LECTURE 1.

1. Why are successful cities dense, expensive, and with few large green patches?

Cities are usually located in areas where growth and productivity of the people thrive. This is as a result of the causal effect interaction between spatial processes and spatial patterns. When a location has a good developmental potential, it attracts more industrial activities. This industrial localisation leverage on their agglomeration to maximise the land use potential by sharing facilities, innovations, services etc, which consequently helps them maximise utility and productivity.

Furthermore, these productive activities are expected to attract people, as they move closer to such are because of the economic prospects. There is in turn, a causal-effect relationship between the activity centre and households. For instance, the industries, can provide economic means for the households via employment and also provides goods and services. In return, the households can provide a market and labour for the industries. In this sense, contiguity and proximity of these activities are necessary and encourage influx of more people to the Central Building District for opportunities.

Because of how cities evolve, there is always more people at the CBD, while the population, commercial activities reduce as one moves outward, due to distance decay effect. Cost of travelling to the CBD increases as one moves outward. This encourages the conversion of green spaces into buildings because of the higher land value and needs for commercial activities, at the CBD while agricultural activities are mostly located at the peri-urban areas.

However, this trend has been found to change slightly in some developing countries as people occupy outer areas due to cheaper cost.

1. Why do cities need policy interventions?

Cities face many challenges, due to their higher population and activities. These problems are especially more pronounced in developing countries with poor coping strategies and policy implementation. Because of the density of activities, many externalities are expected. Some of these include, congestion, pressure on public amenities, increase in crime and social vices, pollution etc.

To curb excesses from the effects of these, policies have to be put in place to guide the growth and ensure sustainable city. Policies which can be formulated, might, for instance, encourage more people to live in the outskirts. Cost of parking can also be increased to decongest traffic at the centre. Transportation network can be improved upon too. A typical example is the länsimetro which spans across Helsinki through to Espoo, Finland. Which such in place, more and more people can live farther and still be able to work at the centre because of the shrunk distance by the metro. This helps to cushion the distance decay effect.

From the foregoing, policy intervention can help to incentivise or disincentivise people in necessary situations for sustainable urban development. Tree planting can also be encouraged to increase green areas. There have been many scenarios whereby, patches of green areas have been reserved even in a very urbanised area.

LECTURE 2:

1. What is a spatial weight matrix(SWM), what assumptions does it make, and how is it used?

A spatial weight matrix is used to evaluate the degree of similarity between values and locations. This is referred to as spatial autocorrelation and spatial weight matrix does this by exerting a neighbourhood structure on the data. These neighbours are usually defined by binary numbers – 0 and 1. With 0 as not neighbour and 1 as neighbour. It is also important to standardise the rows, afterwards.

A typical assumption of SWM is that the fewer the neighbours, the stronger the influence of a location. In GeoDa, the observations/location are characterised by rows and columns in the matrix. Here, the neighbour is 1 and the location is 0. In description of neighbour, contiguity and distance are considered. Contiguity as it the name suggests, refers to the sharing of borders. This includes the rook and queen.

The rook considers the edges while the queen considers the edges and vertices, when deciding which spatial element is a neighbour. Contiguity is directly more suitable for polygon, however, when dealing with points, assumptions can be made about their areas of influence (i.e. the Thiessen polygon). A grid polygon can also be employed but might not be suitable to large scale analysis (e.g. cadastral scale), because great details are required at such micro level which might be lost in the process of using the polygon grid and aggregating the points into polygons

Distance on the other hand, considers the distance band and k- nearest neighbour. It is also able to handle polygon and points directly.

1. What is spatial clustering and what are the various kinds of it?

Spatial clustering is a phenomenon that describes the homogeneity of groups of observations, according to their attribute values. It shows if they are clustered or dispersed. An instance of spatial clustering is the clustering of a disease or crime location data. Here, it clusters the geometries of areas with similar attributes. It can be used to understand the hotspot of occurrence of a phenomenon, other than random distribution.

They can either be positive, negative or random. Positive distribution shows that there is a cluster while negative infers a dispersion. Positive spatial autocorrelation follows Waldo Tobler’s premise that everything is relate but near areas are more related than the distant areas. Here, the clusters could be high-to-high values or low-to-low values while negative spatial autocorrelation is depicted by high-to-low or low-to-high spatial outliers.

Random shows occurrence by chance. Spatial clustering can be assessed by techniques by partitioning, hierarchy or locality-based. Such include the Global and local spatial autocorrelation. The previous captures the overall scenario while the latter zooms in to assess the local clusters.

