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DEVELOPING A SCIENCE OF LAND CHANGE: CHALLENGES AND METHODOLOGICAL ISSUES

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Abstract
Integrated land-change science has emerged as foundational element of global environment change and sustainability science. It seeks to understand the human and environment dynamics that give rise to changes land uses and land covers, not only in terms of their type and magnitude but their location as well. This focus requires the integration of the social, natural, and geographical information sciences. Each of these broad research communities has developed different ways entering the land-change problem, each with different means of treating the locational specificity of the critical variables in question, such as linking the land manager to the parcel being managed. The resulting integration encounters various data, methodological, and analytical problems, especially those concerning aggregation and inference, land-use pixel links, data and measurement, and remote sensing analysis. These problems, which hinder comprehensive understanding and theory development, are addressed here in regard to the social science-geographical information science link. Their recognition and resolution are required for the sustained development of land-change science.

Contemporary concern with climate change, global environmental change, and sustainability has rejuvenated research addressing the human impress on and interactions with the terrestrial surface of the earth. Changes in land systems hold major consequences for climate change (1, 2), biotic diversity and ecosystem services (3, 4), land degradation (5), and the vulnerability of coupled human-environment systems (6-8). Understanding the dynamics of these changes requires attention to land cover (biophysical conditions) and land use (human uses) as a coupled human-environment system (9-12) an approach increasingly adopted by international research programs. The diverse community of researchers engaged in these efforts has spawned a de facto "integrated land-change science" or ILCS (13, 14).[*]

In its brief history, ILCS has been problem driven, especially as it links to international research agendas. ILCS has improved the evidence of different types of land change across space and time (15). It has demonstrated the different suites of factors that stimulate or mediate changes in land use and land cover and provided the spatio-temporal parameters in which the PAT variables of the IPAT identity (Impact = Population x Affluence x Technology) are useful for explaining land change (16-18). Recurrent patterns of specific kinds of land change, such as the forest transition (19), are emerging from the research, and major advances in integrated models of land systems are underway (20, 21).

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[*] For example, the Land-Use/Cover Change (LUCC) effort of the International Geosphere-Biosphere Programme (IGBP) and the International Human Dimensions Programme on Global Environmental Change (IHDP) (www.geo.ucl.ac.be/LUCC/lucc.html); NASA's Land Cover and Land Use Change (LCLUC) program (lcluc.gsfc.nasa.gov/); and the forthcoming Global Land Project of the IGBP and IHDP (www.igbp.kva.se/cgi-bin/php/frameset/php).

Despite these advances, a dominant, integrated theory of land change has yet to emerge, perhaps a product of the complexity of the problem and the level of integration involved. After all, integrated understanding of land systems links the natural, social, and geographical information sciences (GIScience). The problems encountered in natural science-social science linkage have a long history and various solutions. The addition of the GIScience (22), however, introduces a set of fundamental issues arising from the use of geographic information, including those of accuracy and uncertainty, space-time scales, and links between people, place, and environment. The concern of GIScience with the theoretical and practical issues associated with geographic (spatial) information and its systematic study enlarges these issues (22, 23). Therefore, GIScience integrates data, methods, practices, perspectives, theories, and sciences that are linked through their common emphasis on geographic information. For instance, satellite remote sensing observes land covers and tracks their changes over space and time; geographic information systems link remotely sensed data with other data, including that on land systems, for spatially-explicit studies; global positioning systems (GPS) spatially reference the position of social and/or environmental features; spatial analyses define pattern and link to function; and quantitative methods examine linear and non-linear relationships (13, 24-27)

Challenges for Integrated Land-Change Science

ILCS has been hampered by a range of data, methodological, and analytical difficulties emerging from the complexity of integrating diverse processes and the different disciplinary means of addressing them. These difficulties are amplified by the need to address not only *why* and *how* land changes, but *where* and *when* it changes.

