Interactions, Externalities, Time, and Space: Implications for Agricultural Innovation Systems Research

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Introduction

Recent research highlights the potential of the innovation systems framework to enhance our understanding of how agrarian producers in developing countries create, exchange, and use knowledge and technology (Spielman 2006 a,b; Hall et al., 2002, 2003; Hall and Clark, 1995). The framework demonstrates the importance of analyzing complex relationships and interactions among heterogeneous agents in the agricultural sector, and the socioeconomic institutions that condition these relationships and interactions, as a means of better understanding the innovation process.

These descriptions of innovation within a "systems" context suggests that decisions to innovate are often conditioned by the behaviour of other individuals and the social and economic context within which decisions are made (Schelling 1978; Young 1998; Anselin 2001; Brock and Durlauf 2001). This means that the incentives to innovate vary on the basis of individual endowments of wealth, income, or capacity; and collective endowments of a similar nature. Moreover, these interactions have a spatial dimension that influences the pattern and speed of innovation, often in ways that are not immediately intuitive, easily understood, or predictable (Hagerstand 1967; Rich et al. 2005).

These considerations suggest the need for greater sensitivity to the notions of time, space, and spillovers in the creation and diffusion of knowledge that is presently lacking in innovation systems research. This has particular relevance from a policy perspective in developing countries when targeting the utilization and dissemination of novel innovations in geographically, developmentally, and/or economically marginalized areas.

In this paper, we highlight specific elements from the economics and social science literature on innovation, externalities, interactions, and geography to illustrate the importance of these concepts to the innovation systems literature and, in particular, ways to strengthen innovation systems research methodologies. From this review, we present a number of methodological approaches that introduce externalities, time, and space into the innovation process. These include simple theoretical tools from game theory and complex systems theory. We also elaborate on a number of different empirical approaches, including agent-based models and cellular automata techniques (Berger et al. 2006) and social network analysis.

Combined, these models provide innovation systems analysts with a toolkit of both theoretical and empirical approaches that can enhance the quality of analysis with a better understanding of interactions, externalities, time, and space in the context of developing-country agriculture. Indeed, such methods can model the pattern and speed of innovation in ways that better target the impact of new knowledge and technology towards intended beneficiaries, particularly small-scale, resource-poor agrarian producers. Our paper concludes with a research agenda that illustrates the application of identified methodologies with salient research questions on innovation systems in developing-country agriculture. These conclusions suggest a need for stronger development of theory and empirical approaches and stress the value added by multi-disciplinary approaches towards innovation systems research.

Overview of innovation systems and motivation
Spielman (2005a: 46) succinctly defines an innovation system as “a network of agents, along with the institutions, organizations, and policies that condition their behaviour and performance with respect to generating, exchanging, and utilizing knowledge.” This approach is similar in concept and closely tied to the study of value chains (Kaplinsky and Morris 2001; World Bank 2006). In some respects, an innovation system reflects one aspect of value chain analysis by bringing actors together in the application of knowledge within a value chain, a process termed “upgrading” in the value chain literature (Kaplinsky and Morris 2001). Nonetheless, both ideas highlight the need for a holistic approach to the nature and structure of interaction between actors linked together within a system where the application of new or existing knowledge is the key system element.

Despite the integrative nature of an innovation systems approach, typical analyses in the context of developing country agriculture focus largely on case study analysis (Spielman 2005a).[1] The World Bank (2006), for example, presents a series of eight case studies used to illustrate a conceptual framework applicable to analyzing innovation systems, paying close attention to the nature of interactions between actors in an innovation system. This analysis is largely qualitative and descriptive, based on a “checklist” of specific roles, attitudes, behaviors, patterns of interaction, and characteristics of the external environment.

While this framework presents a multitude of needed information to characterize the system in which knowledge is created and applied, the analysis effectively stops at what is essentially “storytelling.” Morover, this storytelling often ends without asking the key question of how alternative policy options can be designed, implemented, and operationalized to enable greater innovation or, in the context of developing-country agriculture, greater pro-poor innovation.

