Promoting Socially Inclusive and Sustainable Agricultural Intensification in West Bengal and Bangladesh (SIAGI)

Review of Integrated Modelling Approaches for R4D in Rural Communities

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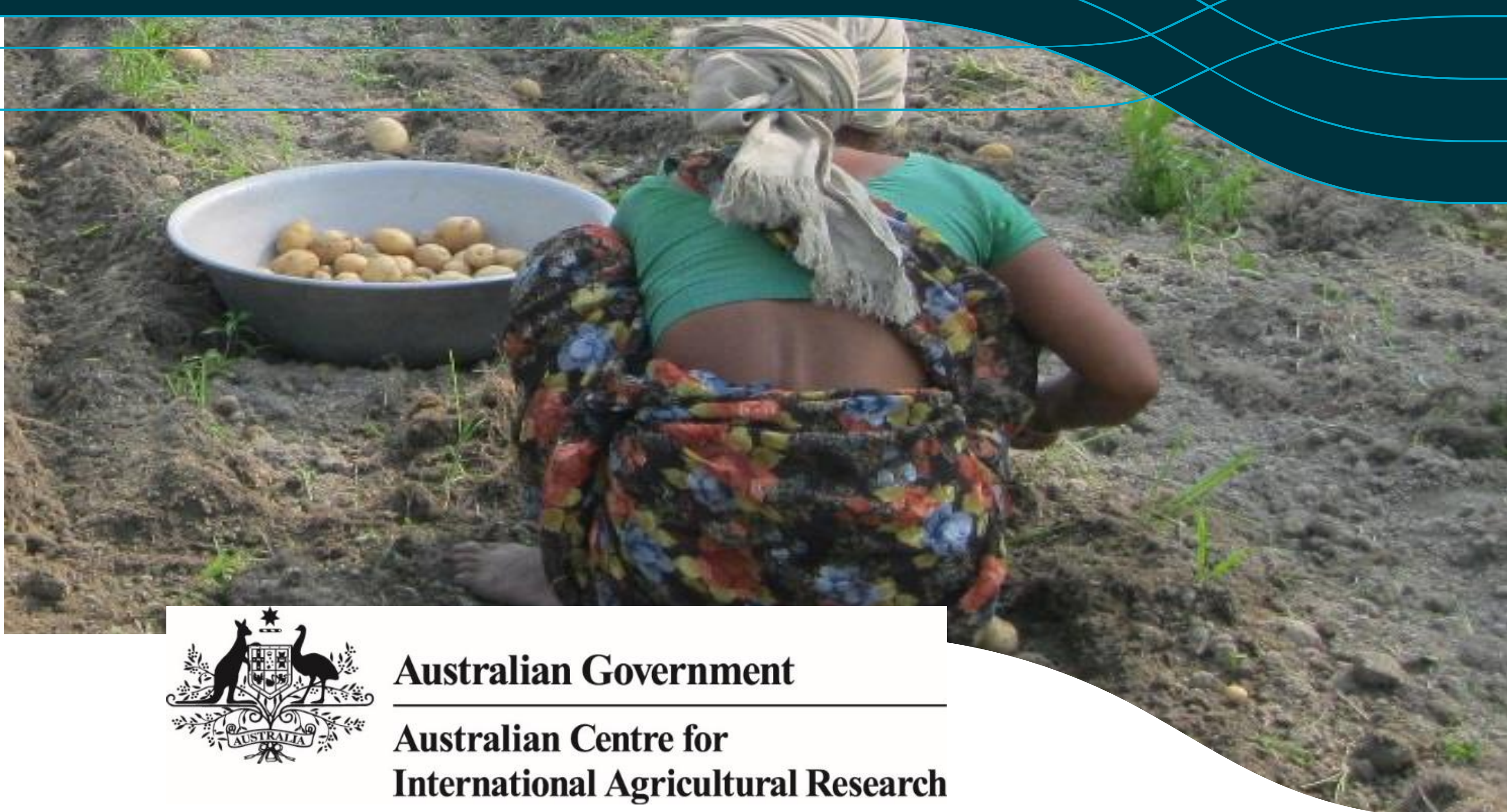

Australian Government
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Summary

This report reviews Research for Development literature that applied integrated modelling (IM) approaches in the context of agricultural systems, land and water resource management, and/or rural livelihoods. This review is intended to generate ideas for the aim, scope and methodology of the SIAGI project's integrated model, and consider possible challenges and opportunities in IM. Five main types of integrated models are considered – agent based models (ABMs), Bayesian networks (BN), coupled-component models, fuzzy cognitive maps (FCMs) and system dynamics (SD). These approaches are assessed in terms of their conceptualisation of the system, data requirements, and their capacity to support participatory and collaborative modelling. We also consider how decision making, people, and equity and equality dimensions can be represented in the models.

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1 Introduction

Research for development (R4D) is progressively moving toward an integrated approach, whereby research methods and conceptual and analytical frameworks are drawn from multiple disciplines. Traditional disciplinary methodologies are increasingly considered inadequate for understanding the complex phenomena that emerge in rural communities in developing countries, namely poverty, gender and social inequality, and food security. This reports considers integrated modelling (IM) as a methodology for improving the understanding of some of these complex phenomena in the SIAGI project.

Modelling is a process in systematically organizing data, knowledge and assumptions for a particular purpose and context. In SIAGI, the broad purpose of IM is to improve our understanding of the risks and opportunities of agricultural intensification for marginalised households in our research communities. IM will serve multiple functions including as: a synthesis tool that integrates multiple sources and types of data, knowledge and perspectives; an exploratory tool to explore linkages and feedbacks between system components; a participatory tool to engage stakeholders, the research team and partners and foster social learning and shared understanding; and a scenario analysis tool to construct and assess a range of plausible scenarios related to agricultural intensification.

There are many different types of integrated models and an infinite number of possible ways to develop and apply an IM. However the most appropriate approach for a given project depends on the purpose of the application and the problem context. This report describes the key features of the SIAGI project and examines what those features mean with respect to the IM requirements (Section 2). This is followed by a brief review of literature on IM used in R4D, to examine how other studies have applied IM and identify aspects of these studies that may be suitable or unsuitable for SIAGI. This review is intended to generate ideas for the aim, scope and methodology of the project's integrated model, and consider challenges and opportunities in IM for SIAGI. An exhaustive review of literature has not been undertaken at this point. However this report will be adapted to include a more comprehensive review of literature, with the intention of submission to a journal (e.g. Environmental Modelling and Software) for publication.

2 A SIAGI perspective on the ten dimensions of integration

This section summarises the project context for the SIAGI project villages that the integrated modelling activities are focused upon: Dhaloguri, Khatail, Sekendarkhali and Uttar Chakowakheti. While there are some similarities, each village has a unique set of sociocultural and environmental characteristics and challenges. The ten salient dimensions of integration posed by Hamilton et al. (2015) are used to frame the text: (i) issues of concern, (ii) stakeholders, (iii) governance setting, (iv) natural setting, (v) human setting, (vi) spatial scale, (vii) temporal scale, (viii) disciplines, (ix) methods, models, other tools and data, and (x) sources and types of uncertainty. These properties will determine the requirements of the proposed model and the appropriate model features (discussed later in sections 4 to 7).

2.1 Issues of concern

The project communities are faced with a broad range of social, health, market, policy, environmental and climate issues related to agricultural intensification. These issues are intricately linked to one another and pose both risks and opportunities to the community. The exposure and prospect of these risks and opportunities can vary for different segments of the community. SIAGI is interested in exploring and promoting interventions that are socially inclusive, and therefore benefit the livelihoods of the community as a whole. A very large number of risks to the communities were identified by the project team and those considered most important with respect to agricultural livelihoods and intensification are listed in Table 1. The broad range of issues are discussed in more detail in Merritt and Hamilton (2018a). These issues are highly interlinked with one another, which supports the use of integrative approaches to analyse risks and opportunities for agricultural intensification.

A key requirement of the proposed integrated model(s) is the ability to capture a wide spectrum of issues, i.e. to provide a 'big picture' of the system that shows multiple components concurrently. In complex systems, a solution to one problem can potentially lead to new, and perhaps bigger, problems in the future or elsewhere in the system. The IM process provides a structure to help think through such unintended consequences of interventions. It can also help detect leverage points, which are "places within a complex system where a small shift in one thing can produce big changes in everything" (Meadows, 1999). An example of a leverage point is women empowerment, which has been demonstrated in many Indian communities to lead to improvements in household health and wellbeing, food security, and agricultural productivity. Various system models will be considered in Section 3.

Table 1 Key issues of concern to the communities in the context of agricultural intensification.