Location specificity generates special problems for most facets of land-change analysis, especially those examined at the micro-scale (i.e., individual, household, community, catena, patch, parcel, or pixel) and involving the dynamic human aspects of land change. A particular land parcel, for example, may change ownership or tenure, be borrowed or rented by distant households, have multiple users adhering to different rules of use, or come under the jurisdiction of multiple and changing ordinances, zoning regulations, and institutions. Such dynamics affect both the principal explanatory constructs employed by social scientists to address resource uses and land change—the behavior/decision making of the change agent, and the institutional structures delimiting the agent's choices.

An array of land uses exists worldwide under highly diverse social and biophysical conditions. The variations and fluidity in tenure and resource institutions noted above are matched by those in land-use systems and economy. Land may be put to any number of production strategies (e.g., cultivation, agro-forestry, pastoral), including recreational and preservation/conservation uses. In many cases, the same land unit may serve multiple strategies simultaneously or intra-annually. The nature of change trajectories of land parcels may encourage subsequent uses and restrict others. In addition, the spatial adjacencies of land uses may further mediate decision-making on the use of nearby parcels. The behavior of land managers and the social structures affecting them are, in turn, related to the degree to which the production/use is geared for direct consumption (subsistence) or commerce (market). Throughout much of the world, households (as land managers) are engaged simultaneously in subsistence and market cultivation. Different parcels, of course, have different biophysical qualities that affect decisions about their use, and households may have control over multiple, spatially

disconnected parcels. Feedback mechanisms with space-time lags further confound relationships and the interpretation of meaning.

These many dimensions of land use and land systems amplify a series of data, methodological, and analytical problems confronting the search for comprehensive understanding of land change.[†] In this paper, we identify those problems that are especially acute for the social science-GIScience intersection of the three axes of ILCS working at the individual-to-community scale (micro-level), drawn from activities that compare case study approaches.[‡] They include aggregation and inference problems, land-use pixel links, data and measurement, and remote sensing analysis.

Aggregation and Inference

Land change science runs the risk of committing an error that was common in social-demographic analysis more than half a century ago, and the underlying reasons are similar: the level of aggregation by which data are delivered to researchers. In the first half of the twentieth century, to protect the confidentiality of individuals and households, census data were aggregated to moderately large geographic units (i.e., counties or districts), and only then released to researchers. Analysts would frequently look for patterns of association among theoretically interesting variables and, in some cases make

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[†] Throughout, data problems refer to the attributes of the data relative to the theory, model, or problem to which the data are employed, such as scalar mismatches, not the issues of generating, archiving, and distributing data.

[‡] Primarily from a workshop held in January, 2002, at the East-West Center (Honolulu, HI) funded by the National Science Foundation (BCS-0083474) and resulting in the volume *People and the Environment: Approaches for Linking Household and Community Surveys to Remote Sensing and GIS* (23) and NASA's LCLUC initiative (13).

inferences about individual or household-level behavior. In a now classic article, Robinson (28) demonstrated that there is no necessary reason why relationships that exist at an aggregated level (e.g., county or district) also exist at a dis-aggregated level (e.g., household or individual). Demonstration of relationships at the household level requires household-level data.

Today almost all census bureaus around the world only release spatially explicit data that are aggregated to some level above the household. Since high quality, aggregated, spatially explicit census data are available for many parts of the globe, the temptation is strong to link it to remotely sensed land-cover data. Such linkage and analysis is fine so long as the variables of interest are appropriately measured at this level of analysis. A Gini coefficient of income distribution for the county or district would be an example, as would be the net migration gain in the previous decade. But if the aggregate-level variable is meant to proxy for an individual- or household-level variable then there is no necessary reason why the aggregate-level relationship would hold at the individual or household level (28-30). Other studies use household-level variables to explain the village- or regional-level land cover, falling prey to imputing causes found at lower-levels (of scale or aggregation) to be the same as operating at higher levels (30).