LECTURE 3: **Spatial Statistics: Spatial Regression Models:**

What is Spatial regression?

Spatial regression is a statistical technique that is used for encapsulating the spatial dependency that occurs in regression analysis. It does this by giving details about the spatial relationships between the included variables. Furthermore, it prevents several statistical issue which include unreliable significant tests and inconsistent parameters. spatio-temporal predictions can then be made based on this spatial relationships.

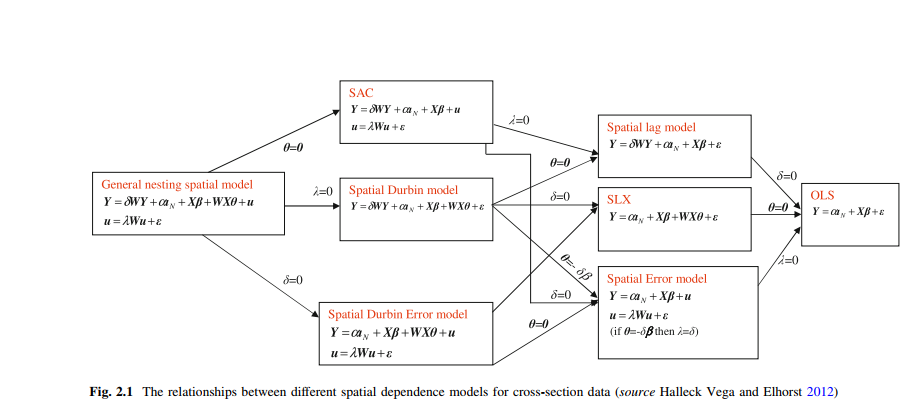
The spatial dependency can be included into the regression model as the common relationship between dependent and independent variable, or as the relationship between the dependent variable and its spatial lag or spatial error term.

Also, spatial heterogeneity between the dependent and independent variables can be captured by the Geographically Weighted Regression which localises spatial regression by disaggregating the parameters by the analysis’ spatial units.

What are the differences between the spatial error, spatial lag, and spatial Durbin models?

Spatial error model(also, nuisance dependence) captures the spatial dependence with spatial autocorrelation. It is suitable when one is interested in correcting potential effect of bias by spatial autocorrelation, because of the use of spatial data(regardless of the spatiality or non-spatiality of the model). Spatial lag model, on the other hand, is a model which incorporates a spatially lagged dependent variable(Wy) as an extra regressor to the spatial dependence in the standard linear regression model. It is suitable when one is interested in evaluating the presence and strength of interaction. Lagrange Multiplier (LM) or Rao Score can be used for distinguishing between spatial error models and spatial lag models.

In addition, Spatial Durbin Model combines the two above-mentioned models - spatial error model and spatial lag model- by taking the advantage that it is possible to define a spatial error model in spatial lag form. It does this by including the spatially lagged predictors(independent variables), however, the parameters are checked by the common factor constraints.



|  |  |  |  |
| --- | --- | --- | --- |
| Model | Spatial Interaction effects | # | Flexibility of spatial spillovers |
| Spatial Error Model | Wu | 1 | Zero by construction |
| Spatial lag model | WY | 1 | Constant ratios |
| Spatial Durbin Model | WY,WX | k+1 | Fully flexible |

**LECTURE 4: Spatial Statistics: Geographically weighted regression.**

**1. What is spatial non-stationarity in regression coefficients and how does geographically weighted regression address it?**

Spatial non-stationarity in regression coefficients explains the modelled relationships that are variable spatially(across space). This causes explanatory variables to have differential effects across space, which consequently, impacts the output of a model. In other words, spatial non.stationarity is a situation whereby the simple global model is not able to explain the relationship of some variables sets. Therefore, the model itself, has to vary over space to reflect a realistic structure within the data.

To deal with this, Geographically Weighted Regression(GWR) fits potentially various coefficient value for per observation, by using spatial weight. This technique calibrates calibrates multiple regression model which permits various relationships over space, and therefore, enables the representation of this variation by estimating local coefficients.

**2. Can you give some examples of spatial non-stationarity in real world phenomena?**

One real world example is assessing housing price, because it is immobile. Hence, variation in traffic conditions, socioeconomic situation, resource richness across different states can result in a scenario whereby the relationship between the dependent and independent variables(predictors) is not constant spatially. Global models might not reflect the true picture at a regional level which could yield a misleading and unrealistic result. GWR attempts to deal with this by creating regression models at every point with estimation of varying coefficients.

