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Agent-Based Modeling in Coupled Human and Natural Systems (CHANS): Lessons from a Comparative Analysis

Li An,^{*} Alex Zvoleff,^{*} Jianguo Liu,[†] and William Axinn[‡]

^{*}Department of Geography, San Diego State University

[†]Center for Systems Integration and Sustainability, Michigan State University

[‡]Survey Research Center, University of Michigan

Coupled human and natural systems (CHANS) are characterized by many complex features, including feedback loops, nonlinearity and thresholds, surprises, legacy effects and time lags, and resilience. Agent-based models (ABMs) are powerful for handling such complexity in CHANS models, facilitating in-depth understanding of CHANS dynamics. ABMs have been employed mostly on a site-specific basis, however. Little of this work provides a common infrastructure with which CHANS researchers (especially nonmodeling experts) can comprehend, compare, and envision CHANS processes and dynamics. We advance the science of CHANS by developing a CHANS-oriented protocol based on the overview, design concepts, and details (ODD) framework to help CHANS modelers and other researchers build, document, and compare CHANS-oriented ABMs. Using this approach, we show how complex demographic decisions, environmental processes, and human–environment interaction in CHANS can be represented and simulated in a relatively straightforward, standard way with ABMs by focusing on a comparison of two world-renowned CHANS: the Wolong Nature Reserve in China and the Chitwan National Park in Nepal. The four key lessons we learn from this cross-site comparison in relation to CHANS models include how to represent agents and the landscape, the need for standardized modules for CHANS ABMs, the impacts of scheduling on model outcomes, and precautions in interpreting “surprises” in CHANS model outcomes. We conclude with a CHANS protocol in the hope of advancing the science of CHANS. *Key Words:* agent-based modeling, coupled human and natural systems (CHANS), cross-site comparison, land use and land cover change, modeling protocol.

人类—自然耦合系统 (CHANS), 以诸多复杂的特色为特徵, 包括回馈循环、非线性性和閾值、意外、遗留效应和时滞, 以及恢復力。代理人基模型 (ABMs) 能够强而有力地处理 CHANS 模型中的复杂性, 并促进对 CHANS 动态的深度理解。但 ABMs 大多仅运用于特定的场所, 并鲜少提供 CHANS 研究者 (特别是从事非模式化的专家) 理解、比较和展望 CHANS 过程及动态所需的共同基础。我们根据概要、设计概念及细节 (ODD) 的架构, 发展以 CHANS 为导向的协定来推进 CHANS 科学, 以协助 CHANS 模式化的从事者及其他研究者建立、记录和比较以 CHANS 为导向的 ABMs。我们运用此一方法, 藉由聚焦两个众所週知的 CHANS 之比较——意即中国的卧龙自然保护区以及尼泊尔的奇旺国家公园, 显示 CHANS 中复杂的人口统计决策、环境过程与人类—自然互动, 如何可与 ABMs 透过相对直接且标准化的方法被再现与模拟。我们从与 CHANS 模型相关的跨地点比较中习得以下四点, 包含如何再现代理人 and 地景、CHANS ABMs 的标准化模型的必要性、调度对模型结果产生的影响, 以及诠释 CHANS 模型结果中的意外的预防。我们于结论中提出 CHANS 协定, 期望以此推进 CHANS 科学。关键词: 代理人基模式化, 人类—自然耦合系统 (CHANS), 跨地点比较, 土地使用及土地覆盖变迁, 模式化协定。

Los sistemas humanos y naturales acoplados (CHANS, por el acrónimo inglés) se caracterizan por muchos rasgos complejos, incluyendo giros de feedback, no linealidad y umbrales, sorpresas, efectos legados y retrasos de tiempo, y resiliencia. Los modelos basados en agente (ABMs) se muestran como potentes en el manejo de tales complejidades en los modelos CHANS, lo cual facilita un entendimiento a profundidad de la dinámica CHANS. Sin embargo, los ABMs han sido empleados principalmente con base en la especificidad de sitio. Muy poco de este trabajo proporciona una infraestructura común con la cual los investigadores de CHANS (especialmente los expertos que no utilizan modelos) pueden comprender, comparar y visualizar los procesos y dinámica de los CHANS. Nuestra contribución al avance de la ciencia de los CHANS es el desarrollo de un protocolo orientado a los CHANS basado en el resumen, conceptos de diseño y detalles (ODD) de estructura para ayudar a los

modeladores de CHANS y otros investigadores a construir, documentar y comparar los ABMs de orientación CHANS. Utilizando este enfoque, demostramos cómo pueden representarse y simularse en CHANS complejas decisiones demográficas, procesos ambientales e interacción humano-ambiental, dentro de una visión estándar relativamente directa con los ABMs, centrando la atención en una comparación de dos renombrados CHANS en el mundo: la Reserva Natural Wolong de China y el Parque NACIONAL Chitwan en Nepal. En las cuatro lecciones clave que aprendimos de esta comparación de un sitio a otro en relación con los modelos de los CHANS se incluye cómo representar agentes y el paisaje, la necesidad de módulos estandarizados para los ABMs de los CHANS, los impactos de programar resultados de los modelos y las precauciones para interpretar “sorpresas” en los resultados de los modelos CHANS. Concluimos con un protocolo CHANS con la esperanza de ayudar así a avanzar la ciencia de los CHANS. *Palabras clave:* *modelado basado en agente, sistemas humanos y naturales acoplados (CHANS), comparación a través de sitios, cambios de uso y cobertura de la tierra, modelando protocolos.*

Many ecosystem services vital to human existence and well-being have been degraded due to population pressures and unsustainable exploitation of natural resources (Vitousek et al. 1997; Foley et al. 2005). This poses a global challenge to scientists and practitioners about how to better understand these changes and manage ecosystem services. Although some researchers have long realized the importance of, and have invested efforts in, coupling human and natural systems, until recently much research still emphasized either human systems or natural systems (J. Liu et al. 2007; An 2012), largely holding the other as exogenous or as background. This approach gives inadequate attention to the reciprocal relationships that often exist between human and natural systems over space and time. Human interference in these systems can have unexpected consequences. For instance, human activities might lead to sudden shifts in natural systems from desirable to undesirable states (Folke et al. 2004), such as from a clear lake to a lake with toxic algae blooms (Folke et al. 2002).

The division between natural and social sciences, along with the assumption that connections between natural and human systems are decomposable into a set of simple, unidirectional relationships, has hindered understanding of these systems. Empirical studies on human–nature systems (e.g., Bian, Quattrochi, and Goodchild 1997; Irwin and Geoghegan 2001; Deadman et al. 2004; An et al. 2005; Crawford et al. 2005; Grimm et al. 2005; Messina and Walsh 2005; Brown et al. 2008; Yu et al. 2009) reveal a range of features that are difficult to address using this traditional approach. These features include (1) reciprocal effects and feedback loops: humans and nature interact with each other and form complex feedback loops; (2) nonlinearity and thresholds: the relationships within or among coupled systems are often nonlinear, and there exist transition points (thresholds) between alternate states; (3) surprises: surprising outcomes are observable as a result

of human–nature couplings; (4) legacy effects and time lags: prior human–nature couplings have substantial impacts on later conditions; (5) resilience: human–nature systems are capable of retaining similar structures and functioning after disturbances; and (6) heterogeneity: even within a system substantial differences exist in socioeconomic variables, human choices and behavior, and ecological conditions and should not be ignored (J. Liu et al. 2007). Corroborating evidence for these features also comes from the Amazon (Malanson, Zeng, and Walsh 2006a, 2006b), the southern Yucatán in Mexico (Manson 2005), northern Ecuador (Walsh et al. 2008), China (J. Liu 2010), North America (Lepczyk et al. 2008; Rutledge et al. 2001), and other places around the world (Rindfuss et al. 2008; An 2012).

In this context, complexity refers to the six features just mentioned along with a set of features not analytically tractable from system components and their attributes alone, such as path dependence, self-organization, difficulty of prediction, and emergence (Manson 2001; Bankes 2002; An 2012). Complexity theory, from the study of complex systems, offers great potential to address these phenomena. With partial origin from general systems theory (Von Bertalanffy 1969; Warren, Franklin, and Streeter 1998), the study of complex systems focuses on heterogeneous subsystems, autonomous entities, nonlinear relationships, and multiple interactions such as feedbacks, learning, and adaptation (Arthur 1999; Axelrod and Cohen 2000; Manson 2001; Crawford et al. 2005). Instead of a cure-all, the complex systems approach provides a unique systematic paradigm to harness complexity instead of decomposing it into (often) oversimplified unidirectional linkages. On account of this capacity, the complex systems approach helps system managers to take innovative action to steer systems of interest in beneficial directions (Axelrod and Cohen 2000).

Building on complexity theory, researchers investigating human–nature systems and ecosystem services

have developed the coupled human and natural systems (CHANS) framework (J. Liu et al. 2007). This framework has evolved in parallel with many closely related concepts similar to or parts of CHANS, including coupled natural and human (CNH) systems, human–environment systems (Turner et al. 2003), social–ecological systems (SES; Ostrom 2007), and social–environmental systems (Eakin and Luers 2006). Both these other integrative approaches and the CHANS framework provide many theoretical advantages and empirical insights, including those already mentioned. Understanding CHANS is by no means a trivial task, however.

Understanding CHANS requires modeling approaches that can represent these relationships and the characteristic structures and processes of CHANS (J. Liu et al. 2007). Given this requirement, agent-based modeling is an ideal modeling tool for CHANS. Agent-based modeling builds in part on the long history in the spatial and social sciences of trying to understand and represent relationships and networks between human actors and landscape change (Latour 1996; Epstein 1999). First, agent-based models (ABMs) can integrate data across spatial, temporal, and hierarchical scales and directly capture the relationships between system components and decision-making processes of individual agents (An 2012). CHANS are defined in large part by the reciprocal relationships between their component parts, or agents. Agents might be human actors on the landscape, or agents might represent structures (e.g., governing bodies) that could constrain and shape processes on the corresponding landscape. At a basic level, CHANS ABMs represent individual agents and their environment in a computer model, where agents of the same type or agents at different levels of a scalar hierarchy (e.g., persons, households, and cities) can interact with one another. ABMs can also represent external forces (e.g., climate, policy, economic conditions) that a modeler might not choose to model directly but that could be important to the processes being modeled within a certain ABM.