Risks	**Description**
Reinforced social norms	Social norms shape how individuals and groups within communities interact, who has (or has no) power or voice, and who makes decisions. Thus they can influence gender roles, control of household assets, inclusion, and (equitable) access to water and other natural resources, extension opportunities, markets and so on.
Elite capture	Often, the wealthier or those with more power disproportionately capture community resources or services. This includes natural resources such as water (e.g. the control of sluice gates in Khatail to favour shrimp operators over poor farmers) and government resources and services.
Nutrition blind development[1]	Marginal households are exposed to risks arising from a general lack of awareness (across the range of local, national, global stakeholders in development research and programming) of the links between agricultural development and nutrition outcomes (and more broadly with ecology and society, sanitation and health, and well-being).
Reduced and variable income	Income-related risks arise from multiple drivers affecting agricultural production and market access and influence, and non-agricultural livelihoods. Across the case study villages, oft-mentioned factors include market access and information (including gender-based differences), bargaining power, production volumes, crop choice (and market demand) and climate variability.
Poor access to information	Access to reliable context-specific information regarding agricultural production system, marketing system, prices of agricultural produce, credit market, etc. is an enabler for farming households to improve their decisions and production system. Across all our case study villages, access to information has not been equitable, reliable or holistic and addressing is a focus of ECE activities.
Lack of financial access	Access to financial services such as credit (especially institutional credit) and insurance can be important for agricultural intensification, as seen with the green revolution which was fuelled by the promotion of institutional credit. Formal finance is often difficult to access particularly for landless and marginal households in the communities SIAGI is working in.
Poor technology transfer	Despite many technological advancements that could help farmers improve their livelihoods, technology transfer is often limited amongst the marginalised. In addition to lack of finances to invest in technology, farmers often lack awareness of or access to these new technologies.
Poor access to markets	Access to market may be constrained for many reasons including distance and difficulty to take produce to market (e.g. Uttar Chakowakheti), social norms or practices around women's mobility (e.g. Sekendarkhali). A lack of access can mean a reliance upon intermediary traders with reduced capacity to negotiate better prices for their produce.
Lack of access to land	Without access to a viable size of arable land ***and*** tenure arrangements that support investment of resources and planning, farmers risk further marginalisation or at the very least remain limited in their capacity to take up intensification opportunities.
Lack of freshwater for irrigation in the Rabi season[2]	The lack of available freshwater for irrigation is a risk facing marginal households disproportionately to wealthier farmers. In Uttar Chakowakheti, this has stemmed from a lack of water reservoirs and groundwater irrigation infrastructure. In our Bangladesh villages, the availability of freshwater in canals is limited in the Rabi season (more so in Khatail) due to natural river salinity increases, and the maintenance and operation of water infrastructure.
Climate-related risks	Climate change and variability poses several risks to agricultural communities, including crop production losses, damage to infrastructure, contamination of water resources, and injury or loss of life to humans and livestock.

[1] This is a highly complex and multifactorial concept and is not feasible to address within the SIAGI project integrated modelling. The collaboration between PRADAN and CSIRO, as part of their Australia Awards Fellowship, is addressing aspects of this emergent issue.

[2] Access to drinking water is a related and important issue. In Khatail and Sekendarkhali, for example, limited storage facilities mean most households can only harvest enough rainwater to meet 5-6 months demand and they must rely on tube wells for remainder of the year.

2.2 Stakeholders

The *SIAGI stakeholder engagement plan* identifies 11 stakeholder groups: funders, project team, partner institutes, farming community, NGO community, research community, local government agencies, state government agencies, national government agencies, private sector and the general public (Roth, 2016). Examples of stakeholders are listed in Table 2. Effective engagement with stakeholders is a critical facet of IM, normally for a more focused purpose than the larger SIAGI project engagement. It is particularly important when there are a broad range of issues as was demonstrated in the previous subsection.

SIAGI has adopted an ethical community engagement (ECE) perspective, whereby the community members are considered project partners and collaborators rather than the subjects of the project. The farming communities of the study villages, particularly the landless, women, tenant and marginal farmers, are the core stakeholders in the project and will be the main target group for engagement in the modelling process. Other stakeholders may be consulted for information about specific issues (e.g. government agencies may be engaged for information pertaining to specific policies or schemes, or specific scientists may be engaged for information related to their research on a relevant topic).

Stakeholder engagement is generally recommended through all steps of integrated model development, particularly those related to problem scoping, framing and formulation, and communication of findings (Hamilton et al. 2015). The problem scoping, framing and formulation complement objective 1 of the SIAGI project, *"To understand how key social, institutional, economic and environmental factors affect livelihood risks, social exclusion, adverse incorporation and environmental degradation in agricultural intensification".* Consequently, these integrated modelling activities have drawn heavily upon stakeholder and community engagement for the larger SIAGI project.

The SIAGI commitment to ECE necessitates the inclusion of participatory aspects in the modelling process. The strong emphasis of SIAGI research on social processes and outcomes means we need to understand how different stakeholders perceive the broad issues of water management and agricultural intensification in the villages, how they interact with each other, and how each can influence outcomes for marginalised households. The literature review later in this report will assess different forms of stakeholder participation in the modelling process (Section 5), as well as how social processes (e.g. interactions between different stakeholders) have been considered within integrated models (Section 6).

Table 2 Examples of stakeholders for the case study villages.

Stakeholders	Khatail and Sekendarkhali	Dhaloguri and Uttar Chakowakheti
Community	WSMC; the farmer groups, individual farmers and community members	6 original DSI4MTF collectives; 2 self-formed collectives; 8 Water Users Associations; Women Self Help Groups
Researchers working in the area or the problem domain	SIAGI researchers; CSI4CZ researchers; Government agencies (e.g. BARI, BRRI); CIMMYT	SIAGI researchers; DSI4MTF researchers
Non-partner NGOs and/or microfinance service providers	Ad-din; BRAC; ASAProshika; BRDB	Bandhon Bank, Farmers Producers Organizations (Satmail Farmers Club), etc.
Private companies	Lal Teer; ACI	Cold storage companies
National government agencies	Department of Agricultural Extension (DAE); Bangladesh Agricultural Research Council (BARC); Bangladesh Water Development Board (BWDB); Water Resources Planning Organization (WARPO)	Department of Agriculture, Department of Irrigation, Department of Fishery, Department of Animal Husbandry Panchayat and Rural Development, District Rural Development Cell, SC/ST/Minority Development Department, Public Health Engineering Department, etc. [All are implementing central / state government schemes]
State/central and local government agencies	Union Parishad; Upazila Parishad; Upazila and district administration	Panchayati Raj Institutions or Gram (village) Panchayat; District Administration
Market actors	Department of Agricultural Marketing; Local and/or wholesale markets; Traders	Department of Marketing, Department of Agriculture; Farmers Organizations; Local and/or wholesale markets; Traders
Extension providers	Growth centres	Farmers clubs; Farmers Producer Organizations
Other	Collaborative programs between Bangladesh and international governments (e.g. the Blue Gold program); Local traditional or religious leaders	Collaborative programs between the West Bengal Government and the World Bank (WBADMIP)

2.3 Governance setting

Governance broadly encapsulates how society or groups organise themselves and make decisions. In the context of agricultural intensification, we are interested in the interventions that may be developed and implemented in order to achieve positive change, as well as the interactions between stakeholders that may inhibit or enhance such change. For SIAGI, this is multi-sectoral, multi-scale, and crosses public and private interests.

Pahl-Wostl (2009) defined institutions as the formal and informal rules governing behaviour of actors (as opposed to specific state or non-state organisations). Across our Bangladesh and Indian case study areas, weaknesses in institutional arrangements have led to some inequitable access to resources and services. Informal institutions are socially shared rules; particularly relevant to SIAGI are social structure and cultural norms which can lead to a lack of agency of women or marginalised persons, prevent their access to resources, and constrain their livelihood opportunities. Formal institutions are codified rules within regulatory frameworks or other legal documents and so are linked to official channels of government bureaucracies (Pahl-Wostl, 2009).

Relevant to SIAGI are governance arrangements around water management, land use and tenure, and agricultural production, extension and marketing. This includes consideration of the government organisations and their policies and management interventions[3], across local to national scales, but equally important are non-government entities (e.g. NGOs, markets, private industry), community-based organisations (farmer producer organisations, farmer groups, self-help groups, water user associations, forest management committees), and individuals. For example, our partner NGOs act as advocates and facilitators, investing heavily in activities which may be designed to build capacity to (or influence how individuals or groups) make decisions, or foster voice and power of marginalised communities. The SIAGI value chain assessments and market reports (Mishra et al. 2018; Hossain 2017) have demonstrated the influence of formal and informal rules about market structure and roles in determining farmers access to markets. The influence of individuals in water governance has been clearly contrasted between Sekendarkhali and Khatail with respect to the functioning of the Union Parishad, its support for local farmers and the history and future risk of elite capture. In West Bengal there is interest in better understanding the role of informal institutions, specifically, self-help groups, farmer groups and farmer producer organisations, in enabling socially inclusive agricultural intensification.

2.4 Human setting

A major premise of SIAGI is that past agricultural intensification has often increased social disparity between the more affluent farmers and the marginalised farmers. In the SIAGI study villages, marginalised farming households include landless, smallholders, women-headed households and tribal minorities. Many of these households live below the poverty line and lack year-round access to food. For example landless, women managed and marginal households of Khatail village have food security for seven, eight and nine months respectively. Farming, particularly cropping, is the main livelihood source in all villages, and a small percentage of the communities partake in other livelihood activities such as wage labour, fishing, driving and small businesses (Tallapragada et al. 2017; Rahman and Das, 2017). The range of livelihood options available also depends on the village; for example there are households in Sekandarkhali who practice aquaculture (shrimp, fish, crab), and in Uttar Chakowakheti, sand mining and forest-based activities are important livelihood sources.

