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Remote Sensing and the Social Sciences

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INTRODUCTION

The challenge in today's practice of remote sensing for the social sciences is that it does not fall neatly into a particular set of sensor systems, does not carry one specific set of approaches, and is carried out globally in diverse systems spanning the natural-anthropogenic divide. In large part this diversity stems from the nature of social science questions to search for answers to more abstract processes that may lack a direct biophysical result (Liverman et al. 1998), necessitating indirect mapping of social processes rather than direct mapping of biophysical phenomena. This legacy starts this chapter's discussion, and motivates the remaining sections that explore how social science applications are at once wholly different from other remote sensing applications, yet function as a microcosm for understanding the accomplishments and challenges facing all remote sensing practicioners. After providing examples of the breadth of social science remote sensing, population–environment interaction studies are examined in more detail as representative of the challenges involved in marrying discrete and continuous data for interdisciplinary analysis of the world's most pressing social and environmental problems. Next, the scale-pattern-process framework as borrowed from landscape ecology and geography is employed as a lens for understanding implications of remote sensing resolutions on data choices and research questions where the assessment of causality and subsequent prediction must face the inherited complexities of mapping often intangible or indirect social processes. Lastly, this discussion is carried into the modeling approaches currently under use and experimentation, with a final discussion about the challenges facing continued use of remote sensing for social science applications.

THE LEGACY OF DIRECT VS. INDIRECT MAPPING

Remote sensing historically was developed for purposes of military reconnaissance and defense, with platforms as diverse as hot air balloons, aircraft, spacecraft, and even pigeons (Jensen 2000). In the 1970s, the development of satellite sensor systems also responded to the needs of the earth science community, particularly with regards to spectral band placement and width as seen in the changes from the Landsat MSS to Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) missions (Jensen 2000). While multiple national governments and private companies continued to expand, refine, or distinguish their own sensor capabilities, in general no single sensor system was built to respond particularly to the needs of the social science community. This legacy continues today, as social scientists work to extract meaningful information from sensor systems designed for other purposes. Yet some would argue that the social science applications of these systems, notably including land change science, have in fact increased the visibility and saliency of remote sensing and related approaches and products, particularly in research applications, more than any other application area (see, e.g., Gutman et al. 2004). At the heart of remote sensing linkages to social science applications lies the juxtaposition of the power and disadvantage of using these data for extracting useful information several orders removed from spectral-based data.

Consider, for example, the fluvial geomorphologist needing to examine changes in landform given perturbations of a flooding regime, or the ecologist wishing to understand vegetation response to shifting climatic events. In each case, the variables of interest (drainage basin patterns, flood extent, vegetative biomass, precipitation pulses) are not directly tied to spectral response but have been shown to be strongly correlated and physiologically related to measurements or indices derived from those spectral measurements. These proxies could be said to be one order removed from the actual spectral measurements taken at sensor. The social sciences, on the other hand, rely upon inferring social processes as manifested by physical phenomenon observable on the landscape via spectral measurements. For example, vegetation indices may be used to capture changes due to management (e.g., agricultural intensification via increased fertilizer, pesticide, herbicide, and irrigation), underlying soil conditions, or climatic conditions (Moran et al. 1994, Walsh et al. 2001, Archer 2004). In this case, the human activity is two orders removed from the at-sensor measurement. More complex (and of greater interest to the social science community) are those phenomena that are even further removed, such as the influence of power structures on household dynamics. In this case, theoretical, physical, and spectral bridges must be built and tested to establish a correlation (or ultimately, a causal connection) between spectral measurements and household dynamics. Further complicating these efforts is the problem of many-to-many relationships, where a given set of household dynamics could result in myriad landscape responses, while simultaneously multiple household scenarios could also possibly lead to a similar landscape (metaphorically equivalent to geomorphology's exposition of the polygenetic continuum). Social science applications therefore represent perhaps the greatest leap of technological, methodological, and theoretical faith faced by remote sensing analysts, further exacerbated by the topical range of their foci. Current application areas include population-environment interactions ranging from migration (e.g., Perz and Skole 2003) to household life cycle assessment (Barbieri et al. 2005), land use management (e.g., Campbell et al. 2005), geographic accessibility (e.g., Verburg et al. 2004), population counts (e.g., Wu and Murray 2007), and landscape ethnography (e.g., Nyerges and Green 2000). Much, though not all, of the literature shows a strong international focus, with projects spanning Asia (Walsh et al. 1999), Africa (Reid et al. 2000), South America (Moran et al. 1994), Central America (Chowdury and Turner 2006) and North America (Walker and Solecki 2004) and covering diverse ecosystems ranging from mountains (Gautam et al. 2004) to desert (Herrmann et al. 2005) to urban (Seto and Fragkias 2005) to Amazonian (Evans et al. 2001). Techniques heavily integrating remotely sensed data include multilevel modeling (Overmars and Verburg 2006), spatially explicit statistical modeling (Geoghegan et al. 2004), model validation (Pontius and Schneider 2001), cellular automata (Yeh and Li 2001), and agent-based modeling (Deadman et al. 2004). As such, the vast and varied applications in the social sciences offer a testing ground for assessing where remote sensing has the greatest potential for societal impact as well as the greatest risk of misinterpretation.

