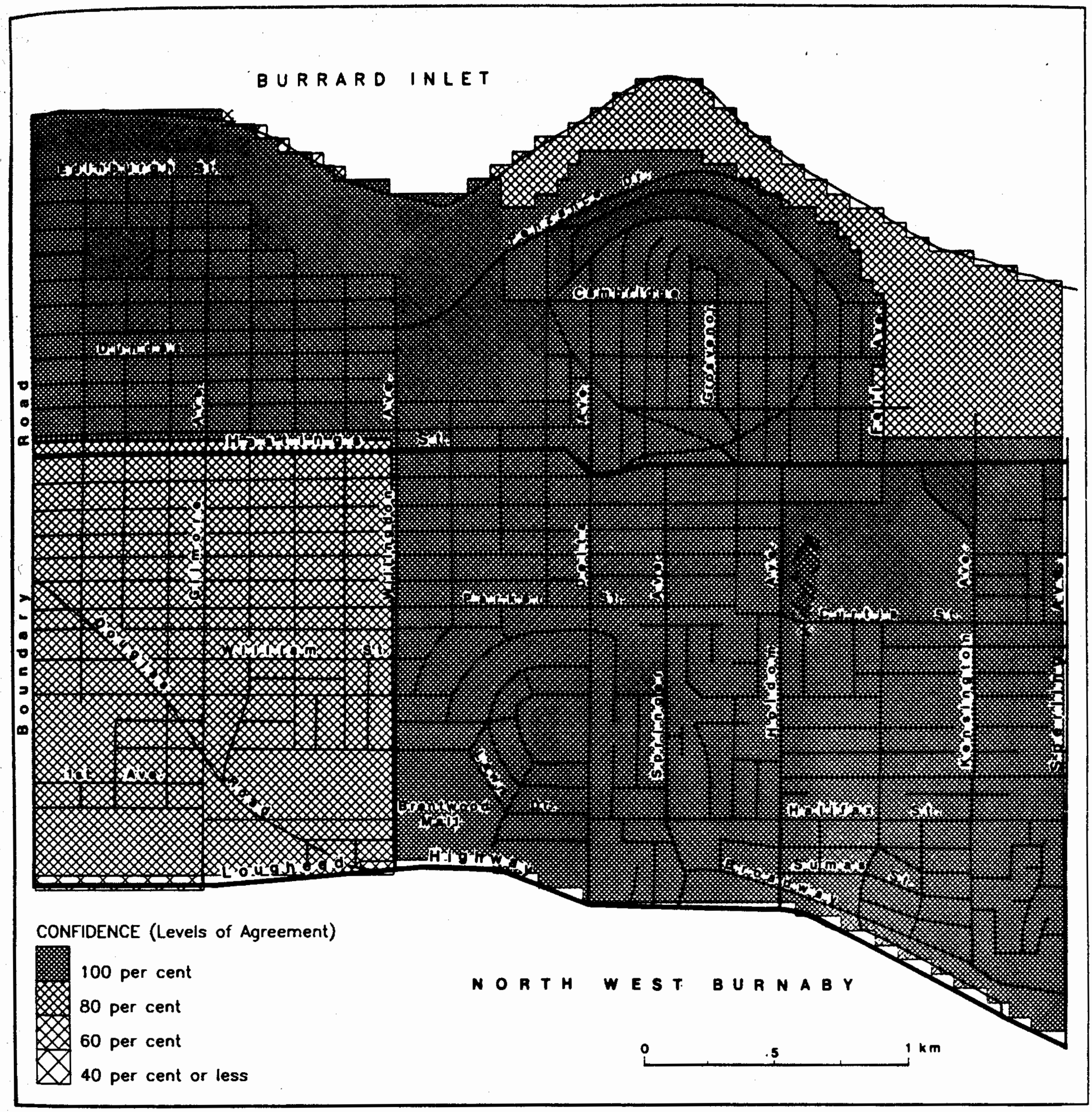


Figure 5.0: Composite Map of Confidence Levels for Panel I.

responses. These aggregations depended on the level of agreement assumed and the number of categories in the topic of the map. For some topics, e.g., housing quality and income, areas might be assigned any one of four categories -- the fourth always being areas for which the other three categories were not applicable. For example, park areas could not be sensibly classified as either high, middle, or low income nor did it make sense to classify these areas as good, moderate, or low quality housing. For the other variables, three categories sufficed; parks, schools, and shopping malls fell into existing categories of housing type (i.e., non-residential), level of crime, and livability.

With these conditions, four hypothetical maps, based on aggregations of random responses, were defined -- these maps existed only in statistical summary form and had no graphical manifestation because, while the statistics were consistent with replication, the graphic representation would not be. That is, the graphical representation of an aggregation of one set of five maps categorized randomly would not be the same as that of another set; however, their statistical summaries should not be significantly different.

A hypothetical map based on aggregating five maps categorized randomly with three categories could be assured of having any given area represented by one of 243 permutations of responses (i.e., 3^5). This occurred because the area on any one map could be classified in three different ways; there were five separate maps, hence the laws of probability assured, through a multiplicative rule, that the number of permutations was 3x3x3x3x3, or 3^5. For maps containing four categories of data, the number of permutations rose to 1024 (i.e., 4^5).

In the hypothetical cases, if one defined agreement as having been reached when at least 60% of the responses were the same for a given area, then it was necessary to determine how many possible permutations satisfied this criterion, assuming that all were equally likely. Again, laws of combinations were used. Since the criterion was "at least 60%", it was necessary to find the number of permutations with exactly 3, exactly 4, and exactly 5 agreements. The general formula is

$$P_{60} = \sum_{r=3}^{5} n \cdot \frac{N!}{r!(n-r)!} \cdot (n-1)^{(n-r)}$$

where P_{60} = number of permutations with at least 60% agreement

n = number of data categories (i.e., 3, or 4)

N = number of responses (i.e., 5)

r = level of agreement (e.g., exactly 3, exactly 4, etc.)

Using this formula, with maps represented by three data categories (for example, single family, multiple family, and non-residential) and assuming that agreement had been reached at a 60% level, then P_{60} = 153. That is, 153 permutations of the 5 responses satisfied the criteria. This represented 63% of the total permutations (i.e., (153/243)x100). The chance of agreement occurring for any given area from random response maps was 0.63; therefore, one might have expected to find agreement at the 60% level in 63% of the total study area.

At the 80% agreement level for 3 data categories, the number of permutations reflecting at least 4 of the 5 responses coinciding was 33, or 13.6% of the total (i.e., (33/243)x100). Thus aggregations of 5 purely random response maps would display agreement at the 80% level over 13.6% of the study area.

Similarly, maps containing random distributions of 4 data categories would correspond in 41.4% of the area at a 60% agreement level, and in 6.2% of the area at a 80% level. These correspond respectively to 424 and 64 permutations of the total 1024 possible permutations.

These values are important when analysing the aggregate maps of the panelists to show that results were better than would be expected from a random process. In other words, they offered a baseline against which to compare and to show that results of the application were statistically significant. In order that results from the aggregation could be analysed and understood, several other terms and statistics in this context were defined. A definition of composite maps according to two criteria for agreement has already been given -- that is, at least 3 of the 5 panelists agreeing (60% level), and secondly, at least 4 of the 5 panelists agreeing (80% level). The degree of correspondence between individual response maps and the composite maps was defined as the percent of the total study area in which the individual's classification agreed exactly with that of the composite map. These descriptive statistics for individual panelists were referred to as "concordances". To measure the amount of dispersion which existed within the individual concordances, an index was developed which related them not only to each other but also with the composites. The index was analogous to the statistic which measures the standard deviation about the mean of a distribution. It was calculated by the formula:

$$D = \sum_{i=1}^{n} (A-C_i)/n \cdot A$$

where D = index of dispersion

A = percent of area for which agreement has been reached

C_i = Concordance for respondent i

n = number of respondents

Since C_i could not be larger than A, this statistic had a theoretical range of values between 0 and 1, and for the purpose of this study was purely descriptive.

5.2.1 Dwelling Types

Each respondent was asked to draw on the base map areas characterized by predominantly single family and multiple family dwellings and also those areas which were non-residential in nature. Being unfamiliar with this type of exercise, they produced results which were sometimes ambiguous in the first round of the process. This was expected, and was not a problem. In fact, a cornerstone of the technique (<u>i.e.</u>, the iterative feedback process) is designed not only to feed additional information into the decision-making process but to allow individuals to clarify their own understanding and response to problems. Thus, ambiguities which occur can be brought to their attention and clarified in subsequent rounds.

During the first round, some ambiguities arose resulting from the manner in which participants represented graphically their concept of areas. Most drew sweeping lines around areas which they felt to be rather homogeneous. As described in chapter 4, this produced overlapping areas, although the intended location of the dividing lines was usually apparent. On the subsequent round with Panel I, this was less of a problem as they tried to be more precise in their graphic representation of areas. Also on the first round, some areas were not categorized. That also produced ambiguous results since the three categories were exhaustive for the variable dwelling type. However, if an area was not categorized as belonging to one of the three given categories, it was, for analytical purposes, assigned a value for a fourth category of "other". In this manner, such areas were legitimately classified and dealt with in the iterative feedback process. Close examination of the individual response maps suggested possible reasons for not categorizing all areas with the three given categories. Primarily, it seemed that there existed differences in interpretation of the category "non-residential". While assuming the obvious, that areas such as parks, schools, and wooded areas did not have residential dwellings located in them, participants were less clear about other types of non-residential uses such as commercial and industrial. In the structured discussion which took place prior to the second round, everyone agreed that these types of land uses (i.e., parks, schools, and industrial) were non-residential and should be included as such in the next round. Specifically, the large area in the northern part of the study area, between Burrard inlet and Capital Hill should be categorized as non-residential. They indicated in the discussion that "that was what they meant" when they filled in the map and that they had assumed that it was so obvious that when the map was being processed, or used, it would automatically be treated as non-residential. There was considerable discussion about this issue and panelists described verbally the limits of these areas. This was taken into consideration as they prepared the second round maps and as these maps were prepared for digitizing. Thus, in the second round responses, there was no area falling in the "other" category (with one exception which will be discussed later). Table 5.1 shows the percentages of the total area falling into each of the categories by individual response maps for the two rounds.

After weighting each response map by its corresponding confidence map, they were aggregated to form a composite map showing areas of agreement. Aggregations were performed at both 60% and 80% agreement levels (Figures 5.1 and 5.2). The first round results indicated agreement over 75.5% and 58.8% of the study area at the two levels respectively. As the criterion for agreement is tightened, one would expect the amount of area to decrease -- it would be impossible to have more area agreed upon at an 80% level than at a 60% level.

Since four categories were used to describe the variable of dwelling type in round 1, one could expect to find agreement in 41.4% of the area at a 60% level criteria and in 6.2% of the area at an 80% level (see section 5.2). It was apparent that the resulting composite maps displayed more agreement than those which might be obtained from random responses. A Chi squared test on the composite maps verified that they are statistically significant at both levels of agreement. Chi-square values of 2285 and 22675 were obtained which were significant beyond a 99.9% confidence interval.

Table 5.2 indicates that for round 1, all participants in Panel I had similar levels of correspondence with the composite map (i.e., 62.4% - 72.8% at the 60% agreement level and 51.5% - 58.8% at the 80% level). The correspondence was measured as a percent of the total study area for which the individual response map agreed with the composite map. This value could not exceed the area for which agreement had been defined, i.e., 75.5% and 58.8% at

Table 5.1

Percent of Total Study Area Assigned to Each Category of Residential Dwelling Type by Respondent— Panel I

CATEGORY	Round	R_1	R_2	R_3	R_4	R_5
Single Family	Round 1	66.7%	100.0%	61.8%	75.6%	5.9%
	Round 2	65.1%	57.6%	67.0%	63.6%	68.9%
Multiple Family	Round 1	1.9%		2.4%		7.8%
	Round 2	1.9%	2.4%	2.0%	0.6%	3.6%
Non Residential	Round 1	31.4%		13.2%	12.2%	14.1%
	Round 2	33.0%	39.9%	30.9%	35.7%	5.0%
Other	Round 1			22.3%	12.1%	19.2%
	Round 2					22.5%

Round 1   Round 2

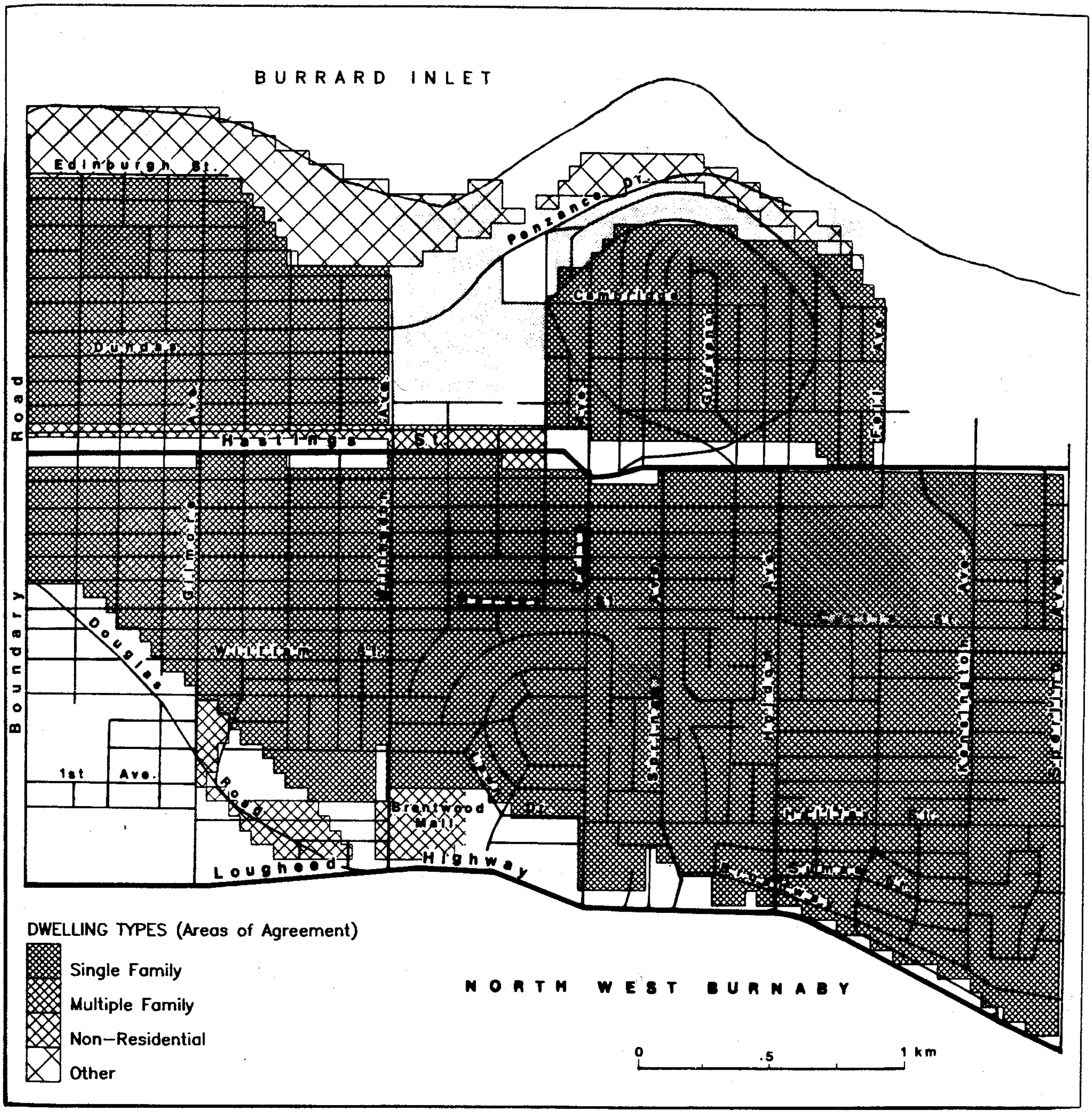


*Figure 5.1: Composite Map of **Residential Dwelling Types** at 60% Agreement Level for Panel I, Round 1.*

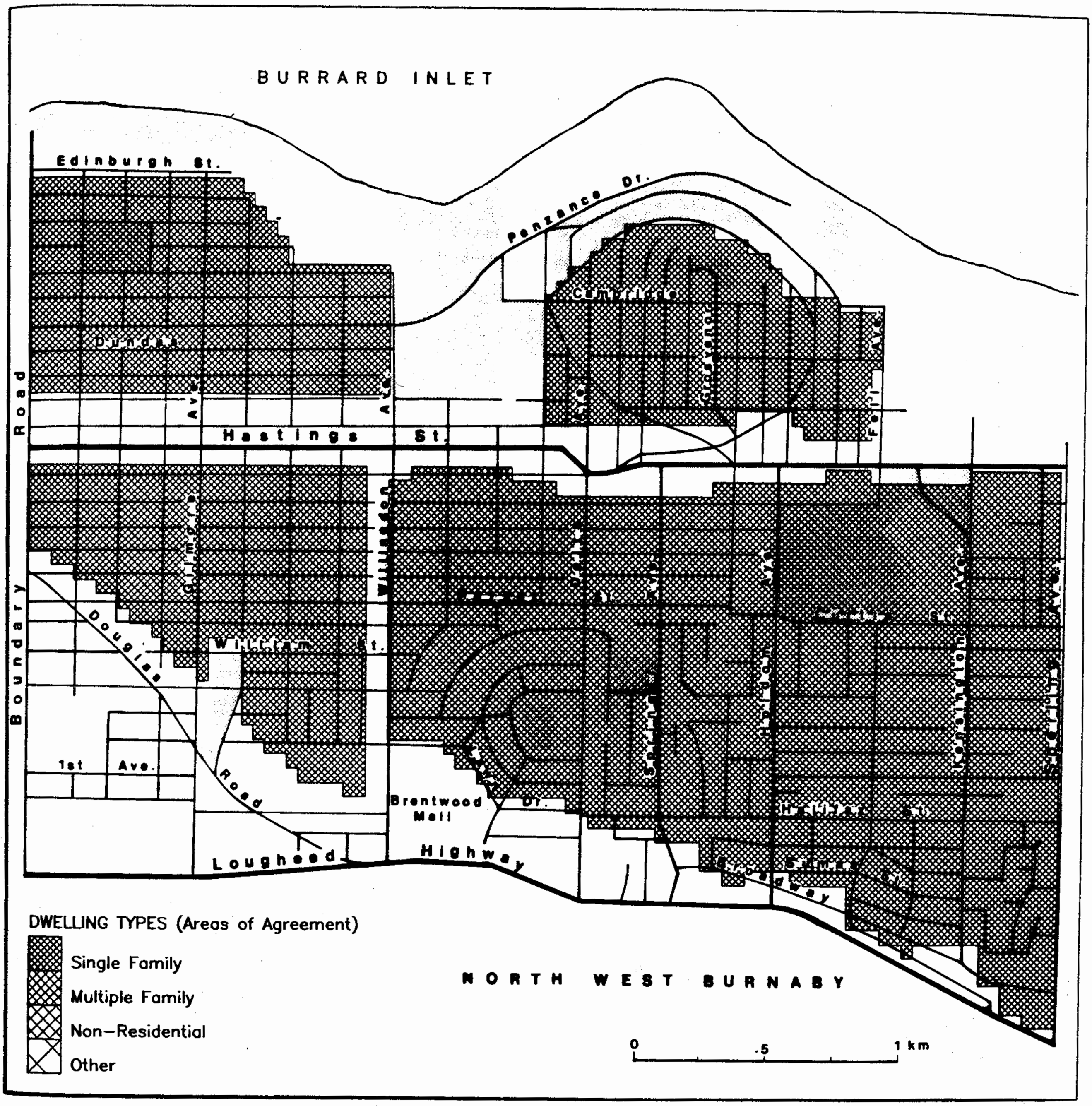


*Figure 5.2: Composite Map of **Residential Dwelling Types** at 80% Agreement Level for Panel I, Round 1.*

the two levels of agreement respectively. It was noted that respondents 2 and 4 agreed almost entirely with the areas on the composite map from the 80% criteria. These results indicated that none of the respondents had markedly discordant opinions about the spatial distribution of the variable. If one were to find an individual differing greatly from a clustering of the other respondents and with relatively low correspondence with the composite map, the indication would be a strong divergence in opinion. In a larger panel, such divergence might reflect a polarization within the group, as might be found, for example, in a group whose members disagree on the location of a proposed facility (e.g., new hospital) for which several viable options exist.

Prior to Panel I beginning the second round of questionnaires, the summary information together with the composite map were returned to the individuals. Each individual then knew what the "average" map looked like and how his/her individual response compared to it. The composite map was explained to them as were the summary statistics. They were encouraged to discuss the composite map in terms of their individual perceptions and beliefs. Particularly, they were urged to examine the areas of disagreement. Important information emerged from these discussions. First, it became clear to them that some of their first round responses were ambiguous and that by more carefully delineating the areas, much of this problem would disappear. Secondly, they noted that the composite map showed no areas of agreement for multi-family dwellings. They then discussed which areas included this housing type with reference to particular buildings and locations.

Similar to the procedures followed in the first round, the individual responses were again aggregated into composite maps weighted by the individual

Table 5.2

Degree of Correspondence between Individual Response Maps and the Composite Residential Dwelling Type Maps, at 60% and 80% Agreement Levels— Panel I, Round 1

a) 60% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
Single Family	59.3	66.6	61	66.1	53.9	66.7
Multiple Family	–	–	–	–	–	–
Non Residential	3.1	–	3.1	1	2.8	3.1
Other	–	–	5.7	5.7	5.7	5.7
TOTAL	62.4	66.6	69.8	72.8	62.4	75.5
	Index of Dispersion = 0.12					

b) 80% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
Single Family	55.3	58.8	57.4	51.5	51.5	58.8
Multiple Family	–	–	–	–	–	–
Non Residential	–	–	–	–	–	–
Other	–	–	–	–	–	–
TOTAL	55.3	58.8	57.4	51.5	51.5	58.8
	Index of Dispersion = 0.04					

confidence maps. All five panelists indicated that no change occurred in their familiarity with the area between the two rounds of questionnaires, therefore, their confidence in the responses remained the same as that for the first round.

Composite maps at both 60% and 80% agreement levels were produced (Figures 5.3 and 5.4). There was consensus over 97.1% of the study area at the 60% agreement level, and 81.7% at the 80% level. This showed a dramatic increase from the first round -- 75.5% and 58.8% respectively. Again, Chi square values of 2375 and 18821 showed these results to be significantly different from results obtained from random responses, and Chi square values of 1199 and 1031 confirmed that the results from the second round were significantly improved from those of the first round.

Table 5.3 indicates a general concordance amongst the panelists with one exception. In this case the correspondence with the composite was only 61.9% at the 60% level compared with 88.7% to 94.9% for the other four panelists. Similar results were observed at the 80% agreement level. An examination of the results revealed that he had similar levels of agreement with the other panelists in all categories except "non-residential". Referring back to his original response map, it was clear why this aberration occurred. In the second round questionnaire, he identified only 5% of the area as "non-residential", while 22.5% of the area was not classified according to the three categories and was therefore interpreted to be "Other" (Table 5.1). This ambiguity was a more common occurrence amongst all panelists in the first round, but was generally resolved through discussion prior to their completing the second round maps.

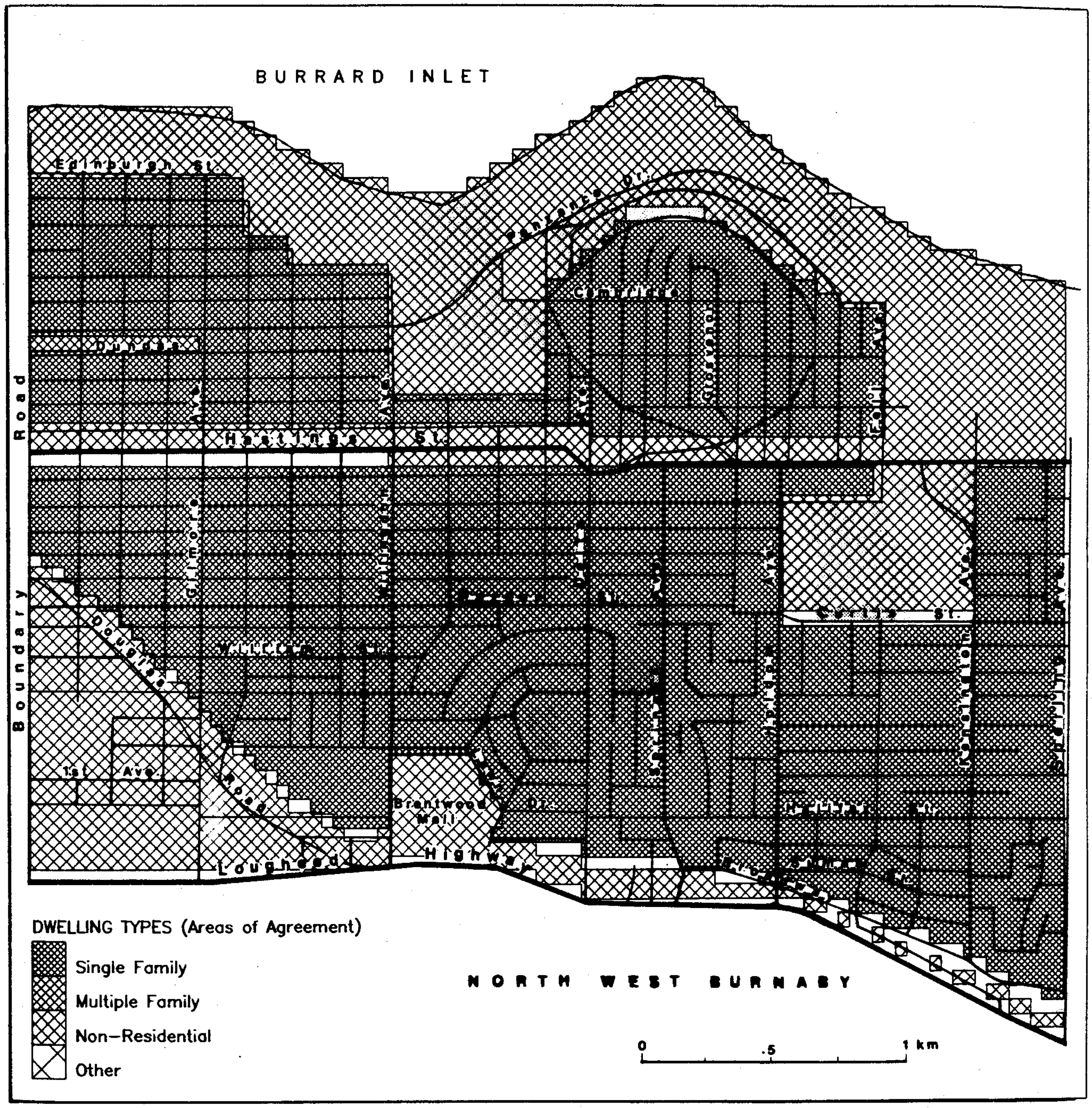


*Figure 5.3: Composite Map of **Residential Dwelling Types** at 60% Agreement Level for Panel I, Round 2.*

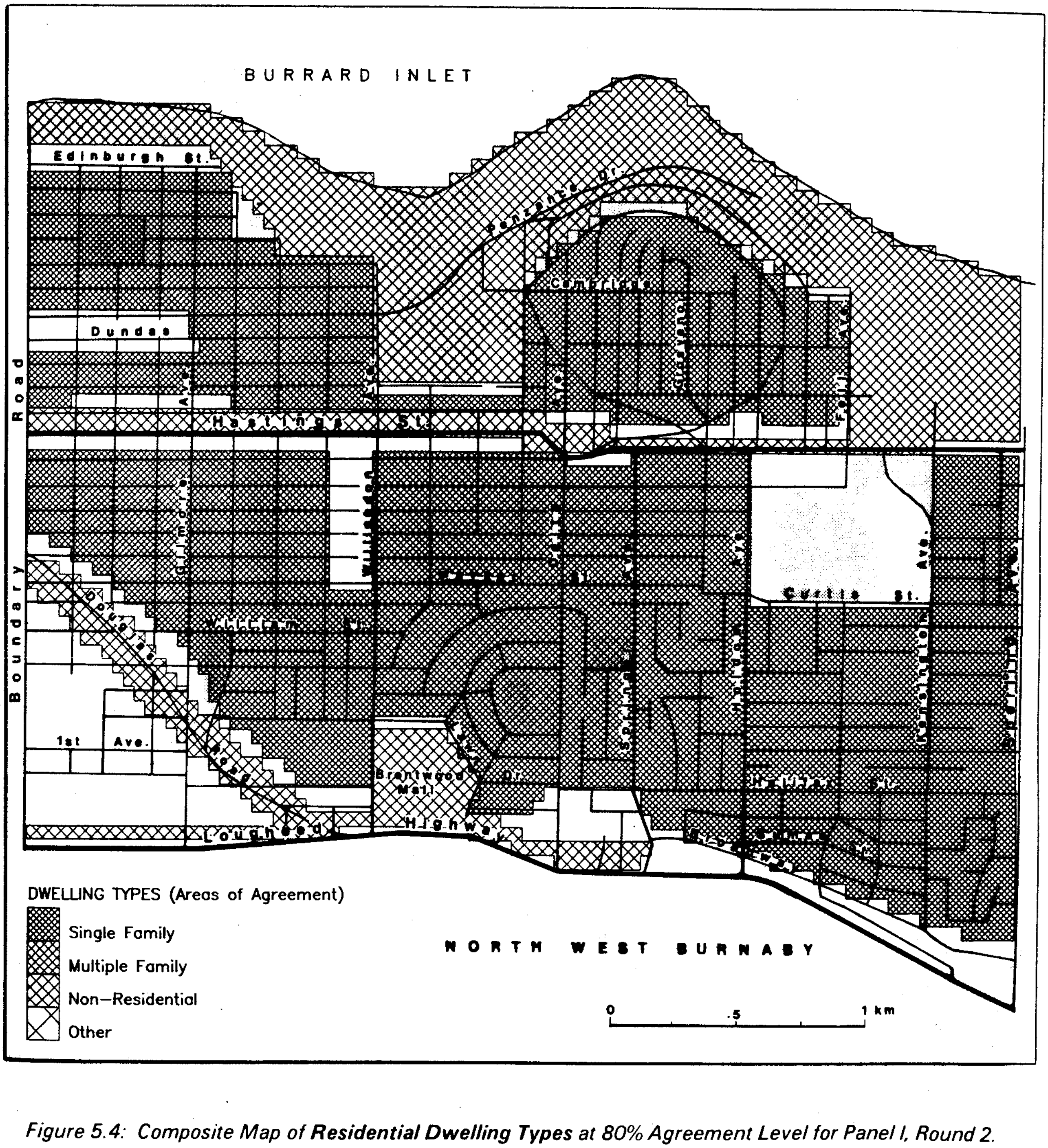


*Figure 5.4: Composite Map of **Residential Dwelling Types** at 80% Agreement Level for Panel I, Round 2.*

Table 5.3

Degree of Correspondence between Individual Response Maps and the Composite Residential Dwelling Type Maps, at 60% and 80% Agreement Levels— Panel I, Round 2

a) 60% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
Single Family	58	57.2	61	60.7	58.5	61.6
Multiple Family	–	0.3	0.3	0.3	–	0.3
Non Residential	30.7	35.1	29.4	33.9	3.4	35.2
Other	–	–	–	–	–	–
TOTAL	88.7	92.6	90.7	94.9	61.9	97.1
	Index of Dispersion = 0.12					

b) 80% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
Single Family	55.4	55.4	57	57.1	55.3	57.1
Multiple Family	–	–	–	–	–	–
Non Residential	24.6	24.6	23.6	24.5	2.3	24.6
Other	–	–	–	–	–	–
TOTAL	80	80	80.6	81.6	57.6	81.7
	Index of Dispersion = 0.07					

Although the results from Panel II cannot be used to demonstrate convergence in opinion because they represent only a single round, they can be usefully compared to those of Panel I to show consistency in the results (Table 5.4). As before, aggregations were performed at both 60% and 80% agreement levels (Figures 5.5 and 5.6). There was agreement over 89.9% of the area at the 60% level and 62.6% at the 80% level. These values were higher than those corresponding in Panel I, _i.e._, 75.5% and 58.8% respectively. These improved statistics reflected the greater attention paid to detail which was observed during the map completion phase. Unlike Panel I, participants in Panel II reviewed the information at a "micro" level; they frequently identified individual buildings and represented some of their answers at a sub-block level. In fact, because of the scale of analysis, and the size of grid cell to be used in the digital representation of the maps, they had to be encouraged to generalize their answers more than they were inclined to do initially. They were encouraged to identify areas which were "predominantly" one class or another, recognizing that some impurities might exist. Because of the nature of their work, their knowledge of the area was good. In some parts of the study area, they described house by house what they knew to be factual, for example, size, style, and color of the house, demographics of the occupants (_e.g._, young family, two kids, middle class), and number of times they were called to the house or the area. Their attention to detail, which is necessary in their type of work, was obvious as they responded to the questionnaire. It was expected that first round questionnaires would take 30-45 minutes to complete. Because of their emphasis on detail, it sometimes required in excess of an hour to complete all maps.