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[3]Three core government bodies in Bangladesh have policies and activities that are closely aligned to SIAGI project objectives. These are the Ministry of Agriculture, the Ministry of Water Resources and the Ministry of Local Government, Rural Development & Co-operatives. A detailed analysis as they relate to SIAGI of these ministries and their component agencies is provided in Jahan (2017). Pertinent policies are National Agricultural Policy, Agricultural Extension Policy and Water Policy of the government of Bangladesh.

In West Bengal, states depend on Central Government programme funding and so state level policies are largely guided by the Central Government policies. A detailed analysis of the policy context to agricultural intensification is provided in Reddy (2017).

In all villages, seasonal out migration of men occurs due to the lack of profitability of agriculture and lack of local work round the year. This out migration leaves the responsibility of tending the farm and household to the women, who face many gender challenges (e.g. difficulties in market participation) stemming from deep-seated cultural norms. Women, as well as other persons disadvantaged by their caste, ethnicity and class, may be subject to social exclusion in terms of restricted access to rights and resources and inequalities in their decision making power. SIAGI is interested in identifying mechanisms that make agricultural intensification social inclusive, rather than exacerbating inequalities. This requires insight into the constraints and opportunities the different types of households face, and some understanding of the values or motivators that drive changes in behaviour and actions.

2.5 Natural setting

Given that the households in our case study villages are predominantly dependent on land- and water-based livelihoods, they are intrinsically reliant on the characteristics and condition of their natural setting. To intensify their agricultural activities, the farmers need reliable access to water, typically achieved through development of groundwater or surface water resources and irrigation infrastructure, and means to improve and/or maintain soil quality. Also important is the capacity of farmers to cope with or avoid damage arising from exposure to extreme events such as cyclones, storm surges, hailstorms and flooding. There are distinct characteristics in the natural settings between Khatail and Sekendarkhali, and Dhaloguri and Uttar Chakowakheti, which affect the constraints and opportunities for agricultural intensification in these villages, including the appropriate interventions for each village.

Khatail and Sekendarkhali, Bangladesh: The south-western coast of Bangladesh consists of alluvial plains within a tidal belt where land is surrounded by a complex network of river and canals. The villages are thus affected by soil and water salinity (more severely in Khatail) as well as cyclones and seasonal floods. In both villages there is potential for rainfed *T. aman* rice (supplemented with limited groundwater irrigation in Amtali). The potential for Rabi crops is higher in Sekendarkhali than in Khatail where dry season salinity is more severe due to greater river salinity and a history of shrimp farming in Dacope. In both villages, a loss of landscape diversity and ecosystem goods and services is a common phenomenon facing farmers.

Some of the environmental risks of the study villages are depletion of ground and surface water, water quality impacts of nutrient and pesticide loading; and reduction in environmental services e.g. communal grazing, fisheries. Rehabilitation of embankments and drainage management of polders is another issue to be addressed. In the study villages, transformation of rice paddy land into shrimp farms has led to many landless people losing grazing opportunities.

Dhaloguri and Uttar Chakowakheti, West Bengal: A lack of reliable rainfall, including late monsoons, droughts and at other times excess rains, is an environmental risk common to both Dhaloguri and Uttar Chakowakheti. Agriculture is also constrained by soils which have low water holding capacity and are nutrient poor. Contamination of rivers with chemical fertilisers and pesticides and summer hailstorms are additional risks. The community of Uttar Chakowakheti faces the additional risk posed by river flooding, sand mining and crop depredation by elephant. This village is in close proximity to forest and the major Kaljani River, both of which provide non-agricultural livelihood opportunities for villagers.

2.6 Spatial scale

Enablers and constraints to attaining positive pathways to agricultural intensification occur at multiple levels or scales. For example, many enablers and constraints to collectives for improving the livelihoods of the poor potentially exist and these range in scale from personal attributes to district or larger scale influences.

Four scales of interest can be considered for the case study villages:

- *intra-household:* (e.g.) control over household resources, who makes decisions
- *community:* (e.g.) the livelihood options available based on local natural assets and resources; how are decisions made around the distribution and use of water resources; community social structures
- *district scale:* (e.g.) infrastructure for water, sanitation, health and transport influence individuals and communities exposure to risks (e.g. salinity intrusion, access to water, access to markets); policies related to drinking water supply, health, education, etc; access to local and regional markers and institutions ; prevailing norms
- *state to national level:* (e.g.) design and implementation of government schemes

The impacts we are interested are mostly expressed at the (intra)household to community scale but they are influenced by drivers operating at a local and larger scales. Understanding the interactions across scales is also important; for example, the connections between the polder and field scale is an explicit agenda for surface and groundwater salinity research within the CSI4MTF project funded by ACIAR.

2.7 Temporal scale

Social and biophysical processes operate across a gamut of time scales. For example, climate change will influence the future viability of agricultural livelihoods in south-western coastal Bangladesh, as the frequency of extreme events increases, sea levels rise and the risk of salinity ingress is projected to worsen. Such long-term time scales are not within the scope of the IM given SIAGI's foci of co-developing agricultural intensification options with community. Some of the project teams' work with community aimed at building their capacity to make and implement decisions around agricultural livelihoods, and to affect change within their communities, may build adaptive capacity to respond to longer term drivers of change.

With the focus on agricultural livelihoods, the time scales of interest to these communities are often seasonal and year-to-year. Most of the marginal households have insufficient savings to invest, and therefore are been unable to plan beyond the current season or year. On the other hand many interventions can take several years or more to achieve and maintain significant impact. This is particularly the case for interventions where the pathway to impact is via building human and social capital. For interventions aimed at building physical capital, for example through access to irrigation infrastructure or machinery, impacts may be realised after one season.

2.8 Disciplines

The research experience of the SIAGI project team is diverse, covering agricultural science, ethics of development, rural development and natural resource economics, poverty studies, value chain analysis, markets for the poor, bioeconomic modelling, climate risk assessment, social psychology, socio-economic impact assessment, livelihoods analysis, institutional analysis, natural resources management, integration science, qualitative and quantitative research, environmental modelling and nutrition sensitive agriculture. Bringing in the practice experience – (e.g.) process facilitation, community mobilisation, strengthening community based organisation – there are opportunities and challenges for integrated modelling. The challenges of integration recognised in the literature hold strong, namely bridging divergences across the domains. Some of these divergences are technical (e.g. methodologies and tools discussed in next subsection) whilst others reflect different conceptual understandings arising from alternate experiences, perspectives or knowledge frames. One member of the SIAGI team identified that integrated modelling itself is challenging for the research team due to their limited exposure to IM and also the types of questions SIAGI is attempting to answer, especially within the context of ECE. SIAGI is also extending the modellers in the team to tackle new challenges, particularly around the representation of social processes and concepts in models beyond the current state-of-practice of integrated modelling. This latter point is discussed further in Sections 6 and 7. Another key challenge for the team is reconciling the depth versus breadth of the IM given the range of issues and disciplinary threads.

2.9 Methods, models, other tools and data

To date, the IM work has focused on conceptual modelling and problem framing. It has drawn on analyses and learnings from all the SIAGI project activities (i.e.): value chain analysis, bio-economic modelling, livelihood analysis, and policy and institutional analysis. These analyses draw on a range of primary and secondary data sources and methods including narratives, focus group discussions, regional market evaluations, desktop analysis of policy documents and environmental literature, and quantitative household survey data from the DSI4MTF project. The IM work incorporates learnings from these activities with engagement and data collection for specific IM activities. With the commitment to ECE, there is an emphasis placed on research methods that are co-designed and complementary such that they do not contradict or repeat one another and do not impose undue demands upon community and its households.

2.10 Uncertainty

Uncertainty can be distinguished into four main types (Ascough et al. 2008), all of which are highly relevant to SIAGI:

- *Knowledge uncertainty* reflecting the limitations of our knowledge about process or model component (data, structure, technical and output). There are several knowledge gaps identified by the SIAGI team, especially around social processes and linkages between social, biophysical, and institutional factors. Some of the major uncertainties, for example regarding the social and institutional factors that ensure the effectiveness of community-based organisations, may be explored by the IM work (see 'Model themes and questions' in Merritt and Hamilton, 2018b).

- *Variability uncertainty* arising from the inherent stochastic and dynamic nature of social and ecological processes. Examples include variability in rainfall, market prices and income, as well as political or institutional changes, and technological advancements. These uncertainties can hinder farmers from making changes in how they farm. While some of these uncertainties can be reduced to some extent (e.g. by diversifying crops, using cold storage, crop insurance), others can only be managed by improving one's adaptive capacity.
- *Linguistic uncertainty* stems from language that is vague, ambiguous and context dependant. This uncertainty is relevant to the research aspect of SIAGI, and is particularly pervasive due to the interdisciplinary nature of the project. This uncertainty was addressed in the conceptual modelling part of the project with the driver-state-impact pathways framework (Merritt and Hamilton, 2018a). Linguistic uncertainty will also be of high importance in the community engagement aspects of the IM work, especially if narratives are used as model input or for communicating model outputs.
- *Decision-making uncertainty* pertains to divergences in social values. Debate can exist, where people hold different values, about how to quantify or compare certain social objectives (e.g. income vs health vs dignity). For example, in relation to the collectives in West Bengal, sense of agency was reportedly more important to some people than money. It is important to consider this uncertainty when designing data collection and interpreting model or research outcomes, and ensure that value judgements are not being imposed.