Another example of spatial non.stationarity could be relationship between car ownership rates and social class and unemployment in Finland. With a universal model developed from this, it might difficult to explain local variation across space because social class and male unemployment vary, at various spatial scale and also from municipal to municipal.

Relationship between land value and accessibility can also be another instance as this varies over space. Others can include:

* Species distribution which could depend on many predictors such as Slope Aspect , climate, which vary across space.

- population density distribution.

- spatial non-stationarity in the relationship of a sea life(e.g fish) and temperature, distance from shore, whereby the direction and the significance of the relationship might vary over an entire area of interest.

LECTURE 5:

**How do cellular automata see and explain the world?**

Simply put, Cellular automata is a concept which sees the world as a plane with grids which consists of cells. Each of the cells is assumed to have one of two colours(e.g black or white). Furthermore, the cells change colour based on the colour of the neighbouring cells. The interaction with neighbours are executed according to some predefined rules. A more complex scenario with more colours can also exist. Overall, the cells change temporally according to the transition rules.

Cellular automata can be one row dimension of cells or multiple dimensional grid of cells.

They are able to explain complex spatial behaviour in the world in a fascinating way. Basic rules could yield some haphazard patterns, causing some uncertainties in predictions. However, a careful and proper design can also give realistic results by stably and steadily predicting evolution of patterns overtime, with careful inter-neighbours interactions. A constraint is usually imposed also, to achieve this realistic result.

This concept has been used in modelling traffic flow, with the development of mechanisms of traffic control which can help to decongest the roads. This considers binary scenario where you have an empty road as 0 and roads occupied by cars as 1, which can be white and black respectively. However, this can be made more complex to allow for cars at various speed(e.g, 1-20), which can then be represented as a colour spectrum(e.g green to red).

Another example where cellular automata can explain the world is in the modelling of wildfires as they spread and predicting their path of burns and burning rate overtime.

In addition, two-dimensional cellular automata has been used to understand both the physical and human world. An instance is in the evolution of a city which can take from simple to very complex rules and can also take into cognisance, the various land use types, morphology of the city, presence of hindrances(such as hills, lakes etc). By using these various interaction rules such as rook(**von Neumann)** and queen(Moore), we can predict phenomenon like urban sprawl. With this, policy makers can formulate a more appropriate sustainable urban planning.

Perhaps, the entire universe is a cellular automaton which expands steadily?

**LECTURE 6: AGENT-BASED MODELS**

1. What are agent-based models and how do they differ from cellular automata?

Agent-based models are models are very strong simulation technique of modelling that have proved to be useful in real world scenarios. Here, agents are used as collection of independent decision-making bodies for modeling a system. Each of the agents make evaluates its situation and decide based on a set of rules. Agent-based models mainly aims to simulate the potential characteristics of agents which cannot be decided from the rules controlling the individual agents.

Agent-based models are quite similar to cellular automata but different in many ways. Neighbourhoods/grids in cellular automata are fixed while in agent-based modelling, the nearest neighbours changes over time. This is because, the agents in agent-based models have the freedom of motion and interaction between one another and their environment. Agent-based models seem to provide more complex agents while cellular automata basically proceed with a few rules which uses the neighbourhood states to update the state of the system.

Because of these more complex rules and interactions in Agent-based model, it will be expected to yield a more realistic simulation(especially in social sphere which is very complex) than cellular automata which employs a much more simplistic approach in determining the evolution of the system based on neighbourhood state.

**2. What sort of point does Schelling’s segregation model make?**

Schelling’s segregation attempts to create independent agents or entities that act based on fairly simple rules which could be learning or random interaction rules. This simple rules can eventually yield complex overall eventual structure or pattern. The model shows that subtle interaction amongst agents can cause segregation.

This patterns evolve by agents assessing their present position depending on their happiness rule which is based on the neighbouring cells. The unhappy agents can change position with one another. This goes on till the agents are happy and this phase depicts the equilibrium result. The eventual result is based on the rule of happiness. An example would be that I want all my neighbours in the class to be international students. This will expectedly result in a complete segregation. Such complete segregation can even be cause by little preferences.

An example of this can be seen in everyday life in school and in our cities. For instance, Africans and Arabs are mainly in the eastern part of Helsinki while the native finns and europeans tend to be in the western part. This does not mean that each of the groups are racist but might have their own individual preferences which aggregate into complete segregation overtime.

This shows that if an area starts as being very segregated, it will be kept that way by natural interaction. Therefore, if diversity is preferred or wanted, it should start at the earliest phase. Furthermore, there might be need to intervene to sustain the diversity and amend the situations as the system evolves. This maybe be due to subtle discrimination and not necessarily pronounced or deep discrimination. This scenario is also applicable to local and international students in any University such as the University of Helsinki.