Thus, while the innovation systems approach offers in-depth assessments and descriptions of the role of interactions between actors, it rarely addresses the broader *context* of these interactions and their *implications* for the innovation process at more aggregate levels of social or economic life. This is of particular importance if interventions designed to improve the use and sustainability of innovations are to be successful.

Figure 1 illustrates these ideas graphically, stressing that the set of potential beneficiaries from an innovation may have specific spatial, temporal, technological, or other boundaries that require further consideration to understand an innovation’s full impact. In this review, we highlight three specific areas in which greater attention is needed in

[1] This critique could likewise be levelled at value chain research as well: see Rich and Narrod (2006) or Rich and Ross (2006).

innovation systems research: the role of externalities (or spillovers), sensitivity towards space, and the importance of dynamics and inter-temporal interactions.

Externalities

The adoption of an innovation by one actor in an innovation system can have positive or negative impacts on other actors which are often unpredictable or unintended. The growing literature on social interactions has examined how decision-making by an agent is influenced by the decisions of those around him in the context of a multitude of social phenomena. Examples include studies on the evolution of conventions (Ellison 1993; Kandori, Mailath, and Rob 1993), predispositions towards crime (Glaeser, Sacerdote, and Schienkmann 1996), herd behavior in markets (Banerjee 1992; Morris 2000), land use patterns (Parker 1999), and technological innovation (Allen 1982; Arthur 1989) among others. While the innovation systems framework recognizes the importance of complex interactions, it rarely explains or measures the unintended impacts, both positive and negative, on agents within a system. More to the point, current methodologies provide insufficient explication of the externalities concept, suggesting the need for alternative analytical tools to provide a more sensitive or nuanced understanding of these interactions.

Space

Externalities do not take place in a vacuum: the magnitude of a spillover is partly determined by the spatial context in which the innovation occurs. Peer effects, for instance, describe how local (e.g., farm-level) innovation behaviours influence decisions made by neighbors, i.e., learning-from-others rather than learning-by-doing effects (Hagerstrand 1967; Foster and Rosenzweig, 1995; Conley and Udry, 2001). Agro-climatic effects describe how different geographic conditions (rainfall patterns, soil quality, etc.) affect innovation behaviours (Griliches 1957). Recently, these spatial determinants of innovation have been incorporated into the notion of development domains (Wood et al., 2005).

Time

Dynamic considerations are also of prime consideration in the innovation process. Indeed, the World Bank (2006) acknowledges the importance of dynamics, particularly in terms of how challenges to the innovation system, in terms of new rules and regulations, consumer tastes, and other factors, may influence patterns of innovation over time. However, what is often overlooked in this process is the potential role of feedback within a system arising from internal or external changes. Because an innovation system is comprised of networks of actors, not unlike that of a value chain, changes in relationships in one part of the network will typically reverberate in other parts of the network over time (Rich and Ross 2006). The process of the speed of innovation diffusion has been explored in a number of contexts in the economics and geography literature. Spatial considerations that influence the strength and number of interactions can further modulate the speed and evolutionary behaviour at which an innovation is transmitted, as explored in a number of theoretical models (Young 1998; Eshel, Sansone, and Shaked 1996; Morris 2000; Rich, Winter-Nelson, and Brozovic 2005; Santos, Pacheco, and Lenaerts 2006; My, Willinger, and Ziegelmeyer 2006). Thus, understanding how an intervention will play out in an innovation system requires much more than a description of potential challenges and mitigations, but sensitivity to rates of change, accelerations in change, and the parameters that affect these movements over time.

Methods to enhance innovation systems research that incorporate interactions, externalities, space, and time

<u>Game theory and cellular automata methods</u>

Spielman (2005b) utilized game theory to demonstrate the process of adoption within an innovations system, given that game theoretic approaches provide insights on agent behaviour that is conditioned by the behaviour and choices of those around a particular agent. Spielman used a variant of the "hawk-dove" game developed by Maynard Smith and Price (1973) that was originally used to characterize the evolutionary behaviour of wildlife. Indeed, we would argue that game theory has greater applicability in the context of an innovation system, particularly when issues of space and externalities are important. In particular, we see value in other types of games and strategic approaches discussed briefly below that more specifically highlight the interactions between agents in an innovation system.