Table 5.4

Percent of Total Study Area Assigned to Each Category of Residential Dwelling Type by Respondent—Panel II

CATEGORY	P_1	P_2	P_3	P_4	P_5
Single Family	61.5%	67.2%	65.4%	66.2%	73.2%
Multiple Family	0.5%	2.2%	3.9%	2.5%	1.6%
Non Residential	38.0%	30.4%	30.6%	13.6%	8.3%
Other				17.5%	16.8%

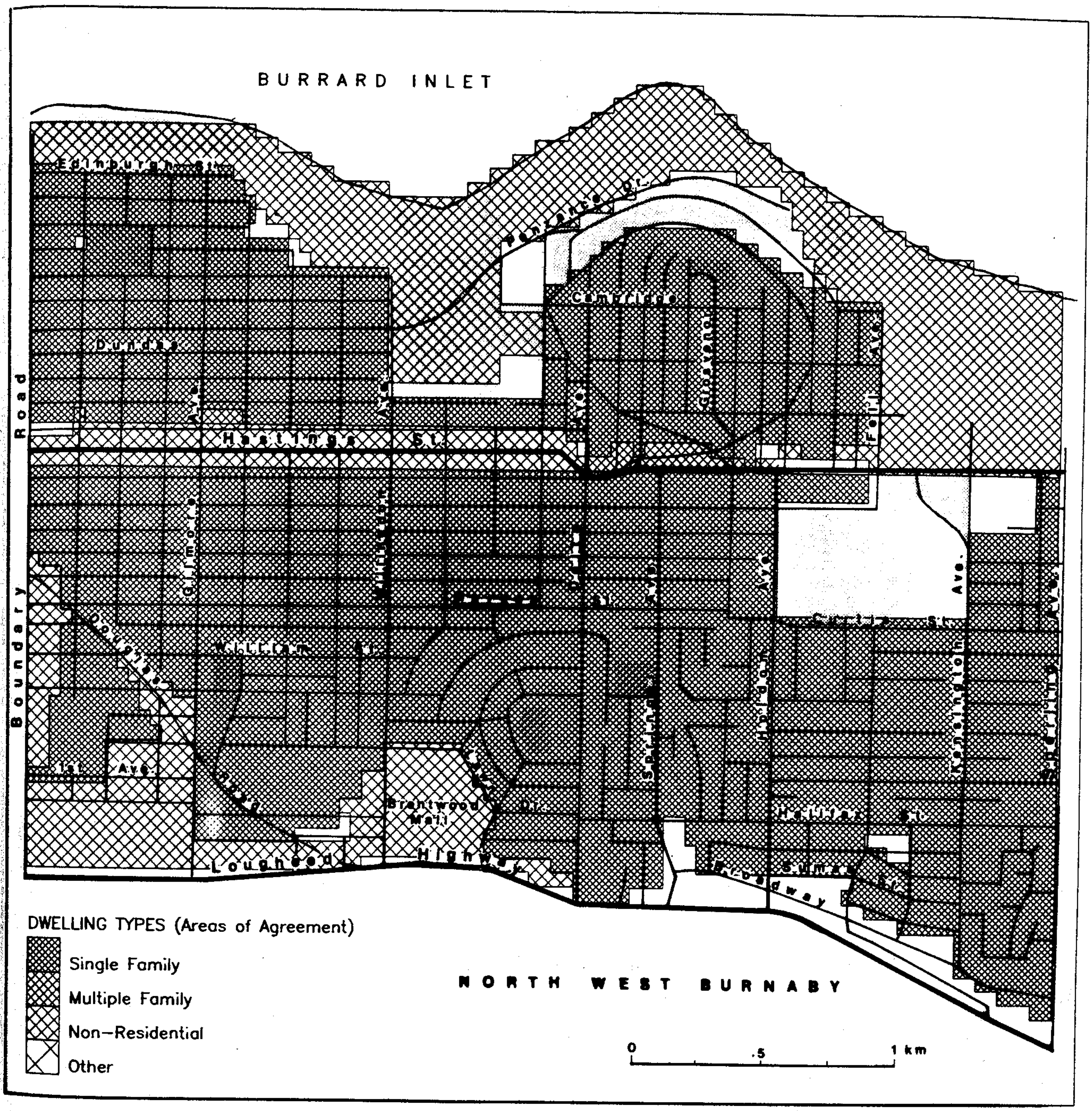


*Figure 5.5: Composite Map of **Residential Dwelling Types** at 60% Agreement Level for Panel II.*

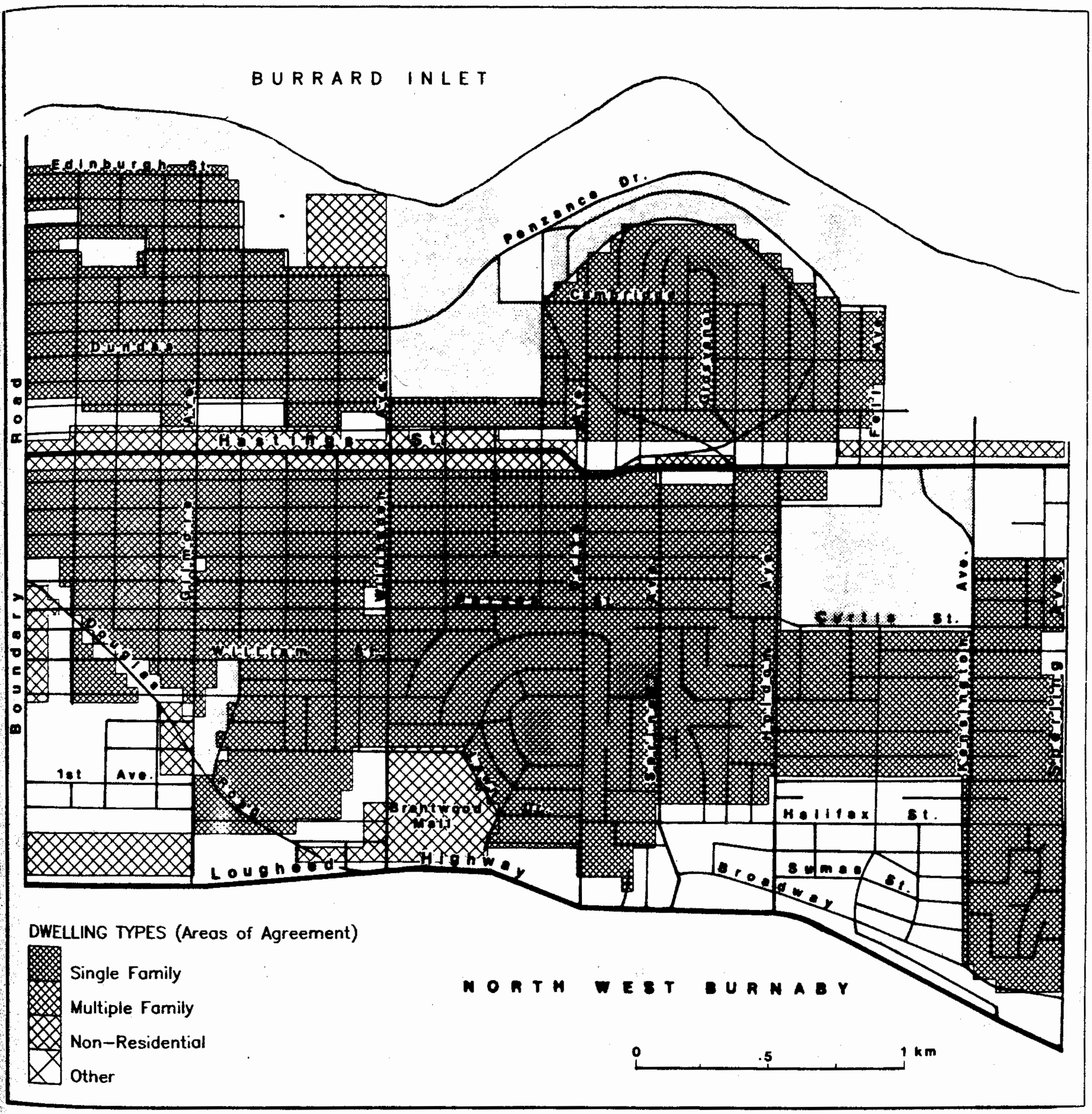


*Figure 5.6: Composite Map of **Residential Dwelling Types** at 80% Agreement Level for Panel II.*

Panel II was similar to Panel I; there did not exist major discordant points of view about the distribution of housing types. The degree of correspondence with the composite maps ranged from 71.2 to 83.3 at the 60% level (D=0.14) and 56.2 to 61.8 at the 80% level (D=0.05) amongst the five panelists (Table 5.5). The process of data collection was modified somewhat with Panel II to accommodate their work and vacation schedules. With the exception of two of the panelists, all filled out the questionnaire on an individual basis, that is, at a different time and place than their colleagues. Great care was taken to ensure that each participant received the same instructions and explanatory information. Since there was no discussion amongst the panelists in the first round of a Strabo exercise regarding the data, it was not surprising to find that they performed as well as the first panel did in round 1. The primary advantage of having the panel convened during the first round is to be sure that all participants get the same instructions, and that they all benefit equally from any clarifications raised. Since it was not possible to convene in this fashion, the study director was careful to pass on the same information to all panelists, although the first ones could obviously not benefit from clarifications raised by panelists completing the questionnaire at a later time.

5.2.2 Housing Quality

The second variable with which panelists were asked to deal was somewhat more subjective than the first. They were asked to identify areas characterized by poor, moderate, and good quality housing (Figures 5.7, 5.8, 5.9, and 5.10). Procedures for eliciting the information were similar to

Table 5.5

Degree of Correspondence between Individual Response Maps and the Composite Residential Dwelling Type Maps, at 60% and 80% Agreement Levels— Panel II

a) 60% Agreement Level

CATEGORY	P_1	P_2	P_3	P_4	P_5	Composite
Single Family	58.3	59.2	57.9	63.1	63.4	65.1
Multiple Family	–	0.6	0.3	0.5	0.5	0.6
Non Residential	22.3	23.5	20.3	8.2	7.3	24.2
Other	–	–	–	–	–	–
TOTAL	80.6	83.3	78.5	71.8	71.2	89.9

Index of Dispersion = 0.14

b) 80% Agreement Level

CATEGORY	P_1	P_2	P_3	P_4	P_5	Composite
Single Family	54.7	52.5	51.5	54.6	54.5	55.3
Multiple Family	–	0.1	0.1	0.1	0.1	0.1
Non Residential	7.1	7.2	4.6	5.4	6.1	7.2
Other	–	–	–	–	–	–
TOTAL	61.8	59.8	56.2	60.1	60.7	62.6

Index of Dispersion = 0.05

those described for housing types. In the first round, many of the ambiguities and confusions described above for dwelling types were also found in the other variables; however, as panelists gained experience with each map in the series, the graphic representation of their ideas and opinions became more precisely defined and less ambiguous.

With this variable, a fourth category ("other", or "not applicable") was recognized, because areas in parks and those used for industry are not residential and should not be classified as containing poor, moderate, or good quality housing. This category was applied to all areas not identified as one of the given three. Table 5.6 shows percent of the total study area assigned to each of the categories. From these observations it is apparent that most of the differences and uncertainties are between classifying areas as "moderate" or "good" quality. From the first round to the second round, some major shifts in opinion occurred between these two categories. Respondent 1 (R_1), for example, lowered his estimate of the amount of area characterized by "moderate quality" housing by 14.4% and increased his estimate by 15.3% for the amount of "good quality" housing. Respondent 5 (R_5) showed the greatest shift -- decreasing his estimate for "moderate quality" housing by 41.3% of the area and increasing his estimate for "good quality" housing by 40.8%.

An analysis of the composite maps showed that the degree of consensus increased between the two rounds (Tables 5.7 and 5.8). At the 60% agreement level, the area over which consensus had been reached increased from 90.2% to 93.1%, but, more noticeably, at the 80% level, the amount increased from 34.1% to 73.3%. Chi square tests showed all of these results to be significantly different from those which might have been expected from purely random

Table 5.6

Percent of Total Study Area Assigned to Each Category of Housing Quality by Respondent— Panel I

CATEGORY		R_1	R_2	R_3	R_4	R_5
Poor Quality	Round 1	17.5%		0.3%	11.6%	10.5%
	Round 2	11.4%		0.3%	10.1%	1.9%
Moderate Quality	Round 1	62.4%	43.6%	43.2%	55.2%	52.4%
	Round 2	48.0%	43.6%	36.4%	40.1%	11.1%
Good Quality	Round 1	2.9%	32.6%	35.3%	16.1%	14.7%
	Round 2	18.2%	16.6%	30.5%	21.4%	55.5%
Other	Round 1	17.0%	23.6%	21.1%	17.0%	22.8%
	Round 2	22.2%	30.6%	28.1%	28.1%	21.3%

Round 1 Round 2

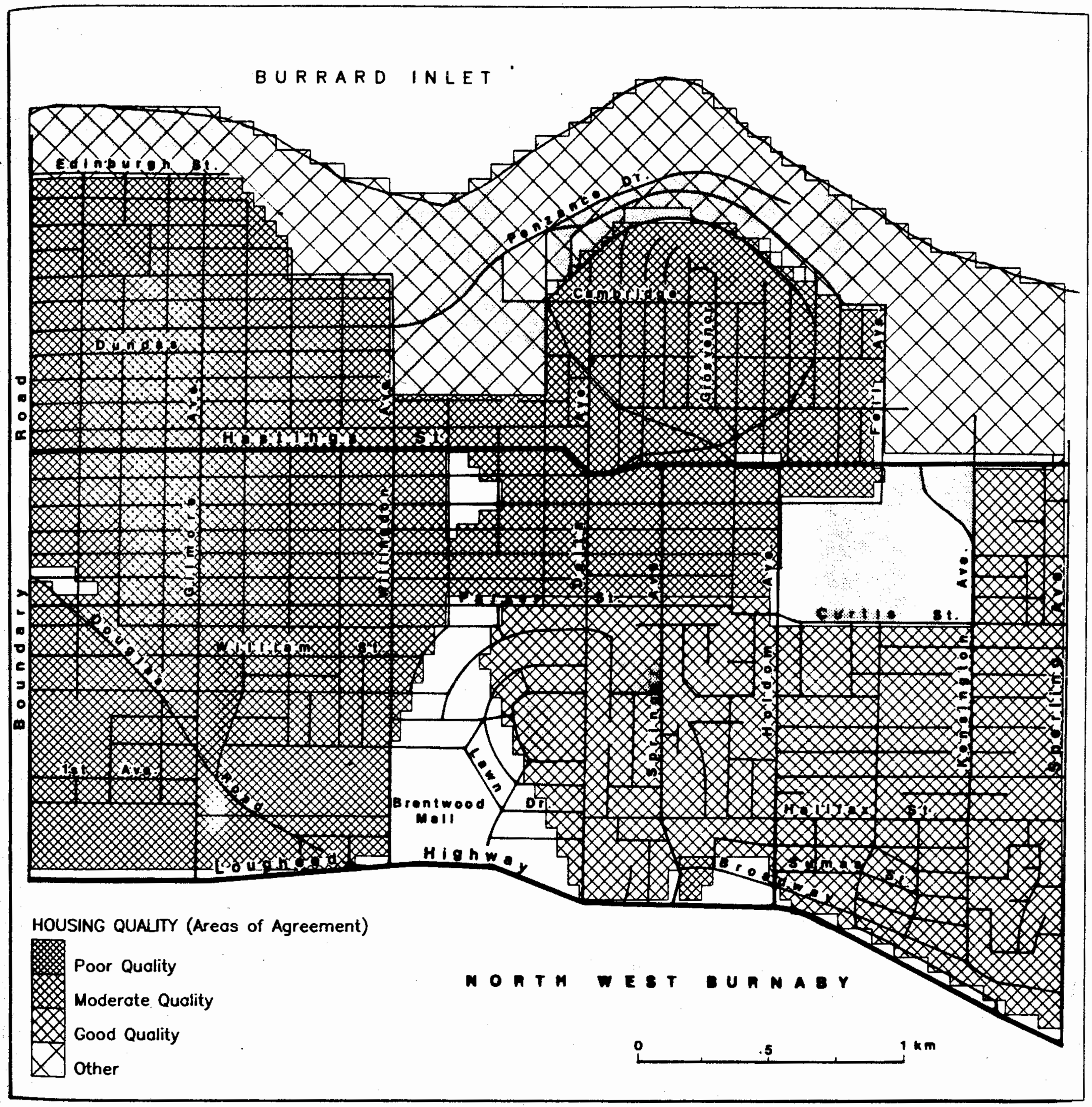


*Figure 5.7: Composite Map of **Housing Quality** at 60% Agreement Level for Panel I, Round 1.*

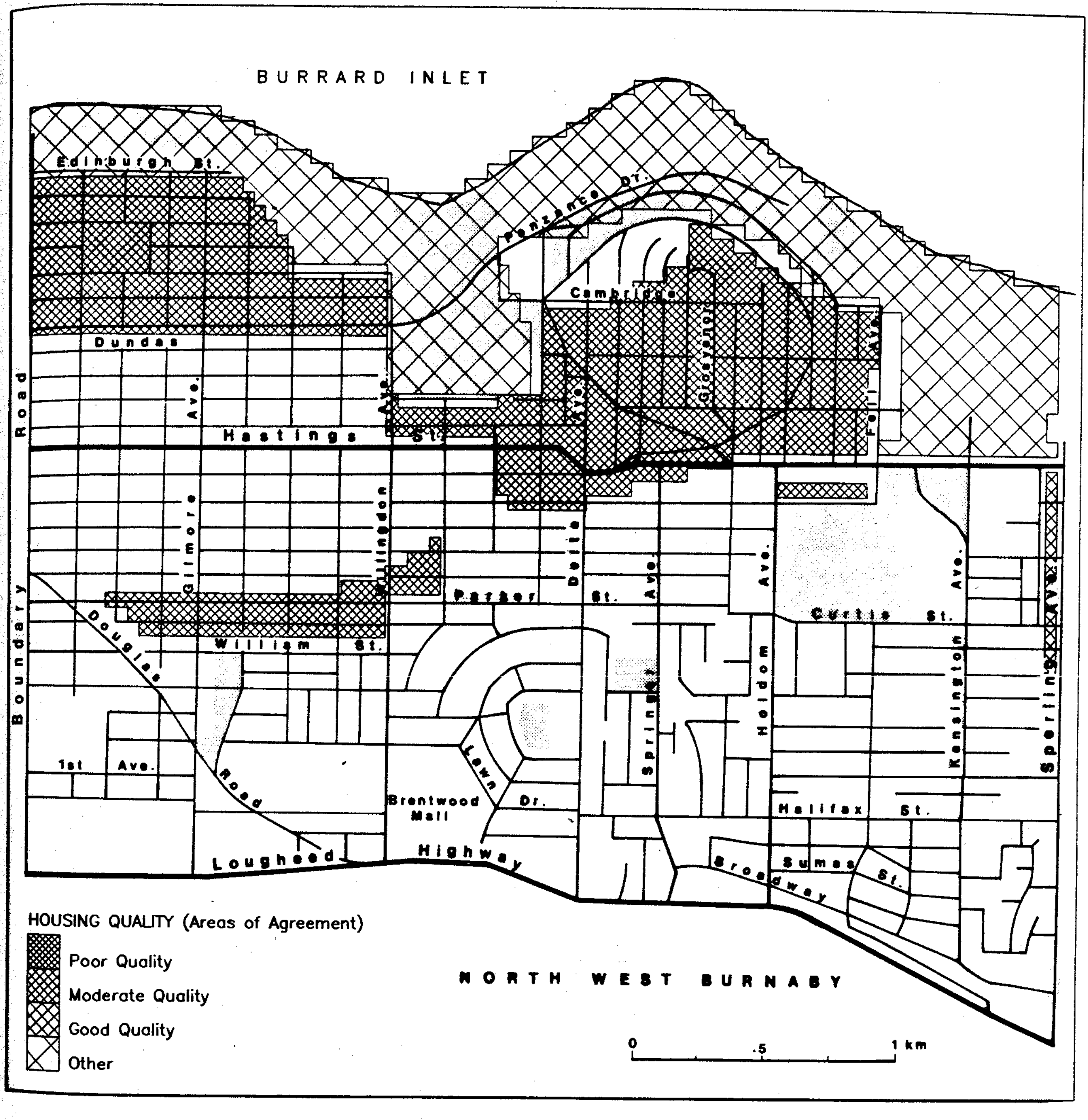


*Figure 5.8: Composite Map of **Housing Quality** at 80% Agreement Level for Panel I, Round 1.*

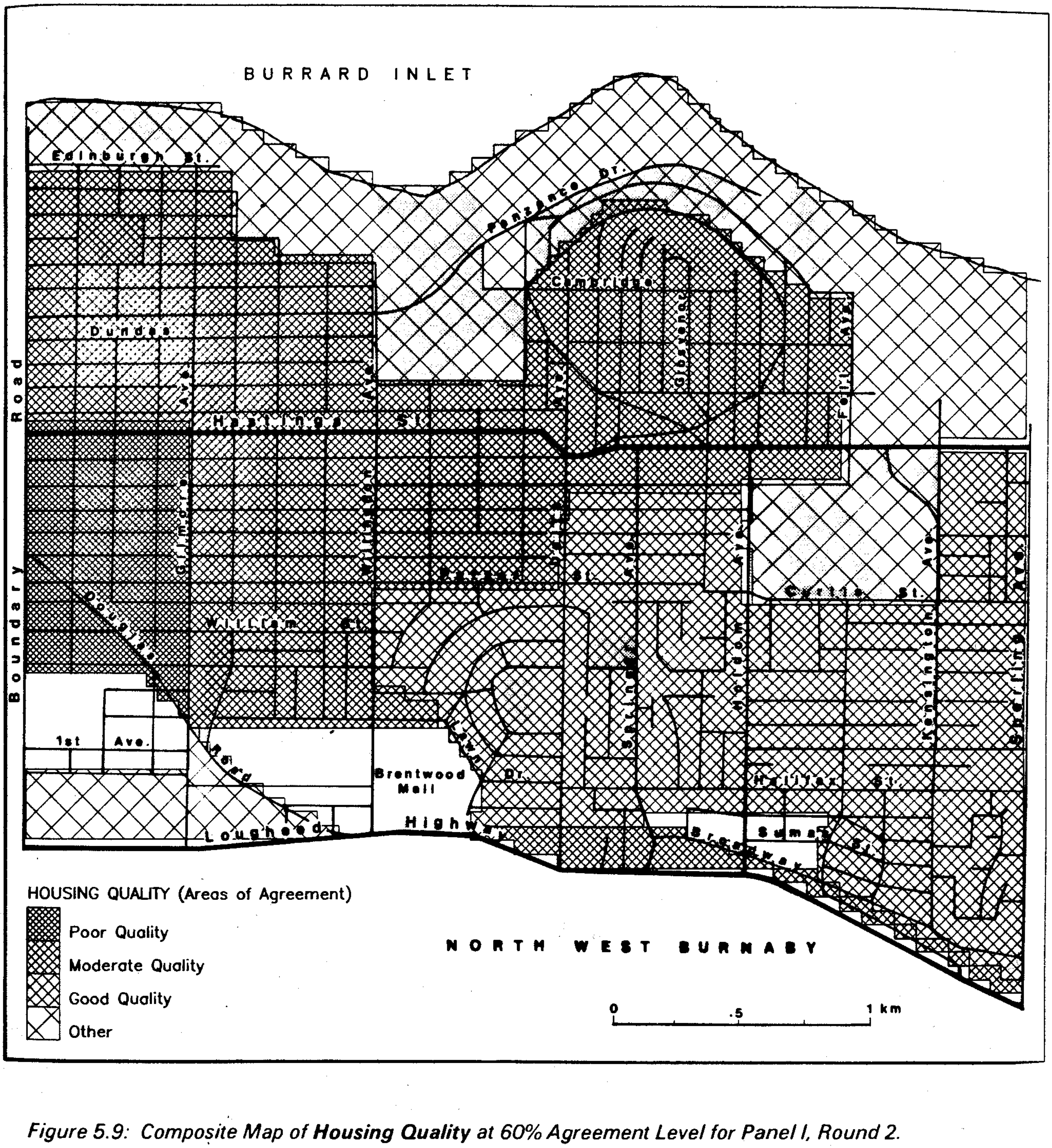


*Figure 5.9: Composite Map of **Housing Quality** at 60% Agreement Level for Panel I, Round 2.*

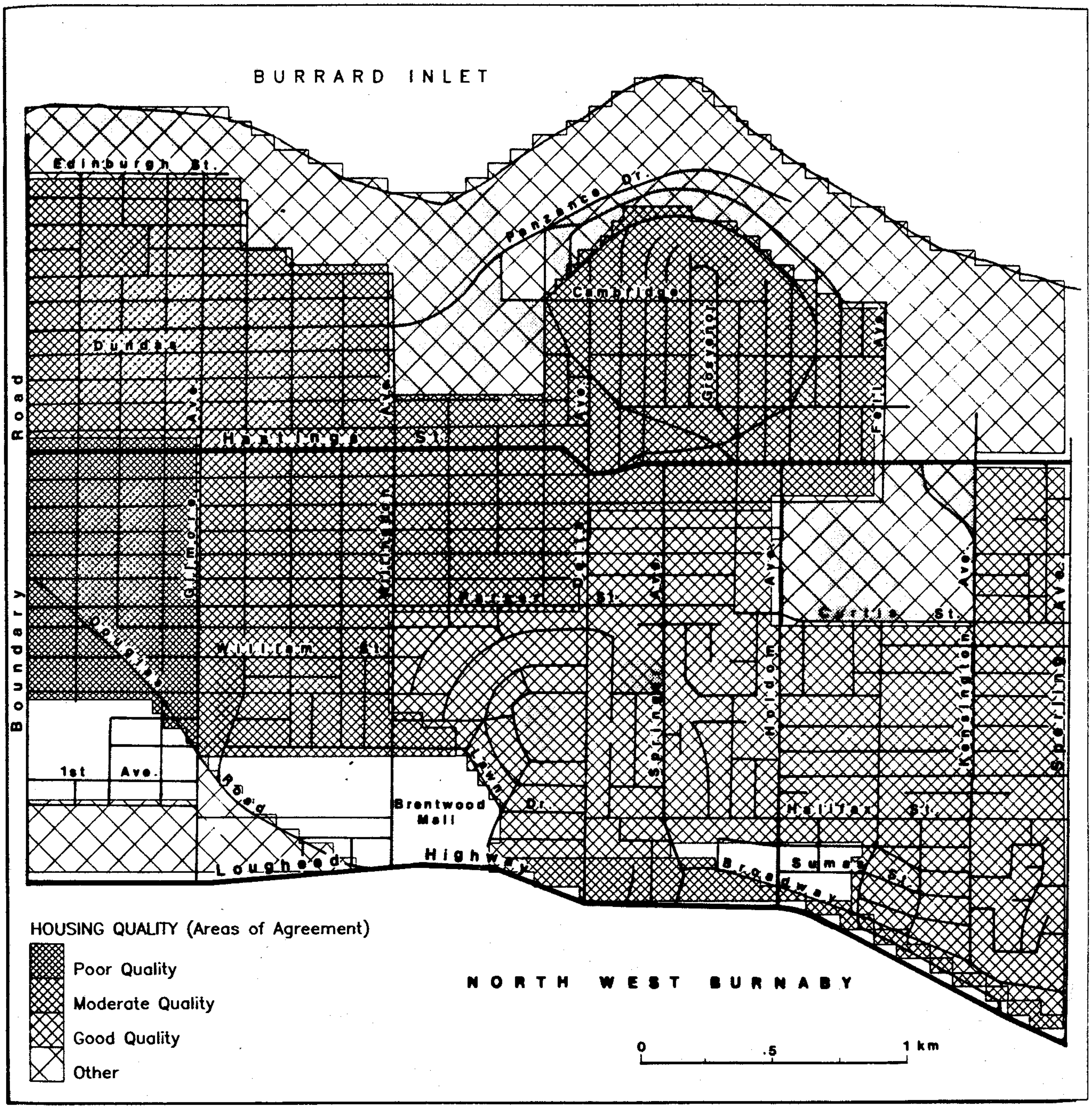


*Figure 5.10: Composite Map of **Housing Quality** at 80% Agreement Level for Panel I, Round 2.*

response maps depicting four categories of information. Furthermore, the second round results were significantly different from those of the first round (Chi squares of 45 and 3256 for the 60% and 80% agreement levels, respectively), and the differences were in the direction of increased consensus.

Again, using the results from Panel II to demonstrate consistency in the first round procedure, agreement existed over a relatively large proportion of the study area at both the 60% and 80% agreement levels (Figures 5.11 and 5.12). Chi square tests confirmed that these were significantly different from those of a random process. However, a comparison of the first round results from the two separate panels showed that Panel II had larger deviations in the individual responses than did Panel I (compare Table 5.6 with Table 5.9). The range in the percent of area covered by each of the four categories in Panel II was 60.6, 38.5, 45.2, and 17.9; this compared with 17.5, 19.2, 32.4, and 6.6 respectively in Panel I. This indicated a wider divergence of opinions in Panel II for this particular variable. This should not be surprising because "housing quality" is not a primary concern for police officials (of which Panel II is composed), however, it is paramount to the real estate industry from which Panel I was drawn.

Because Panel II only participated in round 1 of the Strabo exercise, nothing could be deduced regarding inter-round shifting of opinions and consensus formation. Its results, however, were useful in determining whether or not the method estimated or predicted reality.

Table 5.7

Degree of Correspondence between Individual Response Maps and the Composite Housing Quality Maps, at 60% and 80% Agreement Levels— Panel I, Round 1

a) 60% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
Poor Quality	–	–	–	–	–	–
Moderate Quality	30.8	41.2	42	35.3	37.7	48.3
Good Quality	0.3	23.8	23.8	9.2	14.6	23.8
Other	17	16.4	17.8	16.8	18.1	18.1
TOTAL	48.1	81.4	83.6	61.3	70.4	90.2
	Index of Dispersion = 0.24					

b) 80% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
Poor Quality	–	–	–	–	–	–
Moderate Quality	14.2	16.7	15.9	17.1	11.3	17.2
Good Quality	0.3	0.3	0.3	–	0.3	0.3
Other	16.1	15.8	16.5	16	16.5	16.6
TOTAL	30.6	32.8	32.7	33.1	28.1	34.1
	Index of Dispersion = 0.08					

Table 5.8

Degree of Correspondence between Individual Response Maps and the Composite Housing Quality Maps, at 60% and 80% Agreement Levels— Panel I, Round 2

a) 60% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
Poor Quality	3.9	5.7	4.9	5.8	–	5.8
Moderate Quality	34.5	36.1	34.1	34.5	10.9	36.3
Good Quality	18.2	16.4	26.2	20.1	26.2	26.1
Other	22	24.7	24	24.8	21.1	24.8
TOTAL	78.6	82.9	89.2	85.2	58.2	93
	Index of Dispersion = 0.15					

b) 80% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
Poor Quality	2.8	2.7	2.7	2.7	–	2.7
Moderate Quality	31.6	31.5	30.3	31.5	10.6	31.5
Good Quality	16.3	12.2	17	17	17	17
Other	21.9	21.9	21.2	21.9	21	21.9
TOTAL	72.6	68.3	71.2	73.1	48.6	73.1
	Index of Dispersion = 0.09					

Table 5.9

Percent of Total Study Area Assigned to Each Category of Housing Quality by Respondent— Panel II

CATEGORY	P_1	P_2	P_3	P_4	P_5
Poor Quality	11.0%	0.4%	61.0%	11.1%	5.3%
Moderate Qualily	28.3%	26.3%	6.0%	32.9%	45.0%
Good Quality	25.6%	56.1%	10.9%	22.4%	18.3%
Other	34.9%	17.0%	21.4%	33.3%	31.2%

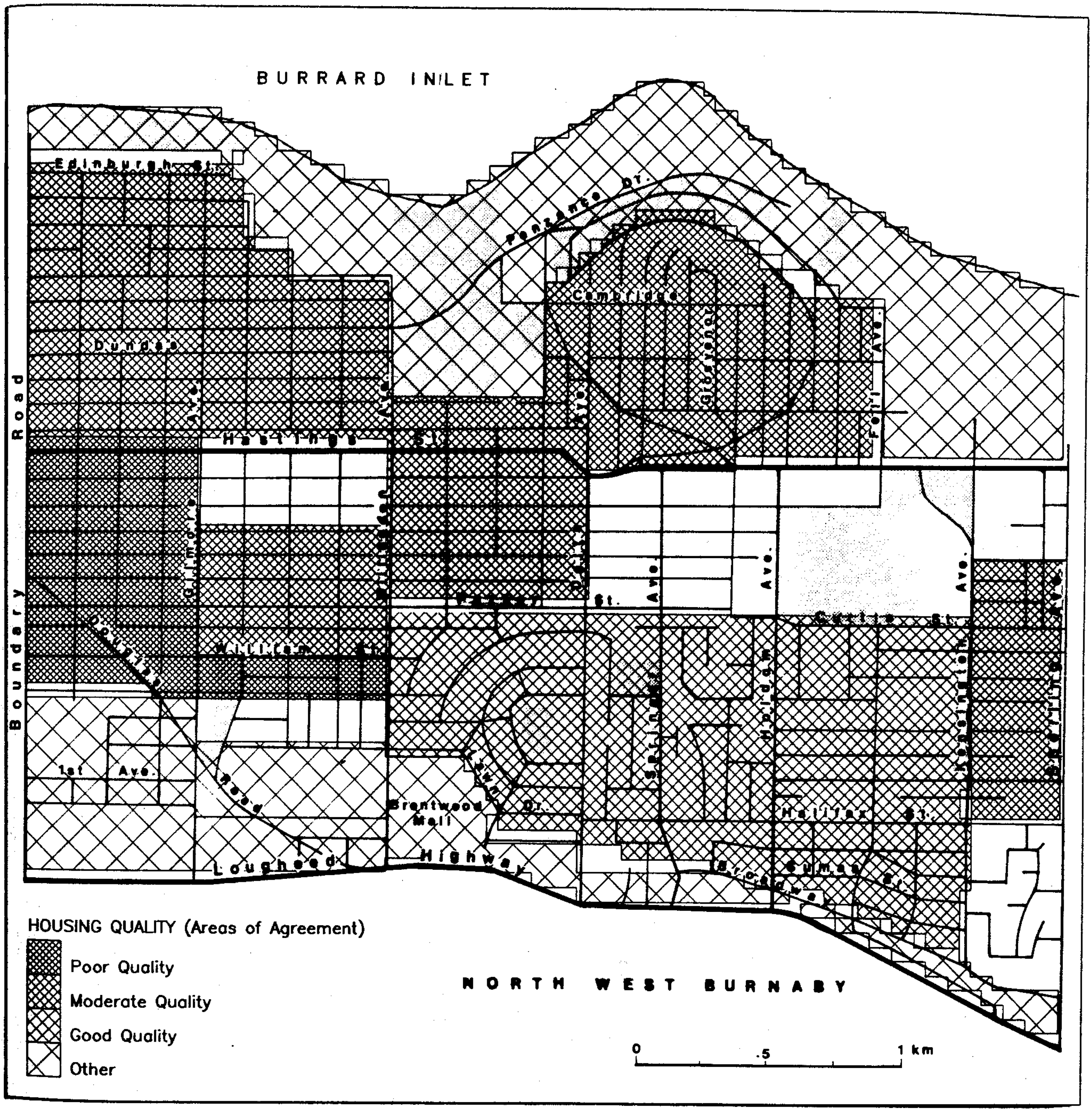


*Figure 5.11: Composite Map of **Housing Quality** at 60% Agreement Level for Panel II.*