DISPARATE DATA REPRESENTATIONS AND POPULATION–ENVIRONMENT INTERACTIONS

If social science applications indeed represent a test of the growth in utility of remote sensing, then population–environment interactions could arguably be used as the microcosm for understanding both the strengths and weaknesses inherent in, tackled by, and challenging remote sensing. The watershed moment for remote sensing support of population–environment research came in 1998 with the publication of Liverman et al.'s *People and Pixels*. Two years earlier, the US National Research Council brought together researchers involved in NASA-funded research as well as the Human Dimensions of Global Change community to discuss the study of human activities with a strong spatial component, such as land use change, and with an eye toward predictive capabilities for socially significant or policy relevant events and phenomena (Liverman et al. 1998). To this point, *social* spatially explicit data were considered to be primarily the domain of household and community surveys, such as with the US Census files. The apparent divide described in *People and Pixels* lay between the remote sensing specialists, whose work was considered primarily biophysical in nature, and the social scientists, whose work was considered to lack any true biophysical systems understanding. But further underlying this divide was a difference more subtle yet to this day more pervasive: that of data models. Social scientists had in fact been using spatially explicit data, particularly in the form of US Census data and related boundary (TIGER) files, but had done so using a vector data model; remote sensing scientists (with some aerial photogrammetrists notwithstanding) primarily worked within a raster data model. The difference was in many camps considered unbridgeable (McNoleg 2003), but the group convened in 1996 recognized that addressing some of the most compelling social-environmental problems of the day required asking both why and where, and that the inherently interdisciplinary approach to melding social science and remote sensing datasets would ultimately require learning when and how to cross or fill the discrete-continuous chasm. The challenge, though addressed by increasingly sophisticated modeling efforts, remains one of the largest hurdles in social science applications of remotely sensed data today (Rindfuss et al. 2003).

