Developing a science of land change: Challenges and methodological issues

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Land-change science has emerged as a foundational element of global environment change and sustainability science. It seeks to understand the human and environment dynamics that give rise to changed land uses and covers, not only in terms of their type and magnitude but their location as well. This focus requires the integration of social, natural, and geographical information sciences. Each of these broad research communities has developed different ways to enter the land-change problem, each with different means of treating the locational specificity of the critical variables, 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. Here, these integration problems, which hinder comprehensive understanding and theory development, are addressed. 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). The diverse community of researchers engaged in these efforts has spawned a de facto "land change science" (LCS), identified elsewhere as integrated LCS (13, 14).

Consistent with the first phase of global environmental change studies and their related international programs, LCS has sought to improve understanding of land-use and land-cover patterns and dynamics affecting the structure and function of the Earth system.[‡‡] It undertakes research at various spatiotemporal scales of analysis to (*i*) document and monitor land-cover changes, (*ii*) explain the coupled human-environment system dynamics that generate these changes, and (*iii*) use this understanding to improve spatially explicit, land-change models that are compatible with Earth system models (12–21). The last two research objectives require integrative approaches linking natural and human subsystems. Such integration is necessary because it is the interactions between the human and natural subsystems that produce land-use and -cover change. Integration in LCS increasingly involves multidisciplinary teams with members from diverse disciplines of the natural, social, and spatial sciences. A series of methodological problems is encountered in mixing and merging analytical traditions from each core research tradition.

These problems are enlarged by the locational variations in the consequences of interactions between human and natural subsystems, heightening the need for spatially explicit analysis and employment of geographic information science (GISc) (22). This science integrates data, methods, practices, perspectives, and theories that are linked through their common emphasis on geographic location, and addresses a set of fundamental spatial issues, including those of accuracy and uncertainty, space–time scales, and links across people, place, and environment (23) that are made more complex in LCS by its practice.

Challenges for LCS

LCS has been hampered by a range of data, methodological, and analytical difficulties emerging from the complexity of integrating diverse phenomena, space–time patterns, and social-biophysical processes, and the different disciplinary means of addressing them (24–27). These difficulties are amplified by the need to address not only why and how land-use and -cover changes, but where and when it changes. Location and time specificity generates special problems for land-change analysis, especially that involving dynamic human aspects of land use examined at the microscale (i.e., individual, household, community, catena, patch, parcel, or pixel). 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 the principal explanatory constructs used by social scientists to address resource uses and land change: (*i*) the behavior/decision making of the change agent and (*ii*) the institutional and societal 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, agroforestry, pastoral), including recreational and preservation/conservation uses. The same land unit may serve multiple strategies simultaneously or intraannually. 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). In many parts 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 or other decision-makers may have control over multiple, spatially disconnected parcels. Feedback mechanisms

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Abbreviations: LCS, land change science; GISc, geographic information science.

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‡‡For example, the Land-Use/Cover Change 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); National Aeronautic and Space Administration Land Cover and Land Use Change (LCLUC) program (http://lcluc.gsfc.nasa.gov); and the forthcoming Global Land Project of the IGBP and IHDP (www.igbp.kva.se/cgi-bin/php/frameset/php).

with space–time lags further confound relationships and their interpretation.

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.[§§] Some of these issues have been addressed within the various disciplines that contribute to LCS, but there has been relatively little attention to problems that emerge as these disciplines work collaboratively on an integrated LCS. Here, we identify those problems that arise from interdisciplinary work and are especially acute for the social science–GISc intersection of the three axes of LCS in which research is focused largely on in-depth case studies at the individual-to-community scale (microlevel). These problems include aggregation and inference problems, land-use pixel links, data and measurement, and remote sensing analysis. They are fundamental problems for linking people, place, and environment. Established solutions exist for some problems; others require major advances. It is the integrative demands of working across the social, natural, and spatial sciences that exacerbates these problems and confounds their solutions.