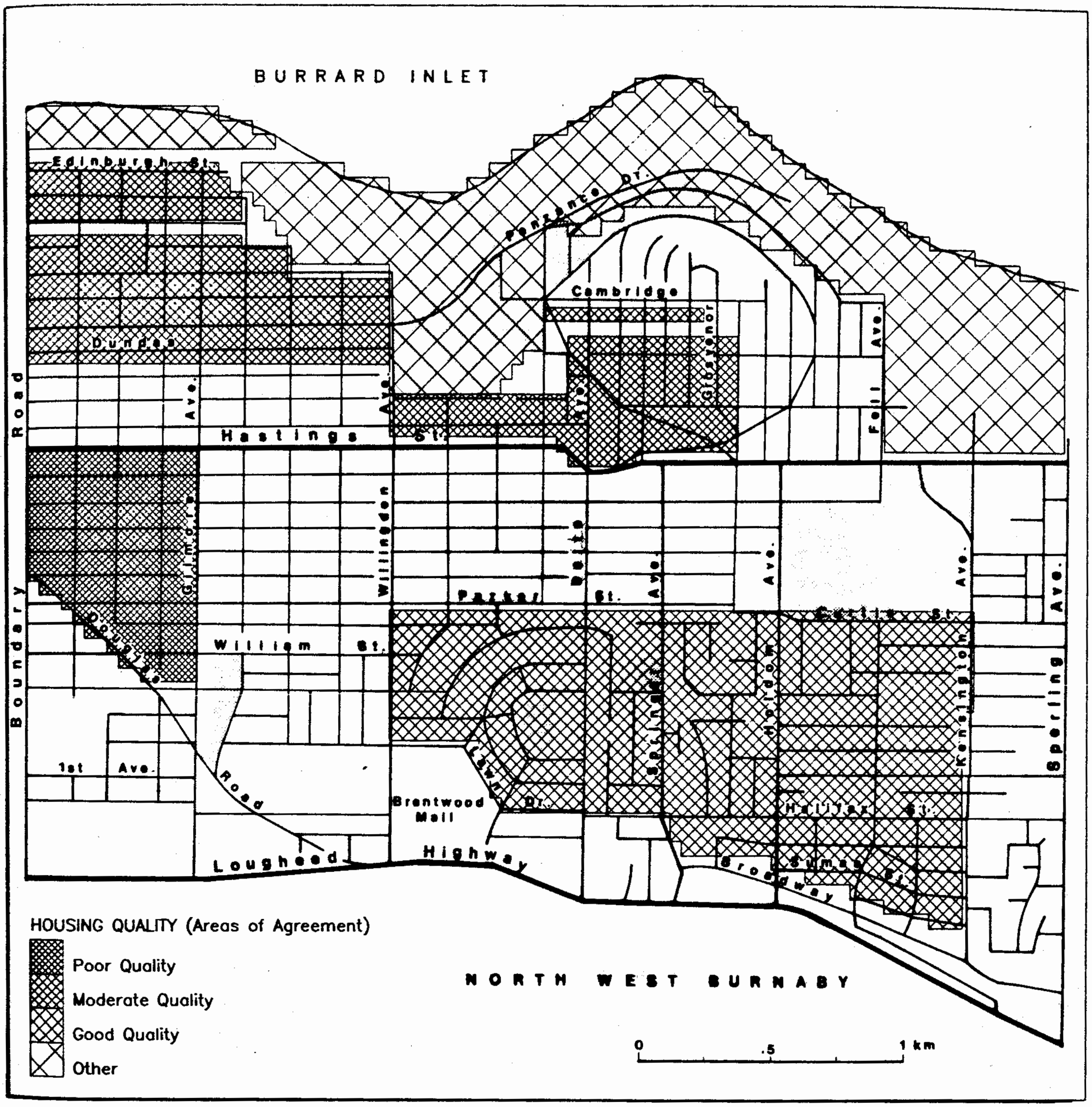


Figure 5.12: Composite Map of ***Housing Quality*** *at 80% Agreement Level for Panel II.*

Table 5.10

Degree of Correspondence between Individual Response Maps and the Composite Housing Quality Maps, at 60% and 80% Agreement Levels— Panel II

a) 60% Agreement Level

CATEGORY	P_1	P_2	P_3	P_4	P_5	Composite
Poor Quality	5.7	–	6.5	6.1	5.3	6.5
Moderate Quality	23.4	22	1.5	25.3	30.7	30.7
Good Quality	17.4	18.2	4.2	18.1	17.8	18.2
Other	26.6	16.9	16.3	26.7	27	27.5
TOTAL	73.1	57.1	28.5	76.2	80.8	82.9
	Index of Dispersion = 0.24					

b) 80% Agreement Level

CATEGORY	P_1	P_2	P_3	P_4	P_5	Composite
Poor Quality	4.2	–	4.2	4.2	4.2	4.2
Moderate Quality	10.8	9.3	1.5	10.8	10.8	10.8
Good Quality	16.9	16.9	4.1	16.9	16.9	16.9
Other	15.8	16.2	15.9	16.3	15.9	16.3
TOTAL	47.7	42.4	25.7	48.2	47.8	48.2
	Index of Dispersion = 0.12					

5.2.3 Income Areas

The third variable which was considered by both panels was spatial distribution of income. They were asked to identify areas which were predominantly "low", "middle", or "high" income in nature. As with "housing quality, a fourth category of "other or not applicable" was recognized to form a set of spatially exhaustive categories. This fourth category covered such areas as parks and industrial property.

The concept of "income areas" is subjective and has an intuitive interpretation for most individuals. There is not a single factor which identifies areas as being of a certain income class. Compared with dwelling types and housing quality, for which dominant visual clues help with the assessment and classification (e.g., there is usually a striking difference between a single family dwelling and an apartment complex), there are no unique indicators to identify income. Instead, one's perception of the "well-to-do'ness" of an area is derived from a number of tangible and intangible factors, such as size of yards, type of landscaping, number and types of cars in driveways, condition of streets, noise level, peoples' dressing habits, among many others. Each individual's assessment of an area may be based on different considerations of various factors and the relative importance of each. In addition, the set of income "levels" is fuzzy in the mathematical sense, and attribution of one of the levels to an area really implies a probability distribution. Two areas, for example, may be assigned to the high income category, but one, whose annual income exceeds one million dollars, is obviously a stronger candidate for that class than is another whose income is one hundred thousand dollars.

Because of the subjective nature of the variable, each participant was asked to described in words his or her criteria for defining areas of different income levels (Appendix VI). Although panelists had some difficulty in responding to such a question (i.e., their written responses were very general, often defining their criteria with other subjective notions, for example, "big yards", "nice neighbourhoods"), the discussion of the results prior to the second round of questions indicated that similar beliefs and criteria were being used. In other words, the group's attitudes on this issue seemed homogeneous; to have found otherwise might be more surprising considering that all participants from Panel I were of similar background, currently in the same occupation, and working out of the same office.

Table 5.11 shows the percentage distributions over the four categories for each of the respondents in Panel I. In the first round, there appeared to be considerable difference in their determination of the limits of the "middle income" category. For example, R_2 set the limits high such that 81.6% of the area fell in either the low or middle categories and none fell in the high category; on the other hand, R_3 set the limits low including 84.9% of the area in either the middle or high categories and only 0.5% in the Low. R_4 set a wide range for the middle category such that 70.4% of the area was included therein, and only 12.8% and 0% included in the low and high categories respectively.

Composite maps were produced according to the 60% and 80% agreement level criteria (Figures 5.13 and 5.14). They showed consensus over 75.2% and 31.6% of the area (Table 5.12). Chi square tests showed both of these values to be significantly different than those obtained from a random process.

Table 5.11

Percent of Total Study Area Assigned to Each Category of Income by Respondent— Panel I

CATEGORY		R_1	R_2	R_3	R_4	R_5
Low Income	Round 1	20.3%	40.9%	0.5%	12.8%	31.1%
	Round 2	21.0%	19.4%	24.7%	10.5%	11.0%
Middle Income	Round 1	44.6%	40.7%	44.9%	70.4%	27.5%
	Round 2	44.3%	51.8%	53.7%	67.2%	66.5%
High Income	Round 1	3.3%		40.0%		23.8%
	Round 2	6.3%				
Other	Round 1	31.5%	18.3%	14.4%	16.7%	17.4%
	Round 2	28.2%	28.7%	21.5%	22.2%	22.4%

Round 1 Round 2

These composite maps indicated that consensus had been reached for 51.2% and 15.8% (at the 60% and 80% agreement levels respectively) of the area as middle income, but no areas were agreed to as high income and only a weak consensus existed for 6.5% of the area classified as low income.

Round 2 produced some major shifts in individual responses and greatly increased the amount and strength of consensus (Tables 5.11 and 5.13). Panelist R_3, for example, increased the amount of low income area by 24.2% (from 0.5 to 24.7) and decreased the amount of high income area from 40% to 0%.

The overall consensus increased from 75.2% to 84.9% at the 60% agreement level and from 31.6% to 78.5% at the 80% level. Not only were these increases statistically significant by Chi square tests, but the consensus had been strengthened between the two rounds. In the first round there was a difference of 43.6% of the area between the 60% and 80% agreement levels. In the second round, however, this difference decreased to only 6.4%. This indicated a stronger consensus over more area in the second round than in the first. The amount of dispersion from the composite map dramatically decreased with the second round. The average difference between the area of agreement on the composite map, at the 60% agreement level, and the individual concordances was 18.7 in the first round but decreased to 6.7 in the second. The Index of Dispersion statistic (D) reflected this improvement as it decreased from 0.27 to 0.07 at the 60% level, and from 0.11 to 0.05 at the 80% level.

First round results from Panel II showed slightly more agreement than was found in the comparable session for Panel I (Tables 5.14 and 5.15).

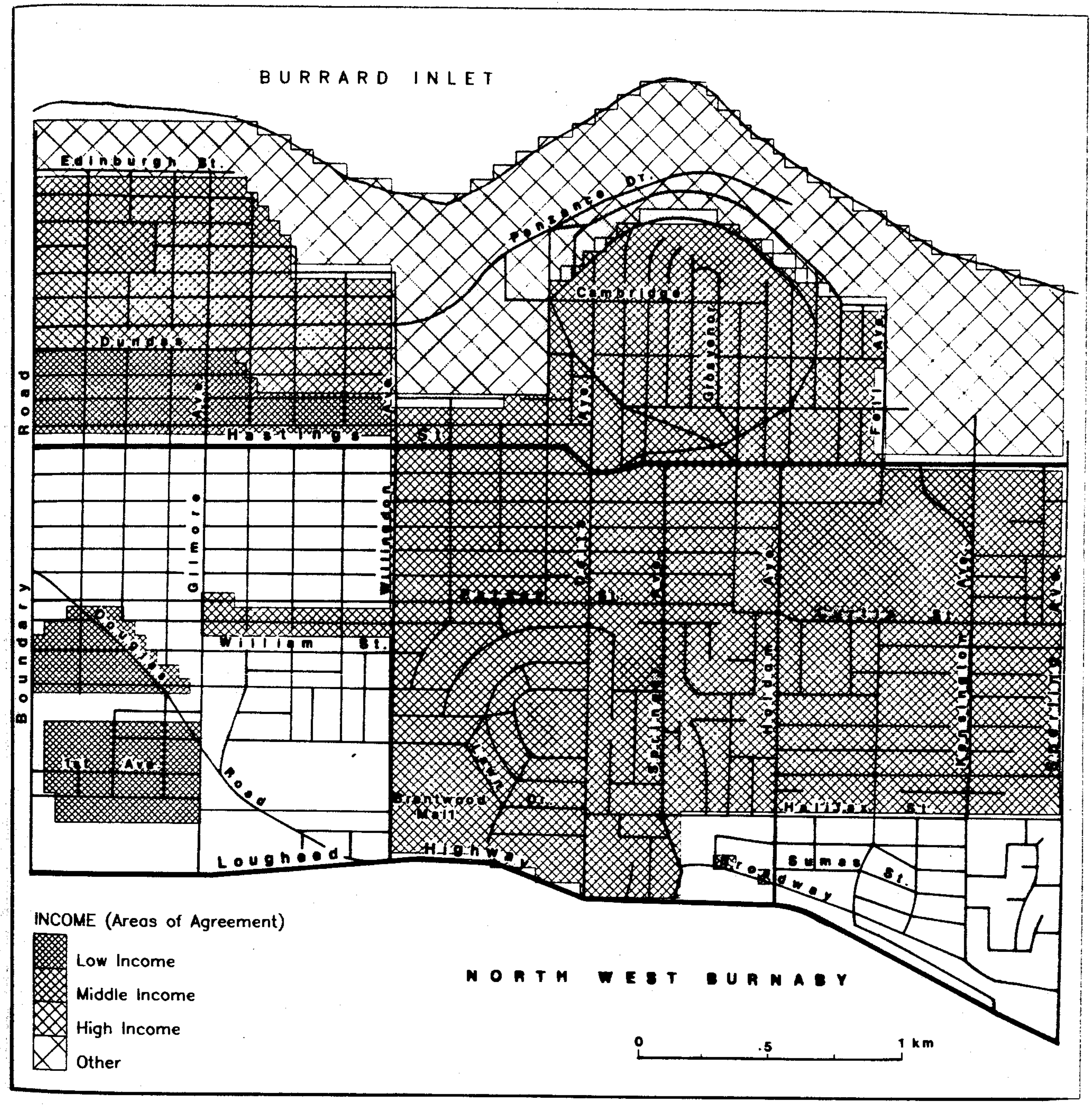


*Figure 5.13: Composite Map of **Income Areas** at 60% Agreement Level for Panel I, Round 1.*

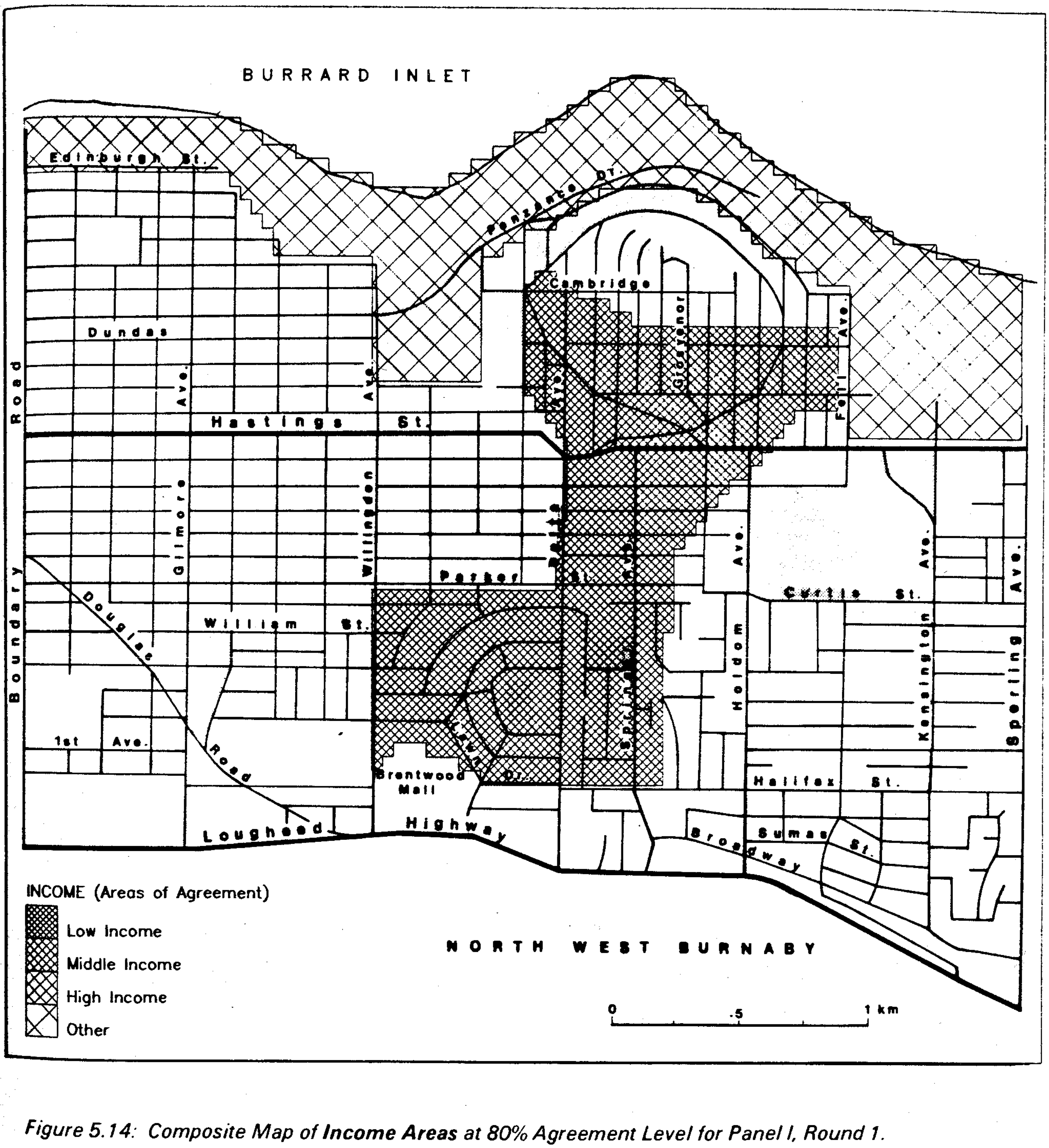


Figure 5.14: Composite Map of ***Income Areas*** *at 80% Agreement Level for Panel I, Round 1.*

Table 5.12

Degree of Correspondence between Individual Response Maps and the Composite Income Maps, at 60% and 80% Agreement Levels– Panel I, Round 1

a) 60% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
Low Income	6.5	6.5	–	3.3	6.5	6.5
Middle Income	40	33.6	17.6	51.2	27	51.2
High Income	–	–	–	–	–	–
Other	17.2	17.4	13.8	15.8	16.8	17.4
TOTAL	63.7	57.5	31.4	70.3	50.3	75.1
	Index of Dispersion = 0.27					

b) 80% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
Low Income	–	–	–	–	–	–
Middle Income	15.8	10.8	5	15.8	15.8	15.8
High Income	–	–	–	–	–	–
Other	15.8	15.8	15.8	15.7	15.3	15.8
TOTAL	31.6	26.6	20.8	31.5	31.1	31.6
	Index of Dispersion = 0.11					

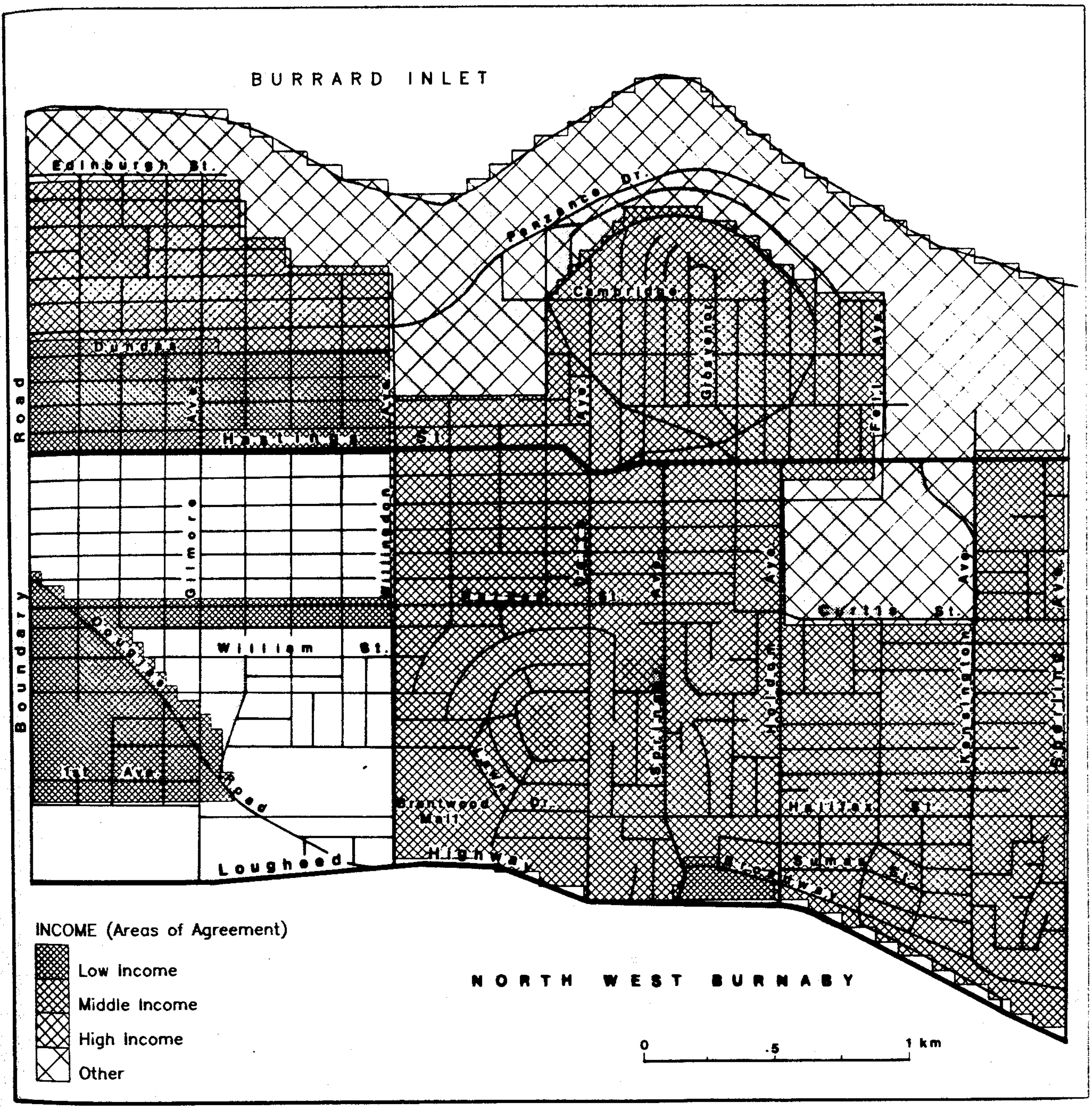


*Figure 5.15: Composite Map of **Income Areas** at 60% Agreement Level for Panel I, Round 2.*

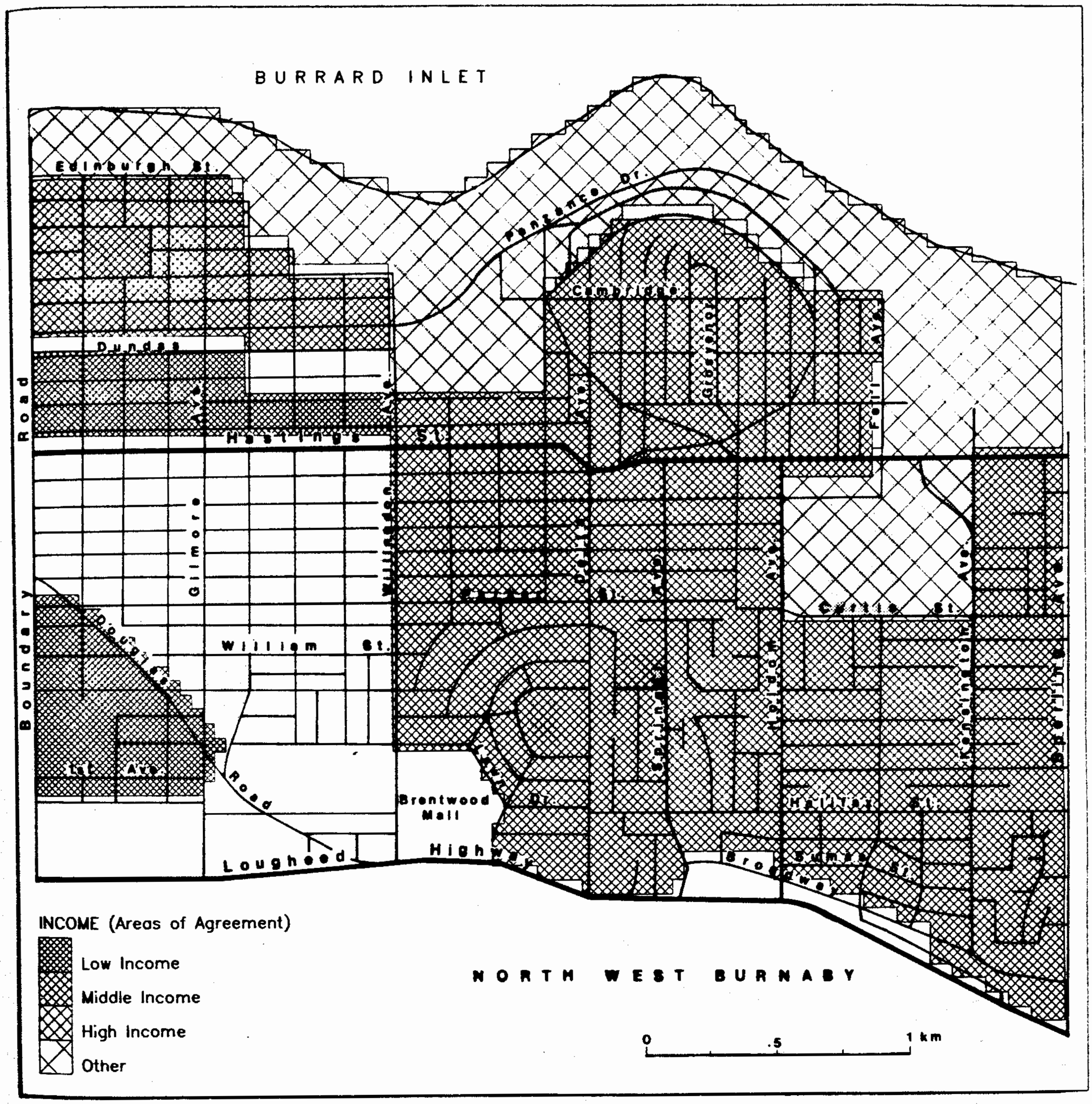


*Figure 5.16: Composite Map of **Income Areas** at 80% Agreement Level for Panel I, Round 2.*

Table 5.13

Degree of Correspondence between Individual Response Maps and the Composite Income Maps, at 60% and 80% Agreement Levels– Panel I, Round 2

a) 60% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
Low Income	10.1	9.5	9.4	7.1	7.5	10.5
Middle Income	39.9	43.8	51.7	52.1	52.4	52.4
High Income	–	–	–	–	–	–
Other	21.9	21.7	21.3	22	22	22
TOTAL	71.9	75	82.4	81.2	81.9	84.9
	Index of Dispersion = 0.07					

b) 80% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
Low Income	6.7	6.7	6.4	6.1	6.2	6.7
Middle Income	39.5	43	49.7	49.8	48.7	49.8
High Income	–	–	–	–	–	–
Other	21.7	21.6	21.3	21.8	21.6	21.8
TOTAL	67.9	71.3	77.4	77.7	76.5	78.3
	Index of Dispersion = 0.05					

Agreement was reached over 81.8% and 44.9% of the study area for the 60% and 80% criteria. There was also a weak consensus for a small area (9.4%) classified as high income. It is considered a weak consensus because it was found only at the 60% agreement level, but disappeared completely at the 80% level. Similar degrees of dispersion existed for the two panels in round 1. At the 60% level the indices were 0.27 and 0.24, and at the 80% level they were 0.11 and 0.13 for Panels I and II respectively.

5.2.4 Crime Levels

The fourth question with which the two panels dealt concerned the distribution of crime in the study area. This variable seemed particularly difficult to deal with because it left a great deal open for individual interpretation. In the first place, no parts of the study area were especially dangerous or notorious from a crime stand point. Discussions with local crime authorities (i.e., the Burnaby RCMP) revealed that, with few exceptions, for example, along Hastings, criminal activity against property had no definite pattern, but tended to be isolated and directly linked to the whereabouts of known "trouble-makers". When such a cause moved within or out of the area, so did the crime problem. A second obvious problem with identifying crime areas stemmed from the very definition of "crime". Police departments identify a large number of distinct categories of criminal activity. The average person can identify at least several major categories including physical assault, vandalism, breaking and entering, theft of property, embezzlement, tax evasion, fraud, among others. Frequently, it is the more visible, physical types of criminal activity which one considers when

Table 5.14

Percent of Total Study Area Assigned to Each Category of Income by Respondent—
Panel II

CATEGORY	P_1	P_2	P_3	P_4	P_5
Low Income	11.8%	16.8%	59.4%	4.4%	9.0%
Middle Income	56.5%	35.9%	14.1%	68.4%	46.8%
High Income		30.0%	4.1%	10.1%	11.6%
Other	31.6%	17.1%	22.1%	16.9%	32.4%

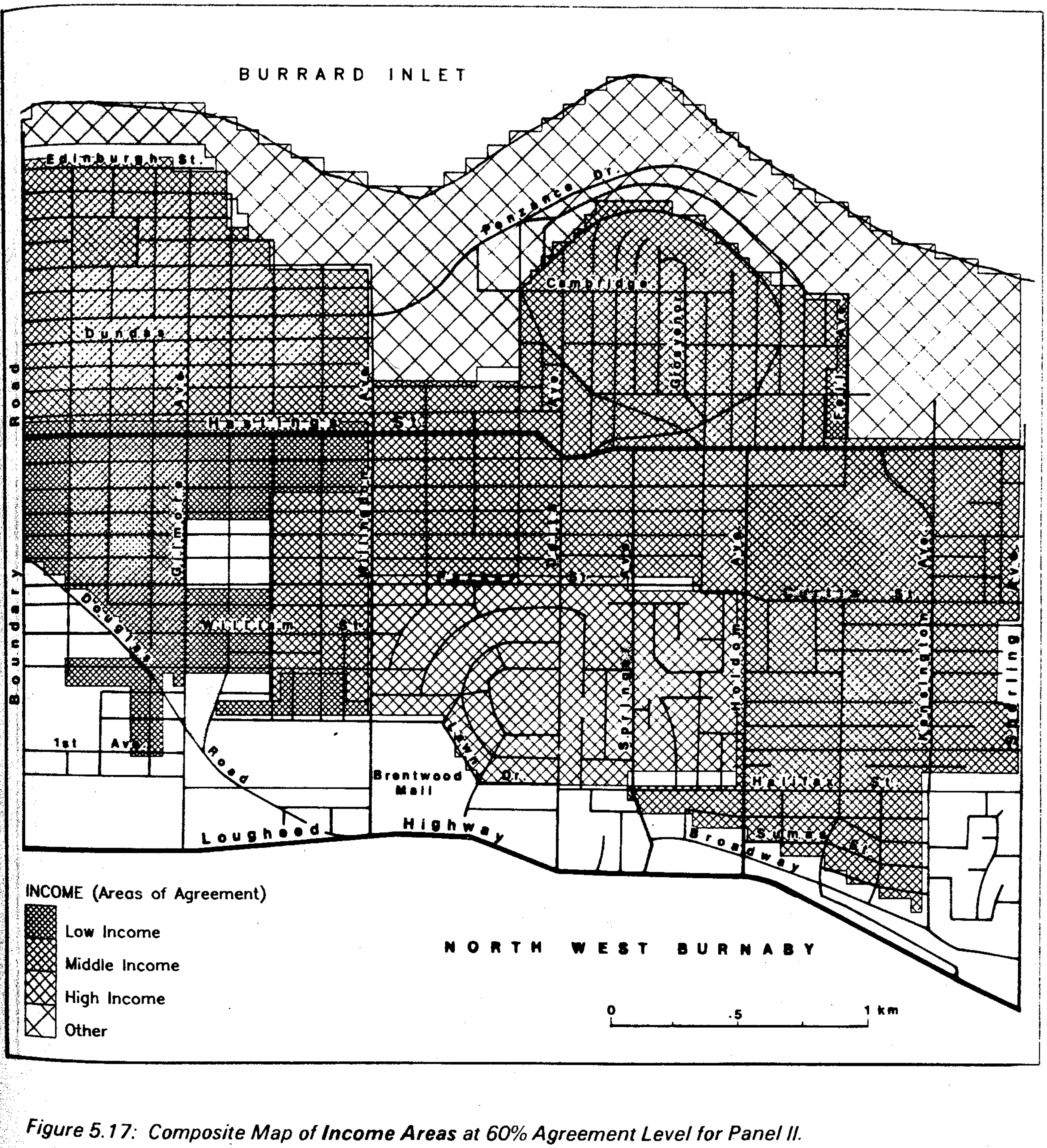


*Figure 5.17: Composite Map of **Income Areas** at 60% Agreement Level for Panel II.*

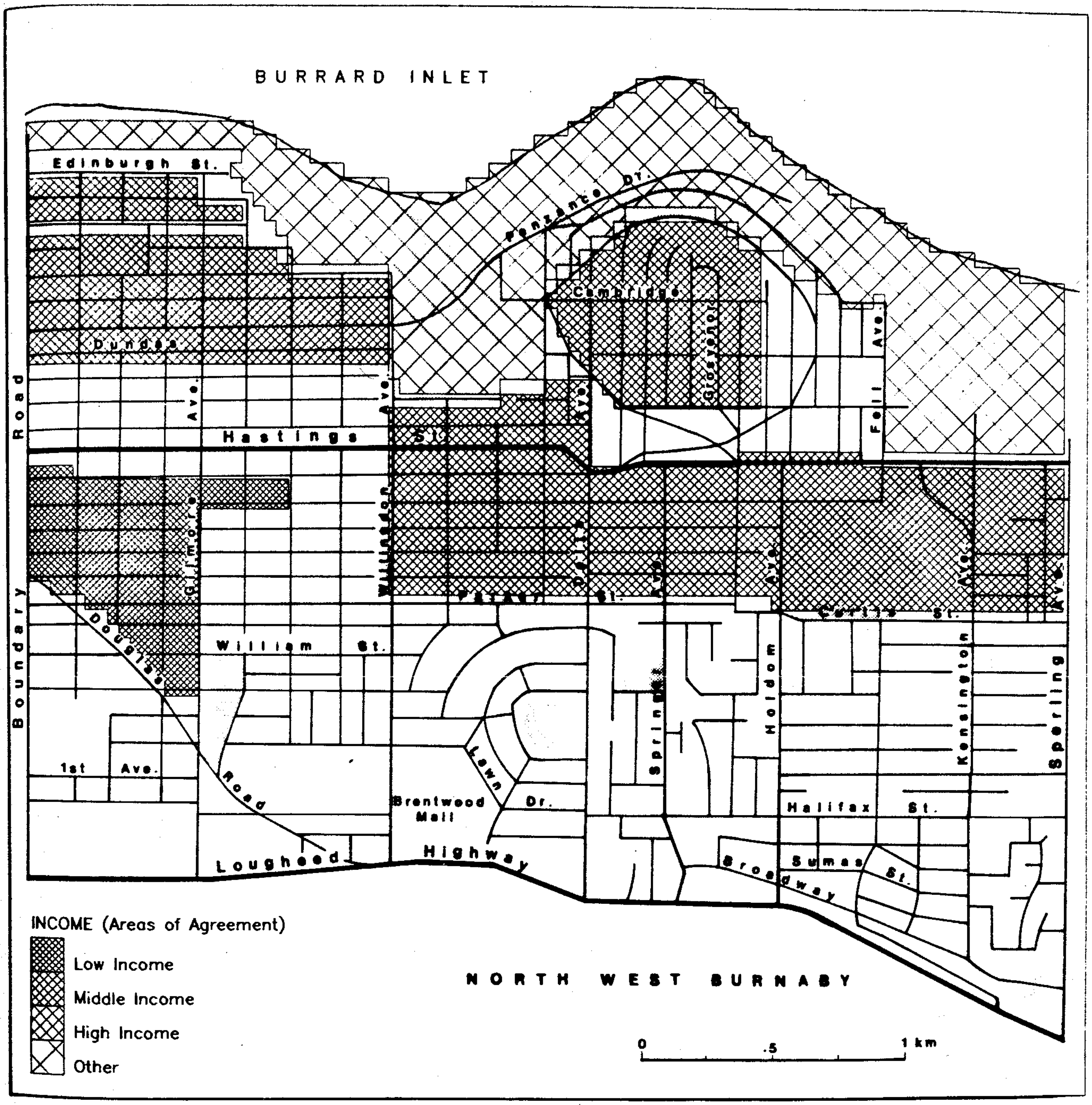


Figure 5.18: Composite Map of ***Income Areas*** *at 80% Agreement Level for Panel II.*

Table 5.15

Degree of Correspondence between Individual Response Maps and the Composite Income Maps, at 60% and 80% Agreement Levels— Panel II

a) 60% Agreement Level

CATEGORY	P_1	P_2	P_3	P_4	P_5	Composite
Low Income	8	6.8	9	2.4	5.3	9
Middle Income	43.1	30.5	8.9	45.4	37.3	45.8
High Income	–	9.4	2.7	9.4	6.6	9.4
Other	16.4	16.6	17.4	16.7	17.4	17.5
TOTAL	67.5	63.3	38	73.9	66.6	81.7
	Index of Dispersion = 0.24					

b) 80% Agreement Level

CATEGORY	P_1	P_2	P_3	P_4	P_5	Composite
Low Income	3.7	3.8	3.8	0.9	3.7	3.8
Middle Income	24.4	23.4	5.2	24.4	20.2	24.4
High Income	–	–	–	–	–	–
Other	15.9	16.2	16.5	16.3	16.6	16.6
TOTAL	44	43.4	25.5	41.6	40.5	44.8
	Index of Dispersion = 0.13					

identifying areas of high or low crime rate. A third problem arose because the respondents were asked to consider Low, Moderate, and High crime rates as being relative to the study rate. This meant that they had to rank the areas with consideration only for northwest Burnaby and not in relation to the entire municipality, the metropolitan area, or the country at large. To assist with this "rescaling", the participants were encouraged to interpret the three categories as being relative to a perceived average for the area, i.e., above average, average, and below average.