The Stag Hunt game is salient in this context (Skyrms 2004). In the stag hunt, agents are each faced with two choices: either to hunt stag or hunt hare. Hunting stag produces a higher payoff than hunting hare, but only if the other agent in the hunt also hunts stag. If one agent decides to hunt hare, it is likewise better for the other agent to do the same. Table 1 characterizes the choice of strategies in this game. There are two Nash equilibrium in this game: both agent 1 and 2 hunt hare (H) or both hunt stag (S). Hunting stag is characterized as "payoff-dominant" because it provides the highest payoff to both players. By contrast, hunting hare is "risk-dominant": it provides an agent with the highest payoff irrespective of the decision made by the other player.

Table 1
A stag hunt game

		Player 2	
Player 1	**Strategy**	*Hunt Stag (S)*	*Hunt Hare (H)*
	Hunt Stag (S)	3,3	0,2
	Hunt Hare (H)	2,0	2,2

The dominance of one equilibrium over another in a system will depend largely on the nature of interactions between players. These interactions are grounded in space, time, and the behaviour imbedded in those interactions. In a dynamic setting, if players base their actions as a "best-response" to the actions made by surrounding players in previous periods, the hunting hare equilibrium tends to evolve as the dominant equilibrium. By contrast, if players instead imitate the decisions made by others, the equilibrium of hunting stag can evolve within society, depending on the initial distribution of actors within the system. Local interactions between agents play a key role in modulating this type of behaviour as does the dimensionality of interaction (i.e., whether agents are in a circle or interact in two dimensions). Indeed, Skyrms (2004) shows that in systems where agents imitate the decisions made by one's surrounding eight neighbours and where the initial population is comprised of 50 percent stag hunters and 50 percent hare hunters, over time, stag hunters will comprise of the entire population in over 99 percent of repeated trials. At the same time, smaller initial populations of stag hunters can lead to states in which there are pockets of both types of hunters co-existing. Further, in one dimensional interactions, random perturbations can disrupt the "all-stag" equilibrium and move it to a state where hare hunting is the dominant equilibrium. The nature of the topology of interactions can also influence the speed by which an equilibrium is reached: Rich et al. (2005) demonstrate that a situation with heterogeneous agents with different numbers of interactions based on where they are located within space can affect the evolution towards equilibrium in ways that are not intuitive. This suggests that strategic decisions to adopt or utilize knowledge within a system are multi-dimensional and warrant more thorough analysis, both from quantitative and qualitative perspectives.

Game theoretic approaches can be further enhanced by the use of cellular automata or agent-based techniques that visually represent the evolution of strategic behaviour over time. Cellular automata (CA) have a long history in mathematics, computer science, and the physical sciences to explain the evolution of a host of physical systems (see, for instance, Wolfram 1985). In a cellular automata model, agents are placed on a two-dimensional grid with behaviours that evolve according to some pre-defined state transition rule. Formally, a cellular automata model can be described as $Q=\langle S,N,T\rangle$, where Q represents the state of the system, S the set of all possible states for each cell, N the neighbourhood of agents influencing a cell, and T the transition rule that describes the change in state from time *t* to time *t+1* (Itami 1994)

In the social sciences, CA-type models were used by Sakoda (1971) and Schelling (1978) in models of migration and segregation, respectively. The first formalized used of CA in the social sciences, however, was Albin (1975), which broadly applied CA to various economic issues, such as the relationship between production systems and social organization, technology change, and social choice theory. Following in the tradition of Albin (1975), Epstein and Axtell (1996) designed a CA system known as the Sugarscape in which agents behave according to both pre-defined transition rules and the characteristics of the cell in which they are located. Each cell is endowed with a particular quantity of "sugar" which gives agents a certain amount of utility; decision rules are set such that agents migrate in search of sugar. The Sugarscape model is used to examine the dynamics of social behavior, based on different allocations of sugar, decision rules, and interaction effects.