Although great progress has been made in modeling CHANS using ABMs in the past decade (J. Liu and Ashton 1999; Axtell et al. 2002; Parker et al. 2003; Deadman et al. 2004; Evans and Kelley 2004, 2008; An et al. 2005; Monticino et al. 2007; Werner and McNamara 2007; Entwisle et al. 2008; An 2012; Chen et al. 2012), generalizing findings from CHANS research remains a continuing challenge. Previous synthesis of CHANS studies prioritizes effort to integrate site-specific case studies to reach broader, generalizable con-

clusions (Turner et al. 2003; J. Liu et al. 2007; Acevedo et al. 2008). Given the degree of site-specific detail that is often included in ABMs, and variations in the design and structure of ABMs of different sites, it can be difficult to compare ABM-related findings from case studies. To address this challenge, we present here a comparison of two CHANS ABMs: one in the Wolong Nature Reserve, China, and the other in the Chitwan Valley, Nepal (Figure 1). Our goal is to highlight the similarities and differences between these two models, to focus on generalizations of modeling approaches, and to raise several issues of importance for CHANS agent-based modeling. We begin by introducing the two CHANS.

The Wolong Nature Reserve, established in 1975, is one of China's flagship nature reserves for the endangered giant panda (*Ailuropoda melanoleuca*; Viña et al. 2008; Tuanmu et al. 2010). The reserve is internationally recognized as part of a global biodiversity hotspot (Myers et al. 2000; J. Liu, Linderman et al. 2001; J. Liu, Daily et al. 2003) and, until the Wenchuan Earthquake in 2008, was a major tourist destination in China (He et al. 2008; W. Liu et al. 2012). Wolong is also home to more than 5,000 local villagers living within approximately 1,120 households (as of 2005; Wenchuan County 2006). These villagers live a subsistence lifestyle and collect fuelwood from forests, an activity that directly affects panda habitat (Chen et al. 2009). They might reduce fuelwood consumption if a subsidy is provided for more use of electricity (the only substitutable energy source) or if available forests become more distant from their households (An et al. 2002). Other legal activities, such as farming and husbandry, exert less direct impact on panda habitat (Viña et al. 2007). Wolong features a rugged and drastically varying terrain with elevation ranging from approximately 1,000 m to over 6,200 m, giving rise to drastic changes in vegetation and land cover type (Liu, Ouyang, Tan, et al. 1999).

Our second case study site, the Chitwan Valley, is located in south-central Nepal along the Nepal–India border. The area, formerly densely forested, was partially deforested in the 1950s to make way for settlement and agricultural land use, and eradication of malaria in the area contributed to a rapid increase in population (Barber et al. 1997). We focus our study on the western part of the Chitwan Valley, which at the time of the last available census in 2011 supported a population of 284,939 people (Central Bureau of Statistics [CBS] 2012). The valley, part of the lowland Terai landscape at the foothills of the Himalayas, is generally flat, with

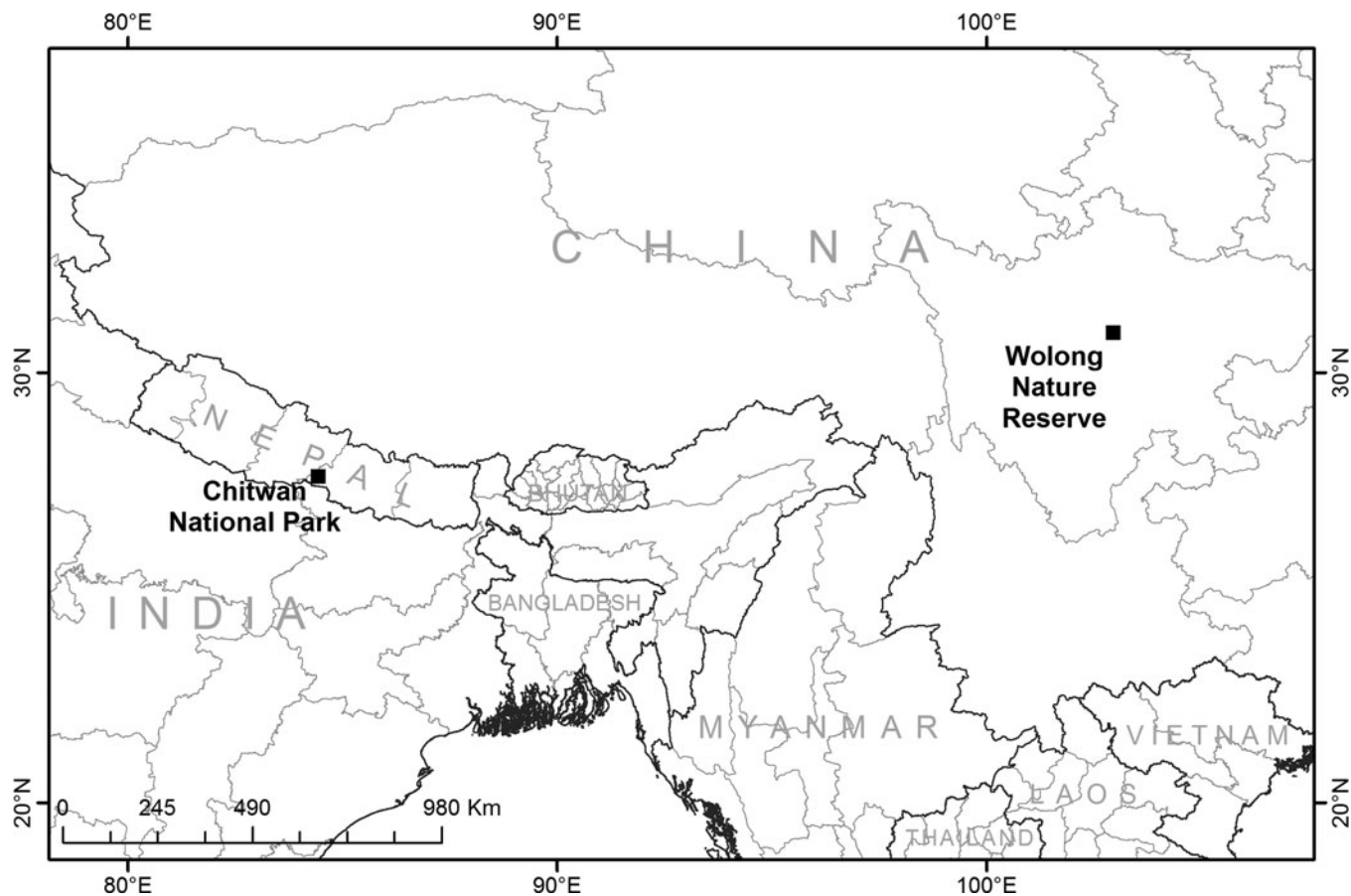


Figure 1. The location of our study sites: Wolong Nature Reserve in China and Chitwan Valley in Nepal.

a mean elevation of about 320 m. The western part of the valley we focus on here is bordered by rivers to the west and north and the Chitwan National Park and Barandabar forest (a protected buffer zone forest) to the south and east, respectively. The 932-km² national park (established in 1973) and its 750-km² buffer zone (established in 1996) provide habitat for endangered species including the Bengal tiger (*Panthera tigris tigris*) and one-horned rhinoceros (*Rhinoceros unicornis*; Carter, Riley, and Liu 2012).

Comparison Approach

The complexity of ABMs can complicate textual description. Making model code freely available is a step toward transparency, but code is often only understandable by experts (Parker et al. 2003; Grimm et al. 2005). Some CHANS researchers are modeling experts interested in duplicating model results (which is certainly important), but generalization of CHANS findings requires making model structure and results readable by a

nonspecialist audience. Thankfully, there has been recent progress in development of communication methods for ecological models (Schmolke et al. 2010) and for ABMs (individual-based models, or IBMs in the ecological literature) specifically (J. Liu and Ashton 1999; Grimm et al. 2006). The overview, design concepts, and details (ODD) framework developed by Grimm et al. (2006; Grimm et al. 2010) and Grimm and Railsback (2012) is a framework for describing ABMs in a standardized format. The ODD framework has been successfully used to describe ABMs in ecology and other disciplines (Grimm et al. 2010) and has also been adopted by many models in the model library maintained by the Open ABM Consortium (Janssen et al. 2008).

Using the ODD protocol, we compare the Wolong and Chitwan ABMs and present the differences and similarities in their model structure. Low-level programming details, including software or platform-specific parameters, are skipped for brevity. The two models are described elsewhere with additional details for a technical audience (An et al. 2005; Zvoleff and An forthcoming).

As ODD is primarily designed to document ABMs rather than to discuss model reliability, we add two additional components to our description—model verification and validation and CHANS characteristic features (under “Model Comparison”). Verification and validation are essential steps before CHANS ABMs can be put into use for purposes such as experimentation, prediction, and scenario analysis (Schmolke et al. 2010). Although debate continues regarding whether models for complex systems like CHANS can be “verified” or “validated” (Oreskes, Shrader-Frechette, and Belitz 1994), we use the term *verification and validation* in the sense that models are tested in relation to their objectives, intended use, and application domain (Overton 1981; Rykiel 1996). Our working definition for verification is to check for proper functioning of the program and for validation is to investigate the correspondence between the software model and the conceptual model (structural validation) and that between model outcomes and empirical data (empirical validation; see Manson 2001; An et al. 2005). By adding model verification and validation and CHANS characteristic features as ODD elements, we extend ODD to ABMs of complex CHANS, enriching ODD to apply to a broader audience of CHANS researchers.