To the remote sensing analyst, a raster view of the world provides simplicity, completeness, and efficient processing: a wall-to-wall representation of a given area is arranged in uniform pixels that not only predefines neighborhood but also makes for streamlined coding. To the social scientist presuming a vector representation of reality, wall-to-wall data are cumbersome when there are areas not of interest within the study area extent, and pixels are only arbitrary units of analysis that hold no meaning for any given phenomenon of interest. Perhaps obviously, two primary options are available for integrating these data in a [mostly] spatially explicit manner: either rasterize the vector, or vectorize the raster. That is, decide which to prioritize: people, or pixels. The options were not new to geographers, particularly those working in GIS, who had been grappling with this type of quandary for some time. What was new, however, were the broader implications of collapsing biophysical data (pixels) to areas of social units (people) or spreading people onto the wall-to-wall landscape (pixels). Embedded in this decision was a still critical dilemma of researchers today: what is the appropriate unit of analysis for population–environment interaction studies? What were the implications of collapsing watershed processes into political administrative unit boundaries, or of spreading household measures of socioeconomic processes onto the landscape? The answer offered suggested that the most compelling question or process should drive the decision; e.g., assessing the impacts of population density on deforestation might entail spreading people on the landscape beyond where their data were collected, but understanding the impact of declining forest resources on household fertility decisions would mean bringing the forest or pixel information 'to the household.' While it is an overstatement to suggest that the NASA workshop or the Liverman et al. (1998) book started a new movement in social science applications of remote sensing, it is accurate to say it popularized the necessity of interdisciplinary teams to address the question from both sides of the raster-vector or continuous-discrete divide, both 'socializing the pixel' and 'pixelizing the social' (Geoghegan et al. 1998). Such is not to imply that the resultant body of work in land use change and population–environment interactions orbited solely around questions of data integration; rather, these researchers recognized that the key to addressing fundamental questions of social and environmental importance using remote sensing data required theoretically and practically remapping methods of data integration. As such, these fields have led social scientists interested in remote sensing applications in conceptual and material contributions (Walsh and Crews-Meyer 2002, Fox et al. 2003, Gutman et al. 2004, Rindfuss et al. 2004).

SCALE-PATTERN-PROCESS AND DATA RESOLUTION

As diverse as the bodies of theory motivating social science research are, they nonetheless have been enriched by principles borrowed from the natural sciences. Particular emphasis has been placed upon lessons learned from landscape ecology that provide a framework for interpreting landscapes in terms of both composition and configuration. This framework is commonly referred to as 'the paradigm of scale-pattern-process' (Walsh et al. 1999, Turner et al. 2001) in geography and, interestingly, as 'process-pattern-scale' in ecology and biology (Crews-Meyer 2006). The central tenets posit that the scale of analysis (here, especially imagery) chosen impacts the patterns that are [remotely] observable, which are used to infer the processes at work on the landscape (Nagendra et al. 2003, 2004, Walker 2003). Or, taken in reverse, processes drive patterns whose observation is scale-dependent. Typically, this school of thought is operationalized with spatial scale, and particularly with grain or resolution more so than extent (Turner et al. 2001). But in theory and practice, other scales of remotely sensed data are easily as impacted or informed. The grain of temporal scale, frequency of observation or return time, impacts whether observable land use/land cover changes can be disentangled into processes with different temporal signatures, whether long-term (e.g., urbanization), seasonal (e.g., phenological), or even diurnal (e.g., tidal) processes. Again, the extent (here, temporal) may impact choice of research questions or data sources. Spectral resolution, or more broadly stated as choice of sensor system, clearly impacts the ways in which phenomena are conceptualized and tested. For example, the impact of changing market conditions on coffee agriculture will be evidenced differently by sensor systems that provide information on vertical structure, such as assessing age structure or understory/shade species via small footprint LIDAR, versus detecting pest invasions or success of pesticides or irrigation via multi- or hyperspectral optical systems.

Obviously no sensor system can maximize every type of resolution or therefore meet the needs of all application areas given that there are trade-offs between resolutions as a consequence of technological and physical realities such as data transfer speeds and orbital requirements (Jensen 2000, Messina and Crews-Meyer 2000). But guidance for place- and process-based applications of remote sensing (see, e.g., Jensen 2000) can be adapted for social science applications: for example, urban and peri-urban study areas (Wilson et al. 2003; Seto and Fragkias 2005) and population- or cadastral-focused studies (Fox et al. 2003, Schelhas and Sanchez-Azofeifa 2006) tend to require higher spatial resolution (grain), while emergency preparedness and disaster mitigation applications require prioritizing temporal resolution. Clearly, a part of the rich tradition in social science applications of remote sensing has stemmed from operationalizing social science theory into its concomitant physical landscape impacts, whether those connections be theorized *a priori* or explained post-observation. The scale-pattern-process framework offers a means of complementing other social science approaches of positing and assessing causal connections between or among social and biophysical processes.