* Does a fuzzy cognitive map represent a phenomenon or the perception of a phenomenon by a group of experts?

fcm are used for representing causal reasoning

Construction of the FCMs Fuzzy cognitive maps represent causal relationships among variables in a system as defined and described by people (Özesmi and Özesmi 2004, Murungweni et al. 2011). Because the method adopts a participatory approach that involves local actors in building the FCMs, it is considered a more transparent way to build a model, deconstruct and capture tacit knowledge, and represent knowledge diversity (Gray et al. 2012). Furthermore

FCM provides a flexible approach to include variables of different nature in the analysis. Hobbs et al. (2002) observed that a common difficulty in ecosystem management is that quantitative processbased models rarely address relationships of public concern that are highly uncertain, difficult to quantify, or not accessible. Instead, by building on expert knowledge, semiquantitative FCM can deal with the components of the system that are not well known, and can incorporate relationships yet to be quantified. Although expert knowledge is in itself not sharp and precise (Salski 1992), this approach helps close some of the gap between the development of the model, plausible scenarios, and the public concerns

The FCMs use fuzzy-graph structures to represent variables, i.e., concepts, and their causal relationships, i.e., directed and weighted connections or edges. The FCM variables can represent logical propositions, state variables, random events, or management decisions (Hobbs et al. 2002). In this study, the FCMs represented local experts’ perception of the interactions among the variables that influence, directly or indirectly, the occurrence of wildfires in the Municipalities of Concepción and Roboré. Variables ranged from concepts that could be measured, e.g., deforestation, to more qualitative concepts, e.g., intention to cause fire

The FCMs were developed in different focus groups, and hence represented stakeholder group knowledge (Özesmi and Özesmi 2004). Overall we facilitated five homogenous focus groups organized by actor type: indigenous communities, private cattle ranchers, local authorities in Concepción, local authorities in Roboré, and regional experts. The last group comprised representatives from the regional government, research institutes, and nongovernmental organizations based in Santa Cruz working on wildfire risk in the Chiquitania. Each focus group engaged five experts, which were selected from the pool of previously interviewed informants based on predefined criteria listed in Table A1.2. Essentially, these criteria helped identify the individuals with most knowledge about the wildfire dynamics in the case study Municipalities and with extensive experience in fire, agriculture and land management.

The main reasons someone uses the FCM approach are [7]: easy of use, easy to construct and parameterize, flexibility in representation (as more concepts/phenomena can be added and interact), low time performing, easily understandable/transparent to non-experts and lay people [8], handle with complex issues related to knowledge elicitation and management, handle with dynamic effects due to the feedback structure of the modeled system. Furthermore, individual FCMs pertaining to a particular domain can be combined mathematically [1,2]. This means that FCMs allow for different experts and/or stakeholder views to be incorporated [9], and can provide a useful mechanism for combining information drawn from many sources to create a rich body of knowledge [10-12]. Finally, vector-matrix operations allow an FCM to model dynamic systems [1,13],

llowing for the dynamic aspect of system behaviour to be  
captured [14]. Thus, FCMs have gained considerable research  
interest and accepted as useful methodology in many diverse  
scientific areas from knowledge modeling and decision  
making.  
This work presents a survey on FCMs applications and  
trends in diverse scientific areas during the last decade  
exploring some of the most representative for each application  
study. The main aim of this study is to give an outline on how  
the FCMs increase their applications and more methodological  
efforts made by other researchers to enhance their applicability  
in different domains. It is difficult to present all the  
representative applications in each domain, as the number of  
FCM papers was extremely increased the last three years. Thus,  
we attempt to figure out only some of the most representative  
works of each domain, during the last decade.

Fuzzy Cognitive Maps (FCM), as introduced by Kosko [10][11][12][13], are meant to be a combination of Neural Networks and Fuzzy Logic that allow us to predict the change of the concepts represented in Causal Maps. The graphical illustration of FCM is a signed directed graph with feedback, consisting of nodes and weighted interconnections. Nodes of the graph stand for the concepts that are used to describe the behavior of the system and they are connected by signed and weighted arcs representing the causal relationships that exist among concepts. Figure 1 represents a fuzzy causal map based on a work presented by Mohr [18]. Each concept represents the actors, entities and social, political, economic or abstract concepts that compose our system. Examples of concepts might be Inflation, the actions of an influent Politic, a Revolution, the Wealth of an individual or a nation, the Welfare of population, Road conditions, etc. Each concept is characterized by a value usually ranging from [0..1] or [–1..1] representing a transformation from its real world value.

