A METHOD FOR EMPLOYING QUALITATIVE DATA IN THE DEVELOPMENT OF SPATIAL AGENT-BASED MODELS

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ABSTRACT

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Developers of agent-based models of socioecological systems are in a power-laden relationship with those they presume to model. It has often been the case that these developers do not inform their model with any sort of rich cultural data, and instead rely upon established methods from areas such as economics, laboratory psychology, and machine learning. While these methods can be effective, ignoring the perspective of the humans being represented in an ABM risks validation of that model for the wrong reasons and a marginalization of the humans represented in the model. Qualitative data collection methods, such as the collection of narratives, can aid not only in the elucidation of cultural ecological complexity, but also in the anchoring of an ABM to the political and ecological perspectives presented. While qualitative methods might lead to ABMs with higher fidelity to their real-world counterparts without as many power issues, making use of qualitative data during model development can be quite challenging, and no clear general methods exist. This thesis proposes a method to utilize long-form key informant narratives in the development of spatial agent-based models by linking the textual analysis of source documents to multiple modeling steps utilizing mental mapping and Object-Process Methodology extended for Multi-Agent-Systems (OPM/MAS). To test this method, narratives from migrants during the American Dust Bowl were analyzed and used to construct grounded models. The resulting model of a migrant agent is simple, easily understood and implemented, and its components can be linked directly to elements in the source narratives.

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CHAPTER 1: INTRODUCTION

Motivation

In the past four decades, agent-based modeling (ABM) has become a popular method of examining phenomena occurring at the human-nature boundary. This popularity stems, in part, from its ability to provide a space for experiments that are difficult or impossible to conduct in a real-world setting (Macal and North 2010; Kohler, Gumerman, and Reynolds 2005; Wilkinson et al. 2007; Quesnel, Duboz, and Ramat 2009). Many of the problems investigated by researchers in the various sustainability fields fit this bill, as they often operate on much wider spatiotemporal scales and involve human subjects in situations that make experimentation difficult or unethical (Duffy 2006). Geographers, for instance, are unable to observe land use change over hundreds of years, but models may be constructed to simulate such a time scale (Bithell, Brasington, and Richards 2008). With the ever-expanding capacity of computation and the ease with which it is accessed, this popularity is on track to grow even more. More and better tools are continuously created to aid in the development of agent-based models, significantly lowering any barriers to entry that might have existed in the now distant 'code-it-from-scratch' era. As a result, agent-based models can be developed with little or no training in computational methods or, as the case may be, agent-based methods themselves. Conversely, it is entirely possible for an agent-based model of human-environment interaction to be developed solely based upon computational and quantitative principles, with only a hint that the agents are, in fact, built out of some conceptualization of actual humans within a social context. An examination of the current ABM literature quickly reveals a lack of attention to social theory, which has been developed over centuries in an effort to explain, in multitudinous ways, how humans and their social institutions behave in almost every situation (Robinson et al. 2007). Instead, what emerges is a picture of agent-based modeling as a field that primarily pays heed to methods from artificial intelligence, psychology, and economics (Zhang and Leezer 2010; Wainwright and Millington 2010).

In purely experimental cases with no grounding in a real social context, this is perfectly fine; however, if the goal of an ABM is to represent faithfully – albeit simplistically – some situation observed in the real world, then significant obligations to those being represented arise (Boero and Squazzoni 2005). In this situation, the modeler is in a position of incredible power, where the fundamental elements of social behavior have been personally chosen and implemented. Contemporary models are being used to evaluate existing environmental policy and management regimes as well as inform the development of new programs (Astier et al. 2012; Parrott et al. 2012). Given the spatial nature of these models, inaccurate representations of agents can produce visual output that can be provocative but misleading, as has been demonstrated in traditional cartography (Monmonier 2005). Further, the spatial and the social are closely interrelated, yet existing agent-based modeling methodologies focus highly on the individual and do not adequately address the social context (O'Sullivan 2004). The modeler, therefore, has an obligation to define these agents, their behaviors, and the environment in which they exist with some degree of fidelity to the actual experiences of those whom the model intends to represent.

Problem Area

Alternative qualitative data collection methods have been proposed in an attempt to better inform the development of models, such as the use of a role-playing game to extract land-use decision making behaviors(Washington-Ottombre et al. 2010; Evans, Sun, and Kelley 2006; Guyot and Honiden 2006). Tools such as role-playing games can also be included as part of a larger suite utilized in the participatory modeling approach, which makes efforts to include the perspective of stakeholders in model development (Ramanath and Gilbert 2004; Castella, Trung, and Boissau

2005; Becu et al. 2003). While solutions such as these are a step toward a better representation of human-nature interactions in policy-relevant and empirically-rich models, they do not adequately consider the full complexity of human social realities. Unfortunately, ethnography, the method that has traditionally been used by social scientists to investigate human social realities, is rarely utilized in the development of agent-based models, and its use has even declined among the more general work done by human geographers, despite its many advantages (Herbert 2000; Atkinson 2008; Lansing 2003). The data produced by ethnography are often in the form of detailed field notes and lengthy interview transcripts. While field notes may be used effectively in addition to other empirical data in the development and parameterization of models, long interviews are significantly more difficult to utilize, as no clear method for doing so exists.

Research Goals and Scope

This thesis seeks to address the obligations of model developers by examining socio-environmental agent-based modeling in a broader framework of contemporary political ecology and human geography, with particular attention paid to the ways in which ideas about nature are constructed and disseminated. This examination justifies the development and use of a multi-step method to generate empirically-grounded agent prototypes using long-form key-informant interviews as the source material. To accomplish this, the large scale migration of Americans from Oklahoma during the Dust Bowl is used as a case study (Worster 1982). Key informant interviews, collected from individuals who migrated during the event, are used as the primary data source. From these, an innovative mental model is constructed which attempts to capture the decision-making process of different migrants before, during, and following this significant migration event. This mental model is then analyzed and used as the groundwork for an agent prototype diagram developed using Object-Process Methodology for Multi-Agent Systems.

Layout

Chapter 2 of this thesis contains a thorough review of the relevant current literature. Chapters 3 and 4 propose and demonstrate the methodology, respectively, and include detailed diagrams of the general Object-Process components and an agent prototype developed using the methodology. I close with a discussion of the methodology, the results and limitations of its use, and the details of future work.

CHAPTER 2: BACKGROUND

Agent-Based Modeling

Agent-based modeling has existed, at least theoretically, for several decades now, but only recently have researchers been able to develop more realistic models that do not have computational demands exceeding available computing power (Zenobia 2008; Miller and Page 2007). The technique emerged from multi-agent systems (MAS), which itself emerged from the field of artificial intelligence (M. J. Wooldridge 2009; Weiss 1999). MAS was originally referred to as distributed artificial intelligence (DAI), as it focused on recreating the reasoning of multiple heterogeneous agents instead of a single agent (Bousquet and Le Page 2004). Agents themselves can be conceptualized in different ways, with some variance across disciplines. For ecologists, it is useful to present an agent as one of a subset of objects within an environment that is an active entity in a system, and geographers prefer to view an agent as an entity in a spatially-explicit environment with which it can interact (Ferber 1999; Janssen and Ostrom 2006; Grimm and Railsback 2005; Bithell, Brasington, and Richards 2008; Parker et al. 2003). Others favor the more general idea of an agent as a system capable of autonomous action within an environment that seeks to fulfill some design objectives (Bousquet and Le Page 2004; M Wooldridge 2013). In any case, the most important features of an agent are that it is an autonomous entity, it exists within a certain environment with which it can interact, and that it follows some set of rules governing its behavior (Bithell, Brasington, and Richards 2008; Epstein 1999). By virtue of these characteristics, agents are supposed to be free to adapt and apply assigned rules independently of the modeler.

Agent-based models themselves can have varying properties as well. In general, ABMs consist of a collection of agents embedded in an environment, though this environment need not be representative of the physical world (Bithell, Brasington, and Richards 2008; Epstein 2006; Miller and Page 2007). In many cases, and most certainly in the case of geographic applications, the environment is represented by sub-models embedded in GIS, such as climate, hydrological, or water quality models (D. G. Brown et al. 2005; Berger 2001; Ligmann-Zielinska and Jankowski 2007; D. G. Brown and Xie 2006). Importantly, the environment and its implemented subsystems have a direct influence on the behavior of its resident agents (Parker, Hessl, and Davis 2008). It is common for cellular automata to be used in combination with agent-based modeling to provide a canvas for these environmental subsystems (Manson 2006). By allowing these agents to freely interact in a dynamic environment , researchers are able to observe emergent properties of the system under examination (Miller and Page 2007; Epstein 2006; Janssen and Ostrom 2006). This characteristic is what gives ABMs their power: the ability to observe how simple and minute interactions between autonomous agents produce macro-level patterns and systems that cannot be explained simply by the sum of their parts (Epstein 1999).