FRONTIERS OF MODELING

Rindfuss et al. (2004) describe both methods used in and methodological issues arising from the study of population and environment in frontier environments. What is fundamental in their description is the many challenges that emerge from the study of how, where, when, and why land use/land cover changes. These issues generally revolve around questions of time, place, motivations, and implications of land use dynamics that collectively acknowledge the relevance of the human dimension, the complex interplay between people and the environment, the interconnections of endogenous and exogenous forces and factors, and the centrality of maps and models in characterizing landscape patterns and the drivers of change (e.g., Walker and Homma 1996).

While most of the mapping needs of the Land Change Science community are generally addressed through a combination of fine spatial resolution (e.g., QuickBird and Ikonos), hyperspectral (e.g., Hyperion), and multi-spectral (e.g., Landsat Thematic Mapper) remote sensing systems, variables that describe the state and/or condition of the environment and the space–time patterns of land use/land cover are used to initialize, parameterize, calibrate, and validate statistical and spatial simulation models. The intent of these models is to link scale-pattern-process relationships by associating the socio-economic, demographic, biophysical, and geographical drivers of land use/land cover change through variable estimations that involve statistical approaches and spatial simulation models.

Statistical models that are used to describe the variation in land use/land cover patterns tend to emphasize multivariate techniques to estimate the significance and magnitude of the relationships between patterns and processes at the scale of the pixel or at a scale more fundamentally related to the human dimension (e.g., household farms, communities, and provinces). A challenge to conventional statistical methods for land use/land cover modeling, such as regression approaches, is the spatial dependence of land use patterns that imposes biases in the model through the presence of spatial autocorrelation – the ordering of data values as a consequence of location. Spatial autocorrelation is often present as a consequence of the spatial structure or organization of landscape features and land use/land cover types that are mapped by remote sensing systems. Also, spatial autocorrelation is generally present in the cross-sectional and/or longitudinal social surveys that are used to characterize the human dimension as households are often sampled in some clustered form, because of logistical constraints of access in the field and the tendency of human settlements to cluster in space. Further, multivariate statistical models also generally assume spatial stationarity where the nature of the relationship between variables is fixed over space. Human and environmental processes, however, are generally non-stationary in that the relationships depend on where the features occur across the landscape

(Fotheringham et al. 2002). If non-stationarity occurs, global modeling techniques, such as regression approaches, are generally inappropriate or unrealistic as they characterize 'average' effects in place of 'local' conditions. Some global approaches are used that are entirely appropriate and realistic to address the drivers of land use/land cover through econometric models. For example, multi-level models have been used to describe deforestation and agricultural extensification processes on household farms (e.g., Pan and Bilsborrow 2005) in the Ecuadorian Amazon. Multi-level models represent processes across hierarchical spatial scales, for example, the effects of communities on household decision-making about land use patterns on farms (Pan et al. 2004). In addition, spatial lag models are global regression models that generalize the relationships across the region, but take spatial dependence of relationships into consideration through the use of a weighted neighborhood matrix that characterizes neighbors and their spatial interactions (Anselin 2002).

Spatial simulations models are often designed to address a variety of 'What if?' questions through scenarios of land use/land cover change that generally involve the complex interplay between people and environment. Whereas experimentation is often an option for natural science questions, in social sciences experimentation is rarely ethically practical, and simulations provide a means for testing how individuals, households, communities, or even countries would react under a variety of contexts. Using complexity theory as the framework, dynamics systems are examined through Cellular Automata (CA) and Agent-Based Models (ABMs). Complexity theory conceives the world as consisting of self-organized systems, either reproducing their state through negative feedbacks with their environment or moving along trajectories from one state to another as a result of positive feedbacks. The goal is to understand how simple, fundamental processes can be combined to produce complex holistic systems. Land use/land cover simulations that are generated through CA approaches rely on growth or transition rules, neighborhood associations, and a set of initial conditions to assess land use/land cover change patterns for some simulation period (Walsh et al. 2006). ABMs involve the use of autonomous decision-making entities (agents), an environment through which agents interact, rules that define the relationship between agents and their environment, and rules defining the sequence of actions in the model (Parker et al. 2003). Macro-level behaviors 'emerge' from the actions of individual agents as they learn through experiences and change and develop feedbacks with finer scale building blocks as agents. The characterization of the transition or growth rules in the CA and agents in the ABMs often rely on social surveys to describe the human dimension and remote sensing to describe the environment.