In agriculture, Berger (2001) and Berger et al. (2006) developed multi-agent models that are similar in spirit to CA models. In multi-agent models, the behaviour of agents is modeled in a more sophisticated manner, with decision rules and actions based on a number of different aspects (Gilbert and Troitzsch 1999). For instance, while pure CA models may employ a simple transition rule, in multi-agent systems, these might be more complex, with decisions made on the basis of multiple criteria and interactions with other agents. In Berger et al. (2006), household land use decisions are shaped by their own knowledge, interactions with others, and endowments in terms of soil and water quality that are spatially represented on a lattice.

Combined, these methods potentially provide innovation systems practitioners with new approaches to understand the process by which knowledge is created and accessed by different actors in an innovation system in a manner that captures these changes over time and directly highlights the interactions and potential spillovers that result from the use of new knowledge. Game theoretic tools provide a potential way to model and analyze the nature and context of strategic behavior that could then utilize CA and multi-agent techniques to understand and visualize the innovation process. Such techniques have important policy implications, particularly in understanding where best to focus investments necessary to improve uptake and capacity of producers and other actors in an innovation system. Indeed, where agents have different endowments and capacities to adopt an innovation, game theoretic, CA, and multi-agent approaches can provide practitioners ways of best targeting capacity to adopt an innovation.

Spatial Econometrics and Spatial Analysis

Measuring and testing for spatial interaction is a difficult task. Spatial econometrics and spatial analysis provide a framework for empirically testing theories of micro-level interaction among agents. If, for example, we suspect that having a neighbour who innovates increases the chance of another agent engaging in similarly innovative behaviour then this can be tested with a spatial lag model. However, it may also be difficult to determine the true cause of the innovation adoption. Was it the result of a learning process or a result of the environmental and economic conditions that the agent shared with his neighbour? This method requires geo-referenced data, which is a significant limitation. As data has become more readily available this problem is rapidly disappearing. (Anselin, 2001, 2002)

New tools from value chain analysis

As noted earlier, innovation systems research and value chain analysis share many commonalities, both in their holistic approach towards understanding the multiplicity of actors that create and use innovation (or value, in the case of value chains) but also in their weaknesses in relying primarily on qualitative approaches. However, recent work by Rich and Ross (2006) suggests that system dynamics tools, used in agribusiness, operations research, and business logistics, hold promise for quantifying the relationships in a value chain, or analogously, an innovation system. This has particular value in understanding the impact of alternative interventions from public policy.

In a system dynamics model, one explicitly examines the flows and relationships between different actors within a system, based on stocks, flows, and feedbacks (Sterman, 2000). A stock denotes the current state of a system, while flows demonstrates rates of change between stocks. Feedbacks relate stocks with flows and are calibrated by exogenous parameters. Whether feedbacks are positive or negative depends on the mathematical relationship between such variables. Figure 2 illustrates a simple system dynamics model in the STELLA programming language in which some product passes through different parts of the supply chain. At each time period, orders are based on previous orders, current stocks, target inventories, sales rates, and various behavioral parameters that relate orders and inventories (McGarvey and Hannon, 2004). Shipments take place over a period of time – in some cases, there may be delays embedded in certain relationships. For instance, the stock “shipped” is represented by a “conveyor” that illustrates the time delay inherent in shipping a product.

This “simple” model highlights the interactions between actors within a value chain; analogous relationships could be modeled within an innovation system as well. Note that in this supply chain, changes in inventory levels, reactions towards shipping or storage goals, or demand will reverberate through the system, changing the dynamics of behaviour within the value chain. Such a model can thus provide concrete, quantitative options to decision-makers that traditional value chain analyses cannot, providing a laboratory to assess the short-run and long-run impacts of alternative public policies or investments that could be instituted within the value chain. More significantly, such models can highlight potential feedback mechanisms that such interventions may have in a system and thus alert decision makers to possible unintended consequences.