It is clear that uncertainties are pervasive and each type needs to be carefully considered. With respect to knowledge uncertainty, the SIAGI team is working to address some of the major knowledge gaps through various research methods including the IM work. Assumptions, including generalisations, are necessary to deal with much of the knowledge and variability uncertainty in SIAGI, however, it is important to acknowledge and assess these assumptions. This is particularly relevant, given that social inclusivity is a focal point of SIAGI (e.g. it may be incorrect to assume all people in the village or group have the same or even similar aspirations). For some of the variability uncertainties, where future changes in value can have major impacts to households, scenario analysis may be appropriate for dealing with uncertainty of future states. Rather than trying to predict these future states (e.g. annual rainfall in 2030, or the number and intensity of storm surges next year), scenario analysis involves constructing and evaluating a range of plausible scenarios, and assessing possible implications (risks and opportunities) associated with them.

3 Modelling Approaches

This section reviews several integrated modelling approaches that have been applied in R4D and other fields. We limited the review to studies in developing countries that captured socioeconomic and environmental variables or processes in their model, and which reference agricultural livelihoods and/or water resource management. In particular, five main integrated modelling approaches were identified as potentially suitable for SIAGI – agent based models (ABM), Bayesian networks (BN), coupled-component modelling, fuzzy cognitive mapping (FCM) and system dynamics (SD). These models were mostly found to serve two broad purposes: 1) to understand how the system functions; and 2) to learn how to affect change. The two purposes are not mutually exclusive; for example Murungweni et al. (2011) use their model to map out and quantify relationships between the assets, activities and outcomes of different livelihood types (*Purpose 1*), and then to run scenarios related to climate change and policy options (*Purpose 2*).

Understanding how the system functions includes identifying key factors (or drivers) and relationships (or processes). Within the literature, models have been developed to understand determinants of quality of life and livelihood options (Ha et al. 2017), land use/cover dynamics (Kamusoko et al. 2009), interrelationships between hydrology, ecosystem function and livelihood outcomes (van Dam et al. 2013), and social and economic drivers for adoption of alternative livelihood options (Slater et al. 2013). Learning how to affect change refers to understanding the possible impact of policy or management options, or other changes to the system. Models developed for this purpose have been used to explore possible economic, social and environmental outcomes of (for example): alternative farm management options or investments such as replanting mangroves in a shrimp pond, new crop varieties, greenhouse agriculture (Schmitt and Brugere 2013; Schreinemachers and Berger 2011), changes in water resources development (e.g. increase in surface water withdrawal capacity; Madani et al. 2009), or policies designed to encourage certain land uses or standards of management (Villamor et al. 2014; Murungweni et al. 2011), abate pollution or conserve natural resources (Reidsma et al. 2012; Varela-Ortega et al. 2011; Wei et al. 2009; Barron et al. 2015). Interventions can also be explored in the context of environmental change; for example Barron et al. (2015) performed climate change scenarios, framed as percentage loss in precipitation, to explore the robustness agricultural water management interventions.

The five integrated modelling approaches considered potentially suitable for application within the SIAGI project are described in the following text. For each approach, the main strengths and weaknesses of each approach is considered, and relevant examples are provided.

3.1 Agent based models

Agent based models (ABMs) seem to be one of the most widely applied IM approaches in R4D; some pertinent examples are summarised in Table 3. An ABM comprises a network of autonomous entities (typically representing humans), referred to as ‘agents’, that interact with one another and their environment. Agents can be individuals, households or other groups, or can be non-human assets (e.g. a water body). These agents can react to changes to their socio-ecological environment and their actions can also affect their environment, leading to dynamics and feedback loops within the system (Kelly et al. 2013; p173). The behaviour of each agent is determined by decision rules set within the model. Many ABM studies focus on the discovery of large-scale outcomes that emerge from small-scale interactions (i.e. emergent behaviour).

Table 3 Examples of agent based models applied to agricultural or livelihoods development.

Study	Model
Schreinemachers and Berger (2011)	ABM was used to understand the effects of agricultural technology, market dynamics and environmental change on farm households and their agro-ecological resources. The agents in the model represented farm households. The model is run in annual time steps, and within each year each agent goes through three decision phases about investment (acquisition of assets such as land, equipment and perennial crops), production (crop choice, agricultural inputs), and consumption. These decisions lead to changes in the household's resource conditions and crop yield. ABMs can represent the feedback between farm decisions and their land. For example, poor farm management decisions can lead to a reduction in crop yields, which can then motivate the agent (farmer) to modify practices (e.g. change crop choice, adopt soil/water conservation methods).
Villamor et al. (2014)	ABM was used to explore policy options related to rubber agroforests, including quantifying trade-offs between local livelihoods and ecosystems. The model development and validation required data on household characteristics, as well as preferences and behaviour associated with land-use decisions; this information was collected via household surveys and role playing games (RPG) with the farmers. The RPG helped to provide insight into the behaviours of farmers (i.e. decision regarding land use) when negotiating with the external stakeholders who were promoting conversion or conservation of rubber agroforests. The modelling provided insight into the potential effectiveness of the policies, initially and after 10 and 20 years. For example the payment for ecosystem services policy option was modelled to have a slow uptake but strong maintenance once taken up, partly due to the insufficient price premiums to achieve good returns for rubber agroforest.
Evans et al. (2011)	The model in this study was developed to explore the implications of changing from shifting cultivation to rubber plantations household-level inequality (defined based on the Gini index calculated from household income), and develop hypotheses to explain the rate of adoption of rubber plantations in the study area. The authors modelled the adoption of rubber as a function of labour, financial capital (initial and annual costs), land use preferences, and expected revenue. An example of how their model captured farmers' preferences concerns the cultivation the rice, given its status as a staple food source. In the model, households first seek to convert >1ha to paddy before they add other crops such as rubber to their portfolios.
Le et al. (2012)	Two model versions were constructed to explore how different mechanisms of human adaptation in land-use decisions (e.g. modifying crop choice based on their previous yields or that of other farmers) can play out at the landscape level. The first model considers a 'primary feedback' loop learning whereby households adapt to the annual change in socio-ecological conditions and direct environmental response to land-use activities. The second model added to this by building in secondary learning mechanisms that allow a household to change their behavioural model in response to longer term changes in socio-ecological conditions.

ABMs can be useful for developing hypotheses about behaviour or preferences of individuals or households, and how interactions between agents can also change agent behaviours. This can help when examining the importance of social networks in driving adoption of new farming crops/practices, through observation and knowledge transfer (Evans et al. 2011). Agent based models can represent heterogeneity among agents (e.g. inequalities, and variability in willingness or capacities to change). This is a key advantage of ABMs as they are able to capture details often ignored or grossly simplified in other models, such as the heterogeneity of socioeconomic conditions of individual farmers or households (e.g. Schreinemachers and Berger 2011), and differences in their behaviour (e.g. different rules governing their decisions about managing their farm). Heterogeneities and the interactions between agents can lead to complex emergent behaviour, as described in the case of Evans et al (2011).

The decision-making behaviours of agents are encoded in the model as sets of rules. Accurately defining decision-making processes and constructing realistic decision rules remains a major challenge for ABMs (Ng et al. 2011) and so ABMs are often based on a number of somewhat unrealistic assumptions. For example in Evans et al. 2011 the model made predictions based on optimal yields, excluding real-world risk factors such as frost, pests and other disturbances. The households were assumed to expend all available labour at each time point. The households were also assumed to have perfect knowledge of the land suitability factors for optimal selection of cells for agricultural production (Evans et al. 2011). Similarly, the model in Le et al. (2012) assumed that all farmers were equally aware of all land-use options.

3.2 Systems dynamics

System dynamics (SD) models represent problems as a network of cause-effect and feedback loops. Variables are represented by ‘stocks’ and the rate of change in stocks are referred to as ‘flows’. The modelling process typically involves first developing a causal loop diagram, which identifies the stocks and maps out their relationships, and then quantifying the model. Developing the causal loop diagram, often referred to as qualitative SD modelling, is a useful process in identifying system variables and interactions, and can itself be the end product (e.g. Ha et al. 2017). Relationships in SD models are typically described by differential equations, which can be estimated from data. In cases where data and system understanding is limited, it may not be advisable to attempt to quantify the model (Coyle 2000).

In SD modelling, the focus is on the interrelationships, patterns of change and processes and in particular feedback loops. Some examples of systems dynamics application to R4D are provided in Table 4. Quantifying the model can be achievable when the processes are relatively straightforward, for example, processes such as groundwater seepage (Madani et al. 2009) or milk production (Lie et al. 2017). However for more complex processes, such as social processes, quantifying relationships becomes very difficult. Madani et al. 2009 noted that quantification of the socio-political and economic components of their watershed model was “very speculative and challenging”. In Ha et al. 2017, the SD model represented factors improving small-holder farmers’ quality of life, including social, cultural, political, environmental and economic factors; for this reason the authors did not quantify this model.