Finally, the focus here is on integration problems emerging in phase one LCS research devoted to understanding the constellation of factors that drive land-use and land-cover change, and not those inherent in the emerging phase two engaging decision making and application directly. Nevertheless, phase one research has included various modeling activities, including cellular automata, agent-based models, and neural network-based models that lay the groundwork for the decision-making interests of sustainability science (20, 21). An important next step in the development of such models is empirically grounded rules about relationships among social and biophysical variables. Confronting and solving the issues raised in this paper helps these modeling activities, especially those involving integrated projection models.

Aggregation and Inference

LCS runs the risk of committing an error that was common in social–demographic analysis more than half a century ago, and the underlying reason is similar: the level of aggregation by which data are delivered to researchers. In the first half of the 20th 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 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 disaggregated level (e.g., household or individual). Demonstration of relationships at the household level requires household-level data.

Today, to protect citizen's confidentiality, almost all census bureaus around the world only release spatially explicit data that are aggregated to some level above the household. Because high-quality, aggregated, spatially explicit census data are available for many parts of the globe, the temptation is strong to link them 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. However, 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). The problem can also exist in the other direction. Some 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 those operating at higher levels (30).

From an abstract perspective, the solution to the aggregation problem is disarmingly simple: the level of aggregation in measurement needs to match the level of aggregation in the theory or hypothesis being examined. Doing so successfully requires methods that have been developed within the various disciplines contributing to LCS. Unfortunately, doing so at the individual or household level can involve expensive and challenging fieldwork, precisely that which some major funding agencies supporting LCS view as beyond their research mission.

Issues of Linking Land Use to Pixels

An important component of LCS undertaken at the microlevel is the one-to-one linkage of people to parcels; that is, linking the land managers or decision makers to the land units they control or affect. This linkage can be difficult for reasons summarized elsewhere (31), many of which involve fundamental differences between ways in which data on people and parcels are generated, the spatiotemporal implications of the collection process, and 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 used 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.

Different research communities begin the linkage by focusing on people or parcels. Either starting point poses problems when used 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 on 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 selection problem concerning the omitted land units (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 biased results (33). For example, the village roster in question would likely not capture those parcels controlled by absentee owners, corporate agents, nongovernmental organizations, or the state. Omitting the behavior and

[§§]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.

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 patchwork pattern of parcels generated in this approach poses challenges for spatial analysis (see below).

Alternatively, beginning with a bounded geographic 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 this is not necessarily the case. For example, this linkage typically includes the agent that retains control of the parcel institutionally (e.g., ownership and 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, locate, and interview 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 yet well understood, an important vulnerability given that the LCS community has begun to explore metaanalysis (comparison of disparate case studies) as one means of providing insights about land-change dynamics at the meso- and macroscales.

Given this vulnerability, several steps are possible. The research community needs to clearly state in publications whether linking procedures started with land or people samples. Among the solutions to linking problems are the use of database procedures that, for example, link parent–child relationships for tracking land subdivisions over time, use land unit centroids in place of polygons to reduce the complexity of handling land parcels, and employ data aggregation techniques that associate dynamic land units to static reporting units, such as county boundaries or drainage basins. For existing data sets, the selectivities generated by starting with people or land need to be examined and statistically controlled if necessary (e.g., ref. 33). Also, comparable analyses of data sets that start with people and those that start with land should be conducted to determine whether they reach similar or dissimilar conclusions.

Data Quality and Measurement Issues

Data Quality and Validation. The integration of GISc 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 pixels in remotely sensed imagery; 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) by 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 when a one-parcel-to-many-households link exists through kinship ties and informal land tenure. Of course, various procedures can be used 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 LCS community has yet to develop the error structure associated with the various linking methods used. 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, LCS relies on the expertise of diverse disciplines, each of which has its own methods of quality control and data verification [e.g., standards for surveys and estimating biases in the social sciences (34–40) and accuracy assessment in GISc (41–46)].