The majority of agent-based models, initially, was primarily theoretical, and served to illustrate the emergent properties of complex social systems. Perhaps the most famous of the early agent-based models are those that combine agent-based approaches with cellular automata, such as Conway's "Game of Life" or Schelling's model of segregation (Gardner 1970; Schelling 1971). Since the 1990's, theoretical ABMs have been used to study land use issues, starting with Epstein and Axtell's SugarScape model (Epstein 2006). More recently, empirical approaches to agent-based modeling have been used to study a wide range of topics. Common applications can be found in land use studies (Manson and Evans 2007; Valbuena et al. 2009; Overmars, Groot, and Huigen 2007), political science (Berger 2001), and landscape ecology (Wainwright and Millington 2010). In the past decade, land use and land cover change (LUCC) studies have begun to make heavy use of agent-based models (Schreinemachers and Berger 2006; Manson and Evans 2007;

Parker et al. 2003; Castella, Trung, and Boissau 2005; Clavel et al. 2012; Overmars, Groot, and Huigen 2007).

Towards a Socially Grounded Approach to Conceptualization and Development of Environments in ABM

The representation of the environment within agent-based models can be somewhat problematic, depending on the goals of the model. Owing to the nature of computational thinking, the environment is typically defined in concrete terms, with recognizable units and measures. A natural affinity exists between this approach to the representation of the environment within an ABM and the techniques used by many geographers. Both vector and raster data have proven useful in the development of agent-based models of land use and land cover change (Deadman et al. 2004; Bousquet and Le Page 2004; Manson and Evans 2007). For models that are focused entirely on the interaction between multiple agents, the environment may be represented by nothing more than coordinate space, as in cellular automata (Schelling 1971). Conversely, agent-based models of coupled human and natural systems may have many sub-models, with the interactions among agents and between agents and the environment feeding back at multiple levels (Parker et al. 2003; D. Brown et al. 2004; Matthews et al. 2007; Evans and Kelley 2004).

Given the irregularity of decision-making methods within agent-based modeling, a crucial question emerges: how does a researcher define agents, choose for them a decision-making mechanism, and support these decisions with data? Oftentimes, agents are defined without direct reference to empirical data, which can ignore important aspects of the modeled scenario, such as diversity among the humans being represented (Valbuena, Verburg, and Bregt 2008). Much debate has surrounded the collection of this data, however. As ABM are designed with a bottom-up approach in order to elicit macro-scale responses from micro-scale behaviors, a researcher must ensure that the data-collecting and processing techniques sufficiently capture these micro processes (Robinson et al. 2007).

When it comes to the environment, however, it is much easier to rely on predetermined ecological models with which agents are able to interact by manipulating inputs and responding to output (Acevedo et al. 2008). This process is reminiscent of Bruno Latour's "black boxes":

> The word black box is used by cyberneticians whenever a piece of machinery or a set of commands is too complex. In its place they draw a little box about which they need to know nothing but its input and output...That is, no matter how complex their history, how complex their inner workings, how large the commercial or academic networks that hold them in place, only their input and output count. (Latour 1987, 3)

In this sense, when a modeler chooses a particular model to represent the environment, he is intrinsically inserting a black box into it. Only the inputs and the outputs matter, and the inner workings and the ideas that went into their creation become irrelevant. In many cases, the same occurs with agent behavior in ABM. When it comes to choosing how agents make decisions based upon interactions with these environmental black boxes, it is common for models to employ existing decision theory (Robinson et al. 2007; Deadman et al. 2004; Ligmann-Zielinska 2009). While this is perhaps due to the need for computability coupled with the difficulty of acquiring and making sense of data to inform decision-making processes in specific contexts, the decision about which one of these models, if any, should be used to represent agent behavior is an event that should not be overlooked.

The development of a model is, ideally, a task focused on the reproduction of reality in a simplified form that allows it to be more easily and clearly analyzed (Epstein 1999; Miller and Page 2007). The level of detail with which these models are created varies according to application, and highly experimental models are often far removed from any real-world context. When considering how to represent the environment and the agents as well as their behaviors in a model, all of which constitute a particular idea of reality, another serious question emerges: whose reality is being represented by these models? In addition to this, who is ultimately deciding what the reality is, and what political processes inform that decision?

In the examination of any issue of sustainability or human-environment interaction, it is important to take full account of how political, social, and cultural forces shape the observed ecological phenomena. Most commonly, this involves an examination of external political pressures on local populations, an understanding of complex, multi-scale power dynamics, and a thorough unveiling of historical conditions that contribute to or account for the observed phenomena (Liu et al. 2007; Robbins 2004; Goldman, Nadasdy, and Turner 2011). In the modeling context, it is, at first, difficult to see how the sociopolitical context is indeed relevant. While some of these concepts may aid in understanding inputs to a particular system being modeled, it also threatens to muddle the boundaries of that system such that it cannot be adequately modeled. Despite this, I advocate the political ecological approach to model development, as its real power is in the examination of the modeler's relationship to the people and communities that constitute the system being modeled. I argue that the political ecological approach could enhance ABM fidelity because of its introspective nature, where we can explicitly account for the modeler's scientific, cultural, and political biases. If closely followed, the political ecology approach results in a model that represents the target society more closely, rather than the modeler's biased view of that society.

Particularly in cases where ABMs are developed to represent a specific real-world phenomenon, models play an important role in the livelihoods of communities under investigation, whether it be through policy decisions supported by models or from changes to academic attitudes toward a particular problem (Matthews et al. 2007; Parker et al. 2003). The decisions about model development, and, thus, how the modeler is presenting the modeled community to consumers of that model, are rooted deeply in the modeler's own social, political, and historical contexts as well as their (oftentimes strictly mathematical) educational background.

Despite this, model developers have no choice but to impose what is sometimes a foreign order on social reality, if for no other reason than to allow its expression in a computational format. This process involves, most prominently, deciding what is and is not modeled (Beven 2009; Bertalanffy 1984). Human-environment interaction is never a simple process, and environmental issues that emerge from these interactions can rarely be reduced to only a few key factors or mechanisms. All are caught up in a broader political and cultural mesh. Articulating that complexity in spoken word or in prose is difficult enough. To do so in a computational form could reasonably take more time than a human has in a lifetime, so for the sake of practicality, boundaries must be imposed. Most of the boundaries imposed are in the form of informed assumptions about human behavior and decision-making as well as the components and function of the natural world they inhabit.

Is this a bad thing, though? Postmodern thinkers have spent decades working toward the deconstruction of most commonly held notions of boundaries, and particularly those that have been taken for granted. Notable among these are boundaries around concepts of identity, race, gender, and the environment. The deconstruction of these ideas has enabled the discussion of social reality from the subject's perspective, and has given a powerful voice to other ways of knowing and experiencing (Robbins 2004; Beck, Bonss, and Lau 2003). Again, though, the deconstruction of boundaries that are taken for granted in modeling can make the task of defining model characteristics problematic. Social theorists thought about this problem decades ago. Most notable among them was Max Weber, who, in tackling the problem of causality, noted that any effect has, when properly examined, an infinite number of causes, yet, "a complex of antecedent conditions has to be conceptually isolated that more or less strongly 'favors' the result to be explained" (Ringer 2000, 67). This process of isolation is, essentially, the reconstruction of the boundaries that postmodernism has worked so hard to destroy. These reconstructed boundaries need not be arbitrary, though. More recently, reflexive modernization thinkers have suggested the discussion be shifted away from deconstructing boundaries and refocused on reconstructing them, acknowledging their arbitrariness while at the same time recognizing their pragmatic necessity (Beck, Bonss, and Lau 2003). This approach relieves some of the pressure placed on the modeler, given an adequate understanding of the boundaries in question.