Issues of Linking Land-Use to Pixels

An important component of ILCS undertaken at the micro-level is the one-to-one linkage of people to parcels—the land managers or decision makers to the land units they control or affect. This linkage can be difficult for a number of reasons summarized elsewhere (31), much of which involves the fundamental differences between the ways in which data on people and parcels are generated, the spatio-temporal implications of the

collection process, and the analytical problems inherent in combining them. Remote sensing resolutions are involved in the process of defining landscape attributes for parcels that are linked to households or other decision-making units. Spatial resolution affects the size of the land parcel that may be distinguished; temporal resolution (and the depth of the archived image set) determines the dynamism that can be observed; spectral resolution affects the discrimination of landscape states and conditions; and radiometric resolution controls how precisely land use and land cover types can be separated. A land parcel is stationary. Although the boundaries of the parcel may change, they rarely exceed the range or extent of the remotely sensed image employed to observe the land cover in question. Land managers, be they individuals, households, or villages, can and do move, change in kind, and combine in complex decision-making arrangements that affect land use. Land parcels can be observed and monitored remotely without permission of the land managers and tracked over time by their geographical coordinates. With few exceptions, data-generating observation of individuals, households, corporate units, and villages requires permission and cooperation of the unit being observed, and tracking the units longitudinally may require complex identification strategies that account not only for their movements but also for their reorganization.

For the most part, different research communities begin the linkage by focusing on people or parcels, either of which poses problems when employed in integrated analysis. Beginning with a roster of village members or households, the associated lands used or owned can be identified and spatially referenced through a variety of approaches (32). With few exceptions, starting with land managers generates a patchwork distribution of discrete parcels across the landscape, each linked to one or more land

managers. The land units within the area not controlled by people on the roster of village members are not part of the sample, creating a sampling problem concerning the characteristics of these agents and their land-use decisions (the same applies whether the land managers on the initial roster are individuals, households, villages, or various types of organizational entities.). Longstanding research demonstrates that such selectivities may lead to biases in results (e.g., (33)). For example, the village roster in question would likely not capture those parcels controlled by absentee owners, corporate agents, NGOs, or the state. Omitting the behavior and decision-making of these managing or controlling agents provides incomplete understanding of the dynamics of the land system and may lead to erroneous projections of land change. In addition, the discrete pattern of parcels generated in this approach poses challenges for spatial analysis (see below).

Alternatively, beginning with a bounded area, land managers can be identified that have decision-making authority over the units within it, providing a spatially continuous distribution of parcels. Linking the complete (or near complete) array of parcels to the managing or controlling agents would appear to resolve the selectivity problem, but not necessarily. For example, this linkage typically reveals the agent that retains control of the parcel institutionally (e.g., ownership, usufruct) in an agricultural system, but may miss the actual land user who rents or borrows the parcel. In addition, it may be difficult to identify all distant land managers. Continuous parcel distributions do permit assessment of neighborhood effects (in this case, the impact on a parcel or pixel given the character of surrounding parcels or pixels), facilitate the identification of cross parcel consequences (e.g., upstream land-use decisions on downstream land cover), and enhance computing spatial trends and variations in land change.

These and related problems have been treated in different ways for specific studies of settled (i.e., permanent or near-permanent) systems of land use. Successional (e.g., shifting) cultivation, commons, and pastoral nomadic livestock systems in which parcels may be difficult to identify or multiple users partake of the same parcel at different times can be even more problematic to study. The potential error produced by data biases in comparative case-study analyses is not understood, an important vulnerability given that the ILCS community has begun to explore meta-analysis (comparison of disparate case studies) as one means of providing insights about land-change dynamics at the meso- and macro-scales.