In short, much research undertaken within the umbrella of LCS 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 LCS study. Emphasis is often placed on one or two components of the study (e.g., remote sensing and demography), rendering less attention to the remaining components (e.g., ecology and spatial science). The composition of science teams and the disciplines they represent also influence practices and protocols followed.

Two steps need to be taken with respect to these issues. First, data quality assessment and reporting standards established within the various disciplines contributing to LCS need to be used by interdisciplinary projects. For example, standard protocols have been established by the remote sensing community to assess the accuracy of land-use and -cover classifications, but not all LCS teams have sufficient expertise and/or resources to employ these practices fully. As image change detections are increasingly used to characterize land-use and -cover patterns across time, validating historical data through a set of best practices also is needed. Second, standards need to be developed for reporting errors that arise from the integrative nature of LCS: for example, those errors that arise from linking a household to its land parcel and then to a set of pixels in a remotely sensed image.

Spatial–Temporal Mismatch. The spatial–temporal mismatch of the various data sources poses yet further complications. The spatial–temporal resolution of remote sensing data are set by sensor specifications, as well as 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 result in spatial or temporal ambiguity (47), creating fundamental problems for their integration.

Various methods have been used to resolve this problem (e.g., refs. 48–51). 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 can follow in pastoral systems in which herds move across the landscape. The need for a high temporal periodicity to coincide with the temporal dynamics of herding patterns could suggest the use of remote sensing systems with high temporal but low spatial resolution (52). In such cases, spatial mismatches may be readily apparent because the herding routes may be areally restricted, occupying only portions of pixels. Conversely, remote sensing data that provide a finer spatial resolution than the land parcel tend to encourage analysis that decomposes the land parcel into arbitrary subunits that may have little relevance to the decision-making unit (53).

The temporal depth of remote sensing imagery is also affected by the quality of the image archive, reductions of landscape views because of persistent cloud patterns, and changes in remote sensing systems. The discrete and "patchy" nature of a remotely sensed time series might not align well with a more continuous time series from survey or administrative data. When a suitable image time series is developed, images can be examined in a pairwise fashion to denote change for specified "slices" of time, "from–to" changes of selected land cover types, and a panel or trajectory of change that tracks "pixel histories" across the time series.

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, when 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 that, more often than not, proves to be costly and time-consuming, and at times impossible.[¶¶]

Time depth in the social sciences is typically provided by repeated cross-sectional data collection or by panel studies. Panel studies are preferred for LCS 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. Although 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. Furthermore, 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 or perhaps a decade in systems involving forest fallow in which successional growth marks parcels. Some evidence, however, suggests that showing respondents satellite images improves the quality of information recalled (54). Imagery assessment as well as other archival data can also be used to validate some aspects of the information provided (55). Alternatively, a prospective data set explicitly tailored for land-change questions may be developed. In other cases, it is possible to retrofit a longitudinal data set that was started for other purposes (31, 51). In both of these instances, the periodicity of the waves of panel data collection is coarser than the periodicity of available remotely sensed data.

Even if the social data exist in a cross-sectional survey, a deep image time series can be useful to characterize the environment before, during, and after the survey. For instance, knowing that a social survey was conducted the year after a flood or persistent drought, at the beginning or end of a deforestation period, or during a time of agricultural extensification in a frontier environment would help understand the motivation and behavior of respondents. These are other spatial–temporal matching issues that are being addressed in various ways (31, 51, 56–59).

[¶¶]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.

Remote Sensing Analysis Issues

Classification and Use of Ancillary Data. Remote sensing classification is the process of identifying spectral similarities and differences in multidimensional spectral space, and then linking them to land-cover categories. A large body of literature details advances and issues in remote sensing techniques relevant to land classification that are not covered in this paper. Rather, one fundamental issue that follows from and affects the integration of social, natural, and spatial sciences is addressed: the potential bias that can arise when ancillary data used to improve a spectral classification are also used to explain land class variability. The usual goal 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 in some land-cover type or spatial patterns of that type. To achieve this product, ancillary information is typically used in conjunction with raw satellite data to reduce spectral confusion across cover types. Knowledge of habitats, environmental conditions, topography, and site conditions that influence land uses or land cover are frequently combined into the classification process as additional inputs or used in a postclassification exercise where landscapes are stratified according to ancillary data layers (60–62).