Central to the discussion of how a modeler should choose to represent nature and the environment are the ways in which the humans in question themselves understand and conceptualize nature and the environment, as well as the boundaries between the social and the natural. Breaking from the traditional approach of assuming empirical, western-biased rationality in the face of stimuli from the external world, some social theorists suggest that nature and the environment are socially constructed, and that the ways in which we perceive the external world and interact with it are situated in a particular cultural context (Greider and Garkovich 1994; Robbins 2004; Demeritt 2001). Greider and Garkovich use the idea of an empty field to represent how landscapes are constructed through symbols (Greider and Garkovich 1994). Landscapes, they argue, are created and transformed in ways that depict our own values and intentions and, as a result, the same physical parcel of the world can be experienced and interpreted in vastly different ways. They illustrate this with an examination of the different ways in which Aborigine people and park rangers view fire:

> To Aborigines, the meaning of fire derives from traditional ecological knowledge that is holistic with respect to their overall knowledge of hunting and gathering… To them, setting fires is the most important management tool used to influence the distribution and relative abundance of plants and animals that form (or formed) the economic basis of their society and culture. Fire setting is not done haphazardly, but is based on a myriad of environmental signs that have been taught orally across generations of Aboriginal people for 35,000-40,000 years (Greider and Garkovich 1994)

The park rangers, on the other hand, "define themselves as scientists," and their knowledge and understanding of fire and their landscape reflects this. According to the park rangers, there are too many scientific unknowns for fire to be considered a safe and desired part of their natural landscape. The Aborigines, however, are not faced with these uncertainties. Greider and Garkovich argue that this is not simply a matter of access to information but the result of identity: the Aborigines' conceptualization of fire and the landscape is brought about by the language and symbols of oral tradition, while the park rangers have constructed their landscape using science (Greider and Garkovich 1994). Paul Robbins continues this discussion more directly:

> …the categories of reality described in much environmental science and state management are ultimately arbitrary and serve specific, often narrow, political interests. Constructivists argue that categories (indigenous, scientific, or otherwise) may adequately capture some commonalities in the pattern of reality but they are no more accurate than any other possible classification. Any given classification

> clusters and excludes different phenomena, but does so in a no more accurate way than its alternative. (Robbins 2004)

Constructionism can appear in a variety of forms. The most prominent distinction between these forms is whether they are "hard" or "soft." (Robbins 2004). Hard constructionism holds that everything is constructed and that humans have no access to the world "out there" – we can only access our ideas and conceptualizations. Soft constructionism takes a different approach, holding that while our ideas and conceptions of reality may be constructed, they are done so by direct observation and interaction with an external reality.

Other scholars have taken yet another approach. Notably, the anthropologist Tim Ingold dispenses with the idea of the social construction of nature altogether. In discussing constructionism, he sets up the constructivist argument as a straw man, "in order to knock it down" (Ingold 2000). He argues:

> …hunter-gatherers do *not*, as a rule, approach their environment as an external world of nature that has to be 'grasped' conceptually and appropriated symbolically within the terms of an imposed cultural design, as a precondition for effective action. They do not see themselves as mindful subjects having to contend with an alien world of physical objects; indeed the separation of mind and nature has no place in their thought and practice. I should add that they are not peculiar in this regard: my purpose is certainly not to argue for some distinctive hunter-gatherer worldview or to suggest that they are somehow 'at one' with their environments in a way that other peoples are not. Nor am I concerned to set up a comparison between the 'intentional worlds' of hunter-gatherers and Western scientists or

> humanists. It is of course an illusion to suppose that such a comparison could be made on level terms, since the primacy of Western ontology, the 'givenness' of nature and culture, is implicit in the very premises on which the comparative project is itself established. (Ingold 2000)

Ingold is making multiple important claims here. First, he suggests that hunter-gatherers are not perceiving a world "out there" and then formulating ideas about it. They do not see themselves as separate from it in the first place. He then suggests that discussing their experience in terms of nature and culture in relation to the Western experience is impossible, since the very ideas of nature and culture were created to reflect the Western experience in the first place. He continues:

> What I wish to suggest is that we reverse this order of primacy, and follow the lead of hunter-gatherers in taking the human condition to be that of a being immersed from the start, like other creatures, in an active, practical and perceptual engagement with constituents of the dwelt-in world. This ontology of dwelling, I contend, provides us with a better way of coming to grips with the nature of human existence than does the alternative, Western ontology whose point of departure is that of a mind detached from the world, and that has literally to formulate it – to build an intentional world in consciousness – prior to any attempt at engagement. … [Apprehending] the world is not a matter of construction but of engagement, not of building but of dwelling, not of making a view *of* the world but taking up a view *in* it. (Ingold 2000)

This argument – that perceptions of the world are not generated through an active conceptualizing of an outside reality but rather through dwelling and moving *within* the world – has significant implications. It is perhaps too forgiving to say that it lets modelers off the hook, but it does make their work fit within a framework that enables the experience of their subjects to remain part of the conversation.

Additionally, it provides strong theoretical support for the concept of intelligent, spatially-aware, adaptive agents in ABM (Michael Wooldridge, Jennings, and Kinny 2000). This is particularly evident in spatially-explicit ABM, where agents would have access to geographic spaces and spatially-dependent processes, with which they can perceive and interact (Chion et al. 2013; Chion et al. 2011).

Methodological Implications

The major question I pose in this thesis asks **how a modeler is expected to define and develop agents and their behavior that faithfully represent the humans they are modeled after**. The issue of faithful representation of subjective realities can be discussed in terms of the data that is used to inform development and the methods used to collect that data across different disciplines. Acquiring data that has high fidelity to a given reality is a significant challenge. Quantitative data can be sterile and lack any real description of relationships, experiences, perceptions, attitudes, power interactions, and other purely social phenomena. Qualitative information, on the other hand, is often expressed in prose presented after an interpretive process performed by the data collector. This opens up questions of misrepresentation and bias and poses a challenge when translated into a numerical (programmable) representation. Between the two types, however, qualitative data has the potential to provide useful information with a higher fidelity to developers of agent-based models. The reasons for this assertion are rooted in the notion of complexity, which is a core tenet of agent-based modeling.

For the purposes of this argument, complexity is a reference to system behavior that cannot be expressed purely as a summation of its parts and, generally, that the removal of a particular unit in that system will render the system either meaningless or without function (Epstein 1999; Manson 2001). Given this, why does qualitative data – with an emphasis on data produced by ethnographic methods – better inform agent-based models?

Ethnography is, ideally, an effort to achieve what Clifford Geertz refers to as a "thick description" of a social situation. That is, it is the goal of the ethnographer to describe a situation in such detail as to elicit not just the raw surface facts, such as when an individual closes one of his eyelids, but also to provide the context and the meaning for these facts (Clifford Geertz 1973). Was the closing of that eyelid done in isolation? Following a witty or sly remark to a friend or a pass at a girl (C Geertz 1987)? In essence, the goal here is to provide a description of the scenario such that it can be known whether this was a twitch or a wink, and what the meaning of that action is in a social context. While this is a very simple example, in ethnographic fieldwork this process is performed over months or years to generate a thick description of a cultural setting. It would seem that this approach is perfectly suited for eliciting complexities within cultures, as it relies not just on surface observations and quantifications, but also on the observed and expressed interactions between actions performed by individuals in a cultural setting, and enables the ethnographer to bear witness to feedbacks from culture itself, in its abstract and ethereal form (Geertz 1973; Atkinson 2008).

Culture is, itself, a complex system of complex systems: language, institutions, interactions, notions of place and time, and identity, to provide just a few examples (Atkinson 2008; Lansing 2003). That is, each of these can be described as a highly complex system, though they can also be described as smaller subsystems in the greater complex system of culture. If ethnography is the process by which these systems are described in detail, what better methodological approach exists to inform the agent-based modeling process? No other data collection method claims the same depth as thick description, yet ethnographic methods are perhaps the least utilized methods within all of modeling (excepting ethnographic literature itself, which is technically a model in prose form) (Robinson et al. 2007).

When ethnographic methods are employed, they are often used sparingly as a component of larger case studies. Olstrom and Janssen describe the role of case studies in model development as one of contextual fitting (Janssen and Ostrom 2006). That is, case studies enable the development models meant to represent a specific scenario, and are not intended to be broadly generalizable. However, the use of ethnographic methods, including interviews and narratives, is minimally emphasized in their work.

While many models employ case studies, only a few prioritize the use of ethnography in the design process. Huigen et al studied land use and settlement decisions in the Philippines using an ethnographically-informed agent-based model (Huigen, Overmars, and de Groot 2006). To develop their model, they developed a method of translating narratives and questionnaire responses directly into the MameLuke ABM platform. This approach allowed the model to outperform a random model, though the authors admit to significant methodological inefficiencies. There are two characteristics of this work that are problematic. First, the authors formulate hypotheses prior to primary data collection and use questionnaires to assess the quality of those hypotheses. While the authors have area and subject matter expertise, alternative approaches built upon Grounded Theory have been utilized to avoid the insertion of any bias into the system, though such an approach would likely have added to any existing inefficiencies (Zenobia 2008; Glaser and Strauss 2008). Secondly, the output of the described methodology is specific to the MameLuke platform. While the authors certainly shouldn't be faulted for this, as that was their intention, it limits the application of the methodology to other research problems and leaves the general methodological question of translation of interview or narrative to model unanswered.

Toward a Socially Grounded Solution

Scholars of both political ecology and science and technology studies have increasingly been paying attention to how knowledge is produced, distributed, and employed (Goldman, Nadasdy, and Turner 2011). As scholars, we actively participate in the production of knowledge that is linked to a specific place, time, and cultural context. The methods with which this knowledge is constructed vary according to discipline, and do not necessarily require any input from that place or the people living there. This is entirely reasonable in many circumstances, but significant problems arise when this knowledge is then distributed and employed in ways that have a direct impact on human livelihoods. The knowledge produced by developers of agent-based models has the potential to be distributed easily and quickly among scholars and policy makers, who may then decide to plan and implement policies that could drastically alter the behavior of those whose cultural ecological system was modeled in the first place.