Data Quality and Measurement Issues

Data Quality and Validation

The integration of GIScience and social sciences raises two sets of interrelated data issues: the validity and accuracy of the link among the social science measures, land units, and remote sensing pixels; and the assemblage of appropriate remote sensing, natural science, and social science skills to address data quality and validation. To simplify, consider the link between agricultural households and the land they own/use. This link can be made in various ways (noted above) using administrative records, key informants, and interviews with the households themselves, each with its associated error structure. Administrative records may miss illegal land users; surveys may miss households that rent or borrow land; and treks to distant fields may miss smaller plots or parcels under different successional vegetation. Parcels may also be “claimed” by multiple households where a one parcel–to–many households link exists through kinship ties and informal land tenure. Of course, various procedures can be employed to rectify

such problems. Households can be asked who uses or controls the parcels adjacent to theirs, key informants can mark on maps those areas where people in the village farm and who farms which parcels, and such information can be linked. These procedures, however, carry their own problems: confusion can occur between formal names and nicknames provided by informants, and distant lands used by the households in question may be missed.

The ILCS community has yet to develop the error structure associated with the various linking methods employed. Perhaps even more troubling, it has not yet worked out methods to check the quality of various types of people-to-parcel linking methodologies. Rather, ILCS relies on the expertise of diverse disciplines, each of which has its own methods of quality control and data verification. For example, the social survey research literature is replete with discussions of standards for reporting response and follow-up rates (34), and estimating the bias that might be associated with less than perfect follow-up rates has been the subject of numerous studies (e.g. (35-40)). Good practice requires reporting response rates and attrition rates, but such reports remain rare in ILCS. Variation in sample design leads to variation in the quality and efficiency of the sample (e.g., (41)) and pre-testing is routine in survey work when addressing topics that have not previously been validated. Again, these details are not yet routinely reported in ILCS, making comparisons across studies difficult.

GIScience is replete with methods of accuracy assessment (e.g., (42-46)). The confusion matrix resides at the core, however. As a simple cross-tabulation of the mapped class label against that observed on the ground or in reference data for a sample

of cases at specified locations, it provides an obvious foundation for accuracy assessment (47). Such accuracy assessments are not routinely reported in ILCS.

In short, much research undertaken within the umbrella of ILCS fails to report on various quality control and validation steps that represent standard practice in the constituent sciences. There are several reasons why this lacuna occurs, including the expense of undertaking equally all parts of an ILCS study. Emphasis is often placed on one or two components of the study (e.g., remote sensing and ecology), rendering less attention to the remaining components (e.g., social and spatial science). The composition of science teams and the disciplines they represent also bias practices and protocols followed.

Spatial-temporal Mismatch

The spatial-temporal mismatch of the various data in question poses yet further complications. The spatio-temporal resolution of remote sensing data is set by sensor specifications, and launch and orbital parameters, affecting the ability of sensors to map land change. If the spatial and/or temporal resolutions of sensor systems do not match the resolutions of the social or biophysical data, the mismatch can create spatial or temporal ambiguity (48), creating fundamental problems for their integration.

Various methods are used to resolve this problem, e.g. (49-52). One method is to tie cadastral information to a longitudinal social survey by linking households organized in nuclear settlements to their specific land parcels (31), even in cases where parcels are relatively small in size and irregular in shape. Remote sensing systems characterize land-cover patterns within the land parcels; however, the grain size of the sensor system is sometimes coarser than the size of the land parcel. A one-to-one spatial correspondence,

in such cases, requires parcel aggregation, diminishing the household (survey) to pixel link. A similar problem follows in pastoral systems in which herds move across the landscape, but their impact is restricted to areal units smaller than the pixel size used to assess grassland conditions (53). Conversely, remote sensing data that provide a finer spatial resolution than the land parcel tends to encourage analysis that decomposes the land parcel into arbitrary sub-units that may have little relevance to the unit of decision-making (54).