Model Comparison

Following the ODD protocol, we summarize the comparison results (Table 1). Guided by this framework, we compare and contrast the similarities and differences between the Wolong ABM and Chitwan ABM and explain the rationale for alternative model design decisions. Our goal is to shed light on the lessons that we can learn for modeling CHANS using ABMs.

Purpose

The Wolong ABM aims to integrate socioeconomic, demographic, and biophysical processes operating at different spatial, temporal, and organizational scales into a systems model and to understand and envision how the habitat of the giant panda might evolve in response to changes in the preceding processes (An et al. 2005). The Chitwan ABM was constructed with similar aims of data integration across spatial and temporal scales. As prior work at the Chitwan study site has uncovered reciprocal connections between environment and human processes, the Chitwan ABM additionally focuses heavily on representing these connections.

Entities, State Variables, and Scales

Next we present a list of agents, their state variables and actions, and the similarities and differences in the two ABMs. We then compare the representations of the environment in the Wolong and Chitwan ABMs.

Structure of Agents. A real human society can include a number of hierarchical levels, such as individuals, households, and communities of different types and scales, regional institutions, and national institutions. Both ABMs follow this pattern, although slight differences exist in how each model creates and manages agents: The Wolong ABM has a hierarchy of person, household, and environment agents (Table 2). This structure is mirrored in the Chitwan ABM with the addition of community-level agents between household and environment. Community agents in the Chitwan ABM represent a cluster of (usually ten to twenty) households that live in close proximity and share common community context—defined as similar access to markets, employment opportunities, schools, bus stops, and health centers. The inclusion of this additional level in the Chitwan ABM is due to the abundant research in Chitwan about how community context might affect demographic and land use decisions (e.g., Axinn et al. 2007; Ghimire and Axinn 2010; Axinn and Ghimire 2011).

The agents in the Wolong and Chitwan ABMs have a set of state variables that vary depending on the type of agent. The state variables associated with each agent type also vary slightly between the two models. We discuss only the major differences between the two models here—for a complete overview of each type of agent and the associated state variables in the two models, see our online supplement (<http://complexity.sdsu.edu/CHANS-ABMs>).

Person agents in both models maintain a set of state variables tracking interrelationships among each other (person agents have unique person ID variables) as well as their personal life history events, preferences, and parents’ characteristics. The key differences between the Wolong and Chitwan models are in (1) fertility: the Wolong ABM includes an allowed number of children parameter to reflect governmental family planning policies in China; (2) parental characteristics: the Chitwan ABM associates with each person agent information on that person’s parents’ employment activities; (3) ethnicity: the Chitwan ABM tracks person agent ethnicity, which explains a portion of the variability in marriage timing, fertility, fuelwood consumption, and migration

Table 1. Comparison of the Wolong and Chitwan ABM models: Summary

		Wolong ABM	Chitwan ABM
Overview	Purpose	Integrate multiscale and multidisciplinary data to envision panda habitat over time and space	Integrate multiscale and multidisciplinary data and feedback between demographic and environmental change
	Entities, state variables, and scales	Persons, households, and their major demographic attributes	Similar to Wolong, except that communities are added
Design concepts	Process overview and scheduling	Initiation of agents and environment; forest growth and fuelwood collection; demographic submodels	Initiation of agents and environment; demographic submodels, land change, and fuelwood submodels
	Basic principles	Agent's self- and environmental awareness; maximizing economic utility; minimizing energy costs	Same as Wolong
	Emergence	Habitat and population indexes vary unpredictably with demographic and socioeconomic conditions	Land use change, household size, and fuelwood consumption vary unpredictably with changing demographics
	Adaptation	Change fuelwood search radius and reduce fuelwood demand when forest becomes farther	Change marriage or first birth timing as land use changes; change consumption as household size changes
	Objectives	Minimize the cost of wood collection; maximize economic utility by switching to electricity	Heuristics used to model decision process (e.g., outmigration follows empirically derived models)
	Learning	Agents "remember" the fuelwood location and distance from their household; change fuelwood search radius when forest becomes farther	Learning not explicitly modeled in the Chitwan ABM
	Prediction	Households calculate the distance to the nearest fuelwood collection site	Prediction is not modeled in the Chitwan ABM
	Sensing	Agents' awareness of demographic and socioeconomic characteristics of themselves and others	Same as Wolong
	Interaction	Marry; household formation (reducing vegetation), fuelwood collection	Marry; household formation (reducing vegetation)
	Stochasticity	Many (e.g., death submodel)	Many (e.g., death submodel)
Details	Collectives	Household agents are one type of imposed collective	Household and neighborhood agents are two types of imposed collective
	Observation	Personal, household, and population attributes and events; panda habitat	Personal, household, neighborhood, and population attributes and events; land use, fuelwood consumption
	Initiation	Create person and household agents and landscape objects using empirical data	Same; neighborhood agents
	Input data	Not used	Not used
	Submodels ^a	Demographic, socioeconomic, biophysical, and human–environment submodels	Same as Wolong

Note: Comparison is made based on the overview, design concepts, and details protocol (Grimm et al. 2006; Grimm et al. 2010). ABM = agent-based model.

^aRefer to other tables for details.

activities in Chitwan. The Wolong ABM only has a parameter *not leave parental-home intention* that is derived from An, Mertig, and Liu (2003). It represents the tendency that married young people, especially those with special sibling situations (e.g., birth order

among siblings), are more likely to leave their parental home and set up their own separate home. Due to lack of data, this parameter is set at an empirically derived constant without being linked to other socioeconomic, demographic, and environmental variables.

Table 2. Entities in the Wolong and Chitwan ABMs

Entity	Wolong ABM		Chitwan ABM	
	Present (n)	Purpose	Present (n)	Purpose
Person	Yes (4,314)	Represents an individual person and his or her attributes	Yes (8,245)	Same
Household	Yes (893)	Represents an individual household and its attributes	Yes (1,522)	Same
Neighborhood	No		Yes (151)	Represents the impact of neighborhood context on decision making
World	Yes (1)	The model world represents the biophysical environment and exogenous socioeconomic factors	Yes (1)	Same

Note: Entities are arranged starting with the lowest level of the hierarchy at the top of the table. ABM = agent-based model.

Household agents are composed of person agents (households could be considered imposed “collectives” in ODD terminology) but also possess their own unique, higher level state variables. In the Wolong ABM, households track their location (x , y coordinates) and electricity quality (price, voltage, and outage levels). In the Chitwan ABM, we track these variables at the community level. We model electricity quality variables at the household level in Wolong because they were the major concerns in local people’s decision to switch from using fuelwood to using electricity (An et al. 2002). In Chitwan, household agents additionally track land ownership (used in the fertility submodels), time of last migration (used in the migration and fuelwood usage submodels), and use of nonwood fuel sources (for the fuelwood usage submodel).

In Chitwan, another type of collective agent represents community context: the community agent. Community agents in the Chitwan ABM track community location (x , y coordinates of polygon vertices in the neighborhood boundary), land use, and community context variables. Community agents contain a set of lower level household agents but also possess their own, community-level state variables. Community context is measured in the Chitwan ABM by a series of variables tracking the distance in minutes on foot to a number of key community services and organizations: markets, employers, bus stops, health centers, schools, and the major urban area in the valley. These metrics are consistent with past work in Chitwan (e.g., Ghimire and Axinn 2010; Axinn and Ghimire 2011) that has documented the influence of changing community context on individual-level decision making.

Representation of Time and Environment. We describe the definition of environment and time in our models in two domains: (1) resolution, or the smallest (spatial or temporal) unit over which the phenomenon of interest is represented, and (2) extent, or geographic scope or time span over which a process operates or is measured. We use a yearly time resolution in the Wolong ABM as most of the data collection (e.g., socioeconomic data in statistical yearbooks), as well as processes or activities (e.g., harvest of crops, collection of fuel wood), occur on an annual, occasionally multiple-year, basis in Wolong. In the Chitwan model, we choose a monthly time step to match the primary empirical data sources behind the model (see “Initialization”), and to match the time scale of demographic processes such as migration. The time span for both models is set at twenty to fifty years depending on the outcome under study. This moderate time span allows considerable change in the modeled systems (e.g., vegetation regrowth) but does not span so long as to make the assumptions underlying the models untenable.

A key difference between the two models is in their representations of the physical environment, which represents the space where the corresponding agents reside or occur, and in many instances make the associated decisions. For instance, a person agent in Chitwan might look into the environment (e.g., surrounding land use) before making marriage timing and first birth timing decisions, and a household agent in Wolong might examine the physical distance between his or her household and the nearest forest before deciding how much fuelwood to collect (Sections 1 and 2, online supplement). The Wolong ABM represents the physical environment in a rectangle of 3,402 km² that

completely covers the reserve boundaries in tangent because our survey and observations show that the impacts of human activities, primarily fuelwood collection, often do not go beyond the reserve boundaries (J. Liu, Ouyang, Taylor, et al. 1999; An et al. 2005; Bearer et al. 2008; He et al. 2009; Hull et al. 2011). This rectangle consists of a lattice of 696 rows by 602 columns if the spatial resolution (pixel size) is chosen to be 90 m or optionally a lattice of 175 rows by 151 columns if the spatial resolution is chosen to be 360 m (An and Liu 2010). Our spatial resolutions are chosen partly due to the 30-m resolution of our major remote sensing data source (Landsat, from which we resample to the preceding resolutions) and partly due to our concerns regarding simulation speed. Too fine a spatial resolution would exponentially slow down simulation, which was a great concern at the time of developing the Wolong ABM, when technological advances (e.g., faster computers, parallel computing) were more limited. At the same time, we believe that the fine resolution of 90 m should suffice in capturing the major influence of fuelwood collection on panda habitat, and we use the coarse resolution of 360 m when higher level socioeconomic or demographic outcomes are of major interest.