3.3 Bayesian networks

A Bayesian network (BN) consists of a network of nodes (variables) that are interlinked by arcs, which represent dependent relationships between nodes. The strength of these relationships are specified in terms of conditional probabilities, which are the degrees of belief that node x will be in a particular state given the states of its parent nodes. The use of these conditional probabilities enables uncertainty due to the stochastic nature of processes and/or incomplete data and knowledge to be explicitly represented. BN also have a modular structure, which allows different sub-models (e.g. crop production, social and economic) to be combined as well as built or revised independently. The approach can handle most types of non-linear relationships and both qualitative and quantitative data, but are unable to readily represent feedback loops and dynamic relationships (Uusitalo, 2007).

Table 4 Examples of systems dynamic models applied to agricultural or livelihoods development.

Study	Model
Ha et al. (2017)	Qualitative system dynamics modelling was used to identify and compare the main determinants of quality of lives and livelihood options for women smallholder farmers in two regions. Information about these factors and the mental models of the farmers was gathered from surveys and stakeholder workshops. The authors found that the approach valuable in providing in-depth understanding of the current situation of women farmers in the two study regions. The analysis helped to identify the similarities and differences between the regions, and highlight potential levers for systemic interventions. The authors found that by developing a holistic view of the situation with stakeholder and community engagement, they were able to better identify adequate interventions to address the respective challenges faced by the women farmers in the regions.
Lie et al. (2017)	Participatory system dynamics was used to model the dairy value chain in a municipality where dairy is the main source of livelihoods. With various stakeholders involved in the group model building (farmers, local processor, local government and institution), the value chain was mapped out and dynamics of the system captured. The system contained four modules, which focussed on: the development of cows from birth; milk production, consumptions and prices; feeding of cows; and profits. Scenarios of changing land allocation and cow productivity were run, to see their impact on milk production and farm profits.
Madani et al. (2009)	A (quantitative) system dynamics model was developed to represent how the different social, economic, political and physical subsystems in a river basin interact. The study focussed on the hydrological system and how indicators of population growth, development in agriculture and industry, and economic development affect water demand. Various scenarios related to climate change, population control, water demand control, and surface water availability were applied to model the response of the subsystems to these changes. The model results indicated that the watershed was highly sensitive to water demand and population growth. The results also suggested the watershed's current problems (e.g. wetland degradation, water supply) could not be fixed with any single solution, but needed a combination of demand management, population control and an increase of water imports.

The BN approach is flexible in that it can be used in either data-rich or data-poor situations. In environmental applications, data alone are often too limited for parameterising BN models (Pollino et al. 2007); this situation is exacerbated further when attempting to model social-ecological systems. However, it is possible to integrate information from different sources, including experts, stakeholders, literature, outputs from other models and field data, as well as handle missing data. This makes them an effective approach in uncertain and/or data-poor situations and have thus they been increasingly applied to rural development domain. It is important to note that, the expert elicitation process becomes increasingly difficult with greater model complexity as the number of probabilities to be specified is exponential to the number of variables and the number of states in each variable; for some problems a more qualitative approach may be necessary.

Table 5 summarises some applications of BN models in the R4D domain. Cited advantages of the approach from these papers were the ability to: consolidate diverse knowledge from multiple stakeholders and domains, use the BN as pre-scoping tool for rapid assessment of interventions, articulate existing knowledge and beliefs about a problem, facilitate a systematic investigation of complex relationships and provide a framework for discussion of potential solutions. Key limitations were the inability to represent spatiotemporal dynamics and feedbacks (van Dam et al. 2013).

3.4 Fuzzy Cognitive Mapping

A Fuzzy Cognitive Map (FCM) is comprised of a network of concepts that represent different characteristics of the system and its behaviour. These concepts are connected to one another by arcs with weights that define the direction (positive/negative) and strength of the cause-effect relationship between them (Stylios and Groumpos 1999). The concepts and the weighted interconnections are often defined by experts or other stakeholders. The weight values elicited from stakeholders can be qualitative (e.g. low/moderate/high) or quantitative (between -1 and 1, where -1 is a very strong negative effect and 1 is a very strong positive effect), although qualitative weights must later be assigned quantitative values. FCM is considered a relatively simple form of semi-quantitative modelling, with the process involving identifying the most relevant/important variables in the system, and the direction and strength of relationships between these variables (Nyaki et al. 2014). For this reason, it has been invoked as an approach well suited to participatory modelling and research (e.g. Henly-Shepard et al. 2015). Although care is needed to develop FCMs with stakeholders who have little exposure to systems thinking, the approach has been successfully applied by other researchers who co-developed their model with the local community including farmers (e.g. Diniz et al. 2015; Murungweni et al. 2011; Halbrendt et al. 2014; Singh and Nair 2014).

FCM has been applied to a few studies relevant to SIAGI and four of these are summarised in

Table 6. Jetter and Kok (2014) argues that FCM *"... is most useful when other, more refined methods fail: in broad knowledge domains with only partial experts, in situations with little or no relevant historic data, and in cases where most information is qualitative and fuzzy"*. FCMs are able to represent concepts that are hard (or not desirable) to quantify and have considerable flexibility to model across domains. FCM lends itself to representing belief systems which Singh and Nair (2014) notes can supplement scientific data and be a tool in itself for understanding human behaviour.

Two critical challenges, particularly for application to complex or contested social-ecological problems, is choosing whose knowledge to represent in a FCM and deciding how to collect and interpret knowledge particularly in a group setting (Gray et al., 2014). Managing complexity in terms of the number of concepts and connections is a challenge to FCM, as it is with other systems approaches (i.e. BN and SD).

Table 5 Examples of Bayesian network models applied to agricultural or livelihoods development.

Study	Overview
Barron et al. (2015) and Katic et al. (2016)	These two papers applied the same BN-based decision support tool. Barron et al. (2015) used the tool to assess the likelihood of success of agricultural water management interventions, whereas Katic et al. (2016) applied it to spatially target small-scale irrigation investments. In both studies, the stakeholder consultation and expert elicitation process during the model development was used to identify the factors critical to their respective problems, and the order of importance of those factors. The models consolidated diverse knowledge from various stakeholders (e.g. policy makers, farmers, researchers, extension agents), and were able to incorporate social, economic, institutional and biophysical factors. Katic et al. (2016) described the model as a pre-scoping tool for quickly and efficiently identifying areas where interventions are more likely to be success, thereby guiding managers or policy-makers in targeting investments.
Schmitt and Brugere (2013)	The BN in this paper modelled the social, ecological and economic impact of shrimp pond management for a hypothetical case study. The model structure was based on literature and the conditional probabilities were populated by senior experts in coastal aquaculture. The authors demonstrated how the model could be used to assess trade-offs between ecosystem service provision, local livelihoods, financial profits and economic development. For example, the model suggested that replanting mangroves in the pond led to shrimp production loss on the one hand, but a reduced risk of loss from disease outbreak or typhoon and a greater likelihood of securing a premium price from production certification on the other hand. The authors noted that the Bayesian network model was not a predictive tool, but useful for articulating existing knowledge and beliefs about the shrimp farming, and for comparing trade-offs associated with different management strategies.
Slater et al (2013)	BN modelling was used in this paper to understand the human drivers influencing the ability and willingness of household decision-makers to consider sea cucumber aquaculture as an alternative livelihood source. Face-to-face interviews were used to collect data such as the respondents' dependence on marine resource, perceptions of marine health and policies, current economic and employment status, and their willingness to participate in sea cucumber aquaculture. Sensitivity analysis of the response variable 'willingness to participate in aquaculture', found that time available for an additional livelihood, gender and years of education had the strongest influence on their willingness to participate. Further analysis of the BN revealed more detail, including which factors were more important for subsets of respondents (e.g. those with low vs. high income, male vs. female, with primary vs. secondary education, etc. The BN generated understanding between factors and drivers beyond that of traditional methods due to their ability to integrate qualitative and quantitative data, deal with complex interactions among variables and uncertainties in human interactions and decisions. Explicitly representing uncertainties provided better context for assessing model results.
van Dam et al. (2013)	The BN model in this paper was developed to understand the interrelationships between hydrology, ecosystem function and livelihood outcomes in a wetland. The model was based on results from ecohydrological and socio-economic research (including empirical and secondary data, and literature), and expert and stakeholder consultation. The model was run to explore how livelihood activities (e.g. fishing, papyrus harvesting) and ecosystem functions (e.g. biodiversity, groundwater discharge) were affected by climate conditions (average/dry/wet conditions).The authors found that the BN approach allowed systematic investigation of the complex relationships in the wetland and a framework for discussion about management options, but was limited by their inability to represent spatiotemporal dynamics and feedbacks.

Table 6 Examples of fuzzy cognitive maps applied to agricultural or livelihoods development.