FCM are about representing causality in dynamic systems. However they represent a very different approach from what is called the “Logic approach to causality” which basically consists in defining “Necessary Causes” and “Sufficient Causes”[22], and leads often to what is known as the “Causation Vs. Correlation” problem: the belief that correlation proves causation, is a logical fallacy by which two events that occur together are claimed to have a causeand-effect relationship. This fallacy is also known as cum hoc ergo propter hoc ("with this, therefore because of this”). The FCM approach relies on the universally agreed facts that to test for causality it is necessary to guarantee that a cause must precede an effect and that an alteration on a cause alters the effect: there is a causal relation between two given concepts whenever a relative variation in one of those concepts cause a relative variation on the other one. For example, there is a negative causal relation between Police Presence and Theft: a major increase in Police Presence will probably cause a large decrease in Theft. Causal relations in causal maps should always involve change: the result of a

So FCM represent knowledge in a symbolic manner and relates states, processes, policies, events, values and inputs in an analogous manner.

A FCM describes the behavior of a system in terms of concepts, each concept represents a state or a characteristic of the system. Particularly, a FCM is a fuzzy signed oriented graph with feedback that model the worlds as a collection of concepts and causal relations between concepts. Variable concepts are represented by nodes. The graph’s edges are the casual influences between the concepts. The causal relationships are expressed by either positive or negative signs and different weights. The value of a node reflects the degree to which the concept is active in the system at a particular time. This value is a function of the sum of all incoming edges multiplied and the value of the originating concept at the immediately preceding state. In general, a FCM functions like associative neural networks. A FCM describes a system in a one-layer network which is used in unsupervised mode, whose

neurons are assigned concept meanings and the interconnection weights represent relationships between these concepts. The fuzzy indicates that FCMs are often comprised of concepts that can be represented as fuzzy sets and the causal relations between the concepts can be fuzzy implications, conditional probabilities, etc. A directed edge Eij from concept Ci to concept Cj measures how much Ci causes Cj . In general, the edges Eij can take values in the fuzzy causal interval [-1, 1] allowing degrees of causality to be represented: a) Ejk>0 indicates direct (positive) causality between concepts Cj and Ck ; b) Ejk<0 indicates inverse (negative) causality between concepts Cj and Ck ; c) Ejk=0 indicates no relationship between Cj and Ck . In FCM nomenclature, model implications are revealed by clamping variables and using an iterative vector-matrix multiplication procedure to assess the effects of these perturbations on the state of a model. A model implication converges to a global stability. During the inference process, the sequence of patterns reveals the inference model. The development of a FCM often occurs within an expert group. Each expert provides its individual FCM matrix, which is then synthesized into a group FCM matrix. The group matrix (EG ) could be computed as

Fuzzy Cognitive Maps (FCM) have found favor in a variety of theoretical and applied contexts that span the hard and soft sciences. Given the utility and flexibility of the method, coupled with the broad appeal of FCM to a variety of scientific disciplines, FCM have been appropriated in many different ways and, depending on the academic discipline in which it has been applied, used to draw a range of conclusions about the belief systems of individuals and groups. Although these cognitive maps have proven useful as a method to systematically collect and represent knowledge, questions about the cognitive theories which support these assumptions remain. Detailed instructions about how to interpret FCM, especially in terms of collective knowledge and the construction of FCM by non-traditional ‘experts’, are also currently lacking. Drawing from the social science literature and the recent application of FCM as a tool for collaborative decision-making, in this chapter we attempt to clarify some of these ambiguities. Specifically, we address a number of theoretical issues regarding the use of Fuzzy Cognitive Mapping to represent individual “mental models” as well as their usefulness for comparing and characterizing the aggregated beliefs and knowledge of a community

There is a wealth of literature from the fields of cognitive science, psychology, and systems science that discusses the use of individuals’ knowledge structures as representations or abstractions of real world phenomena. However, before we can begin our discussion of how Fuzzy Cognitive Mapping (FCM) contributes to these fields, we must first reconcile the various definitions and approaches in the literature used to characterize internal cognitive representations of the external world. Understanding the theoretical foundations of concept mapping, cognitive mapping, mental models and the notion of “expertise” in the elicitation of a subject’s knowledge is of particular interest to our discussion on FCM construction and interpretation. Further, we discuss issues related to analyzing FCMs collected from non-traditional experts, which is a growing area of research that seeks to characterize group knowledge structure to inform community decision-making and compare knowledge variation across groups. In this chapter, we address: how FCM can be used to understand shared knowledge and what trade-offs should be considered in the selection of FCM data collection techniques. 2 Concept Mapping, C