The Chitwan ABM, in contrast, does not have a spatially contiguous landscape like the Wolong ABM. Instead, its physical environment is composed of 151 spatially disconnected communities that range in area from 350 to 300,000 m² with a mean of 75,000 m². These spatially disconnected communities are located within a region of 493 km², representing the full extent of the area north of the Chitwan National Park and west of the Barandabar buffer zone forest in Chitwan (Carter et al. 2013; Zvoleff and An forthcoming). The area of each community is calculated from a ground survey using tapes and compasses. Community-level state variables, including numerical values of the area of each land-use class (agricultural vegetation, nonagricultural vegetation, private buildings, public buildings, and other), are tracked within each community. We made this choice for the Chitwan ABM because the submodels (see “Submodels”; for details, see the online supplement) within the Chitwan ABM do not depend on the spatial distribution of land use within a community and because data limitations prevent the assignment of land parcels to particular households. Similar to the Wolong ABM, the Chitwan ABM also includes a 90-m spatial resolution grid of 319 columns and 189 rows (488 km²) containing elevation data from a Shuttle Radar Topography Mission (SRTM) digital elevation model. This data could support future work considering natural hazards.

Process Overview and Scheduling

Both ABMs, at the initialization step, set up the landscape and create person, household, and community (Chitwan only) agents. Each model reads in input data associated with each agent, and each agent is located on the landscape. The Wolong and Chitwan ABMs run with yearly and monthly time steps, respectively. We leave the explanation of these submodels for later but highlight the relationships between these processes (submodels) as well as differences and similarities between the two ABMs here (Figure 2). We can see that the Wolong ABM leans more toward forest dynamics and fuelwood collection, whereas the Chitwan ABM focuses more on land use that is primarily affected by new household formation. Also, the major demographic processes (i.e., migration, marriage, fertility, mortality) in Chitwan, unlike those in Wolong, are endogenous and thus receive impacts from the environment.

In both ABMs, a particular person agent experiences the demographic submodels within his or her lifetime not necessarily in the order of submodel placement in the code but in accordance with a set of sociodemographic constraints such as the age and marital status of that agent. Consequently, a person agent goes through the submodels in an order that mirrors the sequence of events in his or her personal life course. The mortality and the nondemographic submodels are exceptions, which we place in an order consistent with empirical expectations (see the sections “Submodels” and “Lessons Learned” for the effects of varying the sequence of submodels). To test the potential impact of scheduling on key variables of interest such as population size, number of households, and panda habitat (Wolong) or population size, number of households, and agricultural land use (Chitwan), we reversed the order of these submodels and ran thirty simulations.

Design Concepts

In this section, we discuss the similarities and differences in the design concepts guiding construction of the two ABMs, focusing on basic principles, objectives, learning, adaptation and prediction, sensing and interaction, and stochasticity.

Basic Principles. Both ABMs integrate theoretical findings from the geographic, sociodemographic, and ecological literature in a series of submodels linking human and natural systems at each study site. Both

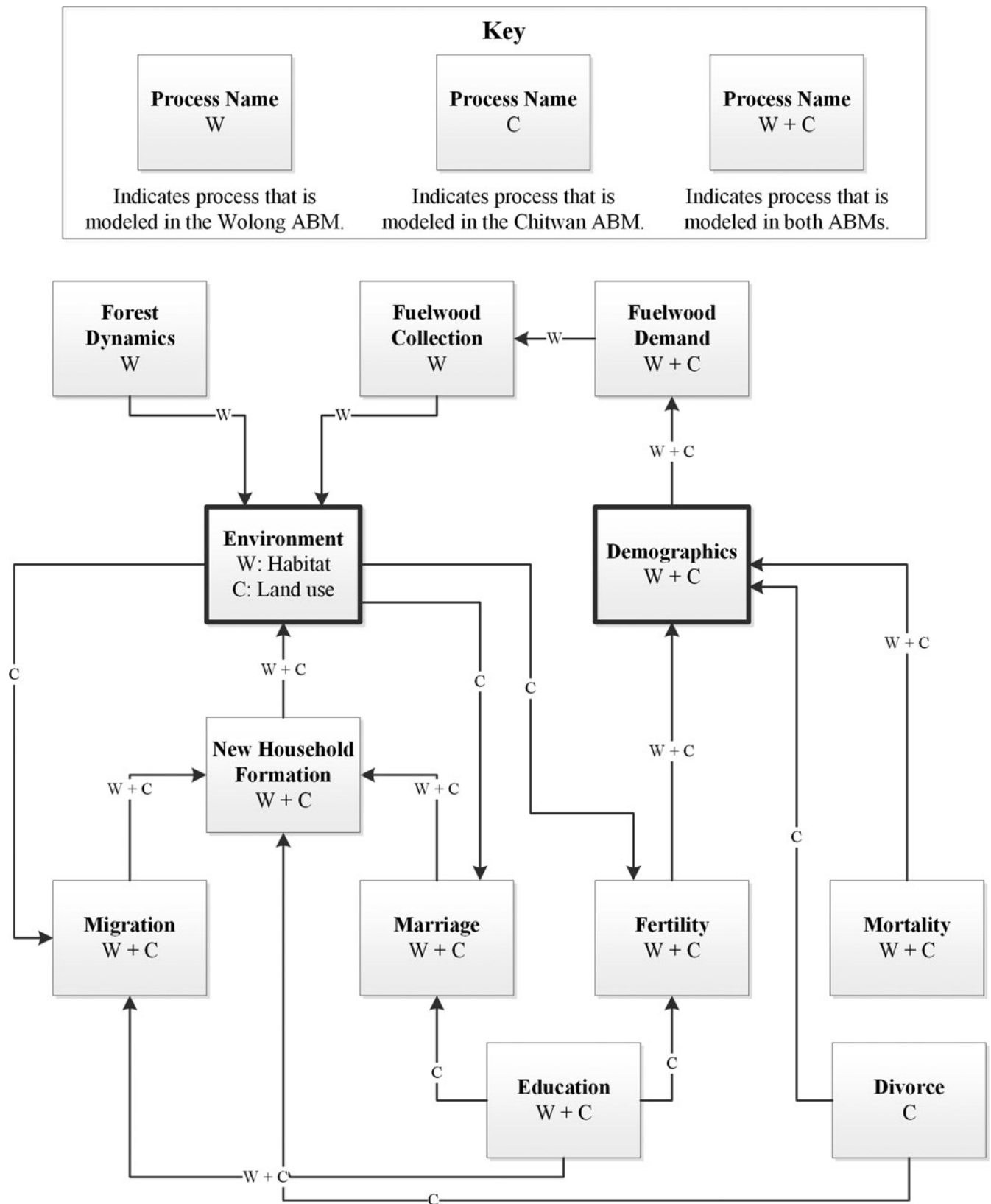


Figure 2. Comparison of the major processes between the Wolong ABM and the Chitwan ABM. The rectangles and arrows represent the major processes and links among them, respectively. Note: W = Wolong; C = Chitwan; ABM = agent-based model.

Table 3. Submodels in the Wolong and Chitwan ABMs

Category	Submodels	
	Name	Brief description
Demographic	Marriage – Marriage probability	The probability is empirically determined (Wolong) or regression-based (Chitwan).
	Marriage – Spouse choice	A qualified agent marries a local or immigrant with consideration of kinship, age, and ethnicity (Chitwan only).
	Fertility – Birth	A married woman bears a child if several conditions are met.
	Fertility – First birth timing	This timing is empirically determined (Wolong) or regression based (Chitwan).
	Household establishment	It follows a marriage with several constraints.
	Household removal	This happens when household size becomes zero. In Chitwan, nonpermanent migrants are allowed.
	Outmigration – Decision to outmigrate	Individuals or households (Chitwan) might migrate out contingent on age, sex, and other covariates.
	Outmigration – Outmigration length	The nonpermanent migrant (Chitwan) will return when enough time (equal to outmigration length) passes.
	Inmigration	Individuals or households (Chitwan) might migrate in contingent on age, sex, and other covariates.
	Divorce	It is controlled by a fixed monthly probability (Chitwan only).
Socioeconomic	Death	Each person may die according to age (and sex in Chitwan).
	Potential fuelwood demand	This is a linear function of covariates that are different in Wolong and Chitwan.
	Tendency to use electricity or fuelwood	The tendency is modeled as a probability function of covariates (different in Wolong and Chitwan).
Biophysical	Vegetation growth	This measures how pixels of different vegetation grow until reaching age or volume upper bounds (Wolong). In Chitwan, very few collect live wood.
Human–environment interaction	Fuelwood collection	A fuelwood collector chooses a pixel with the shortest cost distance (Wolong).
	Land use change	New building construction takes land from agricultural land (preferentially) or nonagricultural vegetation (Chitwan).

Note: See online supplement for details. ABM = agent-based model.

models represent agent decision making with varying degrees of stochasticity, implicitly assuming that agents make rational decisions bounded by certain knowledge or information constraints, to maximize their well-being. For example, we represent the energy transition in the Wolong and Chitwan models based on our understanding of household's attempts to minimize their energy costs. Our stochastic "tendency to use electricity or fuelwood" submodels (Table 3) implicitly represents this economic decision by assigning a probability of fuelwood usage to each household according to a number of covariates.

Both models assume two-way influences between sociodemographic features (or actions) and the local environment. For instance, household-level resource demands depend on a set of socioeconomic, demo-

graphic, and geographic variables in both models. Drawing on the richer longitudinal data available in Chitwan (see "Initialization"), the Chitwan ABM allows for more built-in endogeneity between demographic decisions and environmental change than does the Wolong ABM.

Objectives. The objectives of the agents within each ABM influence the construction, validation, and application of each model (Grimm et al. 2006). In the Wolong and Chitwan models, agents are modeled to encounter a number of decision-making points rather than to maximize "success" or achieve a particular objective. At each decision point, agents make decisions in accordance with the observed data, with a set of techniques (empirically derived probability distributions,

regression models, heuristic models, etc.) used to model decision-making processes. There are two exceptions: The first is the path finding model included in the Wolong model, in which agents seek to minimize the cost of wood collection (see the online supplement). The second is the decision to switch from using fuelwood to electricity, which implicitly aims to maximize household economic utility (An et al. 2002).