Table 5.16 shows amount of area assigned to each category by individual respondents in Panel I. Although the three categories -- high, moderate, and low -- were spatially exhaustive for this variable, it was apparent from the first round results that respondents R_1, R_3, and R_5 did not classify significant amounts of the area by any of the three possible categories. This was attributed to their lack of familiarity with the process and to their confusion as how to deal with "open" areas such as parks. Following the second round discussions, the inconsistency and internal contradictions were resolved. Even in the second round, one panelist (R_2) was unable to distinguish any differences between the levels of criminal activity across the entire area, and therefore labelled everything as "low". The percentages indicated a general agreement that the crime rate was relatively low over most of the area, with some pockets classified as moderate and high.

The aggregate maps for round 1 (Figures 5.19 and 5.20) showed agreement for 52.5% and 24.0% of the area as having a low crime rate. There were no areas of high or moderate rates for which agreement was reached (Table 5.17). There was also a high level of dispersion within the individual concordances

Table 5.16

Percent of Total Study Area Assigned to Each Category of Crime Rate by Respondent— Panel I

CATEGORY	R_1	R_2	R_3	R_4	R_5
High Crime Rate	7.4%		0.6%		26.5%
	9.9%		16.8%	5.8%	9.9%
Moderate Crime Rate	71.7%		46.3%		
	18.4%		16.0%	6.9%	3.6%
Low Crime Rate		100.0%	34.1%	100.0%	56.3%
	71.5%	100.0%	67.0%	87.1%	86.3%
Other	20.7%		18.8%		17.0%

Round 1   Round 2

-- index values of 0.32 and 0.20 corresponded to the 60% and 80% agreement levels. Much of this dispersion could be accounted for by R_1, who had concordance values of 9.8 and 0 for the two levels. The reason for such disagreement was that on round 1, he categorized most of the area (71.7%) as having a moderate crime rate and none as having a low rate. As before, Chi square tests showed these aggregations at the 60% and 80% level to be significantly different from those produced by a random process.

Round 2 produced improvements over round 1 estimates (Table 5.18). The amount of area over which consensus was reached increased to 83.3% from 62.3% at the 3 out of 5 agreement level and to 66.2% from 24.0% at the 4 out of 5 level. Some major shifts of opinion occurred between rounds. For example, R_1 decreased the amount of area assigned to the moderate category from 71.7% to 18.4%. At the same time, he increased the amount of area assigned to the Low category by 71.5%. All respondents agreed on the second round that the three categories were spatially exhaustive and left no area for the "Other" category.

The composite maps for round 2 showed small areas assigned to the "high" category (Figures 5.21 and 5.22). These occurred mainly in the commercial areas along Hastings Street. As with round 1, however, there were no areas of agreement in the moderate category. Again, this reflected the difficulty that Panel I had in perceiving an "average" crime rate. The amount of dispersion within the individual concordances decreased dramatically as shown by index values of 0.09 and 0.04 at the two levels of agreements.

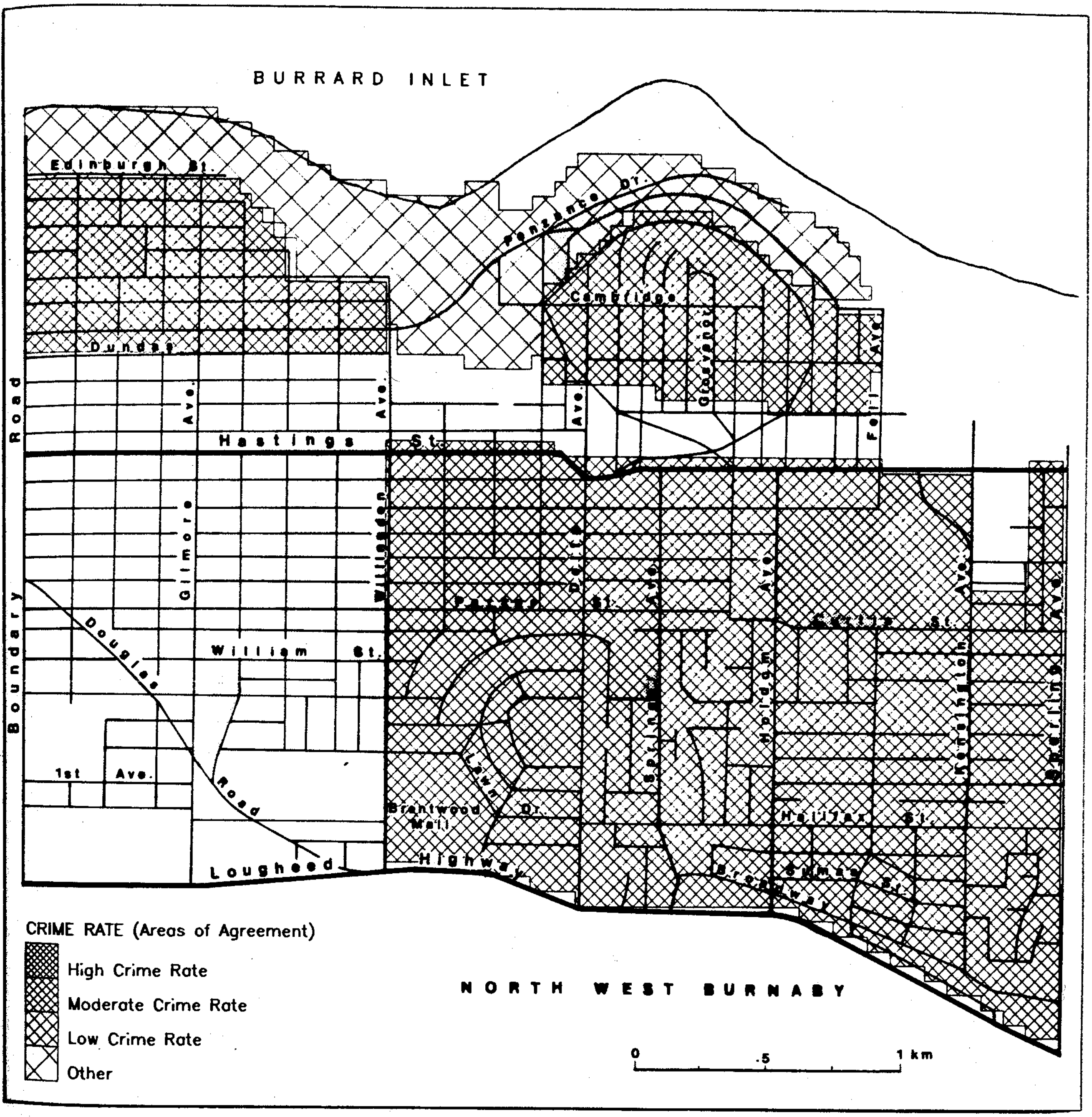


*Figure 5.19: Composite Map of **Crime Rates** at 60% Agreement Level for Panel I, Round 1.*

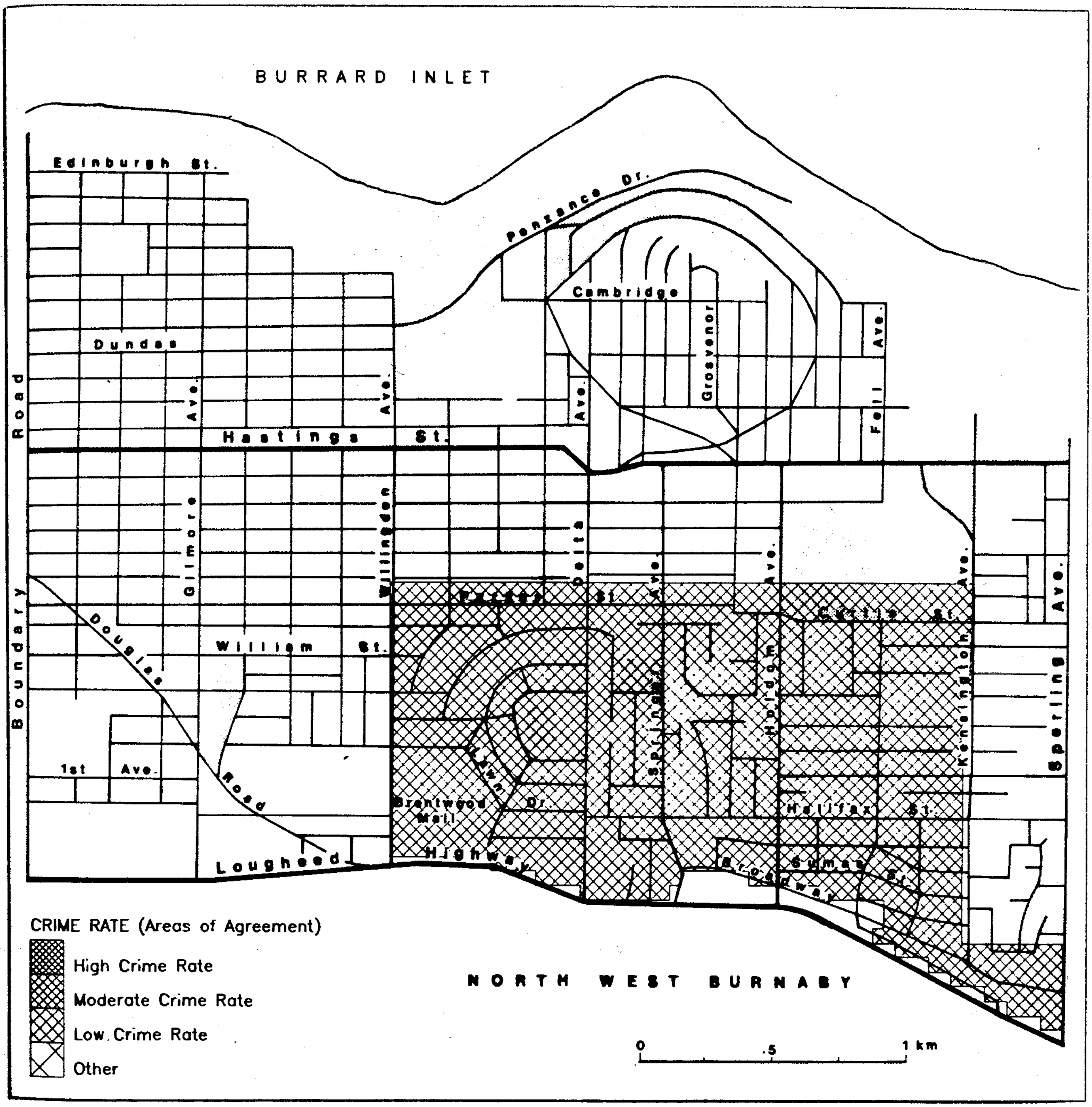


*Figure 5.20: Composite Map of **Crime Rates** at 80% Agreement Level for Panel I, Round 1.*

Table 5.17

Degree of Correspondence between Individual Response Maps and the Composite Crime Rate Maps, at 60% and 80% Agreement Levels— Panel I, Round 1

a) 60% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
High Crime Rate	–	–	–	–	–	–
Moderate Crime Rate	–	–	–	–	–	–
Low Crime Rate	–	52.5	34	52.5	42.5	52.5
Other	9.8	–	9.8	–	9.8	9.8
TOTAL	9.8	52.5	43.8	52.5	52.3	62.3
	Index of Dispersion = 0.32					

b) 80% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
High Crime Rate	–	–	–	–	–	–
Moderate Crime Rate	–	–	–	–	–	–
Low Crime Rate	–	24	24	24	24	24
Other	–	–	–	–	–	–
TOTAL	0	24	24	24	24	24
	Index of Dispersion = 0.20					

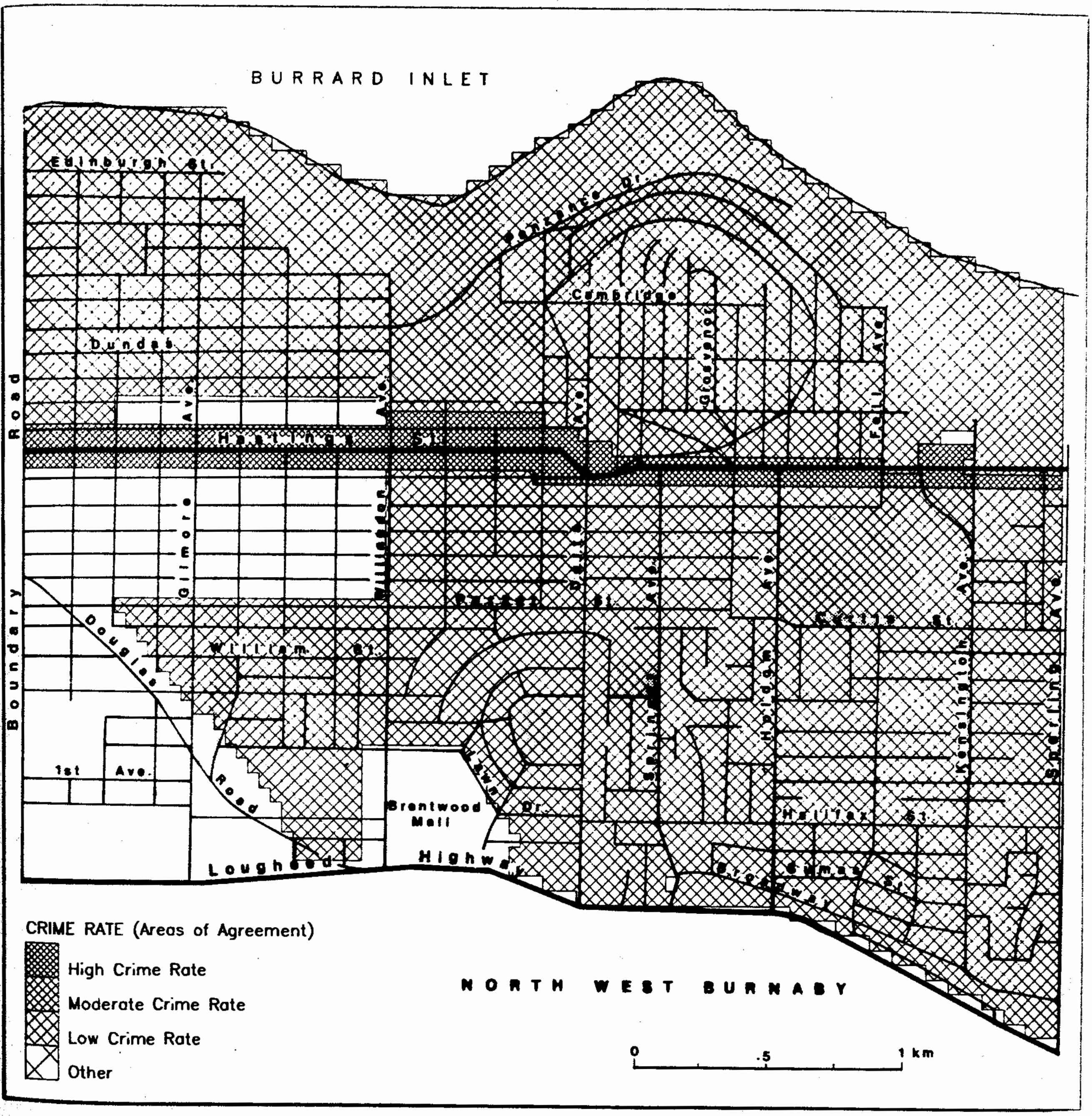


*Figure 5.21: Composite Map of **Crime Rates** at 60% Agreement Level for Panel I, Round 2.*

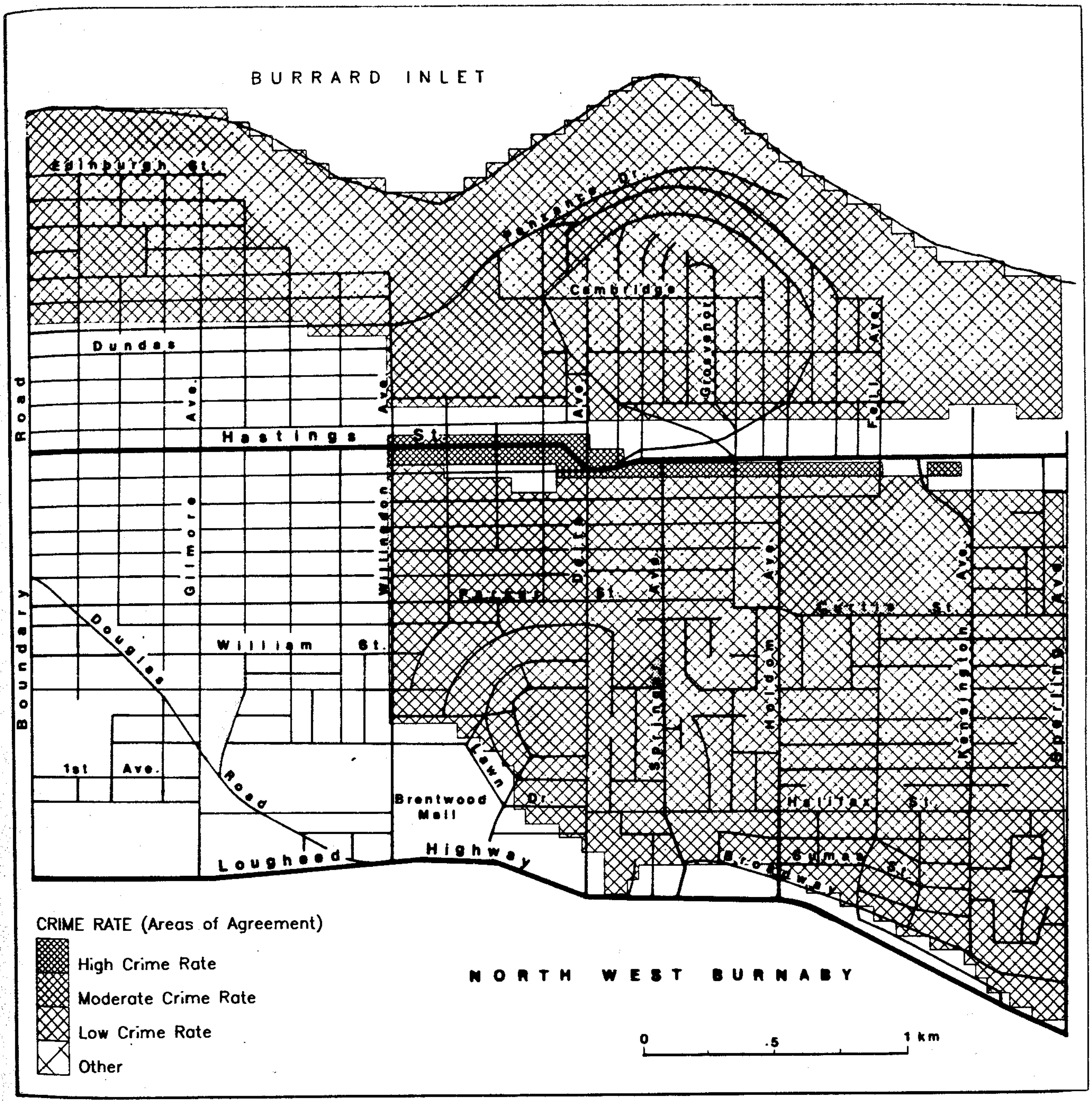


*Figure 5.22: Composite Map of **Crime Rates** at 80% Agreement Level for Panel I, Round 2.*

Table 5.18

Degree of Correspondence between Individual Response Maps and the Composite Crime Rate Maps, at 60% and 80% Agreement Levels— Panel I, Round 2

a) 60% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
High Crime Rate	5.1	–	4.9	3.1	5.1	5.1
Moderate Crime Rate	–	–	–	–	–	–
Low Crime Rate	71.1	78.1	66.6	69.9	73.2	78.1
Other	–	–	–	–	–	–
TOTAL	76.2	78.1	71.5	73	78.3	83.2
	Index of Dispersion = 0.09					

b) 80% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
High Crime Rate	1.4	–	1.4	1.4	1.4	1.4
Moderate Crime Rate	–	–	–	–	–	–
Low Crime Rate	61.5	64.7	64.6	59.4	63.2	64.7
Other	–	–	–	–	–	–
TOTAL	62.9	64.7	66	60.8	64.6	66.1
	Index of Dispersion = 0.04					

Chi square tests were performed on the second round maps and demonstrated that the results were significantly different from those of aggregating random maps, and also significantly different from the first round composite maps. The difference from the first round was in a positive direction, that is, an increase in the amount of area over which agreement was reached.

Similar problems were encountered in the single round responses of Panel II. There was general agreement that most of the area was either moderate or low; however, there was a great deal of disagreement amongst panelists as to which of the two categories was predominant (Table 5.19). For example, P_1 identified 88.2% of the area as moderate and 0% as low; at the other extreme, P_5 identified 3.6% as moderate but 76.0% as low, and P_2 had an almost equal split (43.9% and 35.8% respectively). From discussions with Panel II respondents in the first round, it appeared that these differences resulted from different individual definitions of the terms "moderate" and "low" rather than disagreements with the basic facts. For this variable, Panel II was extremely knowledgeable and able to recite specific statistics for parts of the study area. They demonstrated a better grasp of the temporal nature of the variable than did Panel I. For example, over a period of the preceding year, some respondents were able to identify certain months during which criminal activity increased in an area because of the presence of an active criminal at that time. When the criminal moved or was apprehended, the incidence of crime returned to "normal".

The composite maps from Panel II showed slight superiority to the first round results of Panel I (Figures 5.23 and 5.24). A major difference was that

Table 5.19

Percent of Total Study Area Assigned to Each Category of Crime Rate by Respondent— Panel II

CATEGORY	P_1	P_2	P_3	P_4	P_5
High Crime Rate	11.7%	3.4%	11.1%	7.6%	1.9%
Moderate Crime Rate	88.2%	43.9%	62.7%	88.2%	3.6%
Low Crime Rate		35.8%	7.5%	4.0%	76.0%
Other		16.7%	18.5%		18.3%

most of the agreement lies in the moderate category rather than the low category as with Panel I. Panel II also had initial problems in dealing with spatial exhaustiveness of the three categories. Three of the participants had left 15.7% of the area for an "Other" category (Table 5.20). These areas were primarily "open" areas. Because of differences in opinion between definitions for moderate and low, relatively high dispersions were found in the concordance values -- 0.32 and 0.18 were the index values for the two levels of agreements. These were almost identical to the indices found in round 1 of Panel I.

As with the other maps, Chi square tests showed that the resulting composite maps were statistically significant. Because a second iteration was not performed with Panel II, there was no supporting evidence to show that the level of consensus would have improved. However, having identified the source of much of the discordance -- that is, differences in interpretation between moderate and low -- and assuming that second round discussions would clarify some of the issues as happened in Panel I, there was reason to believe that a second round with Panel II would have significantly improved the amount of and the strength of the consensus.

5.2.5 Livable Areas

The final spatial variable considered was that of livable areas. Of the five variables, this was the most subjective; while it is a concept which has inherent intuitive meaning, it is difficult to define. Panelists were encouraged to interpret the notion in terms of how desirable areas were for

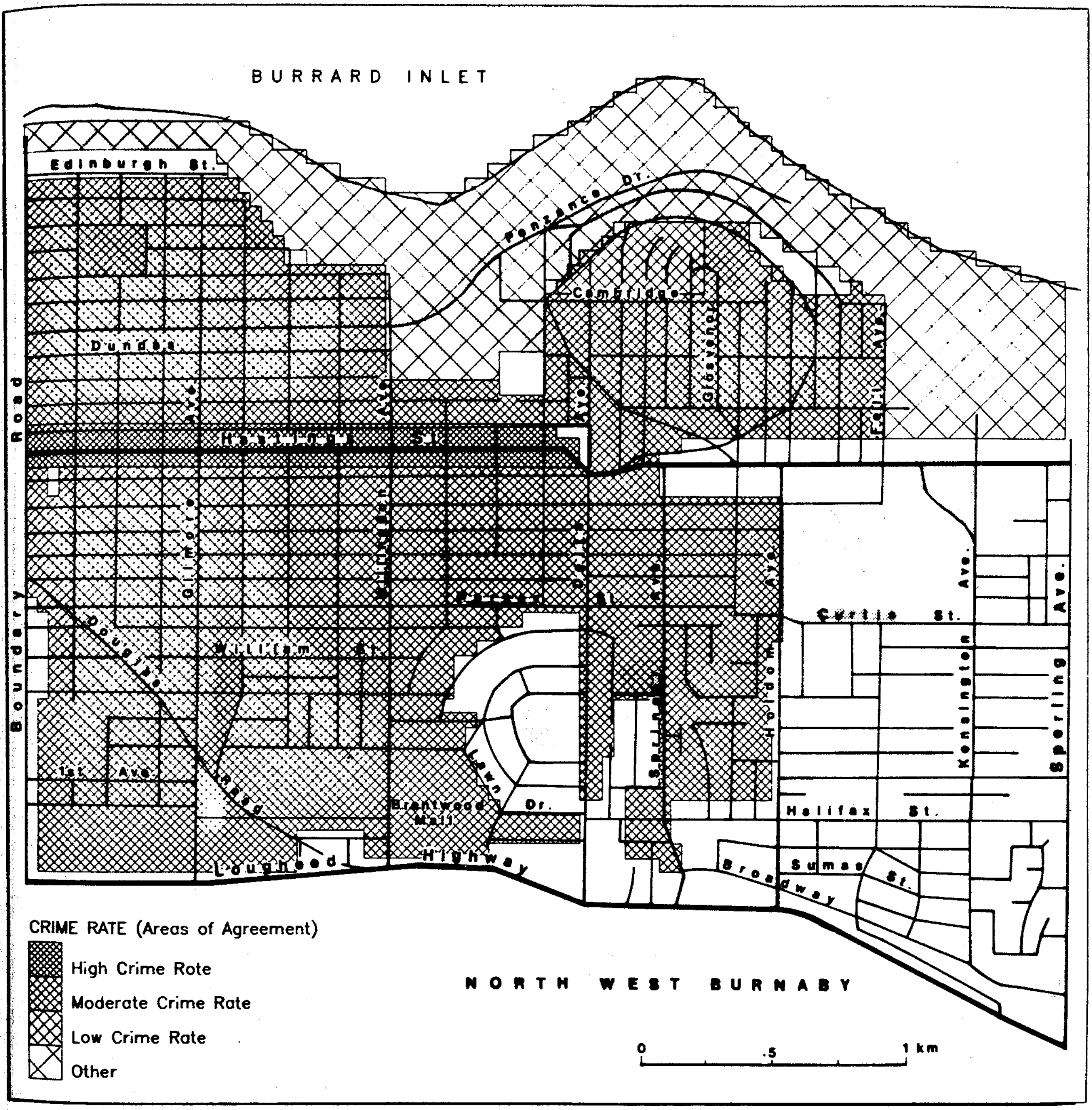


*Figure 5.23: Composite Map of **Crime Rates** at 60% Agreement Level for Panel II.*

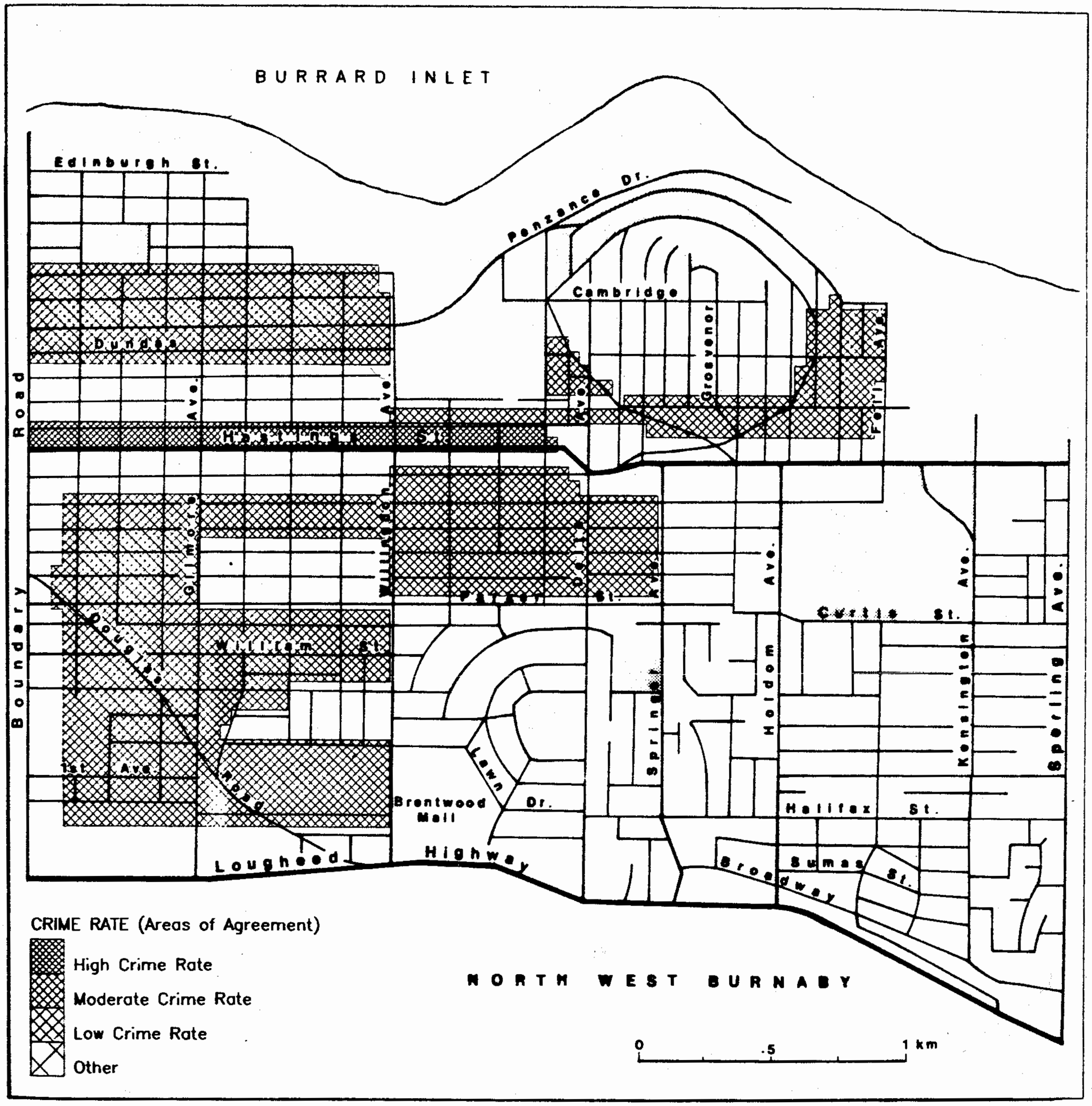


*Figure 5.24: Composite Map of **Crime Rates** at 80% Agreement Level for Panel II.*

Table 5.20

Degree of Correspondence between Individual Response Maps and the Composite Crime Rate Maps, at 60% and 80% Agreement Levels— Panel II

a) 60% Agreement Level

CATEGORY	P_1	P_2	P_3	P_4	P_5	Composite
High Crime Rate	3	3	2.7	1.9	1.6	3
Moderate Crime Rate	47	40.1	39	47.9	3.3	50.3
Low Crime Rate	–	–	1.1	1.1	1.1	1.1
Other	–	15.7	15.7	–	15.7	15.7
TOTAL	50	58.8	58.5	50.9	21.7	70.1
	Index of Dispersion = 0.32					

b) 80% Agreement Level

CATEGORY	P_1	P_2	P_3	P_4	P_5	Composite
High Crime Rate	1.9	1.9	1.6	1.9	1.6	1.9
Moderate Crime Rate	23.1	23.1	23.1	23.1	1	23.1
Low Crime Rate	–	–	–	–	–	–
Other	–	–	–	–	–	–
TOTAL	25	25	24.7	25	2.6	25
	Index of Dispersion = 0.18					

residential living. Three categories of livability were defined -- highly desirable, moderately desirable, and less desirable areas in which to live. To understand better the framework within which each respondent was answering the question, a supplement question asked that each describe in his or her own words how to determine the "degree of livability of an area". The responses to these supplemental questions are summarized in Appendix VI.