THE CHALLENGES AHEAD

Fundamental advantages of remotely sensed data benefiting a variety of application areas do also apply to social science applications as well: a synoptic view, a workaround for inaccessible or unsafe areas, cost-savings compared to field-only collected datasets, and 'seeing' the world beyond the limitations of human visual capability. The question 'What is social?' pinpoints the challenge facing remote sensing for social science pursuits: that few social processes are *directly* manifest on the landscape and thus require using proxies of proxies via indirect mapping. But remote sensing also provides the spatial, environmental, and biophysical context in which social processes occur, without which social science models are left under-specified. With migration, for example, the spatial, environmental, and biophysical contexts clearly change as people migrate, and these changes need to be explicitly included in the model as endogenous factors (Liverman et al. 1998). Understanding how these contexts translate into appropriate choices for selecting remotely sensed data (and methods) is often unclear to social scientists aiming to incorporate remote sensing analysis into their studies, just as remote sensing specialists trained in working with soils and vegetation may not initially understand how remotely sensed data may be best leveraged for studying human populations. To this end, Table 31.1 presents data selection priorities for analysts working to bridge remote sensing and social science applications lacking experience in at least one of these areas.

Ultimately though, just as the social phenomena under investigation, remotely sensed data capture what is often ephemeral, and the snapshot nature of remotely sensed data can impact the certainty with which ephemeral processes or entities are delineated; happily, at least, archival remote sensing does not do the same problems of accurate memory recall that social scientists face when interviewing people for information on past events (Rindfuss et al. 2003). The startup costs of remote sensing projects can be high and pre-startup costs are frequently underfunded (Rindfuss et al. 2004). This is not to say that the costs of other social science primary data collection efforts (such as household surveys) are not sometimes prohibitive as well, but rather to underscore the need for continued improved and subsidized access to remote sensed data such that the entry into remote sensing for social science applications is more easily facilitated.

Table 31.1 Eight tips on data selection for social scientists new to remote sensing, or remote sensing specialists new to social sciences

1	Sometimes cheaper is better; take advantage not only of archived imagery but also of derived products (e.g., SRTM DEMs), particularly when your team lacks a dedicated remote sensing analyst
2	*Caveat emptor:* acquire and read all the metadata, preferably prior to data purchase
3	For slower processes (e.g., urbanization or longer-term migration), target sensor systems with earlier launch dates (e.g., Landsat)
4	For quicker (cyclic or seasonal) change (e.g., short-term displacement or labor migration), prioritize sensors with better return times
5	For areas prone to flooding and/or problematic cloud cover, consider active sensor systems (e.g., radar)
6	Where spatially random processes are occurring or will be modeled (e.g., spontaneous colonization), opt for sensor systems with broader spatial extent
7	For urban, peri-urban, and desert/settlement applications, prioritize high spatial resolution over spectral resolution (e.g., make use of panchromatic bands of multispectral sensor systems)
8	For disaster mitigation (e.g., famine, disease outbreak, natural disasters), opt for broad spatial extent and high return time; also consider higher vertical accuracy of DEMs rather than horizontal resolution (for flooding)

Of paramount importance for all remote sensing applications, not just the social sciences, is the continued development and maintenance of satellite sensor systems designed for broad use. Yet even the workhorse of the US sensor system faces uncertainty, with diminishing funds allocated for earth remote sensing and the Landsat Data Continuity Mission (LDCM) on perpetual standby. The benefits of remote sensing – observation from afar when price, access, or safety prohibit direct observation – are even more important as echoed by recent events ranging in origin from natural (e.g., the December 2005 tsunamis) to anthropogenic (the Iraq War) to in-between (the impacts of Hurricane Katrina). Understanding globally pressing problems such as these requires quality data delivered in a timely fashion at a reasonable price. So what are the implications for scientists and stakeholders that most of the new fine to very fine spatial resolution sensor system development and data provision is becoming increasingly commercialized?