Learning, Adaptation, and Prediction. We group learning, adaptation, and prediction—three separate subcategories in the original ODD (Grimm et al. 2006)—into one category, as they are all related to agent decision making. Learning is a key part of the Wolong fuelwood collection model, in which agents “remember” the location and distance from their household of the last pixel on which they collected fuelwood. Adaptation is interpreted in an ecological sense; that is, as traits or rules of agents in “making decisions or changing behavior in response to changes in themselves or their environment” (Grimm et al. 2010, 2764), where traits or rules themselves might or might not change. Therefore, adaptation is represented in both the Wolong and Chitwan models. In the Wolong ABM, as fuelwood in nearby forest areas is depleted, agents adapt by changing their search radius to consider more distant forest patches. As available forests become farther, local people might also reduce their fuelwood demand and adapt by using more electricity. The Wolong ABM also allows a set of hypothetical conditions (related to electricity price, voltage, and outage) as policy controls, and local agents are modeled to predict the future consequences of such policies implicitly, where the policy-induced change in an unspoken household economic return is represented as inflated or lowered probabilities to use electricity in place of fuelwood.

In the Chitwan ABM, adaptation to conditions is reflected in the rules included in the stochastic submodels. For example, the marriage model uses the results of a logistic regression to predict probability of marriage in a given month for a particular person agent dependent on a set of person-level (age, gender, etc.) and community-level (including land use) state variables. As land use and community context change, marriage rates change at a magnitude determined by the coefficient of the corresponding variables in the regression model. We use similar approaches to model how fertility and migration behavior adapts to changing land use in the Chitwan Valley.

Sensing and Interaction. In both the Wolong and Chitwan ABMs, we assume that all person and household agents know their own demographic and socioeconomic characteristics as well as environmental features in their residence and surrounding areas (see “Entities, State Variables, and Scales” for details). This information informs the agent’s decisions. For example, in the Wolong ABM, when the fuelwood transportation distance varies, household agents change their probability of using fuelwood.

In both models, one of the primary interactions between agents is marriage. In the marriage submodel, two eligible person agents might get married to each other and build a new house or two married agents might divorce (Chitwan ABM only) with probabilities dependent on the state variables associated with that person, household, and community. Agents also interact with their environment. Although new household formation is the primary land change process in Chitwan, agents in the Wolong model also interact with their environment through fuelwood collection.

Stochasticity. Uncertainty is prevalent in many processes in CHANS. There is uncertainty in determining if, when, and where an event will happen. To reflect this fact, CHANS models often include stochastic processes, or processes with a certain degree of randomness. There are many stochastic processes in both ABMs. One example is the mortality submodel. In both models, to decide whether a person agent may die in a given time step, the model creates a random number between zero and one and compares it with the death rate of people in the corresponding age group (the Chitwan ABM is also gender differentiated). The person dies if the random number is smaller than the rate; otherwise, he or she survives to the next time step.

Initialization

The Wolong model is initialized with 4,314 person agents and 893 household agents. The Chitwan model is initialized with 8,242 person agents, 1,522 household agents, and 151 community agents. The primary data sources for the Wolong ABM are the 1996 Wolong Agricultural census (Wolong Administration 1996), the 2000 population census (Wolong Administration 2000), and in-person surveys of 220 households (conducted in 1999; An et al. 2001). The Chitwan ABM is parameterized primarily using data sets from the Chitwan Valley Family Study (CVFS; Axinn et al. 2007), a fifteen-year multilevel panel study launched

in 1995–1996. At the 1995–1996 baseline, a retrospective fifty-year neighborhood history calendar was collected for each sample neighborhood in the study, and a matched retrospective life history calendar was constructed for each individual respondent (Axinn, Barber, and Ghimire 1997; Axinn, Pearce, and Ghimire 1999). In January 1997, the CVFS launched a demographic event registry for all households and individuals in the baseline to track demographic events (births, deaths, marriages, and migrations) in the 151 sample neighborhoods in the western Chitwan Valley. The CVFS also produced detailed maps of land use and land cover and household agriculture and consumption measures in all study neighborhoods in 1996, 2001, and 2006. Additional fieldwork and household interviews were conducted by the authors in 2009 (80 households) and in 2011 (297 households) to further support development of the Chitwan ABM.

The two ABMs differ in the way they select agents to be included in the model. The Wolong ABM is initialized with every resident in the Wolong study area in 1996 represented as a person agent in the model. The Chitwan ABM, however, simulates only a sample of the total population of the western Chitwan study area. The sample used in the Chitwan ABM is taken from the respondents of the CVFS (Axinn et al. 2007). The CVFS sample includes 1,522 out of the 30,838 households in Chitwan as of the 1991 census (CBS 1991). This sample is distributed among 151 communities spread throughout Chitwan, each with a set of household and person agents. The 151 communities in the model act as a set of “windows” into human–environment interactions within Chitwan (Zvoleff and An forthcoming). This “sample” approach allows examination of spatial and temporal variation in demographic processes without the need to simulate all (more than 200,000) individual agents in the model (see “Lessons Learned” for additional details on initialization of CHANS ABMs).

When assigning initial values to agent state variables and submodel parameters, we make a distinction between model parameterization and model calibration. Calibration is the process of tuning the model parameters so that model output matches what is empirically observed (Oreskes, Shrader-Frechette, and Belitz 1994). Parameterization, on the other hand, refers to the process of empirically determining parameter values based on observed data from the system itself, including surveys, plot data, and household registries. To avoid the problem of tuning the model to fit our expectations, we derive the parameter values used in the Chitwan and Wolong ABMs empirically.

Input Data

Neither model uses external data inputs to model external forcings.

Submodels

The two ABMs are imbalanced in the amount of information included in the different types of submodels. Given the multiple types of interactions modeled in each of these CHANS, we break the submodels up into four key categories: demographic submodels, socioeconomic submodels, biophysical submodels, and human–environment submodels. In general, the Wolong ABM tends toward a higher degree of detail in the biophysical submodels, whereas the Chitwan ABM includes greater detail in the demographic submodels. Due to the key role of human demographic decisions in affecting CHANS dynamics and availability of the relevant data (especially in Chitwan), the majority of our submodels are about demographic processes or decisions (Table 3). The other types of submodels in general include less detail and are developed as part of our ABMs according to our site-specific understanding of key CHANS processes affecting our major dependent variable(s) (panda habitat in Wolong and agricultural land use in Chitwan).

The submodels in both ABMs are parameterized drawing on the census and survey data sources (see “Initialization” for details) and a set of standard statistical techniques, including empirically derived probability distributions, ordinary least squares regression, generalized linear models, multilevel modeling, and event history analysis (Zvoleff and An 2014). The brief characteristics of these submodels are summarized in Table 3 with details posted online at <http://complexity.sdsu.edu/CHANS-ABMs>. Next we present an overview and comparison of the submodels in the two ABMs.

In the Wolong ABM, the forest dynamics submodel runs first after the agents and landscape are initiated and mapped (Figure 3). This is a process of natural growth of the four vegetation types (derived from satellite imagery) according to empirical data (Section 3 of the online supplement). Following this natural process, the fuelwood collection submodel (Section 4 of the online supplement) runs based on the fuelwood demand assigned to each household during model initiation. Later all households choose the nearest (in cost-distance) forest patch and cut down trees at an amount determined by the household fuelwood demand submodel. Humans

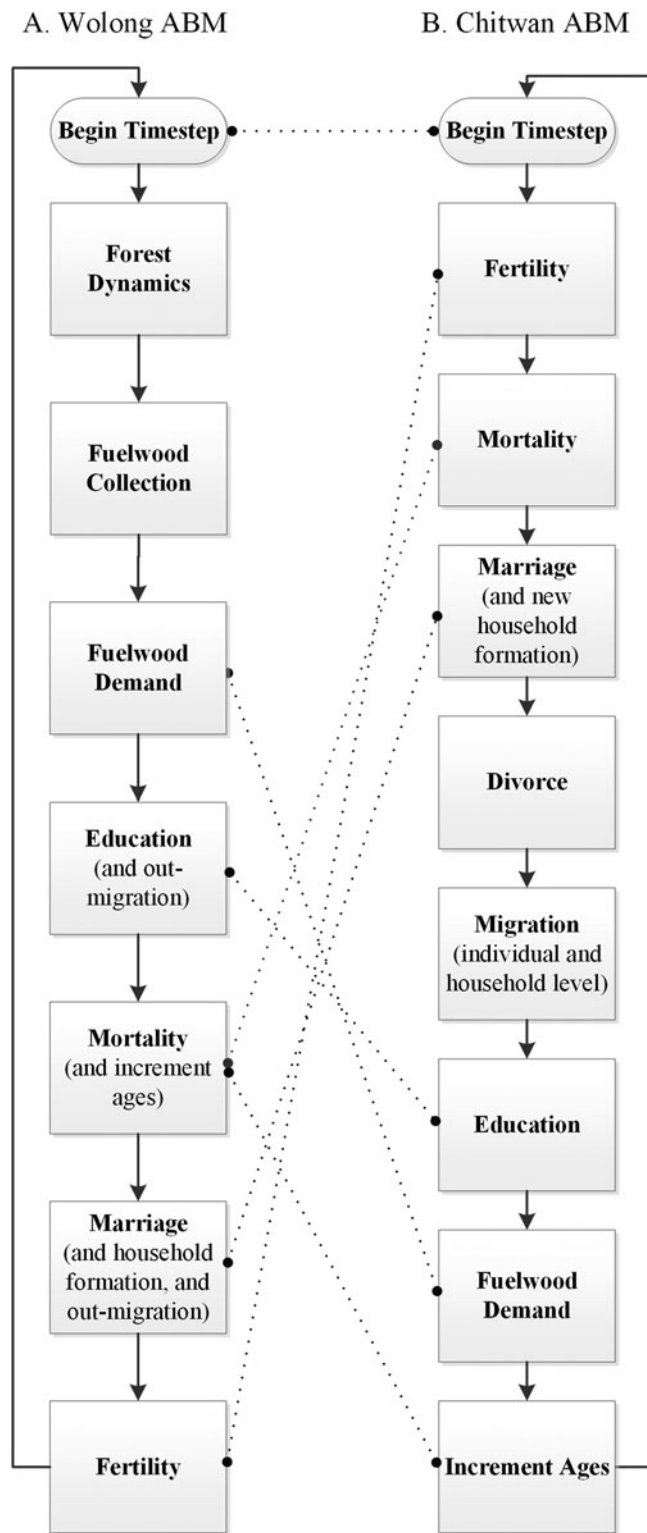


Figure 3. Sequence of the major submodels in the Wolong ABM and the Chitwan ABM. The arrows link submodels that are run in a sequential order (i.e., from the earliest to the latest) at each time step. The dotted lines link similar submodels in both ABMs. *Note:* ABM = agent-based model.