The three categories of livability were sufficient to be spatially exhaustive. However, as was seen earlier, internal contradictions and inconsistencies were apparent in the first round results. Most of the attention was directed toward existing residential areas, and those areas which were "open" or commercial tended to be left for the "Other" category. Second round discussion with Panel I revealed that these areas did indeed have a livability factor, and this was indicated, with one exception, in the second round responses.

The panels had little difficulty in dealing with and understanding the subjective nature of the variable. Panel I respondents were able to distinguish clearly between the three levels of desirability (Table 5.21).

The first round composite maps (Figures 5.25 and 5.26) showed a relatively large area over which consensus was reached. However, the consensus from the first round (Panel I) was relatively weak as was evident by the large drop in area from the 60% agreement criterion to the 80% agreement criterion -- 82.4% to 29.5% respectively (Table 5.22). Within the consensus, there was a high degree of dispersion in the concordance values -- index values of 0.29 and 0.12 indicated considerable differences in first round

Table 5.21

Percent of Total Study Area Assigned to Each Category of Livability by Respondent— Panel I

CATEGORY	R_1	R_2	R_3	R_4	R_5
Highly Desirable	8.4%	21.3%	40.4%	19.6%	23.9%
	8.5%	22.5%	27.7%	17.7%	28.6%
Moderately Desirable	52.2%	17.7%	36.2%	51.9%	41.7%
	44.9%	30.5%	33.4%	33.7%	43.5%
Less Desirable	20.9%	44.1%	4.7%	10.7%	16.7%
	46.4%	46.8%	38.8%	48.5%	6.0%
Other	18.4%	16.8%	18.5%	17.5%	17.4%
					21.8%

Round 1   Round 2

opinions. The Chi square test showed that the composite maps were statistically significant.

Round 2 showed an increase in the amount of area over which consensus was reached at the two criteria levels for agreement (Figures 5.27 and 5.28). At the 60% agreement level, there was consensus over 95.6% of the area, and at the 80% level, over 66.6% of the area (Table 5.23). This indicated that the consensus was strengthened, however, the indices of dispersion for the second round concordance values were still relatively high -- 0.23 and 0.16 for the two levels of agreement. Much of this dispersion could be accounted for through the response of a single respondent.

Round 1 results from Panel II showed similar levels of disagreements in the livability of parts of the study area (Table 5.24). Analysis of the individual responses showed that opinions about how much of the area was highly desirable ranged from 0% to 28.9%. At the other end of the desirability spectrum, a range of nearly 60% (i.e., from 14.8% to 74.3%) occurred. As frequently happened in the first round responses, the unclassified "open" and commercial/industrial areas were assigned to an "Other" category. For some respondents, e.g., P_5, this amounted to 25.4% of the total area. Consensus was reached over 75.4% of the area at the 60% agreement level and over 42.8% of the area at the 80% level (Table 5.25). Corresponding indices of dispersion amongst individual concordances were 0.22 and 0.09 respectively. These were relatively low for first round results and for a variable characterized by a high degree of subjectively.

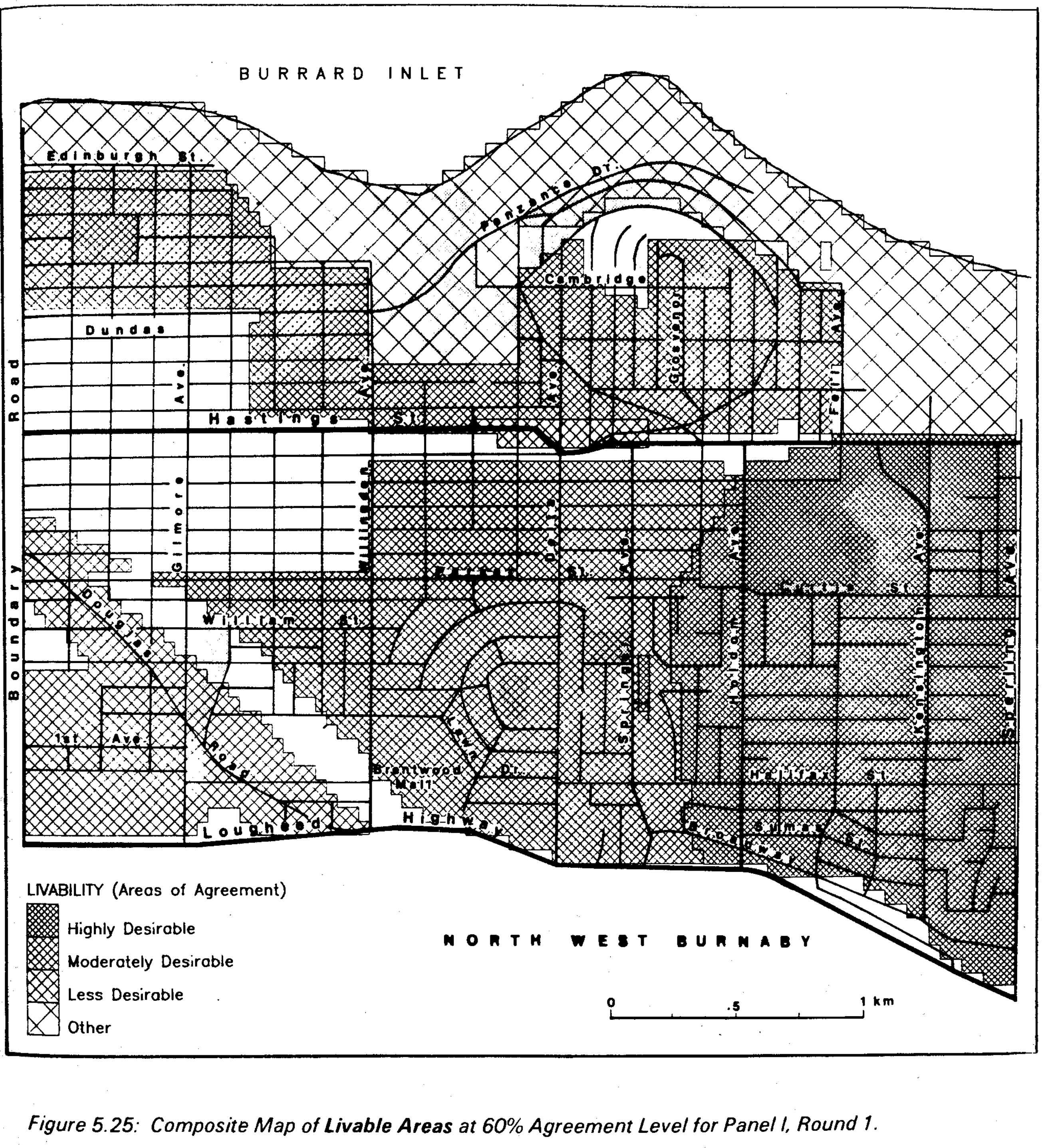


*Figure 5.25: Composite Map of **Livable Areas** at 60% Agreement Level for Panel I, Round 1.*

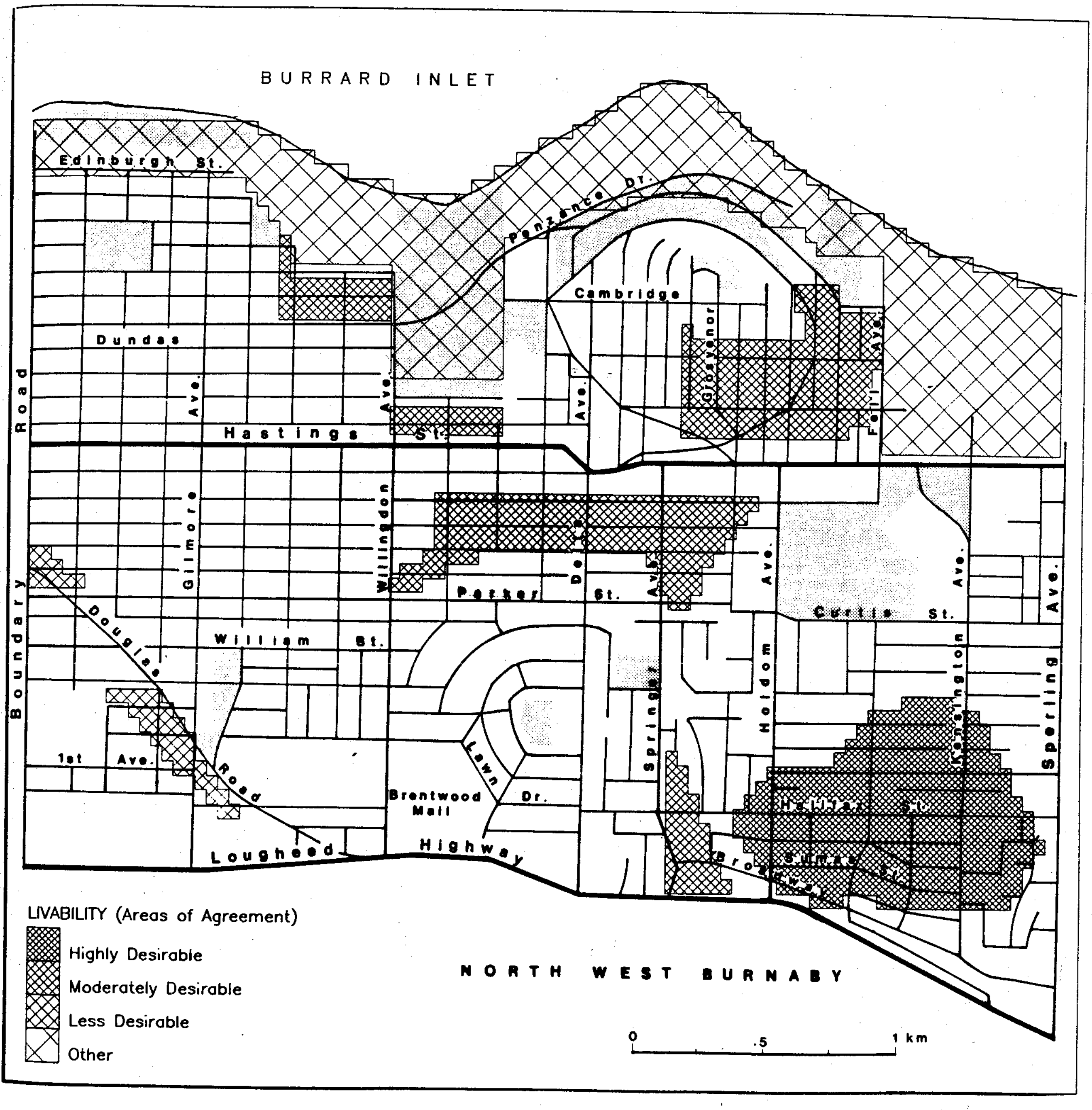


*Figure 5.26: Composite Map of **Livable Areas** at 80% Agreement Level for Panel I, Round 1.*

Table 5.22

Degree of Correspondence between Individual Response Maps and the Composite Livability Maps, at 60% and 80% Agreement Levels—Panel I, Round 1

a) 60% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
Highly Desirable	6.4	20.7	21	–	21.1	21.1
Moderately Desirable	30.7	17	18.4	19.6	29.6	35.4
Less Desirable	5.1	8.4	4.1	7.8	5.7	8.4
Other	17.3	16.1	13.7	16.8	13.9	17.3
TOTAL	59.5	62.2	57.2	44.2	70.3	82.2
	Index of Dispersion = 0.29					

b) 80% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
Highly Desirable	6.1	6.1	6.1	–	6.1	6.1
Moderately Desirable	7.7	3.6	4	7.7	7.7	7.7
Less Desirable	0.8	0.8	0.8	0.8	0.8	0.8
Other	14.9	14.8	12.8	14.5	13.5	14.9
TOTAL	29.5	25.3	23.7	23	28.1	29.5
	Index of Dispersion = 0.12					

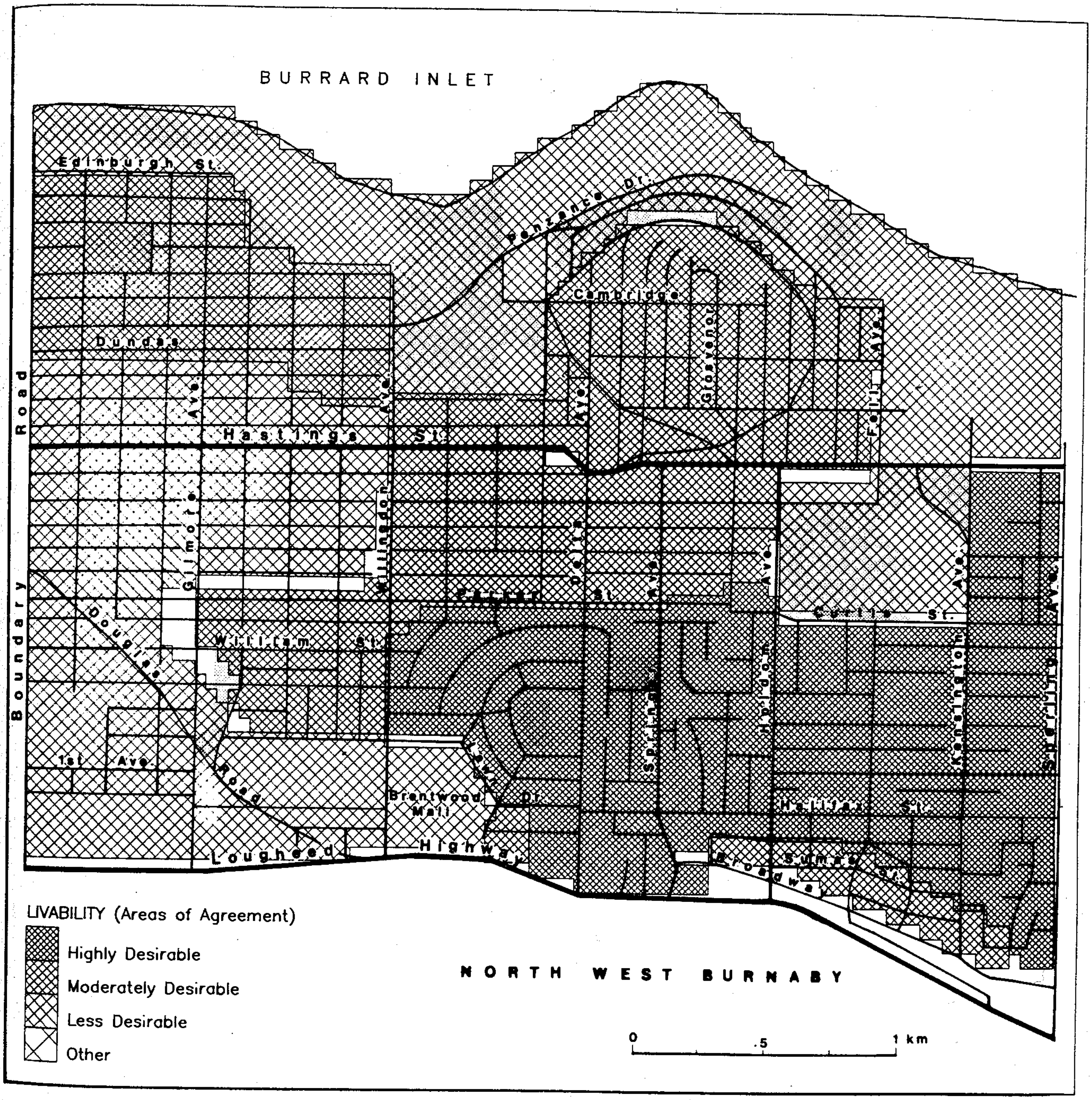


*Figure 5.27: Composite Map of **Livable Areas** at 60% Agreement Level for Panel I, Round 2.*

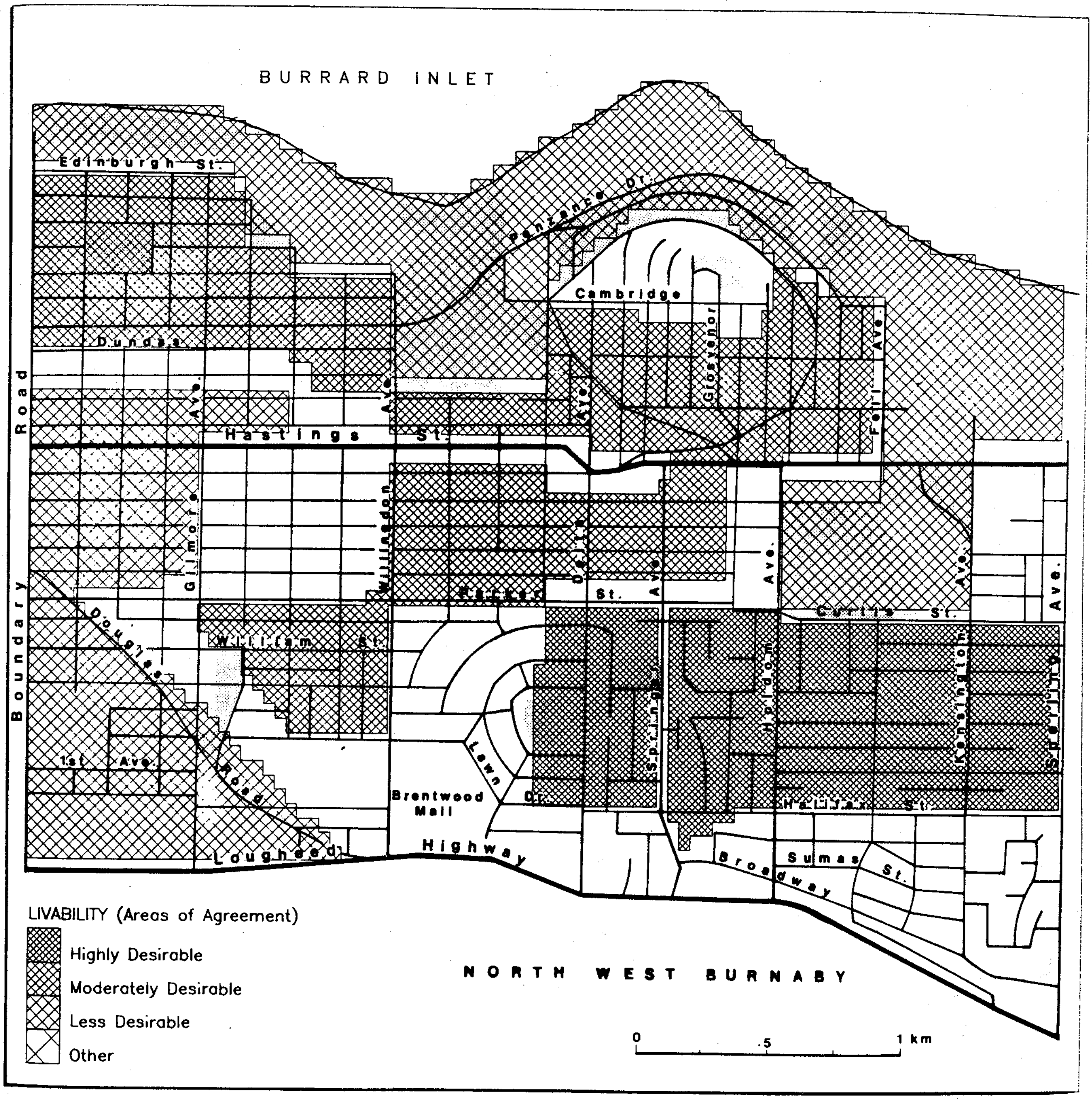


*Figure 5.28: Composite Map of **Livable Areas** at 80% Agreement Level for Panel I, Round 2.*

Table 5.23

Degree of Correspondence between Individual Response Maps and the Composite Livability Maps, at 60% and 80% Agreement Levels— Panel I, Round 2

a) 60% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
Highly Desirable	6	18	23.1	15.2	20.3	23.2
Moderately Desirable	24.1	19.1	29.1	24.9	24	30.5
Less Desirable	40.4	38	37.7	41.3	5.9	41.8
Other	–	–	15.2	–	–	–
TOTAL	70.5	75.1	105.1	81.4	50.2	95.5
	Index of Dispersion = 0.23					

b) 80% Agreement Level

CATEGORY	R_1	R_2	R_3	R_4	R_5	Composite
Highly Desirable	3.1	13.1	13.1	9.9	13.1	13.1
Moderately Desirable	18.6	13.9	21.2	20.8	19.1	21.5
Less Desirable	31.9	31.9	31.9	31.9	5.9	31.9
Other	–	–	–	–	–	–
TOTAL	53.6	58.9	66.2	62.6	38.1	66.5
	Index of Dispersion = 0.16					

Table 5.24

Percent of Total Study Area Assigned to Each Category of Livability by Respondent— Panel II

CATEGORY	P_1	P_2	P_3	P_4	P_5
Highly Desirable	1.7%	28.9%		15.0%	9.2%
Moderately Desirable	37.0%	38.8%	7.0%	29.7%	30.9%
Less Desirable	39.3%	14.8%	74.3%	37.2%	34.4%
Other	21.8%	17.3%	18.6%	17.9%	25.4%

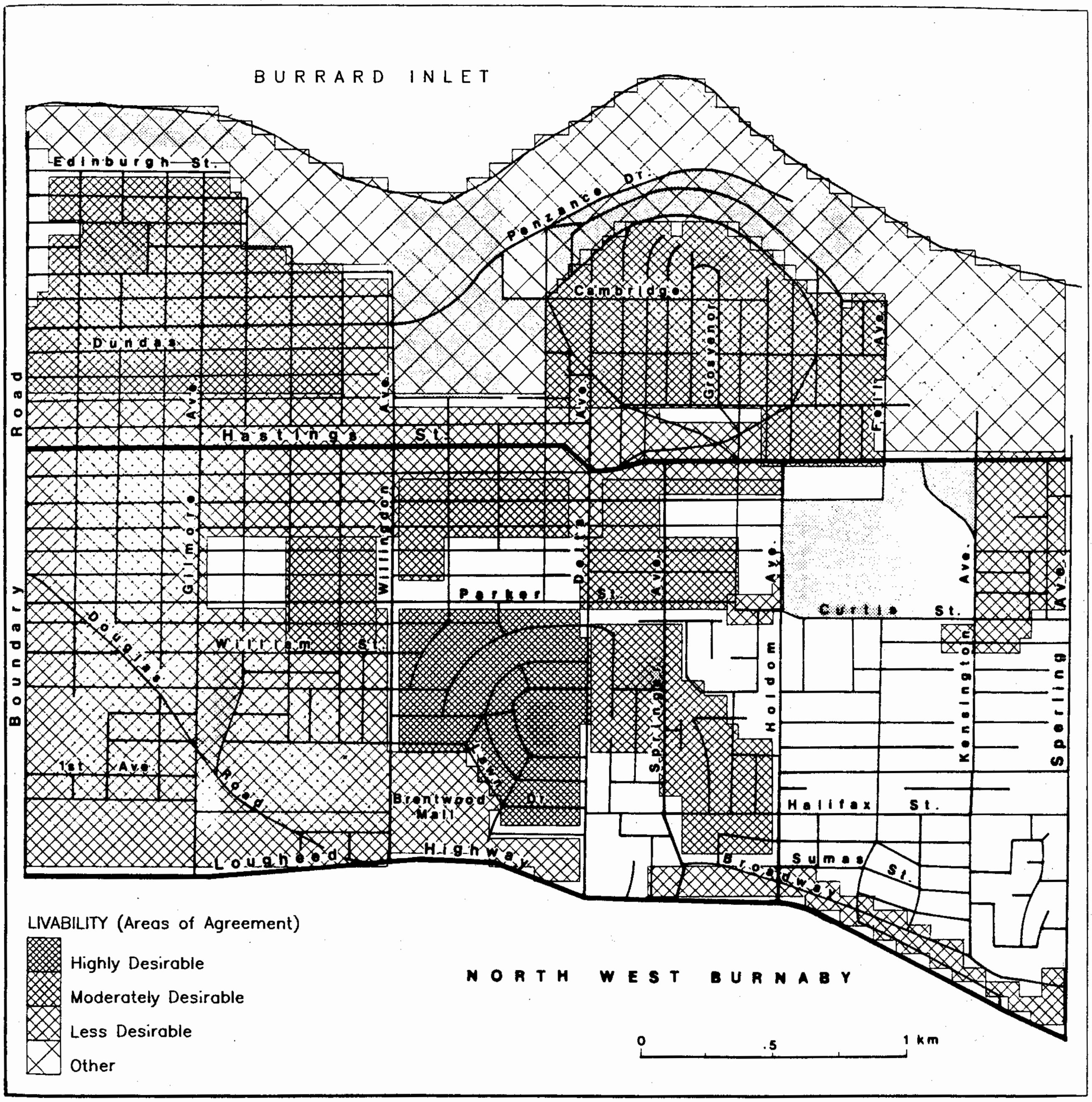


*Figure 5.29: Composite Map of **Livable Areas** at 60% Agreement Level for Panel II.*

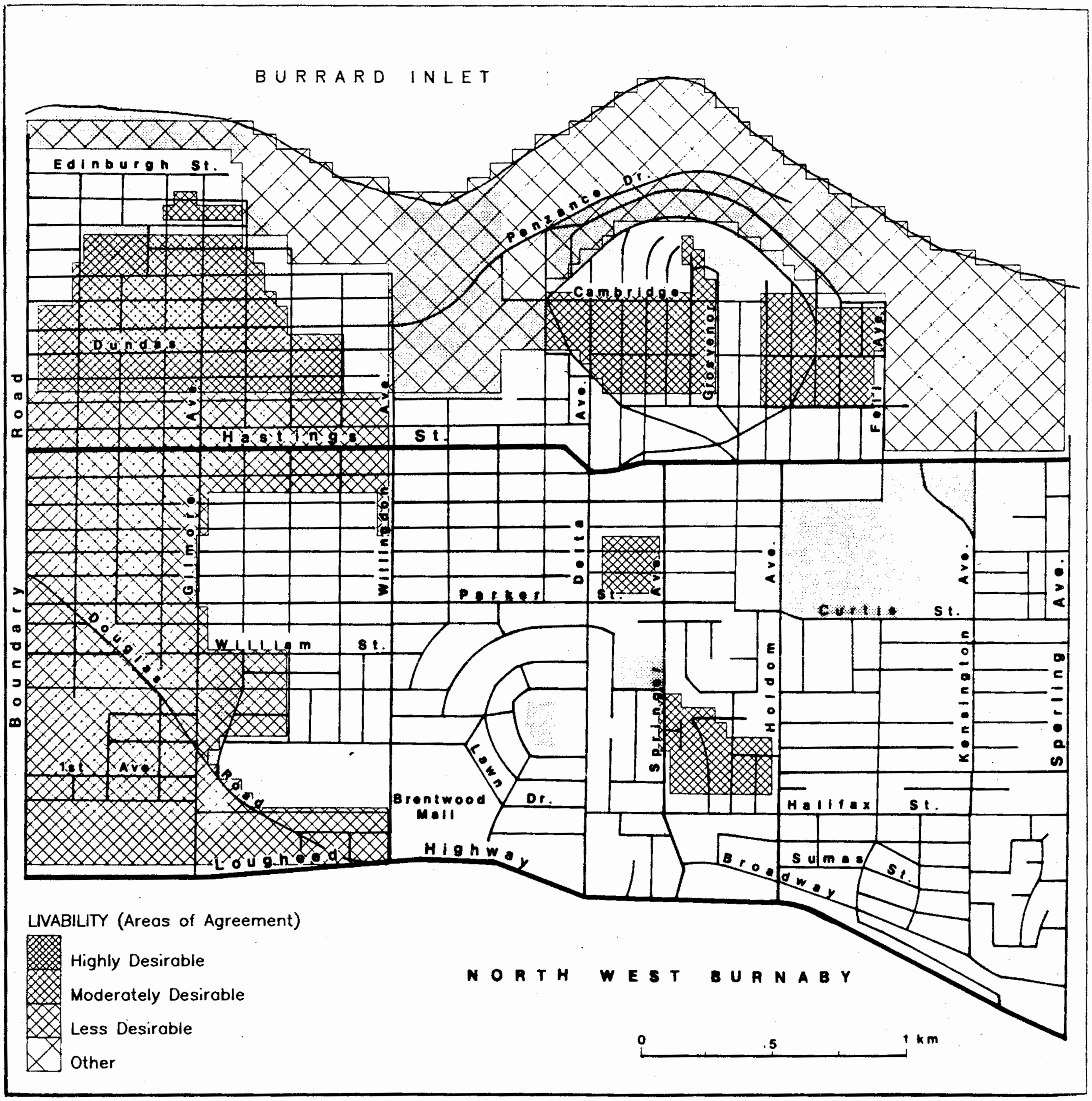


*Figure 5.30: Composite Map of **Livable Areas** at 80% Agreement Level for Panel II.*

Table 5.25

Degree of Correspondence between Individual Response Maps and the Composite Livability Maps, at 60% and 80% Agreement Levels– Panel II

a) 60% Agreement Level

CATEGORY	P_1	P_2	P_3	P_4	P_5	Composite
Highly Desirable	–	4.3	–	4.3	4.3	4.3
Moderately Desirable	20	18.3	5.5	19.7	15.9	23
Less Desirable	24.4	14.5	30.1	25.1	22.5	30.1
Other	17.7	17	17.8	17.1	16.8	17.9
TOTAL	62.1	54.1	53.4	66.2	59.5	75.3
	Index of Dispersion = 0.22					

b) 80% Agreement Level

CATEGORY	P_1	P_2	P_3	P_4	P_5	Composite
Highly Desirable	–	–	–	–	–	–
Moderately Desirable	10.2	9	3.3	10.2	8.1	10.2
Less Desirable	14	14.5	15.8	12.8	12.5	15.8
Other	16.7	16.6	16.7	16.3	16.7	16.7
TOTAL	40.9	40.1	35.8	39.3	37.3	42.7
	Index of Dispersion = 0.09					

All results of the aggregation process were significantly different from those of random response maps. Further, Chi square tests of the round 2 results from Panel I showed that the consensus was significantly increased over that of round 1.

5.3 Strabo's Ability to Estimate Reality

The preceding analysis demonstrated that the Strabo procedure found a consensus of spatial opinions within a group of experts, and that the iterative process strengthened the consensus. That alone is not sufficient. To be of use as a data collection tool or as a predictive model, the procedure must also be reliable. That is, it must be able to estimate reality. This section, then, examines how well the method performed in reproducing the objective reality of the tested distributions. Chapter 4 pointed out that only some of the variables considered in this study could be used to demonstrate the model because the others were very subjective by nature and any attempt to define their reality would only produce another subjective model. Comparing the results from Strabo with such a model would mean comparing two subjective realities; this would not demonstrate reliability in Strabo results since one cannot verify the original model's accuracy.

Three of the variables used in this study -- Dwelling type, Housing quality, and Income -- had objective foundations; however, there were subjective interpretations to the classes of the latter two. For example, household income could be measured accurately in terms of dollars, but the terms low, middle, and high could have different meanings for different people. There was no single, uniformly accepted definition of what each of these categories meant. These problems of comparability are dealt with in following sections which discuss how well the model predicted the spatial distribution of the three variables.

5.3.1 Dwelling Types

The dwelling type variable was the most objectively defined of those examined in this study. Although a great deal of variety existed within dwelling types, for example, house styles and high-rise versus walk-up apartments, the classification was simplified to distinguish only single family, multiple family dwellings, and non-residential. Also, the emphasis was on the primary use of the land -- if a small commercial activity was located in a private house or on the ground floor of an apartment complex, for the purpose of this study, it was considered to be part of a residential structure, single or multiple family as the case may be.

Chapter 4 described how base information was compiled against which Strabo results were compared. Information was collected from aerial photography, municipal land-use maps, and field visits, compiled onto a base map, and put into digital form in the same manner as were the individual response maps.

At the two levels of agreement (60% and 80%), the composite maps were compared with the "reality" map. The comparison looked for areas in which the Strabo composite agreed exactly with reality. The 60% agreement composite map from the first round of Panel I showed a match with the "reality" map in 56.4% of the area (Table 5.26). The 80% agreement composite map from the same session corresponded in 49.4% of the study area. One reason for relatively low correspondences in the first round was the confusion that panelists faced with the "non-residential" and "Other" categories. When the 56.4% correspondence was dissected, 53.7% fell in the single family category and only 2.7% in the non-residential category. This compared to 58.1% and 39.0% in "reality". The composite map only missed 4.4% of the area which was actually single family residential. However, it grossly underestimated the amount of non-residential area by 36.3%. This supported the argument that much of the first round error was attributable to the problem of interpreting non-residential land uses, as has been described in section 5.2.1.

Results from the second iteration showed marked improvement. The composite map from the 60% agreement criterion corresponded with reality in 83.1% of the area. There was little change in the amount of single family area; however, the amount of correspondence in non-residential areas increased to 30.5% -- only 8.5% less than reality.

First round results from Panel II were somewhat better than first round results from Panel I. The amounts of area from the composite maps corresponding to reality were 74.8% and 53.3% for the two aggregation criteria. Although somewhat better than Panel I, this group also had difficulties in dealing with the "open" areas as non-residential, which partly accounted for the low correspondence values (i.e., only 21.6% of the study area was identified correctly as non-residential at the 60% aggregation criterion).