It is at this point that the issues of representation detailed above become a more concrete political issue that intersects with recent sustainability concerns. In the past decade, sustainability scholars have increasingly concerned themselves with the sustainability of sociocultural systems, which refers to, among other things, the preservation of multiculturalism and self-governance. The idea behind this is that, similar to biodiversity, multiculturalism and cultural diversity is critical to the overall well-being of the larger human sociocultural system. This cultural diversity may be threatened by policy decisions that are informed by knowledge produced from agent-based models that do not directly ground themselves in the cultural context they try to emulate. By implementing such policies and imposing behavioral changes, sociocultural systems can be subjected to intense pressures, which result in a forced shift and loss of heritage and tradition and, ultimately, lead to a failure of the sustainability aspects of the policy (the economic and ecological subsystem may survive or even thrive, but the social subsystem miserably collapses).

From this review, one question takes precedence: how does a modeler, equipped with a new understanding of their subjects' experience of the world they live in and the unique and diverse ideas the subjects have about it, go about deciding where to place the boundaries on their subjects' realities? This question can be asked more directly: how should the developer of an agent-based model of complex socioecological systems decide who the agent represents and how that agent should behave? I have discussed the role of ethnographic methods, including the use of key informant interviews and narratives, as being uniquely capable of aiding in this endeavor while being generally underutilized, often to the difficulty of translating such data into model logic.

To overcome this, I propose employing a multi-step method that incorporates a careful textual analysis of key informant narratives, and the development of a mental model, placing pieces of critical information in relationship with each other. Following the completion of these two preliminary steps, a third is proposed: the development of a diagram of agent behavior using Object-Process Methodology extended for Multi-Agent Systems (OPM/MAS) (Sturm, Dori, and Shehory 2010). OPM/MAS provides model developers with a powerful descriptive toolkit that emphasizes design simplicity, readability, and the ontological equality of objects and processes.

CHAPTER 3: PROPOSED METHODOLOGY

To accomplish the goals set forth above, I worked during 2011 and 2012 with a group of interdisciplinary researchers on an analysis of interviews collected from Dust Bowl migrants in the last two decades of the 20th century. This project was motivated by earlier work done by McLeman and Smit, who created a conceptual model to test theories of human migration behavior (McLeman and Smit 2006). These informants represent the various classes of farmers, workers, and businessmen who were forced to migrate as either a direct or indirect response to the Dust Bowl. The analysis of these interviews led to the development of a unique form of a mental model that presents information for both the entire group of Dust Bowl migrants interviewed as well as each informant's personal migration considerations (Louie Rivers III et al. In Preparation).

Generally, mental models are a visual means of representing a given group or individual's epistemology and thought processes (Gentner and Stevens 1983). They have been proven useful in a variety of scenarios, including the analysis of difference between stakeholder knowledge systems in social-ecological systems and in the understanding of weed management practices among farmers in Ohio (Gray 1990; Jabbour et al. 2013). The mental model constructed for this research expands upon the traditional construction and use of mental models in a few key ways. While our primary model focuses on the thought processes, experiences, and perceptions of Dust Bowl migrants, it also contains a secondary model that further explores the migratory decision making process for specific individuals. Also, while mental models are traditionally constructed using data collected from interviews performed by the researchers, our model is built upon historical interviews of Dust Bowl migrants. These interviews and accompanying historical records, while not collected with the construction of a mental model in mind, are nevertheless rich in their descriptions of the migratory experience, and, given the length of time since the Dust Bowl, they serve as one of the few ways in which these experiences might be accessed.

To construct the mental model, our team analyzed and coded a series of interviews using the NVivo software package. Our team first met to collectively examine a few documents in detail to produce general themes and boundaries for the document analyses, including the coding scheme that was to be used. Once the coding of all interview documents was completed, our team identified coding nodes that were common among a majority of the analyzed interviews. These common nodes served as the foundational units in our mental model, which was then constructed using the LucidChart web application (available at https://www.lucidchart.com/). This process ensured that our mental model would be solidly grounded in our data.

The mental model produced by our research group is well-suited for use in the development of an agent-based model because of its focus on individual experiences and decision-making processes. To take advantage of this, I chose to make use of Object-Process Methodology (OPM). OPM was recently developed as an alternative to the more commonly used systems modeling language UML (Dori 2002). This methodology, which grants equal status to both objects and processes and allows them to be placed in relationships with simple markup, was recently extended to provide direct support for the relationships of multi-agent systems (MAS) (Sturm, Dori, and Shehory 2010). One of the primary motivations in seeking an alternative to UML as the language in which our model is to be developed is the ability to effectively communicate model complexity without compromising its ability to be understood (further examination of UML can be found in the Discussion chapter). Additionally, recent work in geospatial sciences has brought to light the need to emphasize processes and events (which can be thought of as processes that have been given discrete boundaries) as being of central interest in answering questions about change (Kuhn 2012).

A more powerful characterization of objects has also been proposed that places them on equal ontological footing with processes and connecting them with a web of interdependencies (Galton and Mizoguchi 2009). As agents in an agent-based system are behavioral entities, this notion of ontological dependency between object and process seems intuitive (Sturm, Dori, and Shehory 2010). OPM supports these concepts by placing objects and processes on an equal footing and allows them to interact and interface with each other in meaningful, easily understandable ways (Sturm, Dori, and Shehory 2010).

The extended version, known as OPM/MAS, shares its predecessor's simplicity and flexibility of expression, enabling its use in a wide array of ABM/MAS scenarios (Sturm, Dori, and Shehory 2010). The OPM/MAS specifications call for the development of object-process diagrams (OPD) at multiple levels of abstraction to fully describe a multi-agent system (Sturm, Dori, and Shehory 2010). At the highest layer, referred to as M2, an OPD utilizes plain OPM to describe a generic MAS metamodel (Sturm, Dori, and Shehory 2010). The layer below this, called M1.5, is used to describe the MAS according to its specific domain. It is on this layer that generic agents and their components are defined (though not fully described) and placed in relationships with other critical components of the system, such as environments, organizations, protocols, and other agents. The specific behaviors of these components, however, are not defined on this layer. A detailed description of the entire model and its specific behaviors, including agent behavior, using the components detailed at higher levels takes place on the M1 layer (Sturm, Dori, and Shehory 2010). As this thesis aims to describe a process by which agent specifications may be developed from qualitative data, it focuses on modeling the M1 OPM/MAS layer, where those specifications will take form. It is assumed that diagrams for the M2 and M1.5 layers have already been detailed. Figure 1 illustrates the symbols of organization and relationship present in the OPD developed for this project. It is not a comprehensive list of available OPM symbols. Rather, it contains artifacts that are necessary and sufficient for the problem under study. More complete descriptions can be found in (Sturm, Dori, and Shehory 2010).

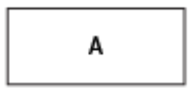
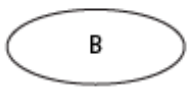
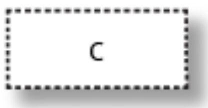
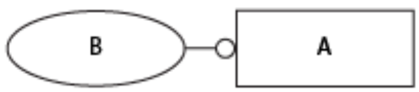
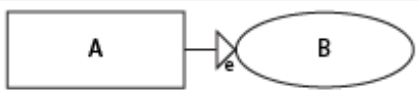
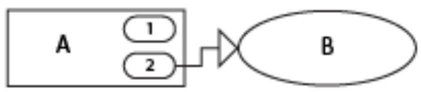
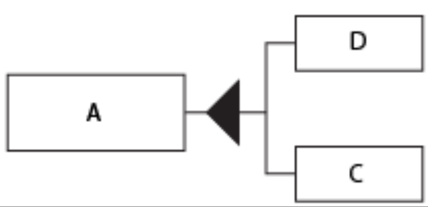
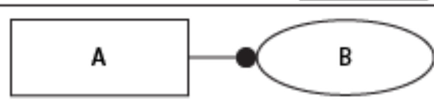
Symbols	Meaning
	**A** is an object
	**B** is a process
	**C** is an object that is physical (non-logical) and environmental (outside the system)
	Process **B** requires object **A**
	Process **B** is invoked when object **A** enters existence
	**1** and **2** are states of object **A** Object **A** invokes process **B** when it enters state **2**
	Process B affects object A
	Object **A** consists of objects **C** and **D**
	Object **A** handles process **B**
	Process **B** yields object **A**

Figure 1: OPM Key

CHAPTER 4: DEMONSTRATION STUDY

To achieve the goal of developing an OPD of a generic agent grounded in qualitative data, the mental model was carefully scrutinized alongside the source documents. Analysis of the mental models and source documents enabled the identification of a displaced farm worker (FW) as a discrete actor in a socioecological system of the Dust Bowl era, so the mental model chosen for use in constructing an OPD was representative of this type of actor. As the mental model was constructed using coding nodes identified as generally common and important among the analyzed documents, the first step in constructing an agent OPD was the identification of nodes in the mental model that directly influenced FW's decision-making and behavior. Our mental model was uniquely constructed with this step in mind, as the key decision-making model components were isolated into submodels created for each interviewed individual. Once this step was completed, the selected components were interpreted as objects or processes and, in some cases, consolidated into new processes. This was an iterative endeavor, and required referencing the source interviews, which was trivialized by the direct link between mental model nodes and document coding nodes.