affect the environment (panda habitat in particular) through this major means (Linderman et al. 2005). Next, the Wolong ABM runs the household fuelwood demand submodel, which calculates fuelwood demand based on household socioeconomic (including electricity substitution) and demographic data (Section 2 of the online supplement). Then the model runs the education (and outmigration) submodel, where all people between sixteen and twenty may go to college or technical school at an empirical probability and thus migrate out of the reserve (Section 1.6.1 of the online supplement). Following that, the model runs the mortality (and increment ages) submodel, in which each individual either dies if the random number generated is less than the corresponding age- and sex-based mortality rate or has his or her age incremented by one year. Then the Wolong ABM runs the marriage (and household formation, and outmigration) submodel, where each person, once eligible (or after passing several checks), could marry a local or outside person according to different empirically derived probabilities. This submodel, when checking all related information (age, sex, sibling order), also incorporates postmarriage establishment of new households and resource (farmland primarily) allocation. Finally, the fertility submodel is implemented, where all eligible women (married without children or married with fewer children than desired, and provided that enough time has elapsed since marriage or the last live birth) may bear children.

The Chitwan ABM runs a similar series of submodels in sequence with a scheduling order that agrees with our data and insights into the system. First, the fertility submodel runs, which handles women's first childbearing after marriage and then handles subsequent births to women who have already had their first child, are within the allowed age range to give birth (age fifteen to forty-five), and have fewer than their desired total number of children. The mortality submodel runs next, in which each person agent is subject to a small probability of dying within the time step, dependent on the agent's age and sex. The marriage submodel follows, in which the results of an empirical model are used to calculate the probability of each eligible agent (unmarried person agents older than age fifteen) marrying within the time step (Yabiku 2006). Married couples move out of the husband's parental home with a fixed probability, the *household fission rate*, which is determined empirically. If they move out, they establish a new household on agricultural land (an empirical observation), converting the land to private infrastructure. We draw the parcel size for the new household from an empirical

probability distribution. Following the marriage submodel is the divorce submodel, in which each married individual is subject to a small probability of divorce within the time step. Next, the migration submodel allows in- and outmigration at the individual and household levels. We calculate the probability of individual outmigration outside of the western Chitwan Valley study area for each eligible person agent (those older than fifteen years old), again based on an empirical model including individual-, household-, and neighborhood-level covariates (Massey, Axinn, and Ghimire 2010). A separate portion of the migration submodel determines the probability a migration will be permanent or, if not, the length of time an individual will be absent from the valley. Household-level in- and outmigration is determined with simpler models (given the limitations of our empirical data). For household-level outmigration, we assign a single probability of outmigration to all households in the model. For household-level immigration, we assign a histogram of the number of households that might immigrate in a given time step. The number of immigrating households is chosen from this histogram. The education submodel uses empirical data from the CVFS to model the final years of schooling each individual will achieve, based on sex, ethnicity, and community characteristics. Finally, in the fuelwood demand submodel, the probability of a household using fuelwood is modeled with an empirically derived logistic regression model, and the total fuelwood demand is determined based on a linear model taking into account household size, ethnicity, stove type, and household gender composition.

As already seen, the scheduling order in the Wolong and Chitwan ABMs differs. To test the effects of scheduling on model outcomes, we reverse the order of the submodels (Figure 3). For the Wolong ABM, we grouped the submodels into three categories: (1) simulating environment (SE), which includes the forest dynamics submodel; (2) simulating human-environment interaction (SHEI), which includes the fuelwood collection submodel; and (3) simulating-sociodemographics (SSD), which includes, given the household-level fuelwood demand determined, education, mortality, marriage, and fertility submodels (in this order) that run at the individual level. To compare with the original order of SE → SHEI → SSD in the Wolong ABM, we reversed the order to be SSD → SHEI → SE and simulated population size, number of households, and area of panda habitat over fifty years. The *t* test (two-tailed assuming unequal variances) results show that at year 50, the population

size and number of households do not change significantly ($p = 0.33$ and 0.98 , respectively). The area of panda habitat at year 50 has experienced changes that are small in magnitude (about 0.33 percent); that is, a decrease from $M = 280.91$ ($SD = 1.04$) in the original order (SE → SHEI → SSD) to $M = 279.98$ ($SD = 1.31 \text{ km}^2$) in the reversed order (SSD → SHEI → SE). The change is statistically significant, however, with a *p* value of 0.0035 (two-tailed *t* test assuming unequal variances).

Because of the abundance in sociodemographic processes in the Wolong ABM, we specifically reverse the order of submodels in the SSD category to be fertility → marriage → education → mortality and then calculate the fuelwood demand at the household level. This reversal causes a significant change in population size ($p = 0.0022$, for two-tailed *t* test assuming unequal variances), even though the magnitude of change is still small (1.02 percent). The number of households and habitat area do not change significantly ($p = 0.27$ and 0.88 , respectively).

To test the effect of scheduling order in the Chitwan model, we performed a similar experiment, again finding that scheduling order can lead to statistically significant differences in model outcomes. Moving the education and migration submodels to occur in sequence at the beginning of the time step, and moving the fertility model to occur after the mortality submodel, in the year 2050, we see an increase of 3.83 percent in the number of households (relative to the original scheduling order), and a decline of 0.24 percent in the total population ($p < 0.001$ and $p = 0.53$, respectively, again using two-tailed *t* tests assuming unequal variances). Comparing the two scheduling orders, we see the largest change in land use (expected given the change in number of households), with a decline in agricultural land of 5.35 percent when we reorder the submodels ($p < 0.001$).

Model Verification and Validation

The Wolong ABM established a protocol to verify and validate complex ABMs, including (1) progressive model building and debugging, (2) uncertainty testing (extreme tests and extreme combination tests), (3) empirical validation, (4) sensitivity analysis, and (5) experience or expert opinion (An et al. 2005). The key state variables, including panda habitat amount, human population size and composition, the number of households, and household size, pass all the above tests (An et al. 2005).

Verification and validation of the Chitwan ABM follows a protocol similar to that described earlier. To ensure the model code in the Chitwan ABM functions as expected (and that there are no software bugs), we also include in the model code simplified alternative versions of each major submodel, which we can turn on or off for testing purposes. Model outcomes from runs using the simplified instead of the more complex submodels should not be identical, but we would also not expect them to diverge radically. Special verification code is also hard-coded into the model to verify that each submodel functions as expected and that all agents have reasonable values for their state variables at all times. For example, we track the age of the oldest person in the Chitwan ABM, and of the mean age of the population, to ensure the mortality model is functioning as expected.

CHANS Characteristic Features

CHANS have been noted to have several characteristic features that can impact system structure and function: reciprocal effects and feedback loops, nonlinearity and thresholds, surprises, legacy effects and time lags, resilience, and heterogeneity (J. Liu et al. 2007). These features are often observed in the outcomes of CHANS ABMs, and we summarize them in Table 4 (see Section 5 of the online supplement for details).

One prominent issue that comes from our comparison is related to surprises. We bring attention to surprises that emerge from the unique characteristics of humans, the environment, and the ways in which humans and the environment interact. Detecting and explaining surprises of this kind, often difficult (if not impossible) by looking at the data alone, often involves some type of modeling, systems integration, or both (agent-based modeling is an excellent tool). Examples include the habitat unresponsiveness within 5,000 m of perceived fuelwood collection distance (Wolong), where less motivation to reduce fuelwood, greater environmental heterogeneity (thus allowing for more disturbance like fuelwood collection), and other reasons might help explain these surprises (see the online supplement for more details). On the other hand, there are surprises that are relatively easy to detect and understand by looking at the available data or weaving together different kinds of information. Examples of this kind include the “sixteen-year dormancy” in Wolong (the number of households remains unchanged for sixteen years when marriages are delayed sixteen years) and fuelwood’s delayed response to population increase in Chitwan (fuel wood demand increases slowly as population size increases, given increased efficiency of resource usage in large households). Surprises of this kind are still informative because they could stimulate in-depth thinking about the model structure, function, and interrelationships among model components and thus

Table 4. CHANS characteristic features

	Wolong ABM examples	Chitwan ABM examples
Reciprocal effects and feedback loops	Intense use of fuelwood, thus distancing nearest forest providing such fuelwood, would feed back into a decreased fuelwood demand	Women in places with more agricultural land get married earlier, bear children sooner, establish households faster, and convert more agricultural land to other land uses
Nonlinearity and thresholds	Habitat is unresponsive when the perceived fuelwood collection is beyond 5,000 m (5,000+ m habitat unresponsiveness)	Per-person fuelwood consumption is nonlinearly dependent on household size
Surprises	Number of households remain unchanged for sixteen years when marriages are delayed sixteen years; see above 5,000+ m habitat unresponsiveness	Fuelwood is tardy in response to population increase
Legacy effects and time lags	Population size, number of households, and habitat area respond to changes in family planning factors with increasing lags	Fuelwood usage lags population increase due to slower increase in household size, decline in fertility, and increase in marriage age as younger population ages
Resilience	Panda habitat would respond very little with increasing fertility	Land use change is resilient to moderate changes in fertility or migration rates
Heterogeneity	All the state variables	The same

Note: CHANS = coupled human and natural systems; ABM = agent-based modeling.

help in model verification (especially for novices). Finally, we bring to CHANS researchers' attention errors in data, mistakes in ABM rules, or bugs in model code that might give rise to seemingly "surprising" outcomes but are essentially not surprises that reveal CHANS characteristic features.