The need for ancillary data is related to the information demands of the classification scheme (i.e., level of detail), the size of the pixel, and the spectral sensitivity of the sensor system. Pixel values are an integrated response from all of 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-grained data are less demanding in terms of ancillary information, but they often have weak temporal resolution, hindering assessment of environments with strong seasonal variation.

Use of ancillary information is appropriate for the descriptive purpose of classification. LCS 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 may serve 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.

Researchers need to consider the tradeoff between maintaining the independence of variables and producing the best possible land-cover classifications. This issue may be exacerbated when the lineage and metadata for processed imagery previously classified by team members or third parties is not thoroughly documented. Its resolution among the LCS community resides first in the explicit recognition of the independence of variables and accounting for them in the research design. Second, metadata reporting protocols must be generated for each image and image-based derivative that specifies the inherent and operational lineage followed in the production of a land classification.

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. If spatial objects are similar in their location and attributes, positive spatial autocorrelation exits. Conversely, negative spatial autocorrelation occurs when nearby spatial objects are more dissimilar in their attributes than objects further apart. Spatial autocorrelation has long been a concern in the statistical and geographic literatures. It has not yet been routinely addressed as part of best practices in LCS (see ref. 27), however, and clustered social or ecological surveys may contain explicit biases as a result.

Survey designs can be adjusted to minimize the effects of spatial autocorrelation by increasing the distance between respondents or data collection points. For instance, using the semivariogram to visualize the structure of spatial autocorrelation (61, 63) 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. By 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 (64).

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, which range from explanatory to integrated assessment models (20, 21, 65–67). Such efforts confront the problem that the pixel of satellite imagery is neither a landscape nor a social unit. It is 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 analyses relatively easily. These image processing packages tend to employ statistical methods that (*i*) treat each observational unit as something meaningful to the phenomenon, (*ii*) assume each pixel is independent of other units in the image, and (*iii*) assume the contents of each pixel are largely independent across space and time; put differently, the stationary or Markovian assumption is often used.

These qualities create several problems when using household–pixel information to inform models of land change with the primary goals of estimating the magnitude of change of each land type, the location of those changes, and the temporal patterns and trajectories of change. Software advances in object-oriented models in remote sensing (and GISc) link pixels (and raster cells) to land units and create additional object attributes for land classifications (23). For instance, characteristics of a household that uses or owns a specific land unit can be linked to its corresponding spectral response pattern from remote sensing systems along with the methods that describe an object's behavior; for example, the spatial relationships between land units and the social ties between households of adjacent properties.

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 (68). The best way to approach this is to include estimates focused only on the area or specific land class of change, by comparing model results to those that would be obtained with a null model that predicts only persistence, or by further advances in measures (68–71).

Finally, scale is a fundamental issue in land-change models. For instance, landscape greenness has been linked to variables describing people and environment in Thailand measured at a range of spatial scales (72, 73), and land use-preference weights of agents has been found to be scale dependent in spatial models of land-cover change in the Midwestern United States (66). The scales of social and biophysical inputs and model outcomes influence the patterns and processes of land-use and -cover change and the approaches used in model validation.

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–GISc intersection working at the individual-to-community scale (microlevel). The various research communities involved maintain different standardized 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 here are substantial and flow from various communities with different ties to land-change programs. It is noteworthy that LCS lags in establishing best and customary practices that are accepted by its practitioners. At present, this problem becomes crucial as the LCS community explores metaanalysis as one means of providing insights about land-change dynamics at the meso- and macroscales. A LCS in which the environmental and human sciences and remote sensing/GISc 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 LCS, however, is such that it is difficult to achieve and invariably requires team-based approaches with high labor costs, especially in those cases starting from "ground zero" in terms of teams and data.

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