Table 5.26

Amounts of Agreement between Strabo Composite Maps and the Actual Dwelling Type Distribution in Percent of Total Study Area

		ROUND 1 COMPOSITE MAPS		ROUND 2 COMPOSITE MAPS	
	CATEGORIES	60% LEVEL	80% LEVEL	60% LEVEL	80% LEVEL
PANEL I	Single Family	53.7	49.4	52.5	50.3
	Multiple Family	–	–	0.1	–
	Non Residential	2.7	–	30.5	22
	TOTAL	56.4	49.4	83.1	72.3
PANEL II	Single Family	52.9	47.3	–	–
	Multiple Family	0.2	0.1	–	–
	Non Residential	21.6	5.8	–	–
	TOTAL	74.7	53.2	–	–

5.3.2 Housing Quality

Evaluation of the quality of housing stock is somewhat subjective; therefore, the objective reality against which the Strabo results are compared has to be viewed only as a model. The model however should be one which is widely accepted and readily identified with. The Burnaby Planning Department (1984) has built into its municipal data base a "quality" attribute assigned to each of the properties. These designations are derived from those of the British Columbia Assessment Authority (BCAA), which has clear guidelines for evaluating properties. Each house was manually assessed and coded on the basis of such characteristics as style, year of construction, architectural design, among others (British Columbia Assessment Authority, 1983). Assessment offices can modify objectively derived scores within a discretionary range based on the general condition of property (Mr. G. Howard, BCAA Burnaby Branch, 1984 -- personal communication).

On the basis of this information, properties have been classified as "Poor", "Fair", "Average", "Good" and "Excellent" (Burnaby Planning Department, 1984, pp. 20-21). For the purposes of this investigation, housing quality data have been aggregated to city block level. The number of properties falling into each of the five categories was extracted from the municipal data base and further aggregated into three categories -- Poor, Moderate, and Good -- to match the categories of the Strabo question. This reduction was done by equating the Good category of the Strabo exercise with the Good and Excellent categories of the municipal data base, and by equating Moderate with Fair and Average. The Poor category remained the same in both classifications. Each block was then designated as either Poor, Moderate, or

Good quality on a simple majority criterion. For example, if a block had 10 properties classified as "Good", 5 as "Moderate", and 1 as "Poor", then, the entire block was classified as "Good". In the case of "ties", two rules were applied -- first, if at least two categories were equal and all three categories were present, then the block was assigned to the "Moderate" category; second, if two categories were equal and the third was not present then the block was assigned according to a random process to one of the two choices.

This map was then digitized in a fashion similar to that used for the dwelling type map. Classified according to the procedures above, 45.7% of the area fell in the Good category while 31.5% and 1.0% were in the Moderate and Poor categories respectively, and 21.8% in the "Other" category.

Comparing the Strabo composite maps from the two Panels with the objective reality as defined by this model produced encouraging results. The composite map at the 60% agreement level in the first round with Panel I agreed with the reality map in 52.1% of the study area. At the 80% agreement level, this correspondence dropped to 26.3%. The corresponding values for Panel II were 51.8% and 37.3% respectively.

As was the case with the dwelling type comparisons, results from the second iteration with Panel I showed marked improvement. The composite map from the 60% agreement criterion matched the reality map in 79.2% of the area, and from the 80% criterion, it matched in 65% of the area. The disaggregated correspondences suggested that the Panels tended to over-estimate the amount of area with Poor and Moderate quality properties and to under-estimate the amount of Good quality area. For example, Panel I in the second iteration agreed that 36.3% of the area was of moderate quality compared to only 31.5% of the area in the reality model. At the same time, they agreed that 26.1% was of good quality compared to 45.7% in the reality model, which represented a significant under-estimation.

Results of this comparison were inconclusive. The Strabo procedure was able to predict reality in 79.2% of the area after two rounds; however, it might be argued that the pattern of over- and under-estimation noted above might be attributable to fitting to an imperfect reality model. It is highly possible that the Strabo results would more closely align with a reality model in which the Moderate category had a broader range, and the Good quality category had a narrower one.

5.3.3 Income Areas

A third spatial distribution against which Strabo results were compared was that of the income variable. Household income statistics were obtained from Statistics Canada for 1981. As explained in chapter 4, although these statistics were already three years out of date, little change had occurred in the study area that would upset their relative rankings. Any increase in income was assumed to be proportional over the entire area.

These income statistics were then transferred to a base map of the study area and converted into digital form similar to the individual response maps. The respondents were asked to prepare maps showing three classes of income areas -- low, middle, and high. These classes are fuzzy in nature and require subjective interpretation. The problem was to classify the objective household income data, obtained from Statistics Canada, into these same three classes in order that they might be compared with those of the composite maps. Because the data were already slightly dated and because no rigorous classification technique existed for this purpose, a parametric procedure was adopted to establish the three classes within the range of continuous values. Standard deviations about the mean of the grouped data, were used to determine class boundaries. Rather than defining classes rigidly for the comparisons, several scenarios based on different class boundaries were used. These were examined in turn to determine how well they corresponded with the Strabo composites.

Three different scenarios of the objective reality were constructed. These used different class intervals based on standard deviations about the weighted mean of the distribution for the study area. Each scenario represented a view of reality against which the composite maps of the income variable were compared.

The first scenario (Scenario I) defined low income as less than one standard deviation below the mean of the distribution for the study area, middle income as those areas between one standard deviation below and one standard deviation above the mean, and high income as those more than one standard deviation above the mean.

The second scenario (Scenario II) defined low income as less than one standard deviation below the mean, middle income as between one standard deviation below and two standard deviations above the mean, and high income as those areas with income values more than two standard deviations above the mean.

The third scenario (Scenario III) defined low income as less than two standard deviations below the mean, middle income as between two standard deviations below and three standard deviations above the mean, and high income as those with values greater than three standard deviations above the mean. With this scenario, none of the area was classified as high. These three scenarios are summarized in Table 5.27, and the amounts of agreement between the Strabo composite maps of the income variable and the "reality maps" based on the three scenarios are shown in Tables 5.28 - 5.30.

In Scenario I, the composite maps from Panel II showed a better match with reality than did those from Panel I (Table 5.28). The results indicated that the panels tended to rate incomes lower in class than as expected from the "reality" model. For example, in round 2 of Panel I's results, 9% of the area was ranked "low" in the 60% composite map and ranked "middle" in the "reality" map; similarly, 15.5% was ranked "middle" by the composite map and "high" by the "reality" map. This appeared to be somewhat less of a problem for Panel II, however, their composite maps did indicate that the boundary between the "low" and "middle" categories reached higher than did that in the reality model.

Scenario II maintained the class limit between the "low" and "middle" categories similar to that of Scenario I, but raised the limit between the "middle" and "high" categories, effectively increasing the size of the

Table 5.27

Three Scenarios for Classifying Areas According to Income Levels

Income Category	Scenario I	Scenario II	Scenario III
Low	$<\bar{X}-1sd$	$<\bar{X}-1sd$	$<\bar{X}-2sd$
Middle	$>\bar{X}-1sd$, but $<\bar{X}+1sd$	$>\bar{X}-1sd$, but $<\bar{X}+2sd$	$>\bar{X}-2sd$, but $<\bar{X}+3sd$
High	$>\bar{X}+1sd$	$>\bar{X}+2sd$	$>\bar{X}+3sd$

Note: "$\bar{X}$" represents the weighted mean of the income distribution within the study area, and "sd" represents the standard deviation of the distribution.

Table 5.28

Amounts of Agreement Between Strabo Composite Maps of Income Areas and the Reality Map (Scenario I), in Percent of Total Study Area*

a) PANEL I, ROUND 1

Reality Map (Income)	% of Area	Composite Map (60% Level)				Composite Map (80% Level)			
		Low	Middle	High	Other	Low	Middle	High	Other
Low	5.3	1	2.1	-	–	-	1	-	–
Middle	63.7	5.5	35.6	–	3	–	6.2	–	1.5
High	15.7	–	13.4	–	–	–	8.5	–	–
Other	15.2	–	–	–	14.4	–	–	–	14.4
	TOTAL	51.0				20.6			

b) PANEL I, ROUND 2

Reality Map (Income)	% of Area	Composite Map (60% Level)				Composite Map (80% Level)			
		Low	Middle	High	Other	Low	Middle	High	Other
Low	5.3	1.4	2	-	–	1	2	-	–
Middle	63.7	9	34.7	–	7.2	5.7	33.5	–	7
High	15.7	–	15.5	–	–	–	14.2	–	–
Other	15.2	–	–	–	14.7	–	–	–	14.7
	TOTAL	50.9				49.3			

c) PANEL II

Reality Map (Income)	% of Area	Composite Map (60% Level)				Composite Map (80% Level)			
		Low	Middle	High	Other	Low	Middle	High	Other
Low	5.3	2	2.8	0.1	–	0.3	0.8	-	–
Middle	63.7	6.9	41	–	3.4	3.4	22.2	–	2.9
High	15.7	–	1.7	9.2	–	–	1.3	–	–
Other	15.2	–	–	–	13.9	–	–	–	13.6
	TOTAL	66.3				36.1			

* Income areas on the Reality Map are classified as follows:
Low – $<\bar{X}-1sd$
Middle – $>\bar{X}-1sd$, but $<\bar{X}+1sd$
High – $>\bar{X}+1sd$

Table 5.29

Amounts of Agreement Between Strabo Composite Maps of Income Areas and the Reality Map (Scenario II), in Percent of Total Study Area*

a) PANEL I, ROUND 1

Reality Map (Income)	% of Area	Composite Map (60% Level)				Composite Map (80% Level)			
		Low	Middle	High	Other	Low	Middle	High	Other
Low	5.3	1	2.1	-	-	-	1	-	-
Middle	72.8	5.5	42.6	-	3	-	11	-	1.5
High	6.4	-	6.4	-	-	-	3.7	-	-
Other	15.2	-	-	-	14.4	-	-	-	14.3
	TOTAL	58.0				25.4			

b) PANEL I, ROUND 2

Reality Map (Income)	% of Area	Composite Map (60% Level)				Composite Map (80% Level)			
		Low	Middle	High	Other	Low	Middle	High	Other
Low	5.3	1.4	2	-	-	1	2	-	-
Middle	72.8	9	43.8	-	7.2	5.7	41.3	-	7
High	6.4	-	6.4	-	-	-	6.4	-	-
Other	15.2	-	-	-	14.7	-	-	-	14.7
	TOTAL	60.0				57.1			

c) PANEL II

Reality Map (Income)	% of Area	Composite Map (60% Level)				Composite Map (80% Level)			
		Low	Middle	High	Other	Low	Middle	High	Other
Low	5.3	2	2.8	0.1	-	0.3	0.8	-	-
Middle	72.8	6.9	41	4.6	3.4	3.4	22.2	-	2.9
High	6.4	-	1.7	4.6	-	-	1.3	-	-
Other	15.2	-	0.2	-	13.9	-	-	-	13.6
	TOTAL	61.7				36.1			

*Income areas on the Reality Map are classified as follows:
Low – $<\bar{X}-1sd$
Middle – $>\bar{X}-1sd$, but $<\bar{X}+2sd$
High – $>\bar{X}+2sd$

Table 5.30

Amounts of Agreement Between Strabo Composite Maps of Income Areas and the Reality Map (Scenario III), in Percent of Total Study Area*

a) PANEL I, ROUND 1

Reality Map (Income)	% of Area	Composite Map (60% Level)				Composite Map (80% Level)			
		Low	Middle	High	Other	Low	Middle	High	Other
Low	1.3	1	0.1	-	-	-	-	-	-
Middle	83.3	5.5	51	-	3	-	15.8	-	1.5
High	-	-	-	-	-	-	-	-	-
Other	15.2	-	-	-	14.4	-	-	-	14.3
	TOTAL	66.5				30.2			

b) PANEL I, ROUND 2

Reality Map (Income)	% of Area	Composite Map (60% Level)				Composite Map (80% Level)			
		Low	Middle	High	Other	Low	Middle	High	Other
Low	1.3	1.2	-	-	-	1	-	-	-
Middle	83.3	9.2	52.3	-	7.2	5.7	49.8	-	7
High	-	-	-	-	-	-	-	-	-
Other	15.2	-	-	-	14.7	-	-	-	14.7
	TOTAL	68.3				65.6			

c) PANEL II

Reality Map (Income)	% of Area	Composite Map (60% Level)				Composite Map (80% Level)			
		Low	Middle	High	Other	Low	Middle	High	Other
Low	1.3	0.2	1.2	-	-	-	0.1	-	-
Middle	83.3	9	44.3	9.4	3.5	3.8	24.2	-	3
High	-	-	-	-	-	-	-	-	-
Other	15.2	-	2	-	13.9	-	-	-	13.6
	TOTAL	58.5				37.8			

* Income areas on the Reality Map are classified as follows:
Low – $<\bar{X}-2sd$
Middle – $>\bar{X}-2sd$, but $<\bar{X}+3sd$
High – $>\bar{X}+3sd$

"middle" category by 9.1%. The amounts of agreement between the composite maps and the model, depicted by this scenario, increased substantially in both rounds of Panel I, but decreased for Panel II (Table 5.29). The main improvement in the results of Panel I were an increased level of agreement in the "middle" category and a reduction in the amount of disagreement between the "middle" category on the composites and the "high" category on the "reality" map.

Scenario III produced the best match between the composite maps and the "reality" map for both rounds of Panel I, yielding 66.5% and 68.3% respectively at the 60% agreement level, but it also produced the least satisfactory results, of the three scenarios, for Panel II (Table 5.30).

Results of these comparisons between the aggregated information and the "reality" models were inconclusive. However, some useful observations and comments could be made. The results must be qualified by stating that the composite maps were being compared to other models which, although quantitatively defined on the basis of parameters of the distribution, were rather arbitrary. The results of comparing Strabo composites with reality models indicated that the class limits did not fall on discrete values. In fact, they appeared to be transition zones between the categories. Other models based on different class limits were also compared; however, their results, which are not reported, were no better than for the previous three scenarios.

The two panels seemed to have different perceptions about the definition of income categories. From the amounts of disagreement in each category, it appeared that Panel II had slightly lower limits for the "middle" and "high" categories, than did Panel I.

For Panel I, the amounts of area for which there was a match with the models increased between rounds. The amount of increase was most notable for the 80% agreement level maps. In fact, there was only small differences between the 60% and 80% agreement level maps in round 2, unlike the large discrepancies found in round 1. This indicates that the iterative feedback had strengthened the amount of agreement over the area and had improved the map's predictive capability.

5.4 Observations and Conclusions

The purpose of the application was to demonstrate the method and to illustrate how a Delphi approach could be used on spatial data to generate a consensus. Also, it sought to demonstrate that the method was reliable and able to produce meaningful information.

Results from iterations with Panel I showed that aggregating individual responses, according to some criteria, produced composite maps which were significantly different from ones which would be expected if the initial responses were random. Because the aggregating process depended on exact agreement amongst a predefined number of panelists (i.e., either at least 3 out of 5, or at least 4 out of 5), a consensus could be claimed over portions of the area after the first round. This differs from the Delphi approach where aggregate responses are usually produced by averaging individual quantitative responses. In that case, averaging a distribution from first round results can not be claimed to represent a "consensus".

The application dealt with five increasingly subjective variables. In the five cases, amount of consensus increased significantly from first round to second round. This was true for both sets of criteria, that is, for the 60% agreement level and the 80% agreement level. Table 5.31 summarizes the consensus levels between the two rounds for Panel I.

The consensus, at the 60% agreement level, following the second round of questions ranged from a low of 83.3% of the area for the "crime" variable to a near perfect score of 97.1% for "dwelling type". More notable, however, was the increase in the amount of consensus at the 80% agreement criteria in the second round. These values ranged from 66.2% for the crime variable to 81.7% of the area for the dwelling type variable. In general, consensus at the more stringent level (80% criteria) increased by an average of 120% compared to only 17% at the less stringent level (60% criteria). This indicated that not only did the area for which consensus occurred increase, but the "strength" of the consensus also increased. That is, more of the panel were in agreement at the end of the second round than at the end of the first.

A cross-variable examination of the indices of dispersion, which measure amount of discordance between the individual responses and the composite map, showed a distinct tendency to increase with the level of subjectivity of the variable (Figure 5.31). For example, the least subjective variable, dwelling type, had the lowest index of dispersion, and the crime rate and Livability variables had the largest indices. Second round results from Panel I showed

Table 5.31

Amounts of Consensus for Two Iterations with Panel I

VARIABLE	ROUND 1		ROUND 2	
	60% LEVEL	80% LEVEL	60% LEVEL (% INCREASE)	80% LEVEL (% INCREASE)
Dwelling Type	75.5	58.8	97.1 (28.6%)	81.7 (38.9%)
Housing Quality	90.2	34.1	93.1 (3.3%)	73.3 (115.0%)
Income	75.2	31.6	85.0 (3.3%)	78.5 (146.9%)
Crime Rates	62.3	24	83.3 (33.7)	66.2 (175.8%)
Livability	82.4	29.6	95.6 (16.1%)	66.6 (125.0%)

less dispersion; however, if one controlled for the fifth respondent, R_5, who did not participate in the discussions prior to completing the second questionnaire, the relationship between dispersion and degree of subjectivity was again direct.

Since no second round results were available for Panel II, it was not possible to make any judgements about increasing the amount or strength of consensus. However, the relationship between the indices of dispersion and the degree of subjectivity was consistent with that found in Panel I. The exception, again, was the livability variable. Both panels had less difficulty in dealing with this variable than might have been expected because of its subjective and intuitive nature. On the other hand, respondents were encouraged to think of livability in terms of how desirable areas were for residential purposes; it might be argued that areas carry with them a reputation about their living standards and that thoughts about any given area, with which one is familiar, conjure up shared mental images. People that live in an area have probably had to make the decision about where to live and have considered a number of alternatives. In their search, they have developed mental images of the various parts of the area. Therefore, although the livability variable is very subjective, people readily identify with it, and opinions about it are based on common perceptions partly attributable to the reputation of the areas.

All composite maps, both at the 60% and 80% aggregation criteria, were analysed to determine statistical significance. Chi square tests were performed on all first round aggregations, demonstrating that the results were significantly different from those which might be expected from aggregating

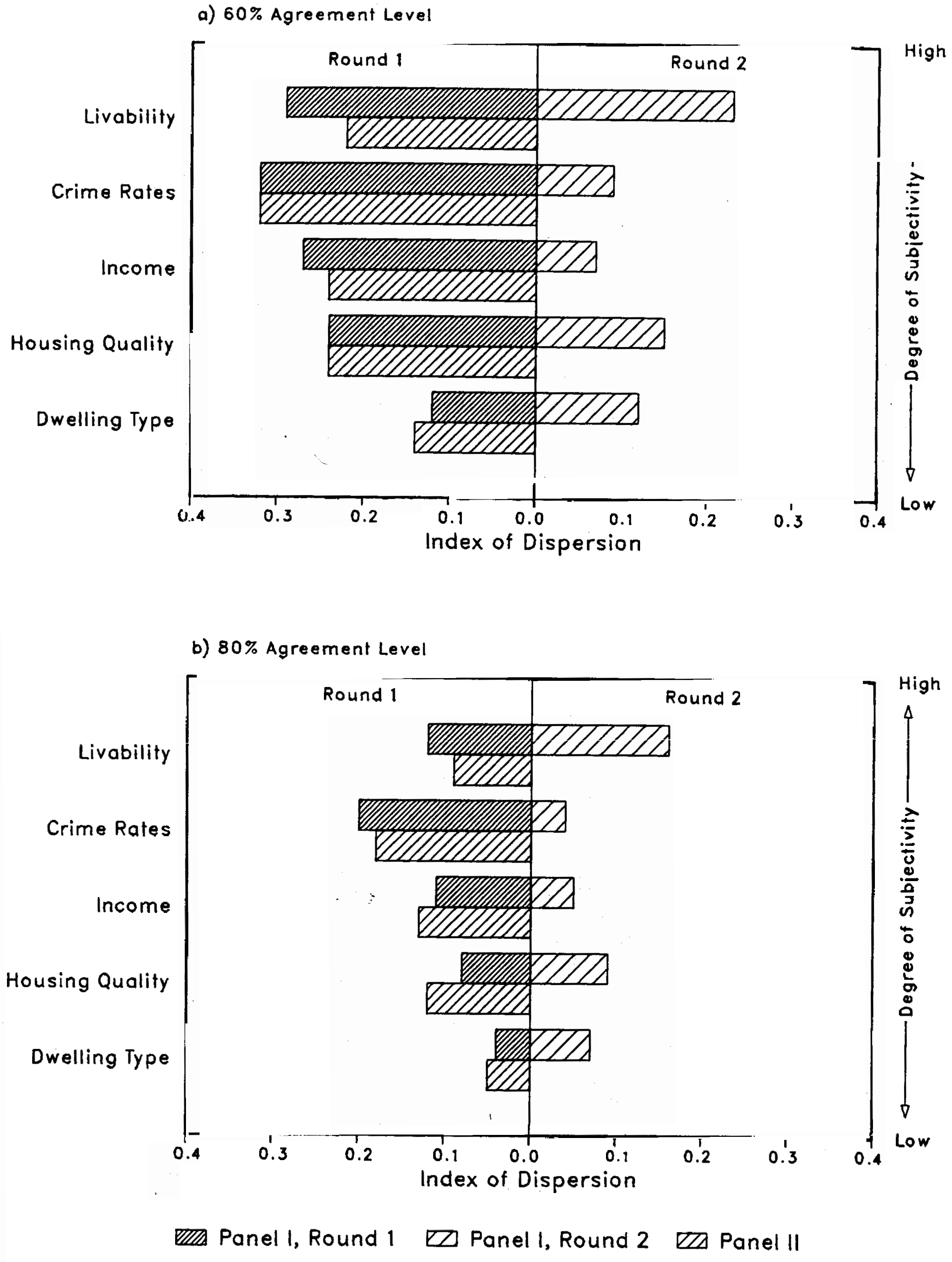


Figure 5.31: Indices of Dispersion Versus Degrees of Subjectivity.

response maps of random distributions of the variables. In all cases, tests showed that results were better than random. Similar tests were performed on all second round maps of Panel I with the same positive results. In addition, Chi square tests were applied to all second round maps, demonstrating that they were significantly different from their corresponding first round composites. Again without exception these tests were positive beyond the 99% confidence level. The second round responses were not only significantly different from random and from those of the first round, but the differences were always in the direction of improved consensus. There was always more area agreed upon in the second round than in the first.

The study then examined whether or not the results were a meaningful reflection of reality. Composite maps for the more objective variables -- dwelling type, housing quality, and income -- were compared to what was already known about the area. As expected, the first round results were poor (although Panel II's 60% aggregate of dwelling types predicted nearly three quarters of the area correctly in the first round). Second round results were considerably better, for example, Panel I was able to estimate accurately the dwelling types in more than 83% of the area.

The other two variables provided less conclusive evidence because the "objective realities" against which the composite maps were compared were themselves subjective constructs. Housing quality, for example, was defined according to a model established by the British Columbia Assessment Authority and the Burnaby Municipality. In this model, dwellings were classified as Poor, Fair, Average, Good, or Excellent. It was necessary to reclassify these to make them comparable with the three classes on the questionnaire.

Likewise, household income from Statistics Canada had to be classified to be comparable with the classes on the questionnaire. Rather than selecting one definitive classification for each of these variables, several scenarios were examined and compared to the composites. The results for these two variables could not be treated conclusively because their "objective reality", even though based on hard data, depended on how the modeller chose to draw the class boundaries. The results from several comparisons were valuable because they showed tendencies, and from these one could begin to estimate subjective breaks in the distribution of a variable. For example, comparing the income composites with the "reality" map suggested that the break between low and middle income was somewhere between 1 and 2 standard deviations below the mean. In this manner, Strabo may be used to work backwards from results to identify objectively measured definitions of subjective concepts and variables.

Results from the analysis supported the original premise that Strabo could be used to build and strengthen spatially-oriented consensus. It was observed and verified, in five test cases, that major improvements occurred with just two iterations of the process. In many situations, particularly where all that is required is a first, coarse look at a spatial problem, two such rounds may be sufficient.

The results also supported the contention that Strabo does reflect reality, however, the extent to which it is successful was less conclusive because of difficulties with defining "objective realities". Major improvements in its estimates were measured between two iterations for the three variables tested.

A final observation dealt with the process itself. It became evident in the second round of Panel I that discussions are a valuable component of the procedure. The one panelist who was not able to participate in these discussions, but who was given the summary information, performed more poorly on the second round than did his colleagues. This feedback information and the subsequent discussion and clarification of problems are key elements in updating an individual's cognitive representation of a spatial concept. It seems that an ensemble meeting of the participants during the first round is less important. During this session, discussion and information centres around procedural issues rather than substantive issues as are dealt with in subsequent rounds. Special care should be exercised in conducting subsequent iterations of the process to avoid, as much as possible, problems of "drop-outs", "late shows", and "deferred participation".

CHAPTER 6: SUMMARY AND CONCLUSIONS

6.1 In Review

Geographers recognize the significance of space as a crucial factor in man's organization of his activities. However, they are often alone in considering spatially distributed information in planning and decision-making processes. With recent introductions of rapid data processing capabilities, spatially-oriented data, or geographic information, are becoming more common-place in those processes. Automated systems have facilitated the management, analysis, and retrieval of large amounts of spatial information. Public utilities use geographic data base management systems to inventory their resources, plan and design modifications, and handle billings. Government agencies use them for maintaining fiscal and legal cadastres, planning future developments, and strategic planning for services and amenities (Christie et al., 1985). Industry uses them to monitor resources, set production targets, and analyse markets. In essence, geographic data -- their collection, handling, and use -- are becoming a regular part of the operations of many companies, government agencies, and individuals.

Geographic data and information are usually extensive, frequently changing, and difficult to measure. For these reasons, among others, it is often expensive and time consuming to establish geographic data handling capabilities. This study was concerned with those environments where geographic data do not exist, are unreliable, or where they are unattainable or prohibitively expensive to collect.

The approach relies on the cognitive structures of experts, or knowledgeable respondents, to derive spatial representations of geographic phenomena. It is called the Strabo technique, after the early Greek geographer of that name (64 B.C. to A.D. 21) who first demonstrated a concern for the "nature" of places. It joins a number of other approaches, mainly in the areas of futures research and technology forecasting, which base their results on opinions of an informed few. Most notable among these is the Delphi method, in which the Strabo technique finds its theoretical underpinnings. Delphi, and its many derivatives, rely on expert opinions and structured feedback to produce consensus about quantitative issues such as "How many troops?", and "When will an event occur?". Strabo uses procedures similar to those in the Delphi techniques to answer the geographic questions "Where?". For this purpose, experts provide their answers in mapped rather than numeric or written form.

The study dealt with data handling problems, and developed and demonstrated an information system approach. It reviewed relevant studies from the literature pertaining to data accuracy, data reliability, and qualitative data handling. It also examined a number of studies dealing with cognitive mapping, subjective information, and subjective probability theory. Several structured feedback approaches, with particular emphasis on Delphi and its derivatives, were reviewed to establish a background for Strabo.

Based on this background and on concepts and principles established in information theory, the Strabo technique was developed as an alternative approach for working in data-poor environments. The approach was defined as a structured communication process in which panels of experts use maps to respond to spatial questions. Individual responses are aggregated, and the composites are fed back as new information into the "belief systems" of the individuals. This iterative feedback procedure builds new information upon which opinions of the previous round are updated.

The study described an application of the method in which some of the underlying assumptions were examined. The case study demonstrated in detail how the procedure should be applied, and determined whether or not the approach could generate and improve consensus in spatial opinions.

Analysis of the results showed that in the five cases tested, the amount of consensus was improved in the subsequent round over that of the first and that the consensus was strengthened, that is, more participants agreed with the results of the aggregation. It also showed that the results did reflect reality for the more objectively defined variables and that this reflection also improved with successive iterations.

6.2 Conclusions

This study has shown that information within the cognitive domain of individuals who have a special knowledge about an area can be used to describe the spatial distribution of geographic variables and to form opinions about value-laden concepts such as quality-of-life. It has also shown that this information can be elicited from individuals in the form of maps. Responses from several different experts may vary somewhat, but aggregation of the responses produces a composite which reflects a group "average". The composite map contains new information about what a significant number of the panelists believe. This new information can be fed back into the decision process to update the cognitive structures. In essence, the group feedback, which occurs prior to successive iterations of responding to the questions, serves as another data source for the individual along with the more usual published statistics, written accounts, and personal observations and investigations. The structured feedback aspect of the approach is a crucial element in the formulation of group consensus.

There are several lessons to be learned from the application used in this study. First, respondents who were not familiar with reading maps or with putting information into graphical form had considerable difficulty in the initial rounds with representing their opinions in map form. Their responses, if taken literally, often contained inconsistencies and internal contradictions. These took the form of overlapping areas, areas left blank unintentionally, and confusing interpretations of the categories within each variable. The results showed that they quickly learned the skill with practice and after they had a better understanding of the procedures. To ameliorate these problems, a short "training" session should be conducted prior to their completing the first round questions. This may not always be possible because of the time commitments required from the respondents. An argument can be made, however, that extra time spent in the beginning, familiarizing the participants with the procedures, might shorten the overall process by reducing the number of iterations necessary to reach a strong consensus.

Face-to-face communication amongst the panelists within the feedback step of the process is important. It facilitates the individual in explaining his beliefs and justifying his opinions. The study director must be sensitive to potential problems with such a feedback mechanism, for example, when one or more of the panelists becomes overbearing and unduly influences the rest, or when open aggressive confrontation develops between panelists. These are easily dealt with by structuring the communication process and by using some of the standard procedures for conducting "efficient" meetings (Bradford, 1976; Zander, 1982). From the application in this study, group communication during the first round was less important than during the subsequent round. This is suggested because Panel I performed no better than did Panel II on the initial round, even though Panel I met ensemble to discuss the project and complete the questionnaire and Panel II did not. During the second iteration for Panel I, one of the respondents was not able to meet at the same time as the rest of the panel and deferred his answers for several days -- as a result, he performed less well than did the rest. In some instances this deterioration in performance could be directly related to his not having participated in the second round discussions.

A third lesson, more difficult to deal with, but directly related to the issues of the preceding paragraph, is that of panel formation, session scheduling, and participant dropout. It can be difficult to get panels of experts together at a single time and place for more than one iteration of the process. It may require a significant contribution of time by the individuals, and unless it has direct benefit to them or their work, other demands on their resources may receive higher priority. The problem can be ameliorated by setting aside one time block in which to conduct the entire process with all necessary iterations. This, however, does not solve the problem of getting commitment for that amount of time. Respondents may have to be paid for their participation, unless the process is of direct benefit to them or their company/agency and their participation is either voluntary or delegated.

The study has raised several fundamental issues about geographic data handling and has attempted to focus attention on them. One is the general problem of data aggregation. Automation has made it almost trivial to manipulate and combine vast amounts of geographic data; however, the problem is what to expect from such aggregations in terms of accuracy levels and confidence limits. There is no definitive answer to the problem. Each case must be considered on its own merits. When combining or overlaying themes of information, one cannot simple use a multiplicative rule of probability to evaluate the accuracy of the final result, because the data layers will seldomly be independent of each other. Even more basic than considering the reliability of an aggregated data plane, is the problem of knowing the reliability of the initial data. This is not only scale dependent but also influenced by data collection and compilation procedures. Seldom is this information carried with the map or data set. Some aspects of the reliability factor are not related to the spatial distributions, e.g., sampling techniques which are consistent for the entire study area, while others are. For example, maps compiled from data gathered at different time periods or from different sources may not have a consistent level of reliability at all places on the map. For these reasons, geographic data should carry with them not only written information about their reliability, such as scale of data collection, degree of generalization, classification techniques, and other elements of their heritage, but also graphic descriptions of spatially-related reliability factors. These graphic descriptions can be in the form of a map, either appearing as a legend item or incorporated into the information on the main body of the map.

The Strabo technique deals with the issue of reliability by establishing confidence maps for each of the initial inputs. These provide the users of the information on the response maps with an indication of how much "faith" can be placed in their content; it is then up to the individual user to decide how he wishes to deal with the data.

Strabo has potential for applications where data are unavailable, difficult to collect, and/or subjective in nature. It is not considered a tool which can provide all answers, but it can, in conjunction with other techniques, improve the geographic information input into the planning and decision-making process, especially in data-poor environments. It can be used to identify general trends or problem areas for which more detailed types of analysis can then be applied. In this sense, it can be used to focus problems and to get a first look at the information in a relatively fast and inexpensive way.

6.3 Areas of Suggested Research

A range of associated research endeavours can be identified, stemming from this study. Some would extend the scope of the method and others would deal in more depth with some of the issues raised in the study. To evaluate the broader potential of the technique, more applications are required, sampling different fields.

A number of questions related to geographic information processing, in general, remain unanswered. More research into defining reliability of geographic data remain to be done. This problem is of current interest and has some urgency because of rapid advancements in geographic information systems technology. Increasingly, these systems and capabilities are finding their way into workplaces of the non-geographer who often has little understanding of the technology and even less of the data behind it. Data are often treated as completely accurate when, in fact, their accuracy is limited. The problem is aptly summarized by Cook (1983, p. 65) "[b]ecause it is difficult to see how to take uncertainty into account, the practice is to ignore it". Research is needed into ways of identifying and "labelling" data reliability and into ways of handling reliability information in spatial analysis. An associated problem is how to perform and interpret aggregations and combinations of geographic variables. To date, little is known about what happens when less than perfect data are combined in multiple overlays of data planes. Indiscriminately combining and aggregating data, as is often done with these systems, is somewhat analogous to the chemist throwing chemicals together not knowing what to expect as a result, or what new compound has been created, but knowing that the product contains all of the original elements. The fields of Bayesian probability and fuzzy set theory contain tools and concepts which may provide solutions to some of these geographic data handling problems.

A Strabo related problem requiring further research is that of calibrating the panelists. This study used familiarity maps provided by the panelists to indicate their confidence in their own responses. It appears possible to work "backwards" from calibration test information to determine the confidence weightings which should be applied over the area. Finding ways of adjusting the spatial answers by using the calibration results would be useful. It is obviously not as easy as spotting extra points to Winkler's (1981, p. 486) "bookie", but a two or three dimensional spatial analogy could be envisioned.

Finally, the psycho-spatial focus of Strabo should generate research into alternate ways of recovering cognitive representations of space from panelists. This study used "completion maps" on which panelists were required to "draw" their opinions. Using "construction maps" (Cromley, et al., 1981), or such other techniques as Multi-Dimensional Scaling (Golledge, et al., 1982), could prove useful in recovering the cognitive representations. Analytical ways of dealing with these spatial constructs would have to be developed. Each response would have its own unique "distortion" of space and ways of making these comparable across all responses would be required.