FCM has its roots in concept and cognitive mapping. Concept maps are graphical representations of organized knowledge that visually illustrate the relationships between elements within a knowledge domain. By connecting concepts (nodes) with semantic or otherwise meaningful directed linkages, the relationships between concepts in a hierarchical structure are logically defined [49, 55]. The argument for representing knowledge with concept maps emerges from constructivist psychology, which postulates that individuals actively construct knowledge by creating mental systems which serve to catalogue, interpret and assign meaning to environmental stimuli and experiences [61]. Knowledge “constructed” in this manner forms the foundation of an individual’s organized understanding of the workings of the world around them, and thus influences decisions about appropriate interaction with it. Influenced by cognitive psychology’s developmental theory of assimilation and accommodation, as theorized by the Swiss cognitive psychologist Jean Piaget, the use of concept maps as representations of an individual’s organized knowledge is further supported. According to Piaget’s developmental theory of learning, individuals’ assimilate external events and accommodate them to develop a mental structure that facilitates reasoning and understanding [17, 58]. Using this theoretical framework, concept maps can be elicited to represent an organized understanding of a general context, thereby providing an illustrative example of a person’s internal conceptual structure [49]. 2 Fuzzy Cognitive M

Another form of structured knowledge representation commonly referred to in the social science literature is cognitive mapping. A cognitive map can be thought of as a concept map that reflects mental processing, which is comprised of collected information and a series of cognitive abstractions by which individuals filter, code, store, refine and recall information about physical phenomena and experiences. Popularized by psychologist Edward Tolman as a replication of a geographical map in the mind, the term has since taken on a new meaning. Robert Axelrod [5] was the first to use the term in reference to the content and structure of individuals’ minds, thereby shifting its applied meaning from referring to a map that is cognitive, to a map of cognition [14, 27]. Using Axelrod’s definition, cognitive maps are visual representations of an individual’s ‘mental model’ constructs, and are therefore analogous to concept maps that represent a person’s structured knowledge or beliefs. Although both concept and cognitive maps are often used as external representations of internal mental models, it is important to note that these graphical representations and mental models are not the same. Cognitive maps, of which FCMs are an extension, are themselves extensions of mental models, but are distinct since cognitive maps are physical constructs, whereas mental models only exist in the mind [14]. First introduced by Craik [11], today the notion of mental models and their usefulness for understanding individual and group decision-making is a widely accepted construct in the social science literature [1, 28], and justifies the methodological appropriation of FCM as external representations of a person’s internal understanding. It is hypothesized that in order to successfully achieve a given objective, individuals must possess sufficient knowledge of their immediate environment in order to craft appropriate responses to a given decision context [47]. In such contexts, mental models are considered to provide the structures that form the basis of reasoning [28]. The perceived utility of internal mental models in decision making contexts lies in their simplicity and parsimony, which permits complex phenomena to be interrogated and salient components selected to form judgments. Inferring causal relationships between a range of factors based on available evidence or beliefs facilitates the generation of workable explanations of the processes, events and objects an individual may encounter within their environment. By encoding these inferences into a heuristic structure, individuals can accrue knowledge incrementally over time, thereby offsetting the limitations of human cognition under conditions of complexity and uncertainty [65]. This process enables individuals to construct an internal model that both integrates their existing relevant knowledge of the world, as well as meets the requirements of the domain to be explained. To enable individuals to make a context-appropriate decision, mental models mediate between knowledge stored in the long-term memory and knowledge that is constructed in the short-term working memory [48]. Therefore, it is hypothesized that individuals constantly rely on mental models to structure their understanding, explain the world, and to some extent, make decisions that reflect this internal process of reasoning. Combining the notion of “mental modeling” with cognitive mapping, FCM utilizes fuzzy logic in the creation of a weighted, directed cognitive map. FCMs are thus a further extension of Axelrod’s definition of cognitive maps, and can therefore similarly be considered a type of mental model representation [21, 29, 35, 52].