Following their identification and categorization, the behavioral components were placed into functional relationships with each other in an OPM/MAS context. Importantly, generalized core tasks were identified to handle all possible scenarios presented in the core documents. This stage of the OPD development process was the lengthiest and most complicated, requiring a complete restart several times. Care was taken to generate a diagram with as much resemblance to the source data and mental model as possible, and as such, many of the object and process names within the OPD are shared. This allows a high degree of readability and comparison between the source data, mental model, and OPD.

Figure 2 illustrates a simplification of this workflow. During the first step, three sections of the narrative are identified as relating to a particular aspect and coded as such. In this case, each identifies a different component of what we considered ‘achieved status,’ which is the identifier that was used during the coding process. After these were coded, the prevalence and relative importance of each code during migration decision-making processes were carefully considered. The most significant codes were used to create nodes in the mental model displayed in the second step in Figure 2. It is worth noting that the mental model displayed in this figure has been truncated to simplify the presentation of the workflow. The third step required translating these nodes into elements within an Object-Process Model and placing them in computational relationships with each other. In some cases, nodes from the mental model were dropped or combined in order to better streamline and simplify the agent behavior.

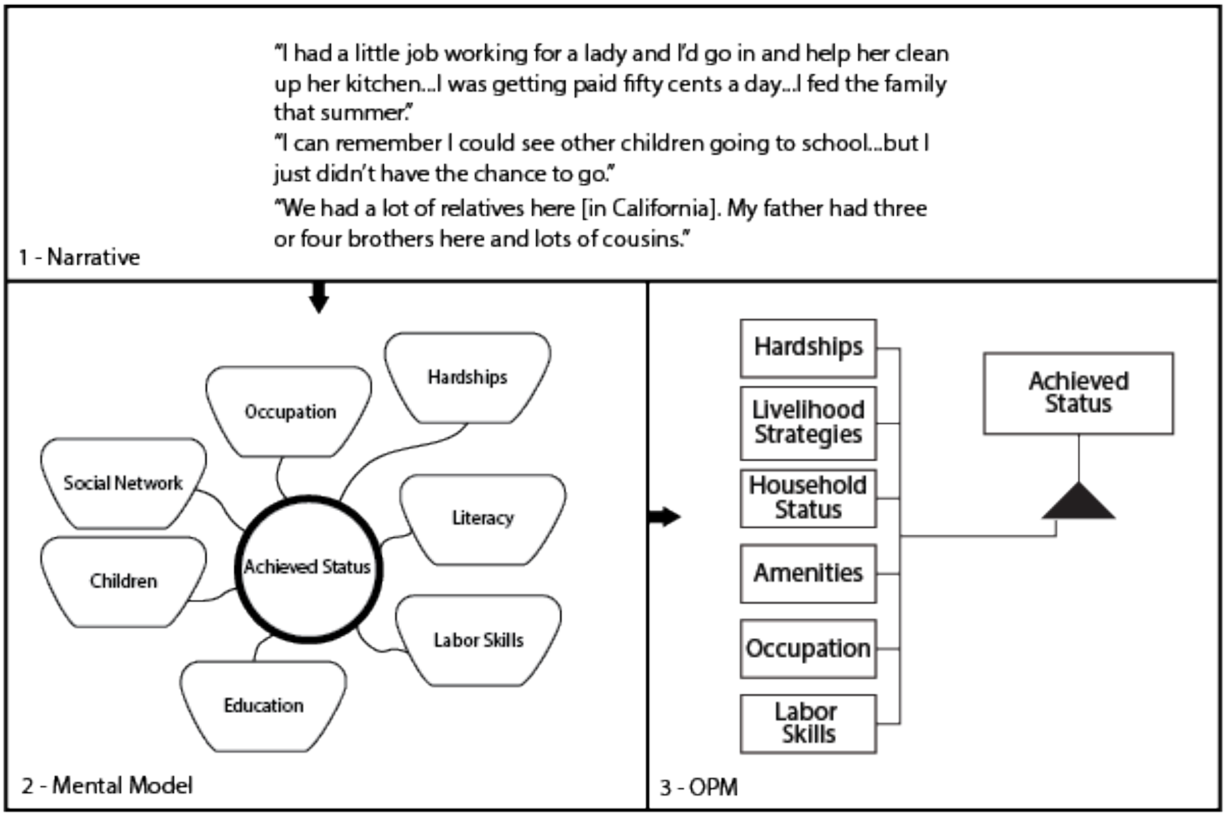


Figure 2: Flow

Object-Process Diagram

The OPD for the migrant farm worker (Fig. 3) is a collection of objects and tasks (represented by process symbols) that regularly emerged as critical in the experiences of the FW informants. A description of the OPD in detail follows, with key components emboldened.

Figure 3 illustrates the **Farm Worker** agent, controlled by the human **User** “Workers,” and its major components. The human user “controls” the agent in the sense that the user is responsible for the execution of the model or simulation. The primary task of the agent was, in essence, a work task. While the specific details of labor and working varied among each informant, they all roughly adhered to a work task that involved a dependence on their occupation and labor skills as well as communication with employers. This employer communication, represented by the **Employers** message, provides the necessary mechanism by which FWs were notified of the presence or absence of paid employment at their current location (**Agent Location**) in their specified occupation. This task yields a **Work Result** object, which is a primary component in the next process identified during data analysis: the **Evaluate Condition** task. This task encapsulates the process by which FWs consider their work (or lack of it) in relationship with other critical factors. Most importantly, in the event of a job-loss **Work Result**, this task incorporates an assessment of coping strategies and resources, including household status, amenities, kinship, and perception of risks, which yields a **Migration Required** object. The **Migration Required** object is either in the binary *yes* or *no* state, as determined by the **Evaluate Condition** task result. If no migration is required, the operation of the agent effectively ends until invoked again by the **User**, which also allows an asynchronous implementation more suitable to our migration scenario.