Lessons Learned

Our comparison of the Chitwan and Wolong ABMs leads to several lessons to take into account in the design, construction, and analysis of CHANS ABMs. We organize this section around the four lessons we learned: (1) What Should the Agents Be? (2) Can We Reuse CHANS Submodels? (3) Does the Scheduling Order of Submodels Matter? and (4) What Are the Surprises That Deserve More Attention in CHANS Research?

What Should the Agents Be?

Choosing what agents to include in a CHANS ABM of course hinges on many related factors, such as objectives of the study, availability of data and understanding of the CHANS of interest, and the modeler's views on the complexity of the system. Making this decision is both a science and an art, as this decision might play a fundamental role in determining the structure of the ABM and in shaping the resultant understanding of the corresponding CHANS. Given the dual nature of any CHANS (humans on the one side and the environment on the other), we recommend first drawing up a hierarchical list of potential agents. For example, this list might include persons, households, lower level communities (e.g., villages), higher level communities (e.g., districts), and environment units, up to the whole landscape. We use this type of agent-based representation in both ABMs. The Wolong ABM has a hierarchical list of persons–households–environment, and the Chitwan has its counterpart as persons–households–communities–environment. Depending on the objectives, CHANS modelers could start from any level in the list and end somewhere later, contingent on including at least one type of human (or community) agent and one type of environment agent such that the dual (human and environment) nature of CHANS is represented. Revolving around this relatively straightforward and self-evident recommendation, a few issues emerge that might deserve more attention.

First, should we choose all individuals or a subset of them in our study site as agents? From our comparison

of the Chitwan and Wolong ABMs, we note the flexibility modelers might have in deciding how to set up the initial agents in a CHANS ABM. We initialize the Wolong ABM with the full population of the study site in 1996—what we call the "population" approach. The Chitwan ABM, however, only uses a subset of the people and households that are spatially scattered on the Chitwan landscape in 1996—the "sample" approach. The Chitwan ABM is, to the best of our knowledge, the first usage of this approach, which is appropriate given its goal of exploring reciprocal connections between population and environment with a heavy focus on community context. To visualize population-level outcomes (total population, etc.), we can upscale findings from our sample to the population level simply by weighting according to the sampling scheme of the original CVFS survey (Barber et al. 1997). Furthermore, given the detailed demographic and socioeconomic data that are available in Chitwan through the CVFS project, we are hesitant to create agents whose characteristics are drawn from aggregate distributions (e.g., mean, standard deviation, histogram) or relationships, as we might lose or dilute the interrelationships between the agents and agent state variables in our model. Finally, a practical concern is the huge (compared to Wolong) population size in Chitwan (284,939 people in almost 67,988 households in 2011; CBS 2012).

In parallel to this flexibility, our follow-up questions are as follows: Should we choose all of the landscape (the spatially contiguous landscape) or a subset (usually a number of spatially discontinuous locations) of our study site as the environment and how fine (or coarse) should the environmental agents be? The spatial extent of an ABM traditionally represents all of the landscape, usually in a raster format. This is reflected in the Wolong ABM. Complementary to this approach, CHANS modelers could also build their simulations on a (not necessarily spatially contiguous) subset of the landscape, as we did in Chitwan, as long as this is taken into account when interpreting, interpolating, or extrapolating the simulation results. In principle, CHANS modelers should choose a resolution and extent that are appropriate for the major processes under investigation. The spatial resolution should be fine enough to capture variability of the major processes and patterns of interest, but it is largely up to the modeler to decide what variability needs to be captured.

Similar conclusions apply to the choice of time span and temporal resolution (yearly for Wolong and monthly for Chitwan), where data availability, major processes of interest, and research goals could all play a

major role. When choosing the simulation time span, we could choose a span that is long enough that all major processes can take place (e.g., a child grows up, marries, and forms his or her own household) but not so long as to allow model uncertainty to escalate, decreasing model reliability to a low level.

Can We Reuse CHANS Submodels?

In our comparison, we show that from a modeling standpoint, many of the submodels in the Chitwan and Wolong models function similarly, even given their different contexts. Given these similarities, using standardized submodels in the two ABMs, and in CHANS ABMs in general, would have several benefits. The first would be to simplify comparison of ABMs, lowering the technical barriers to CHANS ABM construction. The second would be to make the impact of model structure on model outcomes more clear—as modelers will become familiar with standardized modules. At the same time, when multiple users use and test modules, the modules are more likely to be error free and reliable.

Although many of the modules in the two ABMs are similar, some are highly dependent on site-specific context, either due to substantive differences in processes from site to site or due to the same or similar processes being measured differently between the two sites. Due to our modeling focus in this article, we focus on how different processes can be handled, leaving measurement differences to another article in preparation. Falling in the highly site-specific category are the tendency to use electricity and land use and path finding submodels in the Wolong ABM and the marriage timing, circular outmigration, and first birth timing submodels in the Chitwan ABM. Despite such site-specific processes, many of the submodels share a fair amount of similarity while having certain site-specific features. Taking migration as an example, the Wolong ABM allows only permanent outmigration, whereas the Chitwan ABM allows both permanent and circular migration, with the migration decision based on a large number of individual-, household-, and neighborhood-level covariates. The more detailed Chitwan ABM migration model is made possible by the more extensive migration histories available at the Chitwan site (a measurement difference between the two sites).

To arrive at a module that is comparable and reusable across sites, we recommend decomposition of each process down to the lowest level at which we are able to build reusable modules. For instance, we might decompose the process of outmigration into two parts: the de-

cision to outmigrate and the outmigration action itself. For the decision to outmigrate submodel, one model might have more factors represented in the decision-making process than another (in our case the Chitwan ABM has more factors represented than the Wolong ABM). For this example, we would suggest building a standardized migration decision submodel based on the more complicated process representation (the Chitwan ABM) that can be reused in a simplified form in other models (the Wolong ABM).

This approach follows from the fact that many of the decision-making submodels in the Wolong and Chitwan ABMs function similarly in the following aspects: (1) calculate probability of agent performing action, (2) draw random number, and (3) if random number is less than the calculated probability of the agent performing the action, then the agent will perform the action. Parts 2 and 3 do not need to be modified across sites (code tracking agent locations and ID numbers need not be site-specific); for Part 1, site-dependent regressions can be used to compute the probability needed. This modeling approach also allows incorporation of results from regression models (e.g., hazard modeling or logistic regression) that researchers from other fields might already be familiar with from their previous work.

To this end, we have composed a set of modules as pseudo-code, easily readable by nonmodeling experts, which might be adaptable for use in other CHANS ABMs. We have built a preliminary library of these modules in Netlogo and Python (see <http://complexity.sdsu.edu/CHANS-ABMs>), two popular programming languages, and have released them under the GNU General Public License. The goal of this library is to offer a set of modules that is transparent and reusable and subject to improvement and modification from us and other people in the CHANS modeling community.

Does the Scheduling Order of Submodels Matter?

The potential impact of scheduling order (the order in which model processes are implemented) on model output has long been recognized in the literature (e.g., Axtell 2001; Railsback, Lytinen, and Jackson 2006) but has rarely been quantified and taken into account in existing work. Based on our simulation data, we have noticed that statistically significant differences have arisen in several key dependent variables of interest solely from changing the order of the major submodels in the Wolong and Chitwan ABMs. Although statistically significant, these differences are generally

small (often around 1 percent) in magnitude for simulations over a fifty-year time span. On the one hand, the small magnitudes of these differences might indicate that the large-scale patterns of our key dependent variables (panda habitat in Wolong and agricultural land use in Chitwan) are controlled by the major processes and parameters in the model rather than by the order of these processes. This allows us to have confidence in the reliability and usefulness of our CHANS ABMs.

On the other hand, the scheduling-induced differences are statistically significant, suggesting that scheduling order is contributing to the model outcome in a systematic (nonrandom) manner, and in many instances, this contribution will be escalating over time. This is confirmed by our simulation results, where the percentage difference between the default scheduling order and a reordered schedule lead to differences in total population (relative to the default scheduling order) of 0.51 percent ($p < .001$) at ten years, rising to 1.02 percent ($p < .001$) after fifty years for the Wolong model. The Chitwan model exhibits similar sensitivity to scheduling order, with a model with a reordered schedule showing declines in total agricultural land (relative to the default scheduling order) of 0.80 percent after ten years ($p < .001$), and 5.34 percent after fifty years ($p < .001$). The accumulated effects of these scheduling-induced differences could play a key role in CHANS structure and dynamics, especially over long time scales (over fifty years in the case of the Chitwan and Wolong ABMs) or in combination with other complexity factors. For instance, the lost habitat due to a change in scheduling order, although small in amount, might be located in places that break existing corridors for pandas to move from different habitat patches. More interestingly, we posit that scheduling order could be more important for ABMs with a coarse time step, where a single time step can represent a relatively long period in the life of an agent. Our simulation data do not support this proposition, as the Chitwan ABM with a fine (monthly) time resolution has also displayed significant differences arising from scheduling order.