Study	Overview
Singh and Nair (2014)	FCM was used to assess the livelihood vulnerabilities of marginal agro-pastoral communities to climate variability and change). The cognitive maps were obtained directly from the community members. Together all participants firstly identified three main changes in climate observed in the past 6 years (the 'three central variables'). Subgroups (reflecting land holding and gender) identified variables affected by each central climate variable and coping strategies and adaptations to respond to those impacts. They then established the casual relationships and their relative weights. The researchers then combined and condensed the cognitive maps and categorised the variables into the different Sustainable Livelihood asset classes. Financial and natural assets and human health were found to be the most susceptible to climate change, whereas organisational, financial and social assets helped provide resilience against climate variability and change. The authors found that the major strength of FCM is its ability to handle multiple, co-occurring causes of improved or reduced vulnerability to climate change. Its weaknesses include its inability to provide inferential statistical results, and the uncertainty stemming from eliciting parameter values from stakeholders.
Murungweni et al. (2011)	FCM was used to understand the effect of adverse events such as drought on livelihood assets, namely cash and food availability. Working with local people (*who live in the area*), informants *(knowledgeable about local livelihoods)*, focus group (*local **and** with knowledge and interest about particular topic of livelihood research*) and stakeholders (*public servants, NGOs, traditional leaders, private interests*), a multistage approach was used to determine livelihood types, a FCM representing the structure of each livelihood system, and the strengths of relationships in each FCM. Stakeholders and focus groups then defined four scenarios based on expected climate futures and policy options. The authors suggest that by being able to assess the vulnerabilities of livelihood to various hazards, such models can guide policy makers in devising strategies more likely to achieve win-win outcomes.
Halbrendt et al. (2014)	FCM was used to represent and compare the mental models of experts and farmers on the effect of minimum tillage on farm production. The model predictions were then tested against local soil and yield measurements. The data supported the predictions of the majority of farmers that minimum tillage would decrease yield, as opposed to the prediction by the expert model that minimum tillage would improve yield. This study highlighted the value of local knowledge and experience, and the notion that 'best practices' such as conservation agriculture is not always widely applicable and must consider local conditions.
Diniz et al. (2015)	In this paper FCM was used to map local small farmers' current perceptions of the factors affecting their livelihood security and the environmental sustainability in (de)forested landscapes, to analyse differences between individual farmers and relate these differences to their adopted livelihood strategies and, lastly, to explore future changes in livelihoods and forests. The researchers classified households into one of three livelihood strategies and then conducted a workshop with each group to develop FCM. Starting with a list of initial factors that might affect either livelihood security and/or environmental sustainability (using forest cover at the property level as a proxy), farmer participants could argue to add or remove factors, although the factors considered were agreed by consensus. Workshop participants then worked on assigning quantitative weights to model relationships. The three post-processed FCM were used to explore future changes under plausible future scenarios (this activity was not conducted with farmers). The scenario analysis suggested win-win options where both livelihoods and the environment benefit were hard to attain, and helped identify differences between the livelihood strategies that were not immediately clear.

3.5 Coupled component models

Coupled component models combine two or more (typically quantitative) models from different disciplines or sectors so that they exchange information (e.g. some inputs and outputs) and operate together. This approach is particularly suitable for cases where there are existing models that have already been calibrated for an area and when the scope of the modelling problem is quite focused. In the three studies summarised in **Error! Not a valid bookmark self-reference.** the models described certain components of the system in greater detail than other components. For example, the cropping system in Reidsma et al. (2012) and Wei et al. (2009), and the hydrological system in Varela-Ortega et al. (2011) are the central components of these studies. However, there is less coverage of the breath of the system compared to the studies using other integrated modelling approaches discussed in earlier subsections. In particular, social aspects tend to be underrepresented and grossly oversimplified (at least from the SIAGI perspective).

Table 7 Examples of coupled component models applied to agricultural or livelihoods development.

Study	**Overview**
Reidsma et al. (2012)	This study coupled two pre-existing models – a bioeconomic farm model and TechnoGIN – together to assess the impact of different policies on nutrient pollution and sustainable development on economic, social and environmental indicators. TechnoGIN is a crop system model that quantifies inputs and outputs of crop systems (e.g. nutrient and pesticide application, labour, yield, crop residue) based on land characteristics, crop, target yield and technology levels. Whilst the model represents farm production in great detail, representation of livelihood, human health and food security are defined by the respective indicators: net income per labour day, biocide index, rice production.
Varela-Ortega et al. (2011)	A farm based economic optimization model is coupled with a hydrology model in this papers. The economic component models farmer behaviour under different climate, and agricultural and water policy scenarios. At the farm-level, the economic component estimates farm income and water consumption. The latter is then input into the hydrology model, which then upscales water consumption to basin-level and is used to assess the impact of different scenarios on aquifer recharge.
Wei et al. (2009)	In this paper, the authors integrate a farm-level water and nitrogen management (WNM) model with a farm economic model. The coupled model assesses the impact of alternative policies (e.g. water pricing, nitrogen input-based tax) on a range of indicators. These indicators covered economic viability (farm gross margin), social acceptance (food self-sufficiency), and environmental soundness (e.g. water use efficiency, nitrate leaching, N2O emission etc.), and were combined into an overall sustainability index. The model components were linked via the crop yield variable, with crop yield response function estimated using a multivariate regression technique. The different policy scenarios were fed into the economic model, resulting in the simulated farmer's decision, which was then input into the WNM model to simulate the impact of crop production on the sustainability of the agro-ecosystem. This coupled model allowed the tradeoffs between economic losses, food security and environmental benefits under different policies to be examined.

4 System conceptualisation

4.1 System structure

In SD, FCM and BN models, the problem or system is represented as a network of interrelated variables. These variables can represent any feature or factor, be it social, biophysical, economic or otherwise. These modelling approaches therefore lend themselves well to representing systems containing a diverse range of system components. As mentioned earlier, system models that can provide a 'big picture' of the situation (e.g. covering market, biophysical, social, institutional/political, and cultural factors), can help to highlight leverage points that produce positive outcomes through multiple pathways across the whole system. For example the qualitative system dynamics model in Ha et al. (2017) identified a range of factors that improved the quality of life of women smallholder farmers beyond the production system. In one of the study villages in Ha et al. (2017), improving incomes through better market access had positive impacts on other factors including family support and work sharing, participation in social activities and organisations, which subsequently improved knowledge, skills and status, and also gender equity.

Agent based models represent the system as interactions between actors and so necessarily have more a focused problem scope than the network based models (e.g. land use choices). The way in which coupled component models represent the system depend on the components, but the papers we have reviewed to date have focused upon the agronomic, economic and/or hydrological systems.

Regardless of the modelling approach used to model complex systems, it is easy for the scope of the model to become too large and unwieldy, to the point of 'confused complexity' (Lefroy et al. 2009). To avoid such an issue, Kok (2009) limited the concepts included in a FCM exploring agricultural expansion in the Brazilian Amazon to those that operated on relatively short temporal scales and were thus considered 'easy to manipulate'. The authors excluded long-term concepts such as soil degradation or vague concepts like consumer behaviour. All concepts included in the model were direct or indirect drivers of agricultural expansion (Kok 2009). Similarly, BN modellers working across the environmental domain have provided guidance on protocols to manage complexity in influence diagrams, such as limits to the number of parent links, variable states and levels (Chen and Pollino 2012).

4.2 Analytical frameworks

Many analytical frameworks have been developed to explore social-ecological systems. Binder et al. (2013) compared 10 established frameworks (Table 8) categorising them as

- ecocentric frameworks for use in looking at how human activities affect the ecological system *(analysis-oriented)*
- policy frameworks which are most appropriate for developing action oriented strategies for reducing the impact of humans on the ecological system *(action-oriented)*

- integrative frameworks for application to complex social-ecological issues where social dynamics and the interaction between the social and ecological system are to be studied *(analysis-oriented)*
- vulnerability frameworks which are best used to explore options on how to improve livelihoods or reduce vulnerability of poor communities to external forces *(action-oriented)*

The first two categories consider the impacts of the social system on the ecological system, the last category conversely considers the impact of the ecological system on the social system, and the third category explicitly considers two-way impacts.

In the literature we have reviewed to date, three frameworks have been used to underpin the model: DPSIR, HES and SLA (see Table 8 for full names). The SLA – namely some or all of the capitals[4] – have been used to guide: the model structure including selection of variables (Schmitt and Brugere et al. 2013; Barron et al. 2015), analysis of model outputs (Singh and Nair, 2014) or define the typologies represented in the model (Villamor et al. 2014).

DPSIR was used by Wei et al. (2009) to frame the scenario analyses undertaken with their farm-level coupled-component model which explored policy options aimed at improving agro-ecosystem sustainability. The coupled component model is used to model farm decisions and biophysical processes (the state) in response to model inputs that reflect the driving forces (climate, soil, technologies, and policies) which affect groundwater extractions and pollution and N_2O emissions (the pressures). Analysis of the modelled economic, environmental and social output indicators (the impact) can then inform responses, e.g. selection of policy options.