Conclusions

Innovation systems research has provided development practitioners with a holistic, practical way in which to understand the process by which new knowledge is created and utilized. In this paper, we have suggested greater sensitivity in such research to the role of spillovers, space, and time that are often not explicitly a part of these methodologies. To this end, we propose a number of new quantitative techniques that could further elaborate the nature of interactions within an innovation system that could also inform public policy, in terms of the types of interventions that could be undertaken; their potential magnitude, ramifications, and unintended consequences; and ways that such interventions could be targeted to raise the capacity of specific actors. We would suggest a greater emphasis in the future to combine theory from economics and other social sciences with the practical design of present research in the innovation systems field. We see significant promise in such synergies, particularly as such tools can help policymakers to better operationalize and implement policies to enhance the innovation process.

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Figure 1
Innovations in the context of interactions, externalities, and space: A conceptual approach

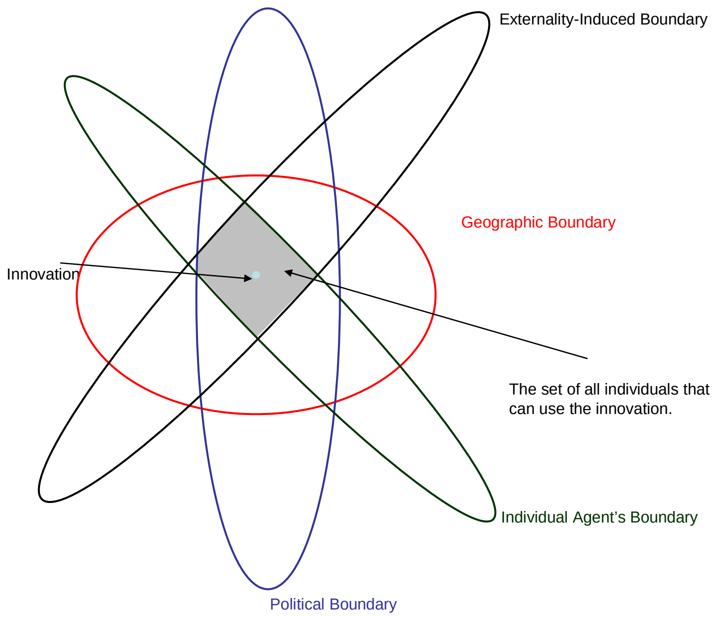
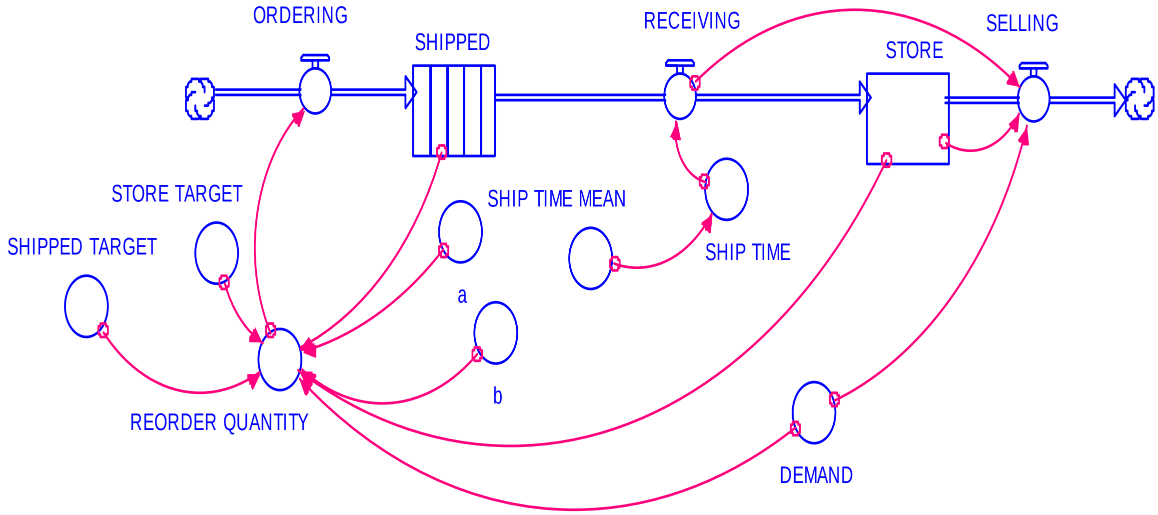


Figure 2
A simple stock management model in STELLA



Source: McGarvey and Hannon (2004)