Given FCMs may serve as semi-quantitative, detailed representations of individual and/or group knowledge structures, either through aggregation of individual’s models, or through group FCM building exercises, they are attracting increased attention in applied research contexts seeking to promote collective decision-making or better understand community knowledge [3, 18, 52]. Using the imprecise nature of common language, FCM permits individuals to interpret and express the complexity of their environment and experiences by combining their knowledge, preferences and values with quantitative estimations of the perceived relationships between components within a particular context of interest [28, 29, 39, 52]. Similarly, from a social science research perspective, employing FCMs as representations of mental models can generate understanding of how different people filter, process and store information, as well as elucidate how these perceptions may guide individuals decisions and actions in a particular context [7]. In a manner analogous to the mental modeling that structures an individual’s cognitive decision making process, eliciting the reasoning and predictive capacity of experts’ mental constructs via FCM has proven to be a useful decision support tool [2, 18, 21, 52]. Although FCM have been proposed as a method to understand mental models, issues regarding whose knowledge is represented, how group knowledge is collected and interpreted, and what constitute best practices for combining mental models in different applied research contexts, have largely not been addressed.

3 Traditional ‘Western’ Expertise and Non-traditional Expertise The collection of FCMs as representations of mental models can be divided into two general categories in terms of ‘whose knowledge is being structured?’. The first, and perhaps most long standing use, is related to FCMs as representations of “traditional” expert knowledge. There is a long history of representing expert knowledge systems using FCM and fuzzy-logic in areas of research where system uncertainty is high and empirical data to validate a hypothesized model is unavailable or costly to collect. This FCM research encompasses a wide range of applications including: risk assessment [25, 43], work efficiency and performance optimization [29, 71] strategic deterrence and crisis management [38, 57], scenario/policy assessment [3, 32] spatial suitability and prediction mapping [4, 45] and environmental modeling and management [2, 24, 26, 40, 60]. FCM based on expert knowledge, attempts to make tacit, expert knowledge more explicit in an effort to represent complex systems and their inherent dynamics that would otherwise not be well understood. “Traditional western experts” in this sense reflect the common use of the term and characterize social elites including physicians [6], scientists [10, 24], and engineers [3]. By collecting mental models from experts considered to hold the ‘best’ knowledge about a system, structure is provided to what would otherwise be loosely-linked, highly complex, or unavailable understanding of a system domain. The second and more recently emerged category of FCMs as representations of mental models, are those collected from non-traditional western experts. These

FCMs are most often employed in participatory planning and management and/or environmental decision-making contexts, and are primarily used to gain an understanding of how stakeholders internally construct their understanding of their world or a particular issue of interest [33, 34]. For example, non-traditional expert FCMs have been elicited from bushmeat hunters in the Serengeti [50], fishermen [40, 70], pastoralists and farmers [16, 51] as well as a range of other stakeholders during participatory planning and modeling contexts [10, 18, 30, 44, 52, 56] Collecting FCMs from non-traditional experts serves as a way to characterize community understanding of a system or collect data intended to help characterize a system that might not be represented by information provided by traditional experts alone [7, 33]. Though there may be some degree of overlap in the need for or desire to use tacit or local knowledge to inform the decision making process, the appropriation of FCM in the collection of local stakeholder knowledge is commonly associated with decisionmaking in the local community context rather than to pool expert knowledge in conditions of uncertainty, where data is limited or not comprehensively linked [34]. Since knowledge exists on a continuous spectrum of expertise from novice to expert, and the degree of expertise is not usually easily determined, the collection of FCMs from non-traditional experts has been largely influenced by research questions and to date, there has been little consideration of the differentiation or potential protocols of FCM collection from experts and non-traditional experts.

4 Disentangling Group Knowledge In addition to questions associated with ‘whose knowledge is being structured?’, there are also research context dependent issues associated with FCM in terms of appropriately representing group knowledge. FCMs are often collected from groups of individuals and aggregated as a way to support decision-making and promote understanding of system dynamics. However, interpreting the cognitive structures of FCMs within the group context raises questions about what this pooled knowledge represents, and how it is useful for research, analysis and interpretation. Although the literature defines mental models as individual’s internal representations of the world, consensus is currently lacking with regard to the theoretical basis of shared cognition as it relates to concept and cognitive mapping. Therefore, there are still questions about what collated representations of individual mental models represent [31, 67]. In the literature, this ambiguity is demonstrated by the variable use of research methods and terms employed in the study of shared cognition [8, 46]. To date, the FCM literature has largely ignored this ambiguity, despite the fact that FCMs are strongly influenced by the individual characteristics and cognitive processes of those who construct them [59], as well as the method by which FCMs are aggregated and analyzed [53]. While it is commonly accepted that individuals within a given community are exposed to the same “reality”, it is also acknowledged that their interpretation of that reality may not be shared [12, 67]. This is because individual mental models are socially-mediated, created with diverse knowledge abstractions,