In summary, we recommend that investigation of the importance of scheduling order be included in the design of CHANS ABMs, such as through randomization of process order, unless we are certain that one process should come before or after others. This way we could minimize the influences of scheduling order on model outcomes, making model outcomes more likely to reveal what they are supposed to reveal. If not able or possible to specifically address the impact of scheduling order, we should at least consider it in the future as part of the

model verification and validation process through, for example, showing that over the time span of simulation, the consequence of scheduling order is negligible and would not substantively affect conclusions to be made from the corresponding ABM.

What Are the Surprises That Deserve More Attention in CHANS Research?

Modeling complex systems such as CHANS using an ABM approach might give rise to many surprising outcomes (J. Liu et al. 2007). Such surprises could reveal essential mechanisms underlying CHANS dynamics that might not be able to be detected using other approaches, providing insightful hints for better policy or management. We recommend paying attention to surprises that arise from unique features and interactions within (and sometimes beyond) the CHANS of interest, however, because these surprises might offer clues and opportunities to obtain unknown CHANS mechanisms and thus deserve more attention. Aside from the example of habitat unresponsiveness beyond 5,000 m in Wolong, we believe that those emerging outcomes from theoretical (e.g., the prisoners' dilemma, the El Farol Bar example; see Axelrod 1984 and Arthur 1994, respectively) and empirical (e.g., the macrolevel land use patterns arising from agent "behavior and heterogeneity in the actors and the landscape"; Brown et al. 2008, 807) ABM experiments belong to this category. The surprises that are relatively easy to detect or understand, although useful in providing understanding of the system under investigation as well as in verifying the ABM to some extent as mentioned earlier, do not provide much "hidden" insight into the CHANS. In addition to the examples presented earlier (sixteen-year dormancy in Wolong and lagged response of fuelwood usage to population change in Chitwan), we see these types of surprises in the literature such as the fishbone (along the two sides of major road networks) style of deforestation in the Amazon (Cabrera et al. 2012).

Equally (if not more) important is to identify various surprises, which could come from errors in input data, bugs in model code, or mistakes in ABM rules. During construction of the Wolong and Chitwan ABMs, surprises of this kind occurred; for example, a dead person agent still goes to college, or a male person agent bears a child. It is relatively easy to find mistakes of this nature if the modeler pays enough attention to model verification (this is one of the reasons we propose adding model verification and validation to the ODD protocol). It

is more difficult, however, to identify some “invisible” (but seemingly reasonable) mistakes. For instance, an earlier version of the Wolong ABM had a habitat jump in panda habitat in year one. This surprise was later found to arise from a bug in calculating panda habitat after landscape and agent initialization. There is no cure-all for this kind of problem, although several steps should help; for example, making the code transparent and making it subject to public screening and testing, breaking complex (often long) code or processes into individual simpler submodels and testing them separately, and running sensitivity and uncertainty tests (An et al. 2005).

Conclusion

Because of this article’s goals, we have focused on several important issues or lessons through comparing two CHANS ABMs. Our comparison of ABMs is a necessary step toward better understanding the interrelationships between real people and real environments because of the large effect of ABM structure on the outcomes of ABM models. Without comparing ABM model structure directly, we cannot appreciate the strengths and limitations of ABM model outcomes.

This type of ABM-focused pursuit, however, by no means depreciates the importance of other non-ABM approaches, especially the so-called top-down equation-based models (Parker et al. 2008). From our work, we can actually see the essential role of different statistical models in providing parameter values or rules for both the Wolong and Chitwan ABMs and in testing model outcomes for statistical significance. Therefore, both agent-based modeling and other top-down approaches are complementary with one another (An et al. 2005; An 2012). Although not a new finding, as with any technique, agent-based modeling has its strengths and weaknesses. Although ABM can capture many characteristic features of CHANS, it is a data-intensive modeling strategy, and there is still a high barrier for novices to enter the field. Additionally, ABMs can be difficult to communicate. A natural question follows: When shall we consider using agent-based modeling in CHANS research?

This is not an easy-to-answer question. We provide some insights from our comparison work here, which does not exhaust all possible situations. First, when feedback (or interaction in a broader sense) between different components is essential to the CHANS processes under investigation, ABM has irreplaceable power and might be worthy of consideration. The Chit-

wan ABM focuses on many feedback loops between land use and population processes. Second (also related to the first point), when systems integration (e.g., integration of data and models from multiple disciplines and scales) and envisioning of systems dynamics under different input parameters are prevalent goals of the modeler, agent-based modeling has unique strength. The Wolong ABM is an exercise in this regard, which integrates data and models from geography, ecology, sociodemography, and other disciplines. Third, when dealing with human behavior and adaptation to social, societal, and environmental changes is of critical importance, agent-based modeling might be the best choice (An 2012). We have discussed how the Wolong and Chitwan ABMs incorporate adaptation rules based on empirically derived behavioral rules. For instance, empirical studies have shown that a decrease in agricultural land would lead to later marriages and lower fertility rates, and this can be easily programmed in the agent decision rules and implemented in the Chitwan ABM. Aside from these three major situations, we acknowledge other situations in which ABMs might also be applicable, such as a context where high heterogeneity in agent or environmental attributes should not be aggregated.

Although this article is based on one published model (An et al. 2005; An and Liu 2010) and one model in review (Zvoleff and An forthcoming), this article is by no means simply a replication of these two models. Recent years have witnessed an increasing number of agent-based modeling applications at different sites and in different contexts (for an ABM review, see An 2012). Although these advances are important and necessary for ABM development and CHANS research, it is difficult, if not impossible, to distinguish between commonalities and site specifics of CHANS ABMs by separately considering individual case studies. This situation points to an urgent need for better synthesis of multiple ABM results to enable generalization of findings and advancement of the CHANS theory. This context has inspired us to distill commonalities in CHANS structure and processes, and to reflect such commonalities in ABM methodology. The unique contributions of this article, enumerated next, constitute a significant advance toward this aim.

First, we have shown that different CHANS share many common structures and processes of interest. Comparing the two ABMs developed with substantially different goals and contexts, we have found a large amount of modeling similarities (e.g., see Figure 2 and Tables 1–4). These similar modeling efforts could arise from similarities in CHANS processes, which might

further justify our comparative approach to better understanding CHANS structure and dynamics.

Second, we have proposed and demonstrated the usefulness of a modified ODD protocol in comparing and distilling commonalities from different CHANS ABMs. The ODD protocol provides a relatively straightforward and standard way for modeling complex demographic decisions, environmental processes, and human–environment interactions in CHANS. As a common infrastructure that we aim to bring into CHANS research, the protocol helps CHANS researchers better comprehend, compare, and envision CHANS structure and process in a standard way that minimizes arbitrariness in presenting or documenting ABM components. Due to the complexity in CHANS, however, ABMs of CHANS usually have more parameters and state variables than specialist models that focus on individual components of a CHANS. Our modified CHANS ODD protocol has less detail in most areas than a full ODD description, as shown earlier and summarized in Table 1. The primary purpose of this modified CHANS ODD protocol, we argue, should be on description for a wider audience.

Additionally, we have enriched the standard ODD protocol by adding two essential components to enhance the accessibility of CHANS model descriptions and to ensure their applicability to a broad audience. As CHANS ABMs are often used as tools for policy recommendation or analysis, it is important that modelers and users be familiar with the process used to evaluate CHANS ABMs. For this reason, we add a “Model Verification and Validation” section to the ODD protocol. The verification and validation process ensures that models function as expected and helps to give modelers and analysts a measure of the uncertainty in model outcomes. In addition, we add another section to the ODD protocol: “CHANS Characteristic Features.” We feel that it is important to provide a space in the standard protocol for CHANS modelers to outline the key complexity features of CHANS model outcomes, as these features can have great importance for policymakers. Although traditional ODD focuses on details of model implementation, evaluating model outcomes (with a focus on complexity features) is essential for policy design and implementation. With these modifications to ODD, we hope to reduce the need for readers to consult separate literatures as they make use of CHANS ABMs.

Last but not least, another contribution of this article is technical development that facilitates CHANS-related agent-based modeling, including the online pseudo-code and preliminary library of reusable modules in Netlogo, and our test of the importance of

scheduling order in ABM modules. All of these features, not previously explored with the Chitwan and Wolong models, should be particularly useful for ABM novices. Aside from embarking on building and testing CHANS ABMs, we provide insights into interpreting agent-based modeling outcomes in the hope that more attention be directed toward surprising outcomes, as these outcomes might offer clues or opportunities to better understand CHANS structure and mechanisms.

In summary, this article addresses the difficulty in documenting and comparing CHANS ABMs with an aim to generalize common features from site-specific case studies in CHANS research. We have proposed a standardized approach to model documentation and comparison based on the modified and expanded ODD protocol, highlighted the commonalities of CHANS ABMs, and pointed out the need for further work on surprises in CHANS and on several technical issues yet to be addressed by the CHANS modeling community. This article began to build CHANS-related pseudo-code and a preliminary library of reusable modules, a pursuit with substantial long-term potential for advancing the ABM methodology. It is our hope that future work, using a similar comparative approach, will synthesize more new and existing CHANS case studies and further development of the theory of CHANS.

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Supplemental Material

Only the major differences between the Wolong and Chitwan ABMs are discussed in this article—for a more complete overview of each type of agent and the

associated state variables in the two models, see the supplementary material named “6. ABM-comparison_Online_Supplement_20140501.pdf” provided at http://complexity.sdsu.edu/CHANS-ABMs/6.ABM-comparison_Online_Supplement_20130427.pdf and on the publisher’s Web site at <http://dx.doi.org/10.1080/00045608.2014.910085>.

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Correspondence: Department of Geography, San Diego State University, 5500 Campanile Drive, San Diego, CA 92182, e-mail: lan@mail.sdsu.edu (An); azvoleff@outlook.com (Zvoleff); Center for Systems Integration and Sustainability, Michigan State University, 1405 S. Harrison Road, East Lansing, MI 48823, e-mail: liuji@msu.edu (Liu); Survey Research Center, University of Michigan, 426 Thompson Street, Ann Arbor, MI 48104, e-mail: baxinn@umich.edu (Axinn).