APPENDIX I

THE STRABO QUESTIONNAIRE

NORTH WEST BURNABY STRABO EXERCISE

The purpose of this exercise is to measure the spatial, or geographic perception of a group of individuals who have a thorough knowledge of an area with which they are familiar. To this end, your cooperation as a participant within the select group will be greatly appreciated. The data gathering process involves "averaging" the responses of the participants in the group, providing summary feedback to the individual participants, and performing subsequent iterations of this process. So as not to bias the results, you are requested NOT to consult other maps or sources of information when you answer the questions; it is your intuitive knowledge of the area which we are concerned with.

The area with which you will be dealing is roughly defined as North West Burnaby. It is bounded by Burrard Inlet on the north, Sperling Ave. on the east, Lougheed highway on the south, and Boundary Road on the west.

● ● ● <u>BACKGROUND INFORMATION</u> ● ● ●

Before proceeding to the map questionnaire, please answer the following background questions. These responses will help describe the basis for the information you will put on the maps.

1) Name (please print):_____________________
Phone number (work):_________

2) Please describe your association with the area under study, (e.g., you are a resident; it is within your market area; you belong to a community group within the area; etc.).

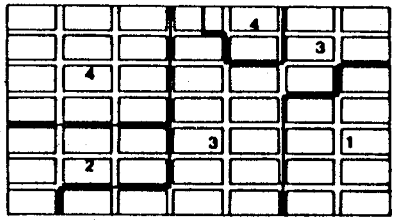
3) Approximately how long have you been familiar with the area? ________ years.

4) Which of the following indicates your highest level of educational attainment?
___ Elementary School
___ High School
___ Post Secondary School

● ● ● <u>MAPPING EXERCISES</u> ● ● ●

On the following maps please draw lines around those areas which represent the specific attributes identified. Be sure to label each and every area with the appropriate designator. This example illustrates the process:

LAND USE STATUS IN A SAMPLE AREA



Legend:
LAND USE STATUS

Label	Description
1 -	Residential
2 -	Industrial
3 -	Commercial
4 -	Park

Figure 1: An Illustration of How to Indicate "Land-Use Status" on a Map.

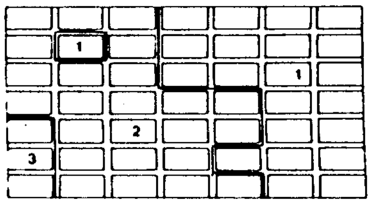
MAP 1: AREA FAMILIARITY

On the first map indicate the parts of North West Burnaby with which you are familiar according to the following categories:

Label	Description
1 -	Very Familiar
2 -	Somewhat Familiar
3 -	Unfamiliar

NOTE: Be sure that you fill in all parts of this map.

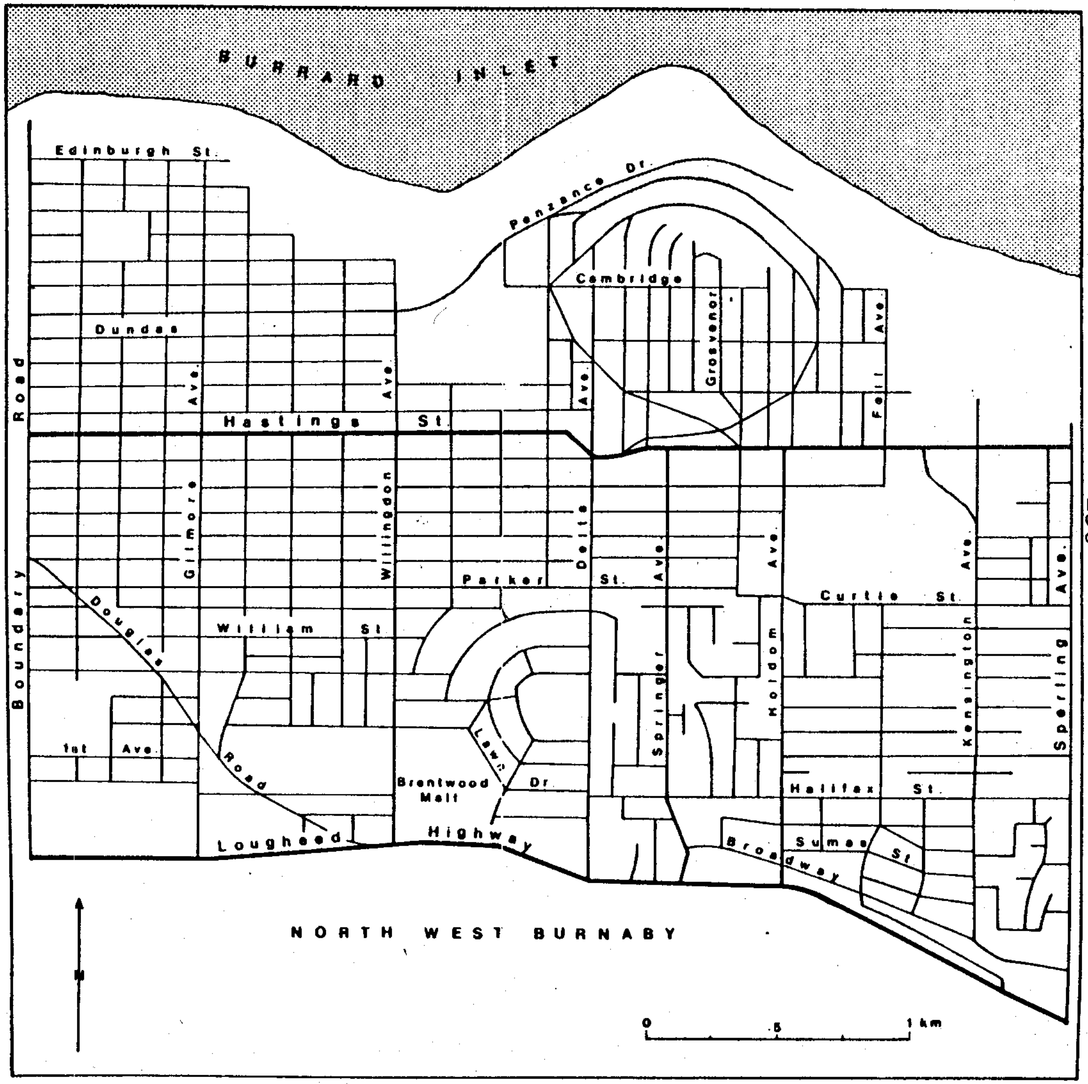
EXAMPLE MAP OF AREA FAMILIARITY



Legend:
FAMILIARITY

Label	Description
1 -	Very Familiar Area
2 -	Somewhat Familiar Area
3 -	Unfamiliar Area

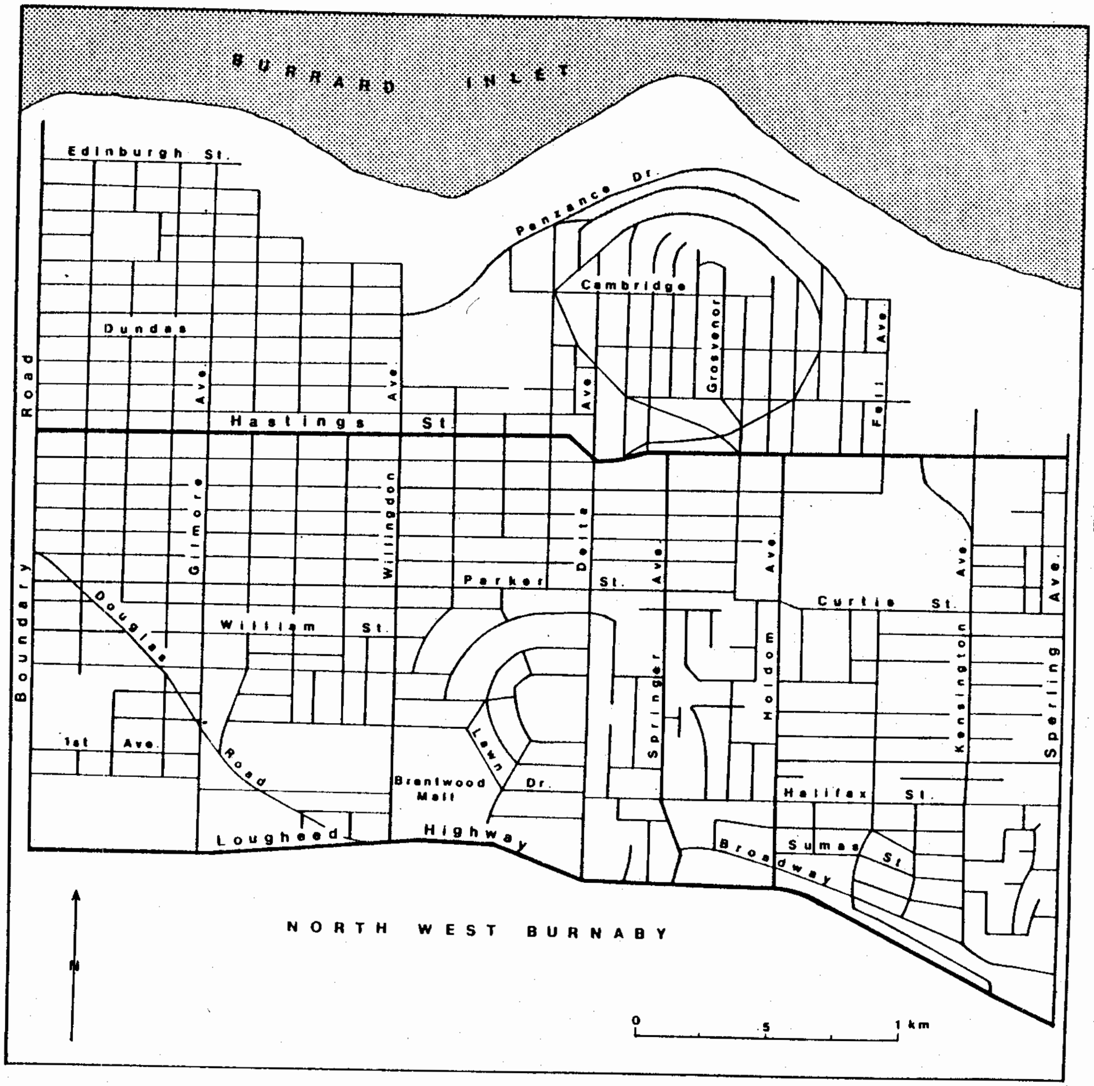
Figure 2: An Illustration of how a respondent might indicate "familiarity" on a map. This illustration indicates that the respondent is very familiar with the area in the northeastern corner of the map while the southwestern corner is largely unfamiliar to him/her.



MAP 2: RESIDENTIAL DWELLING TYPES

North west Burnaby contains various types of residential dwellings. On the second map, indicate the areas which you believe to be predominantly characterized by:

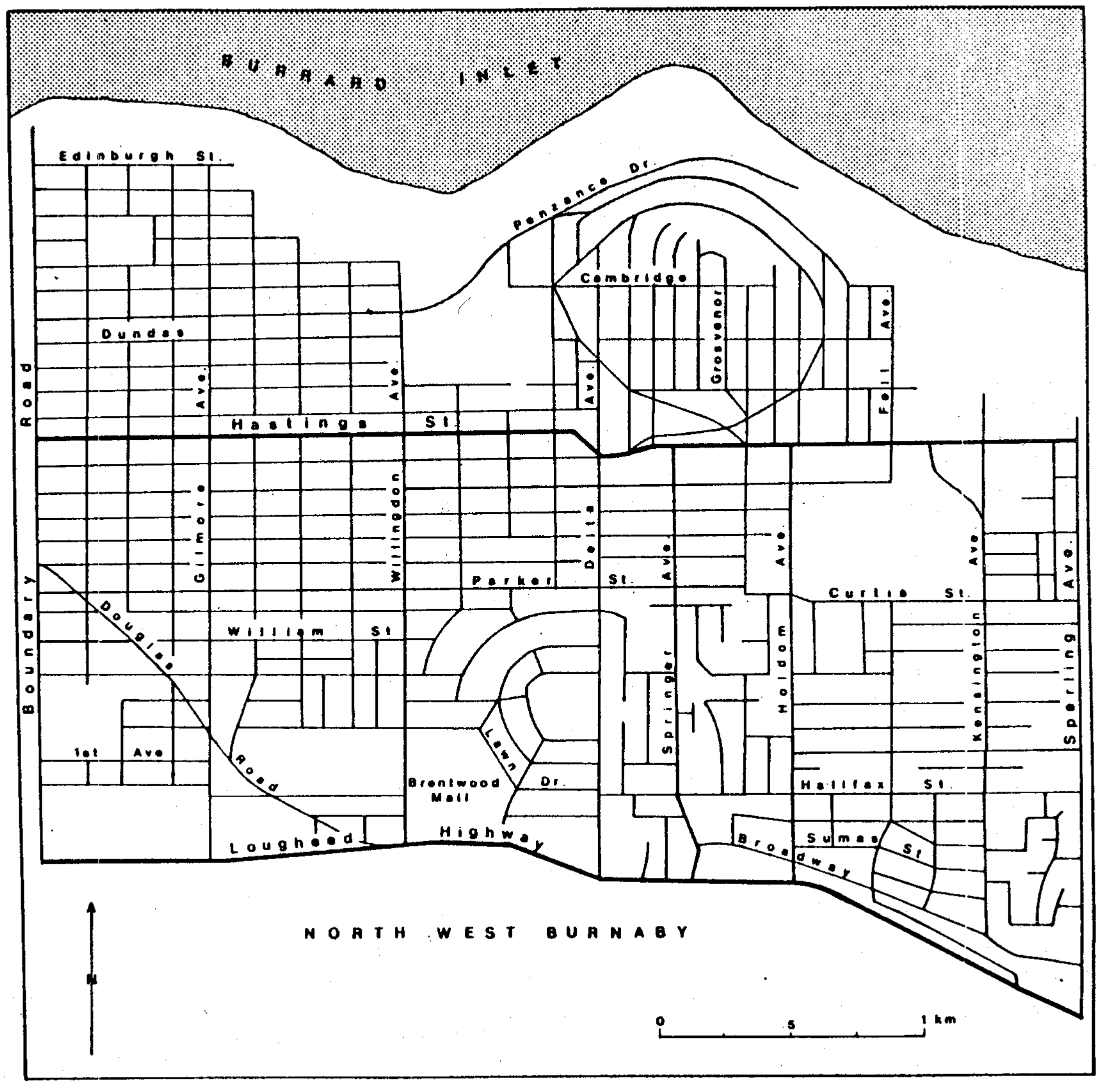
Label	Description
1 -	Single Family Dwellings
2 -	Multiple Family Dwellings (e.g., apartment buildings)
3 -	Non-residential land-uses



MAP 3: HOUSING QUALITY

The condition of existing housing stock in North West Burnaby varies with such factors as age of building, type of structure, among other factors. On the third map indicate the areas which you would characterize as:

Label	Description
1 -	Poor quality housing
2 -	Moderate quality housing
3 -	Good quality housing



MAP 4: INCOME

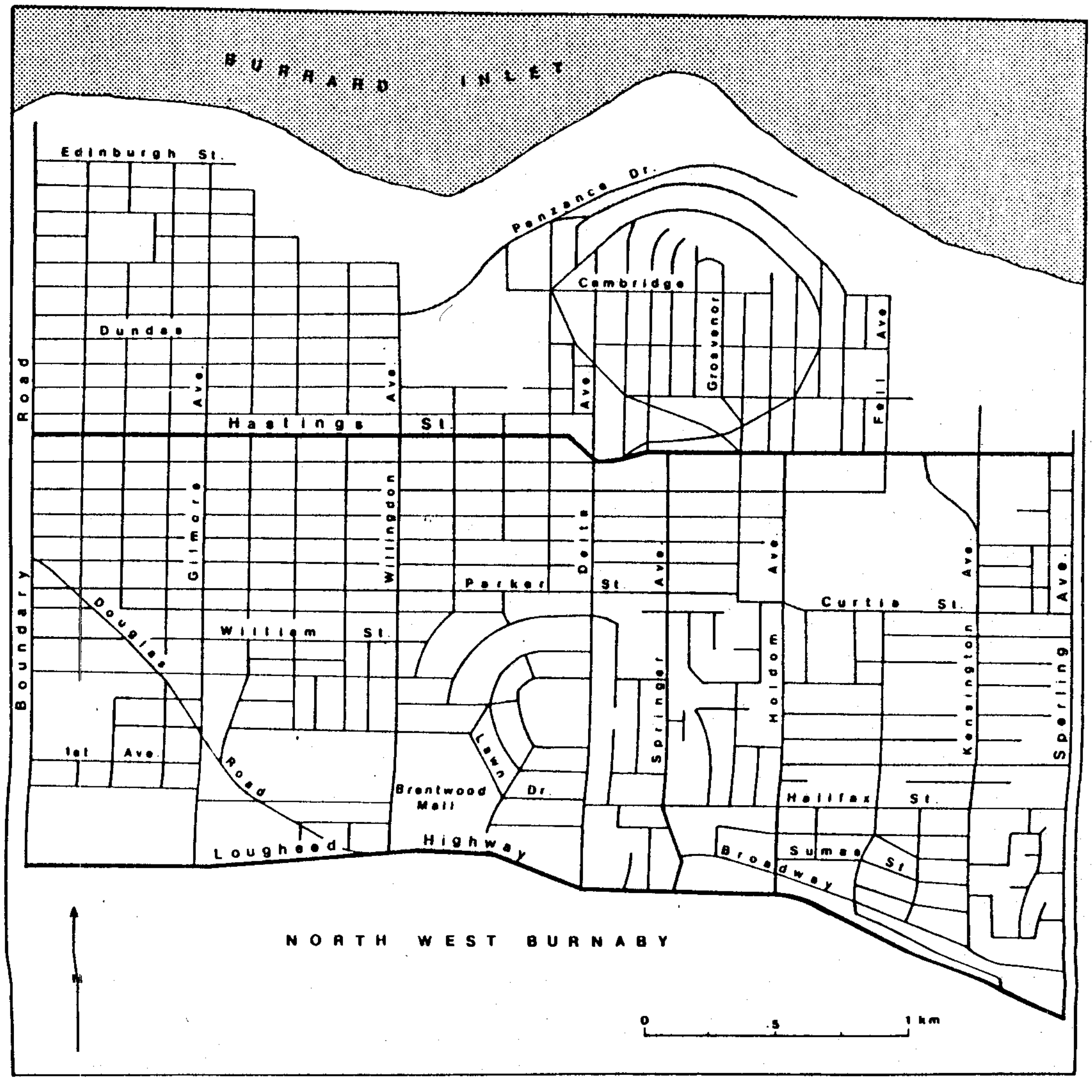
On the fourth map, indicate those areas which you would categorize as :

Label	Description
1 -	Low income areas
2 -	Middle income areas
3 -	High income areas

QUESTION:

Please describe in your own words how one would recognize an area as being either Low, Middle, or High income (i.e., what would be characteristic of these areas?).

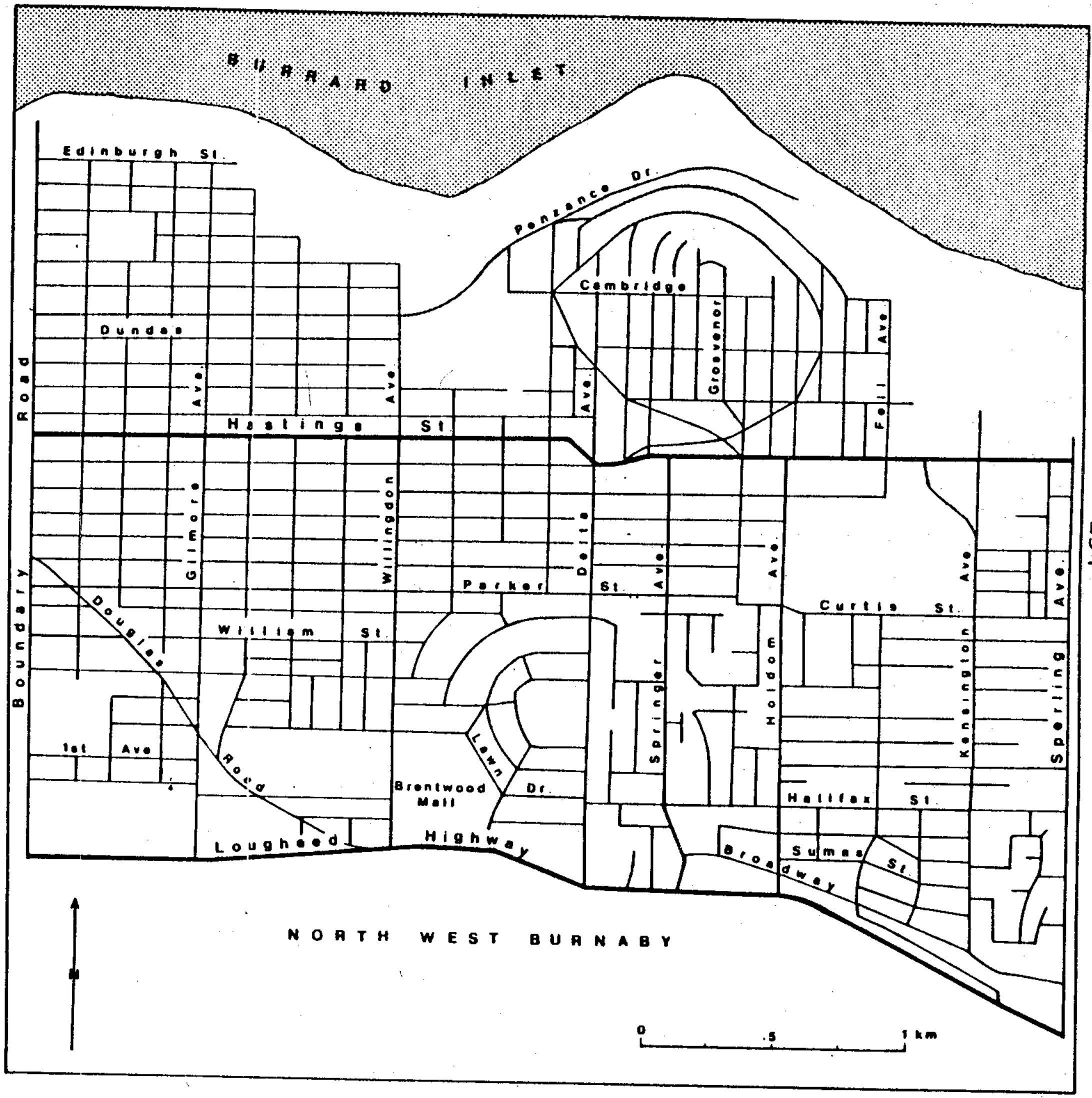
ANSWER:



MAP 5: CRIME AREAS

On the fifth map, indicate the areas which you consider to have:

Label	Description
1 -	High crime rate (above average for the area)
2 -	Moderate crime rate (average for the area)
3 -	Low crime rate (below average for the area)



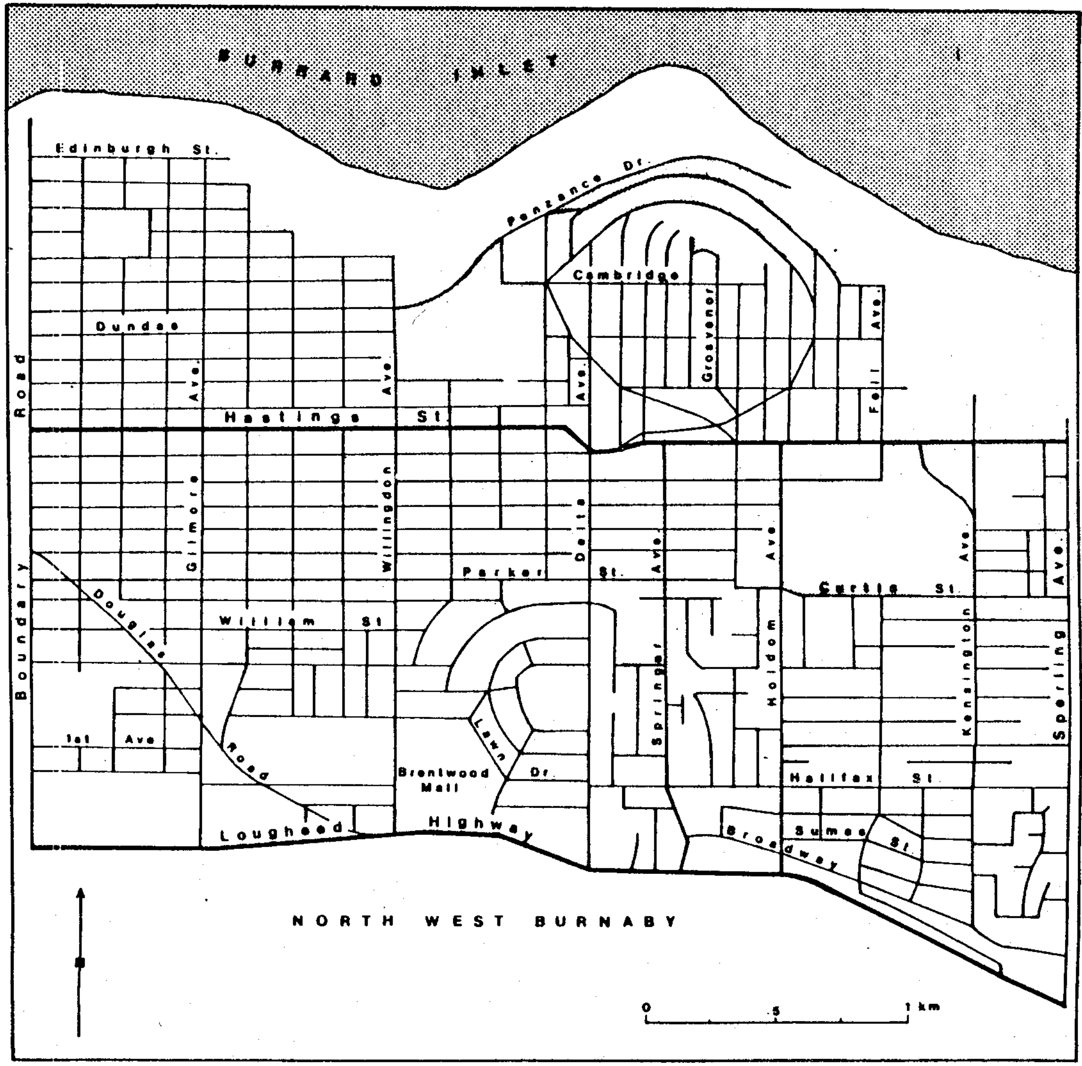
MAP 6: LIVABILITY

The Livability of an area is a subjective concept encompassing many of the "qualities" of the urban environment. This concept might also be thought of in terms of "Quality of Life" or the "desireability" of an area to attract people to live there. On the sixth map, indicate the areas which you would characterize as being:

Label	Description
1 -	Highly desireable areas in which to live (i.e., high degree of livability)
2 -	Moderately desireable areas in which to live (i.e., moderate degree of livability)
3 -	Less desireable areas in which to live (i.e., low degree of livability)

QUESTION:
Please describe in your own words how you would determine the "degree of livability" of an area (i.e., what would be characteristic of these areas?).

ANSWER:



APPENDIX II

FORTRAN ROUTINES TO CONVERT LINE MAPS INTO GRIDDED REPRESENTATIONS

FILE: DIGCON FORTRAN A

```
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC

C
C             CONVERTS DIGITIZED OUTPUT TO FORMAT FOR MAP
C
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
C
C     CHANNEL 7 IS INPUT CHANNEL OF DIGITIZED DATA
C     CHANNEL 6 IS OUTPUT TO TERMINAL
C     CHANNEL 8 IS DIRECT ACCESS WORK FILE (TEMPORARY)
C     CHANNEL 9 IS SEQ. OUT FILE OF LINE SEGS (X1,Y1,X2,Y2,VAL)
C     DEFINE FILE 08(500,80,L,NEXTO1)
      REAL X,Y,LIN(500,5),LINE(5)
      LOGICAL FIRST
      INTEGER RT,LT,DIGLIN,ERROR,Z
      CHARACTER*60 STRING
      WRITE(6,*)'WHAT IS THE STARTING MAP NUMBER IN FILE?'
      READ(5,*)IOUT
         IOUT=IOUT+7
 10   CLOSE (8,ERR=99)
999   OPEN (8,ACCESS='DIRECT',RECL=160)
         IOUT=IOUT+1
      READ(7,700,ERR=99,END=99)STRING
 700  FORMAT(A60)
      WRITE(6,600) STRING
  600 FORMAT(7H FILE: ,A60)
      I=1
      DIGLIN=0
      ERROR=0
  100 FORMAT(' EXECUTION TERMINATED BECAUSE OF ERROR COUNT')
C   READ NEW LINE RECORD
    5 READ(7,*,ERR=90,END=90) X,Y,Z
      IX=X*100
      IY=Y*100
      X=IX/100.
      Y=IY/100.
        IF (Z.EQ.-1) GO TO 90
      IF(Z.EQ.58) THEN
        DIGLIN=DIGLIN+1
        READ(7,*,ERR=99,END=99)DUMMY1,DUMMY2,RT
        READ(7,*,ERR=99,END=99)DUMMY1,DUMMY2,LT
        IF((RT+LT).GT.20) THEN
          WRITE(6,*)'POTENTIAL ERROR IN DIGITIZED LINE',DIGLIN
          WRITE(6,*)'**** RIGHT-LEFT ATTRIBUTES ARE IN ERROR'
          WRITE(6,*)'      A STANDARD FIXUP WILL BE ATTEMPTED'
          ERROR=ERROR+1
          IF(ERROR.GT.10)THEN
            WRITE(6,100)
            STOP
          ENDIF
        ELSE
C         WRITE(6,*)'NEWLIN-- ','RIGHT: ',RT,'  LEFT: ',LT
          FIRST=.TRUE.
            GO TO 5
        ENDIF
```

```
      ENDIF
C   CHECK FOR ERRORS
      IF(Z.NE.51) THEN
        WRITE(6,*)'ERROR FOLLOWING DIGITIZED LINE:',DIGLIN
        ERROR=ERROR+1
        IF(ERROR .GT. 10) THEN
          WRITE(6,100)
          STOP
        ELSE
          GO TO 5
        ENDIF
      ENDIF
      IF (FIRST) THEN
        LIN(I,1)=X
        LIN(I,2)=Y
        FIRST=.FALSE.
        GO TO 5
      ELSE
        I1=I+1
        LIN(I,3)=X
        LIN(I,4)=Y
        LIN(I1,1)=X
        LIN(I1,2)=Y
      ENDIF
C   CHECK IF ORDERED PROPERLY IN MIN, MAX
      IF(LIN(I,4).EQ.LIN(I,2)) THEN
        IF(LIN(I,3).GT.LIN(I,1)) THEN
          LIN(I,5)=RT
        ELSE
          TEMP1=LIN(I,1)
          TEMP2=LIN(I,2)
          LIN(I,1)=LIN(I,3)
          LIN(I,2)=LIN(I,4)
          LIN(I,3)=TEMP1
          LIN(I,4)=TEMP2
          LIN(I,5)=LT
        ENDIF
      ELSE
        IF(LIN(I,4).GT.LIN(I,2)) THEN
          LIN(I,5)=RT
        ELSE
          TEMP1=LIN(I,1)
          TEMP2=LIN(I,2)
          LIN(I,1)=LIN(I,3)
          LIN(I,2)=LIN(I,4)
          LIN(I,3)=TEMP1
          LIN(I,4)=TEMP2
          LIN(I,5)=LT
        ENDIF
      ENDIF
C
C   WRITE LINE TO A FILE
      NREC=I+1
      WRITE(UNIT=8,REC=NREC)(LIN(I,J),J=1,5)
      WRITE(UNIT=8,REC=1)I
      I=I+1
      GO TO 5
C
C   copy direct access file to sequential file
   90 I1=I-1
      WRITE(IOUT,FMT='(A60)')STRING
      READ(UNIT=8,REC=1)NL
      WRITE(IOUT,FMT='(I5)')NL
      DO 110 K=2,NL+1
      READ(UNIT=8,REC=K)(LINE(J),J=1,5)
  110 WRITE(IOUT,FMT='(5F8.2)')(LINE(J),J=1,5)
      WRITE(6,*)'PROCESSING COMPLETED...#LINES OUTPUT=',I-1
C
      GO TO 10
 99   WRITE(6,*)'*****EXECUTION TERMINATING*****'
      STOP
      END
```