Land change also addresses temporal processes, which create data mismatches that can make seamless integration difficult, even if the issue is limited to the last 25 years in which satellite imagery has become abundant. The principal mechanism for providing temporal depth in remotely sensed data is the ability to access archived data, permitting, in principle, the assemblage of a temporal panel which, more often than not, proves to be costly and time consuming, and at times impossible.[§] Obtaining an airphoto time-series has its own special problems, beginning with access to the data itself, particularly in politically sensitive areas. Technical issues including analog to digital conversion, image rectification, and variations in spatial scale and temporal periods of observation need to be overcome. Often, however, the longer temporal depth of record

[§] The ability to assemble temporal depth rests on the quality and coverage of the images archived along with the maintenance of that archive. Unfortunately, aerial photos tend not to be archived internationally, or even nationally, except for some countrywide federal programs (e.g., the U.S. National High Altitude Program). In contrast, many satellite systems have associated archives that can be searched for suitable images to purchase. Problems exist, however, with retrieval equipment and archival maintenance, the loss of ephemeris data and associated header files vital for image corrections by international receiving stations, and omissions apparently abundant during the privatization experiment of Landsat products.

offers an approach to extend the satellite time-series or to interleave it with more local views. Substantial time-series assemblages can be achieved, but they usually are confined to long-running and well-funded research projects (31).

Time depth in the social sciences is typically provided by repeated cross-sectional data collection or by panel studies. Panel studies are preferred for ILCS because the behavior of some land managers can be observed over time. Unfortunately, for the large majority of land-change issues, longitudinal data do not exist and must be created. While some behaviors can be straightforwardly recalled (e.g., migration, child bearing, marriage, and marital dissolution), many cannot, as is the case of the motivations for land-use decisions. People tend not to remember accurately their prior motivations and rarely maintain archival information from which they might be deduced. Further, if respondents used various land parcels, and this set changes over time, there is no evidence that they can accurately recall when they used/owned the various parcels beyond the last few years. Some evidence, however, suggests that showing respondents satellite images improves the time depth and quality of information recalled (55). Imagery assessment as well as other archival data can also be used to validate some aspects of the information provided (56). Alternatively, a prospective data set explicitly tailored for land-change questions may be developed, but the costs of data collection to match the periodicity of remotely sensed data might be prohibitive. In other cases it is possible to retrofit a longitudinal data set that was started for other purposes (31, 52). In both of these instances, however, the periodicity of the waves of panel data collection is coarser than the periodicity of the available remotely sensed data.

These problems are amplified in attempts to integrate remotely sensed and social science temporal data. For instance, a longitudinal survey used to consider changing demographic patterns of households or villages over time may be linked to land-cover information generated from remotely sensed data that is bracketed by the dates of the longitudinal survey (31, 52). Alternatively, imagery may be acquired to bracket a few years on either side of social survey data to provide context and to give new meaning to observed land-change trajectories seen through the imagery (57-59). Assessing the causes and consequences of land-change dynamics, however, is best approached through temporal coherence among the data arrays (60). The problems noted above would increase by adding biophysical processes into the equation.

Remote Sensing Analysis Issues

Classification and Use of Ancillary Data

Remote sensing classification is the process of identifying spectral similarities and differences in multi-dimensional spectral space, and then linking them to land-cover categories. The product of a classification exercise is to produce the best possible categorization of land cover, typically used for some descriptive purpose, such as defining changes in the percent area or spatial patterns of forest cover. To achieve this product, ancillary information is typically used in conjunction with raw satellite data to reduce spectral confusion between or across cover types. Knowledge of habitats, environmental conditions, topography, and site conditions that influence land-use practices or vegetation may be combined into the classification process as additional inputs or used in a post-classification exercise where landscapes are stratified according to ancillary data layers (61-63).

The need for ancillary data is related to the information demands of the classification scheme (level of detail), the size of the pixel, and the spectral sensitivity of the sensor system. Pixel values are an integrated response from all the cover types contained within a pixel's area. As the size of the pixel increases, the possibility for ground cover variation within the pixel increases. Fine grain data, such as the high spatial resolution produced by IKONOS and Quickbird, are less demanding in terms of ancillary information, but they often have weak temporal resolution, particularly for large areal extents, that hinders assessment of environments with strong seasonal variations. For example, most tropical deforestation takes place in seasonal tropical forests in which significant spatio-temporal variation exists in the precipitation experienced and concomitant vegetation responses during the dry season when less cloud cover promote the use of satellite imagery. This variation may generate different signatures for the same land cover within the image or across year. This problem can be addressed in some cases by the use of ancillary data.