Table 8 Ten frameworks for analysing social-ecological systems (Binder et al. 2013)

Category	Frameworks
Policy frameworks	Driver, Pressure, State, Impact, Response (DPSIR) Social-Ecological Systems Framework (SESF) The Natural Step (TNS)
Ecocentric	Earth Systems Analysis (ESA) Ecosystem Services (ES) Material and Energy Flow Analysis (MEFA
Vulnerability	Sustainable Livelihood Approach (SLA) Turners Vulnerability Framework (TVUL)
Integrative (HES, MTF)	Human Environment Systems (HES) Management and Transition Framework (MTF)

The HES framework was developed to structure investigations of human-environment interactions and draws on decision theory and social learning processes, systems science and sustainability science (Binder et al. 2013). Human systems operate at multiple levels (individual-group-organisation-society) each with their interrelated environmental systems and conceptualisations of decisions (e.g. goal and strategy formation, selection and action) and environmental awareness

[4] Typically financial, human, natural, physical, and social capital although some authors further distinguish political capital

(Scholz and Binder 2004). The framework is concerned with examining feedback, decisions and learning within the different levels of HES over time. Not widely used yet, Le et al. (2012) used HES to frame their ABM study in the sensitivity of long-term land-use dynamics to the inclusion of secondary feedback loop learning, whereby the behaviour of households could change in response to longer term changes in socio-ecological conditions (behavioural models are fixed over time in most ABMs).

4.3 Scale

Most models reviewed thus far were developed to capture or generate knowledge at one particular spatial scale, e.g.: villages (Binder and Scholl 2010, Villamor et al. 2014), district (Singh and Nair 2014, Ha et al. 2017, Katic and Morris 2016), or national (Barron et al. 2015). The network-based approaches (BN, SD, FCM) mostly represent an aggregated perspective of situation of that scale. By linking Geographical Information Systems to BN models, Barron et al. (2015) and Katic et al. (2016) were able to spatially identify areas of high/medium/low potential for successful agricultural water management. In most of the ABMs reviewed, farm households are represented as agents, allowing interactions (e.g. sharing information about technologies) between households to be modelled (Schreinemachers and Berger 2011), typically as spatially explicit cells across the modelled landscape (Evans et al. 2011, Le et al. 2012).

BN models generally represent static snapshot(s) in time, whilst FCM do not explicitly model temporal dynamics (Devisscher et al 2016). Temporal dynamics and feedback can explicitly be represented in ABM and SD as well as coupled-component models. Relatively good understanding of or data on processes is generally required to represent temporal functions. In the literature reviewed, this tended to be limited to more physical functions, such as hydrological processes (e.g. Madani et al. 2009) or agricultural production (e.g. Lie et al. 2017). It is difficult to represent social and political dynamics as data are often limited and temporal relationships poorly understood.

5 Stakeholders roles in model development and use

In most of the studies cited in Section 3, researchers engaged with stakeholders primarily to obtain data to build the model; there is less reporting of how (or if) some of these models have been used with stakeholders once developed. Engagement took place with local community, experts, and/or other stakeholders from local authorities, government agencies, NGOs and private organisations. The type and amount of data elicited from stakeholder to develop model relationships, and the methods used to do so depends on problem being modelled, the selected modelling approach and the depth and scale of analysis.

Regardless of the selected model type, focus group discussions (FGD) and key informant interviews are routinely used in the scoping and problem formulation phases of integrated model development. Key informant interviews capture depth of understanding of the informants' knowledge, values, and beliefs about the system (their 'mental model'). These methods have also been used to collaboratively specify the structure of network-based models (BN, FCM and SD). They can be used with stakeholders to directly develop model relationships. For example in van Dam et al. (2013), stakeholders were consulted to provide feedback on the BN model structure prepared by researchers and to populate the conditional probability tables (i.e. parameterise the model). However, reflecting the time and capacities needed to develop model relationships, more often than not modellers develop initial model relationships, perhaps with a select subset of stakeholders (Chan et al. 2010), and then use FGD to test model behaviour and refine the model. FGD can be structured in various ways depending on the information required or the purpose of the exercise. For example, small (relatively) homogenous groups may be established to allow the depth of the participants understanding of the system to be captured and avoid those with power from controlling the direction of discussions. Alternatively, larger diverse groups may be the approach chosen if mutual learning or fostering understanding of other's perspectives is the aim.

Household surveys have been used to collect data to populate ABM (Evans et al. 2011, Le et al. 2012) or BN (Slater et al. 2013). The surveys can be used to reach a relatively large number of respondents (usually farmers in the literature). However, they are most suitable for well-defined (unambiguous) and quantifiable concepts, and so favour breadth of analysis over depth of analysis. Role-playing games are used quite frequently by agent-based modellers to develop the rules that drive ABM and/or to test model behaviour.

Within the modelling literature, there is a growing call for participatory modelling whereby engagement practices explicitly provide for two-way flow of information between researchers and the community (or target stakeholders). There are different approaches to participatory modelling:

1) get individuals or different groups to build different models to compare (Halbrent et al 2014);
2) collaboratively build a shared model that represents consensus among the different groups (Chan et al. 2010; Lie et al. 2017); or

3) a combination of the above two (Henly-Shepard et al. 2015, Murungweni et al. 2011).

The specific reasons for undertaking participatory modelling may be to compensate for a lack of data when populating or testing a model (Lippe et al, 2011), as a means of social learning (Henly-Shepard et al 2015; Murungweni et al. 2011), or to elicit knowledge or beliefs that are hard to define, sensitive or heavily context-dependant (Nyaki et al. 2014).There may be challenges in eliciting information from groups, particularly in large or diverse groups, or where there are strong personalities (Lie et al. 2017); the facilitator plays a critical role in ensuring equal participation. There can also be many advantages of participatory modelling in these larger, diverse groups from the participant's point of view, including the strengthening of social capital through building closer ties with others and a better mutual understanding and appreciation of others' roles and views (Lie et al. 2017).

6 Representation of social processes

6.1 Decisions

Out of necessity, models simplify how people make decisions. Some common simplifications are assumptions of economic rationality and/or perfect knowledge, or coarse or static statements of individuals or groups risk preferences or their level of uptake of interventions. In reality the decision making process is highly complex, based on the individual's sets of beliefs and values. Their beliefs reflect their perception of the problem and situation, and includes facts and opinions as well as the entailed uncertainties. Their values reflect their goals and objectives associated with the problem and the trade-offs involved (von Winterfeldt 2013). Realistically representing these beliefs and values will always remain a challenge.

In ABM, agents are capable of learning and adapting to changes in their socio-ecological environment. For example, an agent can modify their behavioural or decision rule set by imitating neighbouring agents (Villamor et al. 2014). This represents a more realistic decision making process compared to other modelling processes. In ABMs the decision-making rules are made explicit. However as discussed above in Section 3.1, the rules tend to be accompanied by gross assumptions such as the decision maker having perfect knowledge and the absence of common risk factors (e.g. pests, frost). Such assumptions are not limited to ABM and are common in models in general. In other models decision making is often simplified to one objective e.g. as in Wei et al (2009) where decision making was simulated using a linear programming model with an objective function that maximises the expected farm gross margin. Simplifying the decision to this single objective entails assumptions such as the farmer being risk neutral and having perfect knowledge about prices, field resources and technology availability (Wei et al. 2009), and not having other goals with respect to farming (e.g. to produce nutritious food for the family).

Rather than attempt to model decisions and the impact on environmental or livelihood indicators *per se*, a focus of some studies is to improve understanding of the beliefs and values underlying certain decisions and thus behaviour. Using BNs, Slater et al (2013) examined the factors that drove the decision about whether or not an individual would consider an alternative livelihood. In this situation the model is a static snapshot representing the factors influencing decision-making at the time of data generation. In such a case, 'what-if' scenarios can be explored by conditioning states in the model to explore the nature and magnitude of any likely changes. This would be best suited for projects focused on social learning or system understanding, but not prediction.

6.2 Representing people in the model

The way in which people are represented in the models tend to fall into a few main categories (Table 9). Most models aggregated individual people into archetypal groups and then represent their generalised behaviour or characteristics. ABMs are the only model type that has been used to represent the behaviours of individuals or individual households, although it is also common for ABMs to define representative 'agents' based on household typology. The household typology approach is frequently used in the modelling literature we have reviewed to date, across the model types. This perhaps reflects the relatively common framing of models using the sustainable livelihoods approach; the use of typologies in non-modelling livelihood studies is commonplace. Depending on the modelling approach, different models can be built to represent different livelihood types (e.g. FCM, Murungweni et al. 2011) or interactions between typologies (e.g. ABM).

Table 9 Some examples of how people are represented within models

Representation type	Examples
Individual households	[ABM] Evans et al. (2011), Schreinemachers and Berger (2011)
Household typology	[ABM] “Better off”, “Poor” (Villamor et al. 2014) [ABM] "paddy-based & poor", "upland crop & poor", "off-farm & better off" (Le et al. 2012) [FCM] "cattle", "cattle-crop", "non-farm" (Murungweni et al. 2011) [BN] “Landless”, “Small_Marginal”, ”Medium_Large” (Merritt et al. 2016)
By indicator	[BN] Evidence of ‘factors of success’ collected at a household level, such as ‘gender ratio’ or have ‘cell phone’ or ‘remittances’, aggregated to district (Katic and Morris, 2016) or national (Barron et al. 2015) scale [BN] homogenous groups based on land holding and gender (Singh and Nair 2014)
Gender specific	[Qualitative SD] “Women smallholder farmers” (Ha et al. 2017) [ABM] Gender specific land use decisions (Villamor and van Noordwijk, 2015)
No depiction	[Coupled-component model] Wei et al. (2009)
Other	[Structured Mental Model] “Farmer”, “Expert” (Binder and Scholl 2010)

Although the definition of typologies is often based on livelihood activities, land holding size or financial status of a household, other factors can be used to define homogenous groups. For example, Singh and Nair (2014) developed FCM with poor agro-pastoralists in Bhilwara, Western India. In their study participants worked in homogenous groups based on land holding and gender to develop cognitive maps (although the authors did condense these maps into one for their subsequent model development). In Slater et al. (2013), gender was one of the factors considered for explaining the willingness of individuals to participate in sea cucumber aquaculture, and was represented as one of the nodes in the Bayesian network. Model users could select female or male in the gender node to provide gender-specific representation of their model. This revealed gender differences in the importance of factors determining willingness to participate in aquaculture (Slater et al. 2013).