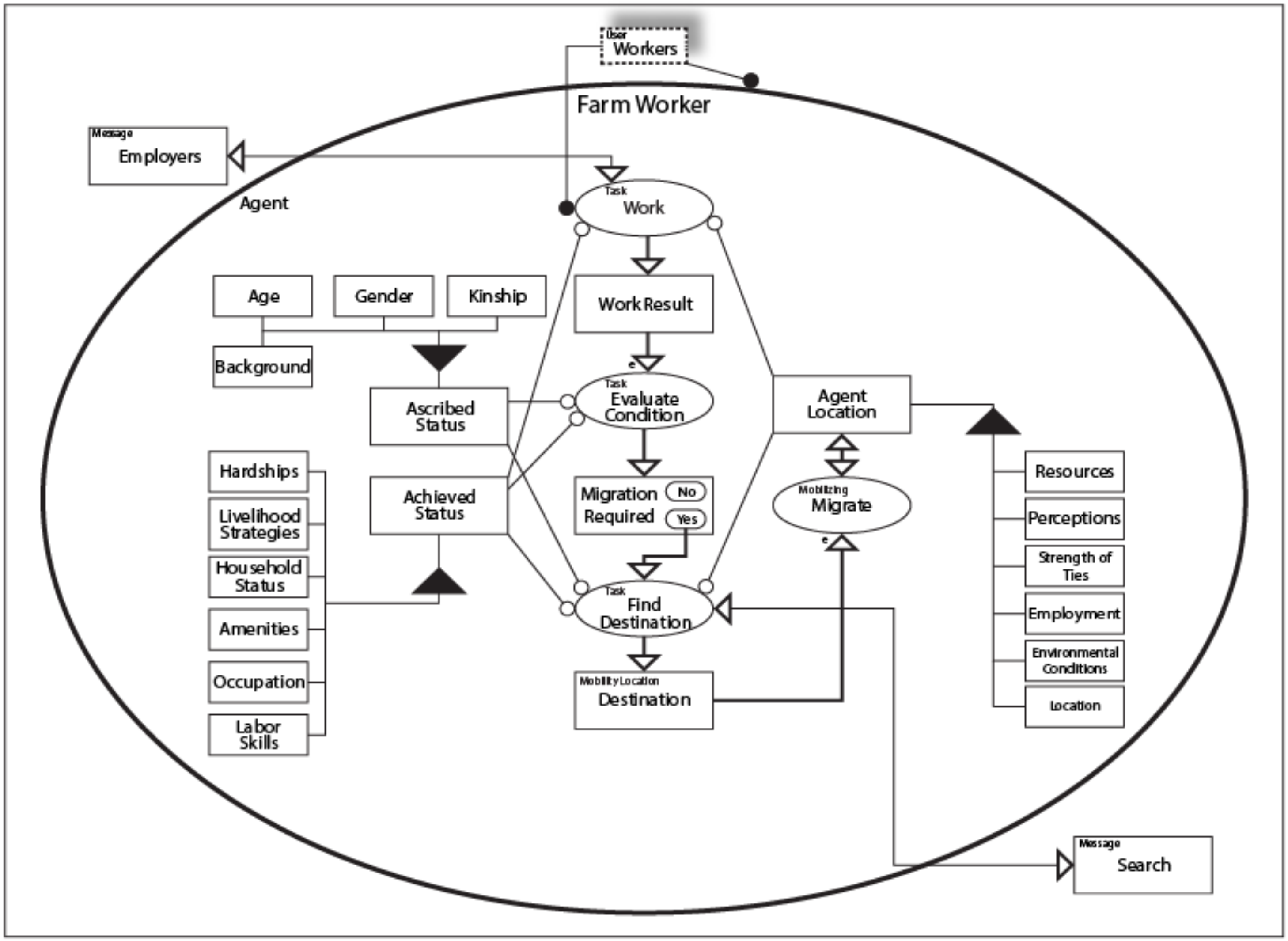


Figure 3: Farm Worker OPD

If **Migration Required** is in the *yes* state, operation proceeds to the **Find Destination** task. This task is one of the most important in the experience of the **Farm Worker** agent, as it incorporates nearly everything the agent possesses and all of its social connections. The **Find Destination** task considers the agent's current location, its amenities, and its various status components and then employs the **Search** message. This message is where communication with the agent's environment and social network occurs, and would include a comparison between the agent's **Agent Location** attribute and the **Agent Locations** of the other agents in its social and kinship network. The **Search** message would also compare locations that are in close spatial proximity to the agent's current **Agent Location**, as the narratives and mental model suggested that agents would exhaust nearby options before deciding to migrate. After invoking the **Search Message**, the **Find Destination** task is responsible for comparing the available migration options and selecting a destination that is determined to be most ideal. This location is yielded upon the completion of the **Find Destination** task in the form of the **Destination** mobility location.

The final process is the actual migration, represented by the **Migrate** mobilizing process. This process is relatively simple, as it moves the agent from its current **Agent Location** to the **Destination** mobility location. After this task modifies the **Agent Location** object, the agent's processing for the current step ceases.

Figure 4 contains a textual description of the components and relationships of the OPD depicted in Fig. 3. This textual description is a core component of OPM that allows rapid comprehension of complex diagrams. It is typically created alongside the OPD using specific language related to the symbols present in the OPD.

Workers User, which is environmental and physical, handles **Farm Worker** Agent, and **Work** Task.
Farm Worker Agent zooms into **Work** Task, **Evaluate Condition** Task, **Find Destination** Task, and **Migrate** Task, as well as **Ascribed Status, Achieved Status, Work Result, Migration Required, Destination,** and **Agent Location.**

Ascribed Status consists of **Age, Gender, Kinship,** and **Background.**

Achieved Status consists of **Hardships, Livelihood Strategies, Household Status, Amenities, Occupation,** and **Labor Skills.**

Agent Location consists of **Resources, Perceptions, Strength of Ties, Employment, Environmental Conditions,** and **Location.**

Work Task requires **Achieved Status** and **Agent Location.**
Work Task affects **Employers** Message.
Work Task yields **Work Result.**
Work Result triggers **Evaluate Condition** Task.
Evaluate Condition Task requires **Ascribed Status** and **Achieved Status.**
Evaluate Condition Task consumes **Work Result.**
Evaluate Condition Task yields **Migration Required.**
Migration Required can be **Yes** or **No.**
Migration Required triggers **Find Destination** Task when it enters **Yes.**
Find Destination Task requires **Ascribed Status, Achieved Status,** and **Agent Location.**
Find Destination Task consumes **Migration Required.**
Find Destination Task affects **Search** Message.
Find Destination Task yields **Destination** Mobility Location Object.
Destination Mobility Location Object triggers **Migrate** Mobilizing Task.
Migrate Mobilizing Task affects **Agent Location.**

Figure 4: OPD Description

To put Figure 3 in broader context, Figures 5 and 6 present the OPD and description of a multi-agent system at a level higher than the Farm Worker agent. Figure 5 is not a project-specific diagram, however. Instead, it represents the building blocks (as proposed by Sturm) that can be used in the construction of a complete system. Of particular interest in this diagram are the relationships between agents and messages as well as the communication loop between agents. These are the primary mechanisms for interaction among agents. Further development of the Dust Bowl mental models will allow for elaboration of these mechanisms. The Environment object is also notable here, as it has, in addition to exhibiting Agents, the ability to be constructed from multiple nested Environments. This is the mechanism by which OPM/MAS easily enables the development of ABM with coupled natural models. Further, Environment may be spatially explicit, giving its exhibited Agents a clearly defined geographic world to operate within. Perhaps most importantly with regards to the theoretical perspective established in this paper, the ability to explicitly define multiple environments allows the representation of individually constructed environments based on the agents' environmental perceptions.

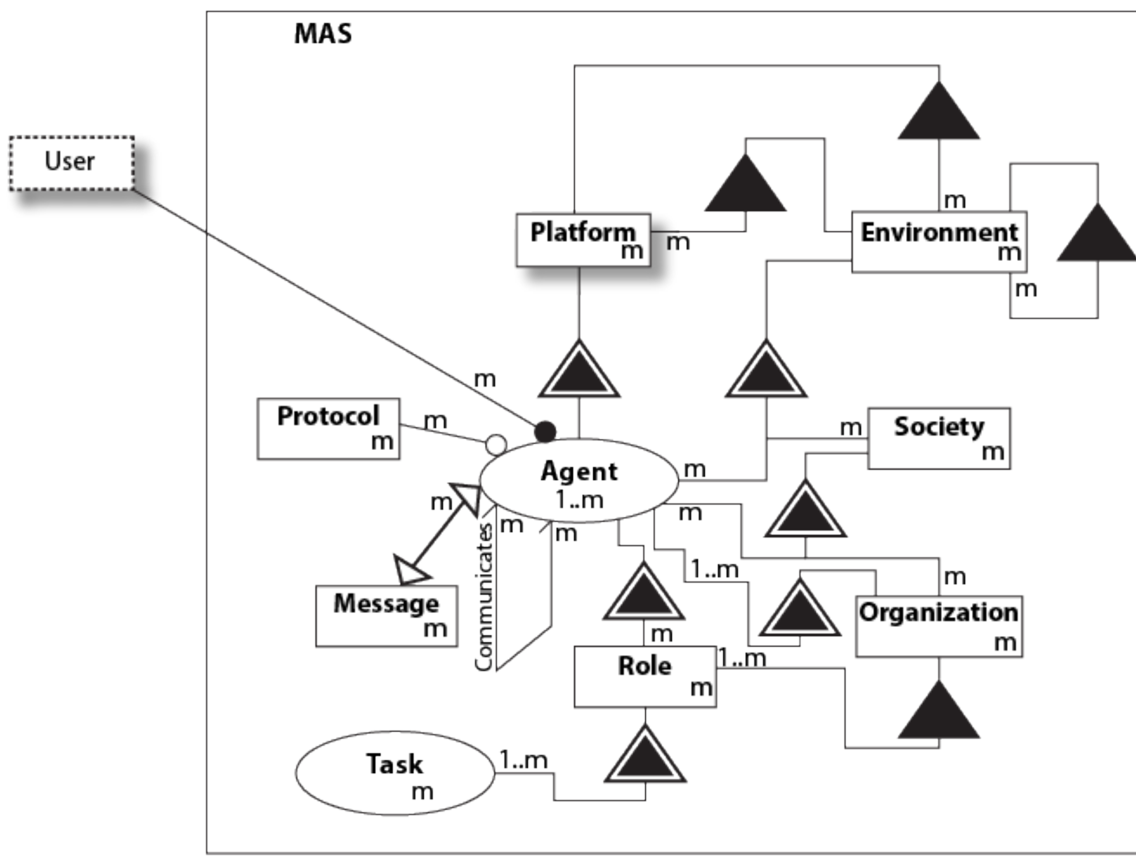


Figure 5: High Level OPD

MAS zooms into optionally many **Platforms**, optionally many **Environments**, optionally many **Societies**, optionally many **Orgranizations**, optionally many **Roles**, optionally many **Protocols**, optionally many **Messages**, as well as at least one **Agent**.