Use of ancillary information is appropriate for the descriptive purposes of classification. ILCS agendas, however, call for assessments of the causes and consequences of land change. In such assessments, land-cover classifications become a critical component of the explanatory and modeling exercises in which the classification serves as a dependent or independent variable. Either way, if variables in the model were used as ancillary data in the classifications, then the assumption of independence behind standard statistical methods is violated. Perhaps the most common error of this kind is the use of a digital elevation model to establish the classification, and then elevation or slope is used as an explanatory variable.

At present, this problem is particularly insidious because ILCS projects rely on interdisciplinary research teams combining remote sensing, environmental, and social science expertise. The best and customary practice within each of these three domains may require the use of variables in tests and models that were used to create land classifications. Countering the methodological issue entails a trade-off between maintaining the independence of variables and producing the best possible land-cover classifications. Such problems may be exacerbated when the lineage and meta-data for processed imagery previously classified by team members or third parties is not thoroughly understood. Accounting for these problems a priori in the research design does not always provide a resolution because, absent the ancillary data, the classification may have unacceptable accuracy or poorly discriminate among land classes. At present there is no consensus on the use of ancillary data in the production of land classes. This problem requires recognition and resolution by the ILCS community.

Spatial Autocorrelation

Spatial autocorrelation is concerned with the similarity in the location of spatial objects and their attributes, and can be defined as the ordering of values as a consequence of location. For instance, if spatial objects are similar in their location and in their attributes, positive spatial autocorrelation exits. Negative spatial autocorrelation occurs when nearby spatial objects are more dissimilar in their attributes than objects further apart. Often, semivariograms are used to explore the spatial structure of spatial objects and landscape characteristics by plotting the semivariance against the lag distance between neighboring samples, searching for breaks in the slope of the plot of the

semivariogram as an indication of the range of spatial scales that are spatially autocorrelated (62, 64).

Land-cover and land-use patterns are generally positively, spatially autocorrelated. For instance, local biophysical conditions such as soil fertility and vegetation patterns, and regional resource endowments such as terrain settings and hydrologic patterns, affect or constrain land-cover and land-use patterns within ranges of spatial (or temporal) scales. Decision-making about the uses of land may also be scale dependent. Land parcels used or owned by households from similar villages may be comparably managed and similar crops cultivated, and nearby parcels used or owned by households from more distant villages may share many of the same resource endowments and limitations thereby necessitating cooperation in the use of water and shared use of technology. Land management schemes and cooperating institutions may also be scale dependent, further spatially organizing land-use patterns across the landscape.

Using the semivariogram to visualize the structure of spatial autocorrelation and an a-priori understanding of the spatial autocorrelation structure among key variables in the study area (from knowledge of the study area, from a previous study, or from some other independent data source), a sampling scheme can be designed that minimizes spatial autocorrelation between the location of biophysical field samples and the position of social survey respondents. For instance, using Moran's Index of Spatial Autocorrelation, it is possible to define the spatial lag distance between sample units and the corresponding degree of spatial autocorrelation. Alternatively, including autoregressive terms in the model is another way of addressing spatial autocorrelation, especially in random or clustered designs. Anselin and Rey (65) demonstrate that

Moran's Index is not reliable however, when other forms of misspecification are present (e.g., non-normality and heteroscedasticity), and can even suggest significant spatial error when none is present. Therefore, a combination of spatial autocorrelation indicators should be used to identify whether the model exhibits spatial lag, spatial error, or a combination.