FILE: RASTER FORTRAN A

```
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
C                                                           C
C          PROGRAM TO CREATE RASTER MAP FROM LINES          C
C
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
C
C  MAIN PROGRAM
C
C    CHANNEL 'INFILE' - USED TO INPUT DIGITIZED LINES
C    CHANNEL 5 - TERMINALINPUT
C    CHANNEL 6 - TERMINAL OUTPUT
C    CHANNEL 8 - SEQ. FILE WITH RASTERIZED MAP
C
C  TO RUN ON MTS:
C   $RUN M.RASTER.OBJ+M.SUBS.OBJ+*FORTRANVSLIB 7=INDATA 8=-TEMP 9=MAP
C
      DIMENSION RLIN(200,5),MXSORT(200),MNSORT(200),
     +          TEMP(50),SCANX(200,2),ANGLE(200),TANG(200)
      LOGICAL FOUND,FLAG
      INTEGER ELIN(25),SCANL,MAP(80,130)
      REAL LIN(200,5),LX,LY,NODE(200,2)
      CHARACTER MAPNAM*60
      COMMON /RASTER/RLIN
      COMMON FLAG
      DATA MAP/10400*-1/
      NCOLS=130
      NROWS=80
C
C  SET VALUE FOR INPUT FILE
      WRITE(6,*)'WHAT MAP DO YOU WISH TO START WITH?'
      READ(5,*)INFILE
      INFILE=INFILE+8
      ITIMES=0
 1000 FLAG=.FALSE.
      ITIMES=ITIMES+1
CC  REPRESENT VECTOR LINES AS RASTER
CC    ESTABLISH GRID SIZE OF MATRIX
      IF(ITIMES.EQ.1)THEN
      WRITE(6,*) 'INPUT XDIM AND YDIM OF RASTER MAP'
      READ(5,*) XDIM,YDIM
      ENDIF
CC  MATCH REAL WORLD COORDS, WITH LOWER-LEFT AND UPPER-RIGHT
      WRITE(6,*) 'ENTER LOWER-LEFT & UPPER-RIGHT X,Y PAIRS: '
      READ (5,*) LX,LY,UX,UY
CCCCCCC
C DEBUGGING OPTION
      IF(ITIMES.EQ.1)THEN
      WRITE(6,*) 'SET DEBUG OPTION: 0-ON  1-OFF'
      READ(5,*)FLG
       IF(FLG.NE.0)THEN
         FLAG=.FALSE.
        ELSE
          FLAG=.TRUE.
        ENDIF
      ENDIF
```

```
CCCCCCCC
C
CC  DETERMINE SCALING FACTOR
      XFAC=(UX-LX)/(XDIM-1)
      YFAC=(UY-LY)/(YDIM-1)
C
C    DETERMINE TOLERANCES FOR NODE MATCHING
      TOL1=(UX-LX)/(XDIM*4)
      TOL2=(UY-LY)/(YDIM*4)
      NNODES=0
      IF(FLAG)WRITE(6,*)'X TOLERANCE: ',TOL1,'  Y TOLERANCE: ',TOL2
C  READ MAP NAME
       IF(FLAG)WRITE(6,*)'VERIFY INPUT LINES'
      READ(INFILE,700)MAPNAM
  700 FORMAT(A60)
       IF(FLAG)WRITE(6,*)MAPNAM
C  INPUT 'LIN' MATRIX
      READ(INFILE,*)NL
      DO 3 I=1,NL
        READ(INFILE,*)(LIN(I,J),J=1,5)
          IF(FLAG)WRITE(6,*)(LIN(I,J),J=1,5)
CC  MATCH END NODES TO ENSURE LINES JOIN EXACTLY
        DO 4 K=1,2
          XPOS1=K*2-1
          XPOS2=K*2
          IF(NNODES.EQ.0) GO TO 16
          DO 16 IN=1,NNODES
            IF(ABS(LIN(I,XPOS1)-NODE(IN,1)).LT. TOL1 .AND.
     +         ABS(LIN(I,XPOS2)-NODE(IN,2)).LT. TOL2) THEN
      IF(FLAG)WRITE(6,*)'CHANGING ',K,' NODE--LINE ',I,' NODE# ',IN
              LIN(I,XPOS1)=NODE(IN,1)
              LIN(I,XPOS2)=NODE(IN,2)
              GO TO 4
            ENDIF
   16     CONTINUE
          NODE(NNODES+1,1)=LIN(I,XPOS1)
          NODE(NNODES+1,2)=LIN(I,XPOS2)
          NNODES=NNODES+1
    4   CONTINUE
    3 CONTINUE
CC
CC  CONVERT ORIGINAL LINES TO RASTER LINES
      IF(FLAG)WRITE(6,*)'--- CONVERTED LINES ---'
      DO 1 I=1,NL
        DO 2 I1=1,2
          ENDPT=(I1-1)*2
          X=ENDPT+1
          Y=ENDPT+2
          RLIN(I,X)=INT(((LIN(I,X)-LX)/XFAC)+1.5)
          RLIN(I,Y)=INT(((LIN(I,Y)-LY)/YFAC)+1.5)
          RLIN(I,5)=LIN(I,5)
    2   CONTINUE
C   VERIFY ORDER OF HORIZONTAL LINES
        IF(RLIN(I,2).EQ.RLIN(I,4))THEN
          IF(RLIN(I,1).GT.RLIN(I,3)) THEN
```

```
            MOVE=RLIN(I,1)
            RLIN(I,1)=RLIN(I,3)
            RLIN(I,3)=MOVE
            MOVE=RLIN(I,2)
            RLIN(I,2)=RLIN(I,4)
            RLIN(I,4)=MOVE
          ENDIF
        ENDIF
       IF(FLAG)WRITE(6,*)'LINE',(RLIN(I,J),J=1,5)
    1 CONTINUE
C
CC CREATE SIMPLIFIED MATRIX TO PASS TO SORT (REUSE 'LIN')
      DO 5 I=1,NL
        LIN(I,1)=I
        LIN(I,2)=RLIN(I,2)
        LIN(I,3)=RLIN(I,4)
    5 CONTINUE
CC  SORT BY MAX Y (RLIN (I,4)) : CREATE MXSORT
      IF(FLAG)WRITE(6,*)'----MAXSORT MATRIX---'
      CALL SORT(LIN,NL,5,3)
      DO 6,I=1,NL
              IF(FLAG)WRITE(6,*)LIN(I,3)
    6 MXSORT(I)=LIN(I,1)
CC  SORT BY MIN Y (RLIN(I,2)  :  CREATE MNSORT
      IF(FLAG)WRITE(6,*)'----MINSORT MATRIX---'
      CALL SORT(LIN,NL,5,2)
      DO 7 I=1,NL
          IF(FLAG)WRITE(6,*)LIN(I,2)
    7 MNSORT(I)=LIN(I,1)
CC
CC  PROCESS LINES
C
CCC  CREATE ANGLE AND TANGENT MATRICES
      DO 46 I=1,NL
      CALL SLOPE(ANGLE(I),I,TANG(I))
   46 CONTINUE
CC
CCC  DETERMINE ELIGIBILITY
      MXPTR=1
      MNPTR=1
      NEXT=0
      DO 90 SCANL=YDIM,1,-1
       IF(FLAG)WRITE(6,*)'============================'
C   ADD LINES TO STACK...
      IF (MXPTR.LE.NL)THEN
        DO 10 II=1,500
      IF(FLAG) THEN
         WRITE(6,*)'MAXPTR= ',MXPTR,' LINENO=',MXSORT(MXPTR),
     1    '  YMAX= ',RLIN(MXSORT(MXPTR),4)
      ENDIF
          IF(RLIN(MXSORT(MXPTR),4).GE.SCANL) THEN
           NEXT=NEXT+1
           ELIN(NEXT)=MXSORT(MXPTR)
        IF(FLAG)WRITE(6,*)'...LINE ',MXSORT(MXPTR),' BECOMES ELIGIBLE'
           MXPTR=MXPTR+1
```

```
          IF(MXPTR.GT.NL) GO TO 15
         ELSE
          GO TO 12
         ENDIF
   10   CONTINUE
   12 ENDIF
C DELETE LINES FROM STACK
   15 IF (MNPTR.LE.NL) THEN
      K=0
        DO 20 II=1,500
          IF(RLIN(MNSORT(MNPTR),2).GT.SCANL) THEN
          FOUND=.FALSE.
          K=K+1
          IF (K.GT.100) STOP
            DO 25 I=1,NEXT
            IF(FOUND) GO TO 20
            IF(ELIN(I).EQ.MNSORT(MNPTR)) THEN
         IF(FLAG)WRITE(6,*)'...LINE ',ELIN(I),' IS DELETED'
              ELIN(I)=0
              MNPTR=MNPTR+1
              IF(MNPTR.GT.NL) GO TO 30
              FOUND=.TRUE.
            ENDIF
   25       CONTINUE
          ELSE
           GO TO 27
          ENDIF
   20   CONTINUE
   27 ENDIF
C REBUILD ELIGIBILITY LINE BUFFER
   30 K=NEXT
      NEXT=0
      DO 35 I=1,K
        IF(ELIN(I).GT.0) THEN
          NEXT=NEXT+1
          TEMP(NEXT)=ELIN(I)
        ENDIF
   35 CONTINUE
C SWITCH TEMP FOR ELIGIBLE LINES
      DO 45 I=1,NEXT
   45 ELIN(I)=TEMP(I)
      IF (FLAG) WRITE(6,*)'STARTING TO SCAN LINES FOR SCANLINE= ',SCANL
      IF (FLAG) WRITE(6,*)'ELIGIBLE LINES:  ',(ELIN(I),I=1,NEXT)
C
CC  SCAN THE ELIGIBLE LINES AND CONVERT TO RASTER
      DO 55 I=1,NEXT
        LINE=ELIN(I)
      IF(SCANL.NE.RLIN(LINE,2).AND.SCANL.NE.RLIN(LINE,4))THEN
        C=RLIN(LINE,2)-TANG(LINE)*RLIN(LINE,1)
        IF(TANG(LINE).NE.0)THEN
          SCANX(I,1)=(SCANL-C)/TANG(LINE)
        ELSE
          SCANX(I,1)=RLIN(LINE,1)
        ENDIF
        SCANX(I,2)=RLIN(LINE,5)
```

```
      ELSE
C  FIND LINES WITH MATCHING END POINTS
        IF (SCANL.EQ.RLIN(LINE,2)) THEN
          XPOS1=1
        ELSE
          IF (SCANL.EQ.RLIN(LINE,4)) THEN
            XPOS1=3
          ENDIF
        ENDIF
        MINANG=180
        SCANX(I,1)=RLIN(LINE,XPOS1)
        DO 70 II=1,NEXT
          IF(SCANL.EQ.RLIN(ELIN(II),2)) THEN
            XPOS2=1
C       CHECK IF LINE IS HORIZONTAL
            IF(RLIN(ELIN(II),2).EQ.RLIN(ELIN(II),4)) THEN
              IF(RLIN(LINE,XPOS1).EQ.RLIN(ELIN(II),3)) THEN
                XPOS2=3
              ENDIF
            ENDIF
          ELSE
            IF (SCANL.EQ.RLIN(ELIN(II),4)) THEN
              XPOS2=3
            ENDIF
          ENDIF
          IF(RLIN(LINE,XPOS1).EQ.RLIN(ELIN(II),XPOS2)) THEN
            A=ANGLE(ELIN(II))
            IF(XPOS2.EQ.3) A=180-A
            IF(A.LT.MINANG)THEN
              SCANX(I,2)=RLIN(ELIN(II),5)
              MINANG=A
            ENDIF
          ENDIF
   70   CONTINUE
      ENDIF
   55 CONTINUE
C
CC SORT SCANX(I,2) WITH REGARD TO SCANX(I,1)
      CALL SORT(SCANX,NEXT,2,1)
C  SWITCH TO ASCENDING ORDER
      N=NEXT/2
      DO 80 I=1,N
        SAVE=SCANX(I,J)
        SCANX(I,J)=SCANX(I1,J)
        SCANX(I1,J)=SAVE
   85  CONTINUE
   80 CONTINUE
C
CC PLUG VALUES INTO MATRIX 'MAP'
C
      DO 95 I=1,NEXT
        IPOS=INT(SCANX(I,1)+0.5)
        IVAL=SCANX(I,2)
       IF(FLAG)WRITE(6,*)' SCANL=',SCANL,':  COLUMN=',IPOS,
     1 '  VALUE=',IVAL
```

```
   95 MAP(SCANL,IPOS)=IVAL
   90 CONTINUE
C
CCC   FLOOD THE MATRIX -- MAP(YDIM,XDIM)
      DO 200 I=YDIM,1,-1
        IF(MAP(I,1).LT.0) MAP(I,1)=0
        IVAL=MAP(I,1)
         DO 210 K=2,XDIM,1
          KEEP=MAP(I,K)
           IF(MAP(I,K).EQ.-1) THEN
              MAP(I,K)=IVAL
           ELSE
              IVAL=MAP(I,K)
           ENDIF
  210    CONTINUE
  200 CONTINUE
C
C  DRAW THE MAP ON UNIT 8
      WRITE(8,805)MAPNAM
 805  FORMAT(' NOTE:   *** RASTER MAP ',A60)
      WRITE(8,*)' GRID FOR ATTRIBUT'
      IXDIM=XDIM
      WRITE(8,815)IXDIM
  815 FORMAT(' (I3,1X,',I3,'I1) ')
      J=YDIM+1
      DO 100 I=1,YDIM
        J=J-1
        IF(MAP(J,1).LT.0) MAP(J,1)=0
        WRITE(8,800) I,(MAP(J,K),K=1,XDIM)
  800 FORMAT(I3,1X,130I1)
  100 CONTINUE
      WRITE(8,*)'-1 '
      WRITE(8,*)'READ ON 4'
C
C CHECK IF ANOTHER MAP TO READ
       WRITE(6,*)'YOU HAVE PROCESSED ',ITIMES,' MAPS'
      WRITE(6,*)'DO YOU WANT TO PROCESS ANOTHER MAP IN THE SERIES ',
     +  '(1-YES OR 0-NO)'
      READ(5,*)I
       IF(I.EQ.1)THEN
         DO 150 I=1,NROWS
           DO 150 J=1,NCOLS
           MAP(I,J)=-1
 150  CONTINUE
      INFILE=INFILE+1
      GO TO 1000
      ELSE
C
      WRITE(6,*)'*****EXECUTION TERMINATIONG******  '
      ENDIF
C
      STOP
      END
```

FILE: RASTSUBS FORTRAN A

```
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
C            SUBROUTINE TO CALCULATE SLOPE                 C
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
C
      SUBROUTINE SLOPE(ANGLE,LNUM,TANG)
      DIMENSION RLIN(200,5)
      COMMON /RASTER/RLIN
      COMMON FLAG
      LOGICAL FLAG
C
      RISE=RLIN(LNUM,4)-RLIN(LNUM,2)
      RUN=RLIN(LNUM,3)-RLIN(LNUM,1)
       IF(FLAG)WRITE(6,*)'...IN SLOPE..RISE= ',RISE,' RUN= ',RUN
      SIGN=1
      PI=3.1416
      DEGREE=180/PI
      TANG=9999999
      IF(RUN.EQ.0) THEN
        ANGLE=90
      ELSE
        TANG=RISE/RUN
        ANGLE=ATAN(TANG)
        ANGLE=ANGLE*DEGREE
        IF(ANGLE.LT.0) ANGLE=180+ANGLE
      ENDIF
      ANGLE=ABS(ANGLE)
       IF(FLAG)WRITE(6,*)'IN SLOPE..ANGLE ',ANGLE,' TANG ',TANG
      RETURN
      END
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
C             SUBROUTINE TO SORT 2-D ARRAY                    C
CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCC
C
      SUBROUTINE SORT(X,NROWS,NCOLS,COL)
C
C         SUBROUTINE SORT BASED ON ALGORITHM 201 ... ACM
C         SORTS COLS OF X(NROWS,NCOLS) SO THAT ELEMENTS OF
C         COLUMN 'COL' ARE IN ASCENDING ORDER
C
      INTEGER COL
      REAL X(200,NCOLS),SAVE(20)
      M=NROWS
  100 M=M/2
      IF (M.EQ.0) THEN
        DO 10 I=1,NL
   10     WRITE(6,*) (X(I,J),J=1,5)
        RETURN
      ENDIF
      K=NROWS-M
      DO 400 J=1,K
        I=J
  200   L=I+M
        IF (X(I,COL).GE.X(L,COL)) GO TO 400
      DO 300 W=1,NCOLS
        SAVE(W)=X(I,W)
        X(I,W)=X(L,W)
  300   X(L,W)=SAVE(W)
      I=I-M
      IF(I.GT.0)GO TO 200
  400 CONTINUE
      GO TO 100
      END
```

APPENDIX III

FORTRAN ROUTINE TO CONVERT GRIDDED MAPS INTO GIMMS VECTOR-FORMATTED INPUT

FILE: MAP2GIMS FORTRAN A

```
C******************
C
C   PROGRAM TO CONVERT A "MAP" FILE TO GIMMS FORMAT
C
      DIMENSION MATRIX(100,100)
      INTEGER ZERO,OLDX,OLDY,CVAL,OUT,VAL(100)
      CHARACTER*4 LABEL(0:10),SLASH
      CHARACTER*1 FORMAT(12)
      LOGICAL FIRST
      DATA SLASH/' /  '/,ZERO/0/
      LABEL(0)=' L0 '
      LABEL(1)=' L1 '
      LABEL(2)=' L2 '
      LABEL(3)=' L3 '
      LABEL(4)=' L4 '
      LABEL(5)=' L5 '
      LABEL(6)=' L6 '
      LABEL(7)=' L7 '
      LABEL(9)=' L9 '
      OUT=8
      LABEL(OUT)='OUT '
      READ(7,700)FORMAT
 700  FORMAT(1X,12A1)
      WRITE(6,*)'FORMAT IS: ',FORMAT
C...READ DIMENSION OF MATRIX...N COLUMNS BY M ROWS
      READ(7,*)N,M
C...READ NUMBER OF HEADER RECORDS
      READ(7,*)NHEAD
      DO 2 I=1,NHEAD
    2  READ(7,*)
C...READ MATRIX
      DO 3 I=M,1,-1
      READ(7,FMT=FORMAT)(MATRIX(I,K),K=1,N)
    3 CONTINUE
C....CALCULATE TOP EDGE
      DO 5 I=1,N
    5 VAL(I)=MATRIX(M,I)
      CVAL=VAL(1)
      OLDX=0
      DO 10 I=1,N
        IF(CVAL.NE.VAL(I))THEN
          WRITE(8,*)LABEL(CVAL),
     +     LABEL(OUT),OLDX,M,I-1,
     +    M,SLASH
          OLDX=I-1
          CVAL=VAL(I)
       ELSE
       ENDIF
   10 CONTINUE
      WRITE(8,*)LABEL(CVAL),LABEL(OUT),OLDX,M,N,M,SLASH
C
C....CALCULATE LEFT EDGE
      DO 6 I=1,M
    6 VAL(M-I+1)=MATRIX(I,1)
      CVAL=VAL(M)
```

```
      OLDY=M
      DO 20 I=M,1,-1
      IF(CVAL.NE.VAL(I)) THEN
       WRITE(8,*)LABEL(OUT),LABEL(CVAL),ZERO,OLDY,ZERO,I,SLASH
       OLDY=I
       CVAL=VAL(I)
      ELSE
      ENDIF
   20 CONTINUE
      WRITE(8,*)LABEL(OUT),LABEL(CVAL),ZERO,OLDY,ZERO,ZERO,SLASH
C
C.....CALCULATE RIGHT EDGE
      DO 7 I=1,M
    7 VAL(M-I+1)=MATRIX(I,N)
      CVAL=VAL(M)
      OLDY=M
      DO 30 I=M,1,-1
       IF(CVAL.NE.VAL(I))THEN
        WRITE(8,*)LABEL(CVAL),LABEL(OUT),N,OLDY,N,I,SLASH
        OLDY=I
        CVAL=VAL(I)
       ELSE
       ENDIF
   30 CONTINUE
      WRITE(8,*)LABEL(CVAL),LABEL(OUT),N,OLDY,N,ZERO,SLASH
C
C.....CALCULATE BOTTOM EDGE
      DO 8 I=1,N
    8 VAL(I)=MATRIX(1,I)
      CVAL=VAL(1)
      OLDX=0
      DO 40 I=1,N
       IF(CVAL.NE.VAL(I))THEN
        WRITE(8,*)LABEL(OUT),LABEL(CVAL),OLDX,ZERO,I-1,ZERO,SLASH
        OLDX=I-1
        CVAL=VAL(I)
       ENDIF
   40 CONTINUE
      WRITE(8,*)LABEL(OUT),LABEL(CVAL),OLDX,ZERO,N,ZERO,SLASH
C
C....DO THE MIDDLE PART OF THE MAP
      DO 101 K=1,N-1
       OLDY=M
       FIRST=.FALSE.
       DO 100 I=M,1,-1
        IF(MATRIX(I,K).NE.MATRIX(I,K+1)) THEN
          IF(.NOT.FIRST) THEN
            OLDY=I
            FIRST=.TRUE.
          ENDIF
        IF(I.GT.1) THEN
         NEWY=I-1
         IF((MATRIX(I,K).NE.MATRIX(I-1,K)).OR.
     +   (MATRIX(I,K+1).NE.MATRIX(I-1,K+1)))THEN
          WRITE(8,*)LABEL(MATRIX(I,K)),LABEL(MATRIX(I,K+1)),
```

```
     +   K,OLDY,K,NEWY,SLASH
          OLDY=NEWY
          FIRST=.FALSE.
         ENDIF
        ELSE
         WRITE(8,*)LABEL(MATRIX(I,K)),LABEL(MATRIX(I,K+1)),
     +   K,OLDY,K,NEWY,SLASH
        ENDIF
        ENDIF
  100 CONTINUE
  101 CONTINUE
C
C....SCAN EACH COLUMN
      DO 201 I=M,2,-1
       OLDX=0
       FIRST=.FALSE.
       DO 200 K=1,N
        IF(MATRIX(I,K).NE.MATRIX(I-1,K)) THEN
         IF(.NOT.FIRST)THEN
          OLDX=K-1
          FIRST=.TRUE.
         ENDIF
         NEWX=K
         IF(K.LT.N)THEN
        IF((MATRIX(I,K).NE.MATRIX(I,K+1)).OR.
     +   (MATRIX(I-1,K).NE.MATRIX(I-1,K+1)))THEN
        WRITE(8,*)LABEL(MATRIX(I-1,K)),LABEL(MATRIX(I,K)),
     +   OLDX,I-1,NEWX,I-1,SLASH
         OLDX=NEWX
         FIRST=.FALSE.
        ENDIF
       ELSE
        WRITE(8,*)LABEL(MATRIX(I,K-1)),LABEL(MATRIX(I,K)),
     +   OLDX,I-1,NEWX,I-1,SLASH
        ENDIF
       ENDIF
  200 CONTINUE
  201 CONTINUE
C
      WRITE(8,*)'END'
      WRITE(8,*)'*SYSPARM INPUT=5*'
C
      STOP
      END
```

APPENDIX IV

MAP ROUTINES USED TO PRODUCE STRABO'S COMPOSITE MAPS

```
NOTE : DATA INPUT
QUIET
NOTE   READ ON 5
MAP 0 FOR TOTSUM
NOTE * * * READ RESPONDENT MAPS AND CREATE GRID MAPS * * *
READ ON 9
NOTE WEIGHT RESPONDENT MAP--BB
READ ON 8
RENUMBER CONFID FOR CONFID ASSIGNING 1 TO 1 THR 2 /
         ASSIGNING 0 TO 3 THR 4
MULTIPLY ATTRIBUT BY CONFID FOR ATTRIBUT
RENUMBER ATTRIBUT FOR ATTRIBUT ASSIGNING 1000 TO 1 /
         ASSIGNING  100 TO 2 /
         ASSIGNING   10 TO 3 /
         ASSIGNING    1 TO 4
ADD ATTRIBUT TO TOTSUM FOR TOTSUM
NOTE
READ ON 9
NOTE  WEIGHT RESPONDENT MAP--KK
READ ON 8
RENUMBER CONFID FOR CONFID ASSIGNING 1 TO 1 THR 2 /
          ASSIGNING 0 TO 3 THR 4
MULTIPLY ATTRIBUT BY CONFID FOR ATTRIBUT
RENUMBER ATTRIBUT FOR ATTRIBUT /
         ASSIGNING 1000 TO 1 /
         ASSIGNING  100 TO 2 /
         ASSIGNING   10 TO 3 /
         ASSIGNING    1 TO 4
ADD ATTRIBUT TO TOTSUM FOR TOTSUM
NOTE
READ ON 9
NOTE WEIGHT RESPONDENT MAP--MA
READ ON 8
RENUMBER CONFID FOR CONFID ASSIGNING 1 TO 1 THR 2 /
          ASSIGNING 0 TO 3 THR 4
MULTIPLY ATTRIBUT BY CONFID FOR ATTRIBUT
RENUMBER ATTRIBUT FOR ATTRIBUT /
         ASSIGNING 1000 TO 1 /
         ASSIGNING  100 TO 2 /
         ASSIGNING   10 TO 3 /
         ASSIGNING    1 TO 4
ADD ATTRIBUT TO TOTSUM FOR TOTSUM
NOTE
READ ON 9
NOTE WEIGHT RESPONDENT MAP--MC
READ ON 8
RENUMBER CONFID FOR CONFID ASSIGNING 1 TO 1 THR 2 /
          ASSIGNING 0 TO 3 THR 4
MULTIPLY ATTRIBUT BY CONFID FOR ATTRIBUT
RENUMBER ATTRIBUT FOR ATTRIBUT /
          ASSIGNING 1000 TO 1 /
          ASSIGNING  100 TO 2 /
          ASSIGNING   10 TO 3 /
          ASSIGNING    1 TO 4
ADD ATTRIBUT TO TOTSUM FOR TOTSUM
NOTE
READ ON 9
NOTE  WEIGHT RESPONDENT MAP--WM
READ ON 8
RENUMBER CONFID FOR CONFID ASSIGNING 1 TO 1 THR 2 /
         ASSIGNING 0 TO 3 THR 4
MULTIPLY ATTRIBUT BY CONFID FOR ATTRIBUT
RENUMBER ATTRIBUT FOR ATTRIBUT /
         ASSIGNING 1000 TO 1 /
         ASSIGNING  100 TO 2 /
         ASSIGNING   10 TO 3 /
         ASSIGNING    1 TO 4
ADD ATTRIBUT TO TOTSUM FOR TOTSUM
NOTE
ECHO
NOTE:  RETURN TO GENERAL COMMANDS
READ ON 7
READ ON 5
STOP
```

FILE: MAPPRG   COMPOSIT A

```
NOTE:  (SET FOR 60% AGREEMENT LEVEL)
NOTE * * * CREATE COMPOSITE MAP * * *
QUIET
MAP O FOR COMPOSIT
COPY TOTSUM FOR SUM
MAP 1000 FOR FACTOR
DIVIDE SUM BY FACTOR FOR CLASSUM
RENUMBER CLASSUM FOR TEMP ASSIGNING O TO O THROUGH 2 /
                          AND 1 TO 3 THROUGH 5
ADD COMPOSIT TO TEMP FOR COMPOSIT
MULTIPLY CLASSUM BY FACTOR FOR TEMP
SUBTRACT SUM MINUS TEMP FOR SUM
MAP 100 FOR FACTOR
DIVIDE SUM BY FACTOR FOR CLASSUM
RENUMBER CLASSUM FOR TEMP ASSIGNING O TO O THROUGH 2 /
                          AND 2 TO  3 THROUGH 5
ADD COMPOSIT TO TEMP FOR COMPOSIT
MULTIPLY CLASSUM BY FACTOR FOR TEMP
SUBTRACT SUM MINUS TEMP FOR SUM
MAP 10 FOR FACTOR
DIVIDE SUM BY FACTOR FOR CLASSUM
RENUMBER CLASSUM FOR TEMP ASSIGNING O TO O THROUGH 2 /
                          AND 3 TO 3 THROUGH 5
ADD COMPOSIT TO TEMP FOR COMPOSIT
MULTIPLY CLASSUM BY FACTOR FOR TEMP
SUBTRACT SUM MINUS TEMP FOR CLASSUM
RENUMBER CLASSUM FOR TEMP ASSIGNING O TO O THROUGH 2 /
                          AND 4 TO  3 THROUGH 5
ADD COMPOSIT TO TEMP FOR COMPOSIT
RENUMBER COMPOSIT FOR COMPOSIT ASSIGNING 9 TO O
MULTIPLY COMPOSIT BY MASK FOR COMPOSIT
READ ON 5
STOP
```

APPENDIX V

MAP ROUTINES USED TO COMPARE TWO MAPS

FOR LEVELS OF AGREEMENT

```
FILE: MAPPRG   COMPARE  A


NOTE : COMPARE INDIVIDUAL MAPS WITH COMPOSITES
QUIET
READ ON 9
CROSS ATTRIBUTE WITH COMPOSIT FOR TEMP /
       ASSIGNING 1 TO 1 1 /
       ASSIGNING 2 TO 2 2 /
       ASSIGNING 3 TO 3 3 /
       ASSIGNING 4 TO 4 4
RENUMBER TEMP FOR TEMP /
         ASSIGNING 9 TO 0
MULTIPLY TEMP BY MASK FOR TEMP
WRITE ON 11
NOTE: COMPARE BB WITH COMPOSITE
DISPLAY TEMP SPECIFYING
00 0
01 1
02 2
03 3
04 4
09 9
-1
WRITE ON 6
READ ON 9
CROSS ATTRIBUT WITH COMPOSIT FOR TEMP /
       ASSIGNING 1 TO 1 1 /
       ASSIGNING 2 TO 2 2 /
       ASSIGNING 3 TO 3 3 /
       ASSIGNING 4 TO 4 4
RENUMBER TEMP FOR TEMP /
         ASSIGNING 9 TO 0
MULTIPLY TEMP BY MASK FOR TEMP
WRITE ON 11
NOTE: COMPARE KK WITH COMPOSITE
DISPLAY TEMP SPECIFYING
00 0
01 1
02 2
03 3
04 4
09 9
-1
WRITE ON 6
READ ON 9
CROSS ATTRIBUTE WITH COMPOSIT FOR TEMP /
       ASSIGNING 1 TO 1 1 /
       ASSIGNING 2 TO 2 2 /
       ASSIGNING 3 TO 3 3 /
       ASSIGNING 4 TO 4 4
RENUMBER TEMP FOR TEMP /
.        ASSIGNING 9 TO 0
MULTIPLY TEMP BY MASK FOR TEMP
WRITE ON 11
NOTE: COMPARE MA WITH COMPOSITE
DISPLAY TEMP SPECIFYING
00 0
01 1
02 2
03 3
04 4
09 9
-1
WRITE ON 6
```

```
READ ON 9
CROSS ATTRIBUT WITH COMPOSIT FOR TEMP /
        ASSIGNING 1 TO 1 1 /
        ASSIGNING 2 TO 2 2 /
        ASSIGNING 3 TO 3 3 /
        ASSIGNING 4 TO 4 4
RENUMBER TEMP FOR TEMP /
          ASSIGNING 9 TO 0
MULTIPLY TEMP BY MASK FOR TEMP
WRITE ON 11
NOTE: COMPARE MC WITH COMPOSITE
DISPLAY TEMP SPECIFYING
00 0
01 1
02 2
03 3
04 4
09 9
-1
WRITE ON 6
READ ON 9
CROSS ATTRIBUTE WITH COMPOSIT FOR TEMP /
        ASSIGNING 1 TO 1 1 /
        ASSIGNING 2 TO 2 2 /
        ASSIGNING 3 TO 3 3 /
        ASSIGNING 4 TO 4 4
RENUMBER TEMP FOR TEMP /
          ASSIGNING 9 TO 0
MULTIPLY TEMP BY MASK FOR TEMP
WRITE ON 11
NOTE: COMPARE WM WITH COMPOSITE
DISPLAY TEMP SPECIFYING
00 0
01 1
02 2
03 3
04 4
09 9
-1
WRITE ON 6
ECHO
READ ON 5
```

APPENDIX VI

WRITTEN RESPONSES TO SUPPLEMENTAL QUESTIONS

CONCERNING INCOME LEVELS AND LIVABILITY

A. INCOME

Question: Please describe in your own words how one would recognize an area as being either Low, Middle, or High Income (*i.e.,* what would be characteristic of these areas?).

Answers:

PANEL I --

Respondent 1: "Low -- nicely kept, renters.
Middle -- not so nice & less renters.
High -- very nice, least renters."

Respondent 2: "By the housing standard, upkeep of the area (landscaping, cut lawns, etc.). Apartments would be classed as middle to low."

Respondent 3: "Type of Homes; age of homes; location; type of people; value of properties."

Respondent 4: "By size of homes, style of homes and their maintenance."

Respondent 5: "By style and quality of houses; how well the properties are upkept; how residents appear."

PANEL II --

Respondent 1: "Low -- run down houses; not landscaped; rental properties.
Middle -- average housing; \$85,000 - \$125,000.
High -- individual styling -- +\$250,000."

Respondent 2: -- "Condition of housing -- poor/rundown -- (i.e., multiple dwellings in rundown condition) attributed to low income areas;"
-- "Dress and physical appearance of individuals who occupy residents (i.e., low income generally shabby appearance);"

-- "Landscaping -- low income, little or no care taken for yards, etc.;"

-- "Type of complaints -- low income areas comparatively receive high percentage of domestic type complaints usually associated with excessive use of alcohol."

Respondent 3: "Low -- condition of homes; older areas not clean; size of lots are small; condition of streets poor; heavy transportation.

Middle -- well maintained residence; better dressed residents.

High -- new homes; new cars, etc.; good dress and appearance of residents."

Respondent 4: "Low -- poorly kept houses and property; grounds littered.

Middle -- house and grounds kept up and worked at.

High -- housing size and condition, construction type of building, property upkept."

Respondent 5: "Low -- generally by how housing in area is maintained, i.e., let it be run down;ranshackled. By status of people living in area.

Middle -- as in low, but maintained better. People having more motivation in pursuit of their livlihood. Neat but lacking the ultra appearance.

High -- everything well maintained; hired staff (gardener); expensive recreation vehicles and cars."

B. LIVABILITY

Question: Please describe in your own words how you would determine the "degree of livability" of an area (i.e., what would be characteristic of these areas?).

Answers:

PANEL I --

Respondent 1: "Degree of livability -- generally they are great; however, certain areas are more desirable habitat than others."

Respondent 2: "Good housing, parks, large lots, upper income residents."

Respondent 3: "Livability is dependent on the type of a community that is made up by the various type of people living there which is highly characterized by the way they derive their income. Majority of Burnaby communities are very desirable to live in although there is a higher tendancy of poor quality of people living in some of the multi-family buildings and surrounding areas."

Respondent 4: "Conforming houses; eye appealing properties with large lots; well maintained with few investment or rental properties."

Respondent 5: "Nice neighbourhoods; size of houses; quiet."

PANEL II --

Respondent 1: "High -- property with a view; quiet neighbourhood; very little vehicle traffic; no teenagers or singles; large lots.
Moderate -- more vehicle traffic; no view; smaller lots; some duplex/multi-family units.
Low -- apartments; multi-family units; absentee landlords; rental units in general."

Respondent 2:
- -- "Housing available: not desirable to live in an area of poor rundown housing (i.e., area of predominantly low income)."
- -- "Traffic: not desirable to live in area of high volume traffic."
- -- "Highly desirable area: average/above average homes -- well maintained and occupied by middle to high income families; low volume of traffic; availability of schools/recreational facilities for children; low crime rate."

Respondent 3: "Class of people; pollution; crime rate; access to shopping centers, schools, parks, etc."

Respondent 4: "Highly desirable -- quality housing and neighbourhood, away from high schools and junior secondary schools, crime rate moderate to low. Away from through traffic streets, quiet neighbourhoods."

Respondent 5: "Prefer to live in areas away from business districts, parks, schools, lower class, and multiple dwellings."

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