Platform is physical.

Platform exhibits optionally many **Agents**.

Agent exhibits optionally many **Roles**

Role exhibits at least one **Task**.

Agent communicates with optionally many **Agents**.

Agent requires optionally many **Protocols**.

Agent affects optionally many **Messages**.

Platform consists of optionally many **Environments**.

Environment exhibits optionally many **Agents**, as well as optionally many **Societies**.

Environment consists of optionally many **Environments** and optionally many **Platforms**.

Society exhibits optionally many **Organizations**, as well as optionally many **Agents**.

Organization exhibits at least one **Agent**.

Organization consists of at least one **Role**.

User is environmental and physical.

User handles optionally many **Agents**.

Figure 6: High Level OPD Description

In OPM/MAS agents can have ontological terms for things in the world, and these ontological terms reflect the agent's perceptions and understandings (Sturm, Dori, and Shehory 2010). In extension, the agent would be perceiving (a process) the effects of the environmental processes and using the perception (object yielded from a perception process) to make decisions (the decision making is another process). It's just a way of organizing data in this case. As ABM development is, ideally, an iterative endeavor, certain objects within the Farm Worker agent could potentially be moved into different locations. Environmental conditions might be best as a yielded object from an observation task that examines the results of an external process contained within a higher level Environment object representing a spatially explicit model of a natural system (e.g. a rainfall or soil quality model). Such decisions could be made as the rest of the model is fully developed. Whether or not a model component should be an object or a process is, in a way, tied to the natural language you'd use to describe it. Nouns and adjectives generally represent objects and their states.

For example, if a Farm Worker agent makes a decision based on the idea “it is hot,” then “it” (the temperature) is a piece of data most easily conceptualized as a thing, or object, that is in the state “hot.” Verbs, then, generally refer to processes. Of course, this is not a rule, only a conceptualization tool. In some scenarios, modeling purposes trump natural language, as in the case of the agent itself. While the Farm Worker agent certainly represents something that we’d consider an object in the real world (a person), the agent in an ABM exists to *do*, not to *be*.

CHAPTER 5: DISCUSSION

While the development of an object-process diagram is not, in itself, a software agent in a fully realized agent-based model, it does provide a critical stepping stone in the overall ABM development process. A major issue with the development of agents using qualitative data is the difficulty in developing computational relationships between various actors and objects. When being interviewed, it is not necessarily a subject's instinct to relate his story and the actors and events in it using computational terms and logic. In the end, this task falls to the researcher analyzing the data and developing an ABM. Traditional qualitative data analysis techniques can enable quantitative comparisons, but still do not necessarily enable computation. The method described in this thesis provides a means of developing computational logic from the source documents without the a priori assumption of adherence to various behavioral logics.

The object-process diagram created for this thesis depicts only the logic extracted from interviews of subjects who worked on farms and were forced to migrate in direct or indirect response to the Dust Bowl. Because of this, certain logic is not present in the diagram. As OPM allows for the in- and out-zooming of diagrams, it enables the visualization of encapsulated components that contain hidden logic until they are zoomed into. Some of the tasks in the agent diagram are represented by encapsulated components because they require logic that is dependent on further data analysis. Most importantly, the research team responsible for the creation of the mental models (of which I am a part) must analyze interviews of subjects that were not forced to migrate and ideally described themselves as landowners that employed farm workers. These analyses would allow more a detailed definition of farm worker agent behavior and the full description of messaging protocols between the agents.

Under ideal circumstances, this would be possible without further analysis, but the current source data provides little explanation of the interactions between individuals, their employers, and their social networks. This exposes one of the primary issues affecting the entire endeavor: the source data was not collected with the development of an agent-based model or mental model in mind. In fact, the interviews used in the development of the mental models were largely open-form narratives. Because of this, eliciting complex computational behavior was significantly more difficult. It was, however, entirely possible, which exhibits the descriptive power of such interviews.

OPM/MAS vs UML

It is reasonable to question the use of OPM/MAS for modeling multi-agent systems, particularly since the end product of such an endeavor is likely to be a physical implementation, when alternatives such as UML already exist and, while not prevalent in ABM, they have nevertheless been put forth as possible standards. To adequately respond to this, it is necessary to first address UML's object-oriented approach and then compare it to OPM.

Galton and Mizoguchi, in addressing the historical conflict between object-priority and process-priority ontologies, suggest that objects and processes mutually presuppose the other and that objects act as interfaces between their internal and external processes (Galton and Mizoguchi 2009). Further, they argue that our perception of objects is a function of what processes we see as important. Using their example, one of many ways to conceptualize a train is as an object that is moving. This identity reflects its external process (moving). The train, however, cannot move on its own, so it utilizes its internal processes of fuel consumption and wheel turning to interface with another object that converts turning wheels to forward motion. In the case of the train, rails serve as an interface between internal and external processes. Galton and Mizoguchi consider the rails as an auxiliary object that, fulfilling a role, enacts internal processes of an object. Frank (2012) argues a similar ontological perspective's importance to GIScience, stating that focus in GIS should not be so much on the structure of static things but rather the processes and their interactions. According to Frank, "The car is a car because the processes interact, not because the static pieces are in some specific arrangement" (Frank 2012, 16).

Galton and Mizoguchi extend this example to humans. In the case of humans, the human itself and its functional parts (lungs, heart, brain, eyes, etc.) act as an interface between internal processes (e.g. breathing, circulating blood) and external processes (e.g. talking, walking, moving). Importantly, they state that "the stability of the human as a persistent object is maintained by the constant ongoing relationship between the internal processes and the external processes they support" (Galton and Mizoguchi 2009, 19).

This ontological orientation suggests that the way in which a modeler defines agents in an ABM is dependent on how that modeler perceives the internal and external processes of that agent, and not on a perception of an agent object itself. The agent object and its functional components may be defined to serve as an interface between internal and external processes. In our case study, farm workers are defined according to what they do, and the processes internal to them that sustain them, such as making decisions and perceiving the environment.

OPM/MAS was chosen for this project in response to Galton and Mizoguchi's arguments, as OPM places objects and processes on the same ontological level. This allows a diagram to be constructed of a system that fully captures both the processes and objects that, together, define and maintain an agent as an entity. It should be noted, however, that in his definition of OPM/MAS syntax, Sturm (2010) chose to use the notation for processes as representative of agents. While this seems to conflict with the ontology I have just presented, it is best to perceive the agent processes in

OPM/MAS as encapsulations of the entire set of external processes that the agent entity might have. At the same time, however, the agent process can be considered more abstractly as the internal process that interfaces with a larger entity and enable its external processes. The interaction of these agent processes allows the agent group entity to exhibit emergent outward behavior.

Object-oriented diagramming approaches generally lack the ability to capture these kinds of interactions with ease. Since UML has become the de facto diagramming approach used in software development, it has been offered up as the future standard for diagramming agent-based models. Hugues Bersini, in his recent effort to promote UML for ABM, noted that UML diagrams were notably absent from most ABM publications, despite their ubiquity elsewhere (Bersini 2011). He continues with a well-reasoned argument for the use of UML in ABM development, but his reasoning illustrates why UML might be absent from ABM publications in the first place. In particular, Bersini's arguments are highly focused on the physical implementation of the ABM -- the code -- and the software development process. While UML certainly facilitates the development of ABM software, I am not convinced that it facilitates the development of ABM at a higher level.

Figure 7 provides a basic side-by-side comparison of UML and OPD. UML diagram **A** depicts activity flow, **B** depicts system state, and **C** depicts class composition (Fowler 2004; Bauer and Odell 2005). Diagram **D** is a simplified version of the farm worker OPD presented earlier in this paper that combines activity flow, state, and composition in a single graphic. To represent a model's structure at a given level in addition to its behavior, multiple UML diagrams are required.