Ignoring spatial autocorrelation affects the assumption of data independence, thereby, influencing parameter estimates and measures of significance in statistical models, which may lead to an incorrect interpretation of findings. Although there are statistical techniques to adjust for clustering in the sampling design, they may not account for all the aspects of spatial autocorrelation. For instance, in regions of the world where access is restricted, it is common for land classifications from remotely sensed data to be stratified by the existing road network so that field validation samples might be more efficiently drawn. This spatial ordering of samples has implications for the derived assessment of error and uncertainty in the land classification. Even though spatial autocorrelation has been examined in the statistical and geographic literature, it has not yet been routinely addressed in land change science (c.f. (27)).

Accuracy Assessment of Land-Change Models

A major thrust of most household-pixel linkages is to generate data that inform and improve models of land change (e.g., (66)). Such efforts confront the problem that the pixel of satellite imagery is neither a landscape nor a social unit. It can be convenient, however, to treat the pixel as a unit of observation because data are often organized around it and software packages are designed to perform pixel analysis relatively easily. These packages tend to follow statistical methods that are not appropriate to analyze

raster maps because they: (i) treat each observational unit as something meaningful to the phenomenon; (ii) assume each observation is independent of other units in the map, whereas pixels in a raster are spatially auto-correlated; and (iii) assume the contents of each pixel are independent of the contents at other times, whereas time-series maps tend to display temporal auto-correlation.

These qualities create several problems for practitioners seeking to use household-pixel information to inform models of land change. Two main goals of land change models are (i) to estimate the proportion (i.e., magnitude) of each land type on the landscape and (ii) to estimate the location of the types. Unfortunately, many statistical approaches used to measure the accuracy of these estimates fail to account for landscape persistence. This issue is acute for landscapes in which large portions have no change (e.g., small-holder cultivation in a tropical forest), because large tracts of "no-change forest" elevate the accuracy of the simulation model results when, in fact, the accuracy for the pixels that changed may be relatively low (67). This problem can be addressed by comparing model results to those that would be obtained with a null model that predicts persistence only. A second problem concerns precision. Typically, the precision of the data is finer than the precision at which the model can simulate the phenomenon. Therefore, the model might succeed at predicting the correct general pattern of change, but fail at specifying the precise locations of change, which will result in low levels of accuracy as computed on a pixel-by-pixel basis. This second problem can be addressed by analysis at multiple spatial scales (i.e., multiple resolutions). New techniques of accuracy assessment are under development that account for the roles of spatial resolution, magnitude, and location (68-71) that promise to enhance our understanding of

the results of our models and the added value of including micro-scale, household-pixel linked information.

Summary

The challenge to develop comprehensive understanding of land change that couples biophysical and socioeconomic processes is underway, perhaps building toward integrated theory. The challenge is daunting because of the complexity of integrating diverse processes and the different disciplinary means of addressing them. This paper addressed data, methodological, and analytical problems that are especially acute for the social science-GISscience intersection working at the individual-to-community scale (micro-level). The various research communities involved maintain different standardized approaches and methods of data collection and analysis that pose problems when integrated for land-change study. These problems follow from different data collection and linking methods, and generate problems for validating the quality of these links, matching spatial and temporal data from different sources, using ancillary data in classification, dealing with spatial autocorrelation, and assessing the accuracy of land-change models.

The issues discussed in this review are substantial and flow from various communities with different ties to land-change programs. It is noteworthy that land-change science lags in establishing best and customary practices that are accepted by its practitioners. At present, this problem becomes crucial as the ILCS community explores meta-analysis as one means of providing insights about land-change dynamics at the meso- and macro-scales. An ILCS in which the environmental, human, and remote sensing/GIS sciences unite to solve various questions about land-use and land-cover

changes and the impacts of these changes on humankind and the environment is an important development. The integrated character of ILCS, however, is such that it is difficult to achieve and invariably requires team-based approaches with high labor and fiscal costs, especially in those cases starting from "ground zero" in terms of teams and data.

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