reliant on personal experience and highly dependent on prior knowledge [65]. As evidence of this, the aggregation of individuals’ knowledge structures has been shown to show considerable variation and when aggregated, the group level “knowledge structures” sometimes fail to reflect the sum of individual members’ mental models [31, 67]. FCMs have been proposed as a unique tool for aggregating diverse sources of knowledge to represent a “scaled-up” version of individuals’ knowledge and beliefs [52]. The product of the aggregation of individual’s FCMs is sometimes referred to as a “social cognitive map” and is often considered a representation of shared knowledge [18, 52]. The concept of shared knowledge in the form of social cognitive maps has been used in a variety of distinct applications using of FCMs including: to gain a more comprehensive understanding of complex systems; to describe consensus in knowledge among individuals and to define differences in individual and group belief or knowledge structures. Further, as FCM evolves beyond its foundations as representations based on traditional expert systems towards the integration of more non-traditional expert knowledge for participatory engagement, it is necessary to understand the nature and appropriateness of FCM aggregation in order to ensure that interpretations are theoretically sound. Therefore, in an effort to further expand the appropriation of FCM to a new generation of social science researchers, it is of critical importance to: (1) understand what is meant by “shared” knowledge of individuals and (2) establish data collection protocols based on common FCM research goal typologies.

Conversely, an alternative option is to engage in group modeling, whereby a group of participants constructs an FCM as a collective. Group FCM construction is most often aligned with research priorities that seek to promote and represent the outcome of social learning. In these research contexts, more emphasis is placed on model building as a process, and less emphasis placed on capturing individual-level representations of knowledge. The FCM is therefore an outcome of social interaction and represents the group construction of knowledge, achieved through the collective sharing of aspects of individuals’ mental models. Group modeling is often less resource intensive compared to the collection of individual models since members of a community can be organized to create a model in a workshop or group setting. In these cases, model aggregation reflects community knowledge, and the role of the researcher is less pronounced since more control of group knowledge representation is afforded to the community. Given that the integration of individuals’ knowledge structures is socially negotiated in the group model building context, the resulting consensus model is ultimately dependent upon the personalities, strength of expertise, relationships and level of equality of the group. It may, however, be difficult to accurately assess the distribution of contributed knowledge across group membership or weight each member’s expertise. In such contexts, the resulting FCM is most appropriately used as a tool for creating consensus related to the context of inquiry, and for facilitating group discourse for the promotion of shared understanding and collective learning. The model itself represents a socially negotiated form of collective knowledge that can be used to represent community understanding; however, it cannot be scaled down to represent individual understanding.

7 Conclusions  
Structuring human knowledge through the collection of FCMs has obvious use  
beyond simply characterizing traditional expert systems, and also provides a way to  
represent community understanding as a form of scaled up “mental modeling”. As  
the field of FCM continues to evolve and the usefulness of FCM continues to be seen  
through novel appropriations, continued research is needed to establish best practice  
standards which match specific techniques with different research contexts, backed  
by discipline appropriate theoretical foundations. Although FCM provide a powerful  
tool for both traditional experts and non-traditional experts to model complex  
systems, evaluate structural differences between the knowledge held by groups and  
individuals, and functionally determine the dynamic outcome of this understanding,  
there are still issues regarding the interpretation of FCMs as artifacts of individual  
knowledge and group beliefs. In this chapter, we have sought to provide a theoretical  
background to inform the collection and interpretation of FCM as representations of  
shared knowledge when individual FCMs are aggregated together, compared across  
individuals within the context of group interaction, or created collectively by individuals  
within a group context. More specifically, we can summarize the lessons  
learned as follows:  
• When FCMs are used as representations of individual mental models or group  
knowledge or beliefs, the research objective should be carefully aligned with the  
appropriate cognitive theory and data collection method.  
• FCMs, like all concept maps, have the ability to be used as both measurements  
of individual and group understanding and as a tool to promote social learning to  
facilitate group decision-making. Researchers should be clear about their appropriation  
when drawing conclusions about FCM as representation of knowledge  
and beliefs.  
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• Researchers engaged in FCM research should justify, based on tradeoffs, the selection  
of FCM data collection and aggregation techniques.  
• Continued evaluation of existing methods, and the development of new methods,  
is currently needed in the areas of aggregation tests, sample size sufficiency,  
knowledge heterogeneity, and expert credibility

* • In which cases the two above-mentioned alternatives might converge?

when the experts are credible and their knowledge are justifiable.

when fcms are well systematically connected, they are able to grow knowledge bases which can allow for representation of phenonmena, especially in soft knowledge domains such as military, history, poitical science, organisationaional theory and international relations, where the concepts or rwlationhip of the system and language of the meta-system are essentially fuzzy