At the same time, data confidentiality is becoming a larger and larger issue (Rindfuss et al. 2004, VanWey et al. 2005). The advent of new data storage and streaming technologies has rendered products and services such as Google Earth nearly mainstream to novice computer users, and GPS technologies have become near omnipresent in many countries through vehicle and cellular phone use in addition to recreational GPS units. But as remotely sensed data become more and more widely available, so too does the ability to link these spatially precise depictions of people without their consent to other data layers. Privacy issues loom large, particularly in a climate of escalated concerns regarding terrorism and security. Yet have or will researchers' noble obligations to privacy and confidentiality become moot in the face of this information available for sale to others around the world with varying motivations and ethics? As the public's expectation of privacy becomes diminished, what is the role of social scientists working with spatially explicit and remotely obtainable data – to act as vanguard to the last bastions of privacy, or to lead the exploration of these data?

On the technological side, there remains the challenge of integrating discrete and continuous data in a way meaningful for social science research. New, multiscale data models are under development, and the rise in popularity of object- or feature-based (as opposed to pixel-based) classification suggests a continued move toward a continuity of data representation. Another answer may lie in better conceptual models of human activity space now that several decades of case studies of spatial patterns of land tenure regimes and impacts on people's movements and activities have been completed, though migration and migratory-based peoples (e.g., pastoralists) continue to stretch the capacity of spatial databases to house temporally dynamic datasets (BurnSilver et al. 2003). Improved temporal and spatial data integration also likely holds the key to unlocking best practices for working with historical datasets in order to understand the landscape legacies of environments and peoples that came before typical remote sensing time series origination (Klepeis and Turner 2001), lest grave mistakes in interpretation of landscapes or cultures be made (Fairhead and Leach 1996).

The boon of complexity theory into social science simulations based on remotely sensed data appears to be a robust path for continued exploration, but modeling efforts require further validation and testing (Pontius et al. 2006). Because the results of spatially explicit simulation models are not, in fact, spatially explicit (or rather, deterministic) in outcome, they remain difficult to interpret and a hard-sell for policymakers. Probability maps (typically with probability of events without regard to actual location) are of little comfort to local stakeholders or decision-makers, particularly when the conveyance of an understanding of uncertainty is unclear (Pontius et al. 2006), though they may provide useful guidance for regional policymaking. The propagation of error and uncertainty also remains problematic for a variety of applications of remotely sensed data (Brown et al. 2004), though particularly for social scientists.

The real challenge to the interspersion of social science and remote sensing may be how to get social scientists think bigger, conceptually. What can social scientists contribute to or learn from larger scale sensor systems such as GRACE and findings regarding mass water movement and shrinkage of polar ice caps? Typically social scientists employ finer scaled datasets for the bulk of their research, but surely remote sensing of the collective impacts of anthropogenic activity on the Earth's climate or water balance (and the reciprocal impacts as well) should have some bearing on social science pursuits at scales beyond the local and semi-regional. In what other ways can social scientists push the conceptual frontiers of landscape and population assessment: to detect and predict landscapes of fear, of equity, of security? Lastly, should social and remote sensing scientists encourage greater public and policy participation? If so, how can such be done beyond a case study basis and in a more systematic way (Castella et al. 2005)? Ultimately, these questions of data integration, data confidentiality, simulation modeling, error/uncertainty, and conceptual frontiers reveal the strength of the integration of remote sensing and social sciences: social science applications of remote sensing push the boundaries of data usage in unique ways, while remotely sensed data and methods push the boundaries of defining the social and society.

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