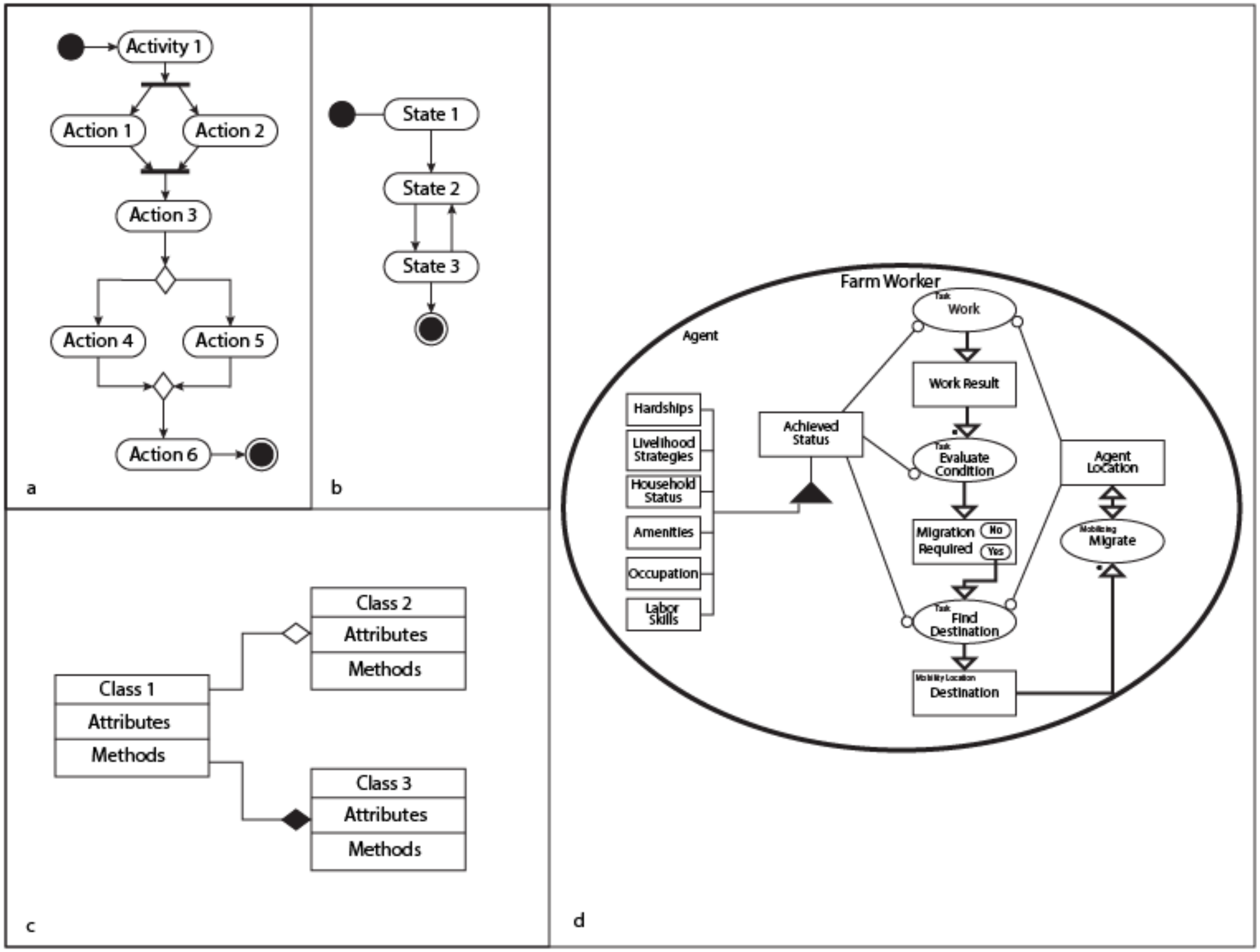


Figure 7: OPM vs. UML

Further, representing standalone processes requires wrapping that in object notation (a utility class, for instance). OPM solves these problems by allowing objects and processes to be depicted on the same diagram while explicitly stating their relationships, as well as the results of their interactions. On one OPD, you can capture the entirety of the structure and behavior for an ABM at a given scale. Generally, the only scenario in which multiple OPDs are needed is when a model needs to be shown at multiple scales. In this case, OPM enables the in- and out-zooming of model components, which itself facilitates the modeling process by enabling iterative or recursive development.

Reinhartz-Berger and Dori conducted a study investigating the comprehensibility of systems diagrams constructed using UML versus those constructed using OPM. Their results suggest that, in most scenarios, diagrams constructed using OPM were easier to understand and interpret. The primary scenarios in which UML performed better were those involving system components that UML had specialized notation to deal with. It would follow, then, that a version of OPM that has been extended to accommodate multi-agent systems would allow the creation of OPDs that are highly comprehensible and easily constructed.

While UML may have the upper hand where software development is concerned, particularly when considering the abundance of automation tools available, OPM allows a great deal of clarity as well as flexibility. Importantly, its ability to represent processes independent of objects immediately frees model developers from the constraints of object-oriented programming, which may not always be appropriate. This is particularly advantageous when considering that a common language of choice for model developers due to its scientific capabilities is Python, which, while enabling object-oriented functionality, is not a strictly object-oriented language. While I have argued that the proposed methodology is more theoretically sound and highly pragmatic, particularly when compared with approaches utilizing UML, it does fare worse than UML in terms of its ubiquity and familiarity in software development. While OPM may produce models that are easier to comprehend and understand, UML has the advantage of age, which means that there are more tools available to create, document, interpret, and even generate code from UML diagrams. Given its current lack of familiarity in the software world, it is not likely that OPM will have many tools available for it anytime soon, which means that ABM developers will have to forego them or roll their own.

The proposed methodology is, however, more ideal than existing alternatives, particularly when complex social behaviors need to be captured and quantitative approaches are not effective. Returning to Huigen's methodology (2006) when constructing the MameLuke settlement model, it is evident that, in comparison, the use of mental models in combination with OPM/MAS is much more versatile in terms of its implementation, as it is not dependent on any existing framework. Huigen's methodology is also less able to be adequately informed by long-form qualitative textual data, such as can be produced when ethnographic methods are employed.

Earlier in this paper, I asked how a developer of an agent-based model of complex sociological systems should decide who the agent represents and how the agent should behave. This, as I've argued, requires an understanding of both the agent's cultural and political contexts at multiple scales. In addition, the developer's own sociopolitical context must be considered to ensure that the production and dissemination of scientific knowledge based on the ABM is not exploitative in any way (Robbins 2004). Political Ecology provides insight into this issue, and served as a general guideline for the development of our methods and our products.

Importantly, it provided additional theoretical support for the use of qualitative methods to address some of the more challenging aspects of a culturally-aware ABM. As individual and cultural perceptions of the environment vary significantly, it is important to make use of the insights that qualitative methods such as ethnographic interviews provide (Atkinson 2008; Ingold 2000; Lansing 2003). In doing so, a model developer can not only ensure that his model does not impose his own environmental perceptions on the modeled individuals, but also ensure that the model more accurately represents the socioecological phenomena under investigation. By unifying existing techniques into a single workflow as described in this thesis, researchers unlock new organizational structures for their data that better highlight relationships found in qualitative data sources. This provides more obvious and defensible motivations for specifying agent behavior that reflects the experience of Dust Bowl Migrants. Further, the use of OPM enables the representation of multiple subjective realities within a single model, which may be required following in-depth analyses of data. This is quite important, considering the emphasis placed on "the individual" and heterogeneity within ABM (Miller and Page 2007; Epstein 1999).

It is worth considering the possibility of further reducing the a priori boundaries within models. Environments do not necessarily need to be represented as entirely discreet entities within a model, but could be broken into components that have been identified within the data as major environmental actors. Within OPM, these environmental components could be represented as either objects or processes and be truly embedded within the larger socioecological system rather than an isolated environment with which the social system interacts. While this has not yet been done with our current project, the methodology proposed in this paper certainly enables such an approach, particularly if the model developers make use of Grounded Theory (Zenobia 2008; Glaser and Strauss 2008).

CHAPTER 6: SUMMARY

The goal of this thesis was to establish an approachable yet effective method for utilizing long-form key informant interviews as data sources in the development of agent-based models. To achieve this goal, a few important hurdles had to be cleared. The justification for using this data source had to be made, which included a discussion of the politics of model development and the ways in which people perceive and interact with the spaces around them. Once that had been accomplished, I presented a method for accessing this data using an innovative mental model that captures the various thought and decision making processes of the informants. This mental model provided clear and direct linkage between model components and elements in the source data, which made it ideal for use in production of an agent model. Keeping in line with the theoretical and ontological perspectives presented earlier in this thesis, Dori's Object-Process Methodology, which was later extended by Sturm for Multi-Agent Systems, was chosen for use in the development of the agent model diagram itself. The resulting Object-Process Diagram retained clear connection to the data presented in the mental model while presenting both the structure of the agent and the behavior it exhibits. This multi-step process, starting with key-informant interviews and ending with the production of an OPD, provides a simple and elegant solution to problems faced when incorporating qualitative data into the ABM development process. Additionally, it avoids adhering too strictly to any physical model structures, as would be the case if alternative modeling approaches had been used.

Future work in this regard should investigate the overall flexibility and appropriateness of Sturm's OPM/MAS for complex spatial socioecological systems, and would perhaps include revisions that adjust its representation of agent groups and cultures to be more in line with recent trends in human geography, anthropology, and sociology. Doing so could significantly enhance the ability to model the migration events discussed in this thesis. The proposed methodology itself should be expanded in the future to incorporate full coupling of other human and natural systems and elegantly handle the inclusion of associated quantitative data.

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