One potential drawback of defining representative groups is that it may obscure the variation within groups. Whilst we may not be interested in the ‘interactions between individuals and their impact on the system’ (a critical reason why modellers use ABM; Kelly et al. 2013), we may still want to capture some degree of variation or uncertainty. BN models can explicitly represent intra-group variation within their underlying conditional probability tables. Representing such variations is possible although more problematic for other modelling approaches. Whether this is an issue depends on the purpose of the modelling. With respect to FCM, Gray et al (2014) note that where the research priorities "seek to promote and represent the outcome of social learning" the focus is typically on model building process and exchange of ideas and knowledge between participants, with lesser emphasis placed on "capturing individual-level representations of knowledge".

Reflecting their focus on biophysical and/or economic representations, the coupled component models we have review to date have not explicitly represented people in the model. Rather, scenarios are developed which might reflect policy drivers or the level of farmer uptake of technology and management practices and then these scenarios are compared based on modelled output indicators that are typically agricultural production, economic or environment related.

6.3 Equity and Equality

In the reviewed literature, equity dimensions are not explicitly represented as indicators in integrated models. This is consistent with Stojanovic et al. (2016) literature review critiquing social-ecological systems research, whereby the authors note that *"resource extraction, population, and material benefits receive greater consideration than values, equity, nonmaterial and psychological aspects of well-being"*.

Equity dimensions are more likely to be considered during the IM activities of problem scoping and formulation and the use and communication of model results. Two examples that reflect the author's intent to capture either breadth of perspectives (or at least those of their target groups) from the problem formulation phase are provided by Ha et al. (2017) and Singh and Nair (2014). In the study of Ha et al, the participants included a balanced representation of ethnicity and of rich, fair and poor within the target group. Similarly, Singh and Nair (2014) purposively established groups based on individuals' landholding size and gender, so as to avoid the risk of certain members exerting too much influence during the cognitive mapping exercise. Assuming indictors that could be reasonably expected to vary between individuals or groups were scoped in the early phases of model development, and were represented as variables in the model, issues of equity can be explored using a participatory scenario analyses that look at trade-offs across variables. Schmitt and Brugere (2013), for example, used a BN as a tool to synthesise knowledge on the range of impacts of coastal aquaculture on human and ecological systems, and to explore trade-offs (what the authors termed "social conflicts over interest and values") and uncertainties associated with six management scenarios. Trade-offs were judged based on model outcomes for a range of variables such as resilience of local community, biodiversity and long term contribution to the country's shrimp exports (Schmitt and Brugere 2013).

Inequalities are dynamic, and can be exacerbated with agricultural intensification. Some studies have explored changes in inequality through time albeit constrained to framings around tangible assets such as household income. Evans et al. (2011) developed and ABM to assess how household-level inequalities changed as a result of the adoption of rubber plantation in the village. Inequality was measured using the Gini Coefficient based on household income. This index is a commonly used indicator of inequality in the field of economics. The model was run for the 1984 to 2006 period, and showed that the Gini Coefficient was low in the village (i.e. high equality) up to 2000, and rose dramatically thereafter. The rise occurred when the rubber trees became ready to harvest, 6-7 years after the trees were first planted by the early adopters who reaped most of the benefit (i.e. improved incomes). Le et al. (2012) also used the Gini index in their ABM.

7 Synthesis

The description of the ten dimensions of the SIAGI project in section 2 suggests the following characteristics of the IM (model/process) are required:

- The ability to represent multiple, diverse system components and issues;
- It supports participatory/collaborative modelling;
- An ability to represent more complex, multifactorial interventions such as the formation of community based organisations (e.g. community based water management, farmer groups, etc); and
- The capacity to use different types of information, including qualitative data sources, in defining model structure and model relationships.

All the modelling approaches reviewed have good potential to synthesise and formalise knowledge and data about the SIAGI systems, as well as generate better understanding of the relationships between components. In general they all have the capacity to incorporate qualitative and quantitative data, which allow capture of a diverse range of components.

The needs for representing both spatial and temporal scale are highly dependent on the specific problem that is to be modelled. The spatial and temporal dynamics have not been explicitly identified as phenomena of interest to model within SIAGI. Also given the spatial and temporal data limitations, it is unlikely that sufficient information is available to model these dynamics. Therefore, a rather simple treatment of time and space may be more suitable, for example a non-spatial model or lumped spatial model. Of the modelling approaches reviewed, this may only preclude quantitative system dynamics as suitable for SIAGI, given that its simulation is governed by time-dependent functions (Madani et al. 2009).

One important distinction of the modelling approaches, with respect to their suitability for SIAGI, is their capacity to serve as a tool for community or stakeholder engagement. There is increasing recognition within the R4D literature that understanding community perceptions and expectations is important, especially when the intent of the research is to impact policies and community-level interventions (Slater et al. 2013). The ethical community engagement perspective of SIAGI extends this further by stressing the importance of partnership between researchers and the community. This corresponds to more collaborative processes of two-way discussion, co-design and co-decision making (Basco-Carrera et al. 2017), as opposed to a one-way downward flow of information as seen in more traditional research methods. Ethical engagement attempts to avoid overburdening of communities, especially in terms of their time; this means we need to complement the IM work with other SIAGI analyses. Ethical engagement is expected to produce multiple co-benefits, including improving the conditions for positive change and generation of more meaningful research outcomes. A tradeoff exists between model complexity and the ability to use the model as a tool to engage stakeholders. Accordingly, the extent of community engagement that is supported in the modelling process is a crucial consideration for selection of integrated modelling approach within SIAGI.

Simpler, and more intuitive models such as FCM, BNs and qualitative SD are easier to explain and require data that can be readily elicited from non-experts and so these approaches are more suitable for participatory and collaborative modelling. Of these three, FCM and BN have the advantage of quantifying the strength of relationships, albeit at a crude level. This means the values of the model outputs for FCM and BN cannot be taken as absolute values, but rather in relative terms only. However, this is the case with many models where relationships are defined with mathematical formulae, such as quantitative SD, as results tend to be high assumptive and useful only in providing indications of trends (not values etc). One exception may be some cases of couple component models, particularly for simpler systems with a long history of data, where the models are fully calibrated and tested and can be used for prediction. However, coupled component models are unsuitable for SIAGI due to the lack of existing models of the system components and the breadth of the social-ecological system being considered.

FCM and BN seem to be the most suitable approaches given their proven capacity to serve as tools for collaboration and engagement with interdisciplinary teams and diverse stakeholders. BNs are better than FCM at representing uncertainties, which they do by quantifying relationships in terms of probabilities. The relationships in BNs can be either monotonic or non-monotonic. However, one major disadvantage of BNs is their inability to readily represent feedback loops. Whilst FCM can only handle ordinal variables and monotonic relationships, they can incorporate feedback mechanisms and they also have another advantage over BNs in that their relationships are more intuitive to quantify. BNs are quantified by populating conditional probability tables, whereas FCMs are quantified by using weights between -1 and +1. ***This suggests the FCM approach will better support co-development of IM with the research team*** (including the community). Thus the approach has been trialled for use in SIAGI and will form the basis of future modelling activities (Merritt and Hamilton, 2018b).

Our review indicated that the representation of social processes and impacts in models is generally lacking or disproportionately simplified compared with ecological or hydrological processes. A key example in the R4D literature is limiting representation of inequity to household income-based Gini index. Outside of the R4D literature, it has been suggested that subjective perceptions of environment (e.g. aesthetics), social conflicts and other concepts (e.g. equity, non-material or psychological component of well-being) may be best considered by discussing with stakeholders the implications of interventions or scenarios, rather than explicitly modelling social components within the model itself (Stojanovic et al. 2016). On the other hand, the co-development of models with stakeholders can bring rich insight into the problem, including the social aspects. The application of FCM approaches within the organisational behaviour and social psychology literature suggest that we should be able consider such concepts explicitly within our modelling, and then use the models to support reflection and discussion amongst the project team. Within these fields of literature, FCM have been used to contrast the communication patterns of high and low performing teams (Tchupo et al. 2017), explore the influence of competing concepts on organisational behaviour (Craiger et al. 2006) and identify, analyse and reflect upon individuals or groups subjective beliefs (Swan 1997). There are similarities between these studies and questions around perceptions, interactions and decision-making for our case study communities (Merritt and Hamilton, 2018b). Therefore, FCM shows promising potential in SIAGI not only for modelling the diversity of issues and complexity of the systems, but also as a tool for exploring complex social concepts with the team and our partner communities.

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