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CHAPTER 5

Identifying data challenges to representing human decision-making in large-scale land-use models

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5.1 Background

The importance of mapping and forecasting land use and land cover change (LULCC) is well established in literature and within the chapters of this book. At local scales LULCC can affect natural (e.g. runoff and erosion, Dunn et al., 1993; temperature, Betts et al., 1996; and albedo, Pielke et al., 2002) and human (e.g. aesthetic quality, Parsons & Daniel, 2002; and congestion) systems, which have cumulative impacts at regional and global scales (e.g. climate, Kalnay & Cai, 2003; Stohlgren et al., 1998). Acknowledging, representing and modelling the integration of these systems and their feedbacks are essential to understanding how mapped patterns are formed and the plausible pathways to alternative futures.

Due in part to the complexity associated with land use as a coupled natural-human land system, it has also been characterised as a socio-ecological system, emphasising that the Earth's surface is shaped by the ongoing interaction between humans and their biophysical environment (Dawson et al., 2010). As a consequence, a major challenge in modelling

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land-use change involves the accurate representation of both the social and the biophysical factors that influence land-use change processes. This challenge is both a design choice, that is what are the sufficient conditions for a useful model, and a measurement issue, that is how much confidence do we have in the absolute values of our quantitative outputs.

While there are contemporary efforts to calibrate and validate natural system models at the scale of human decision-making to justify their use in socio-ecological systems modelling (e.g. Meinen & Robinson, 2021), we focus here on human decision-making in land-use models as the representations best suited to, and most in need of, calibration using empirical data. Despite the human-centric nature of land use (i.e. how humans use the land) and its change over time, the majority of land-use models represent human decision-making implicitly. The implicit representation comes in the form of independent variables (e.g. spatial dependencies or time lags in land-use change) that have their correlation to land use quantified through various statistical approaches (e.g. Sun & Robinson, 2018). Complementing these approaches, agent-based land-use models (ABLUM) are increasingly being used to explicitly represent human actors and heterogeneity in their characteristics and decision-making methods (An et al., 2021).

In an agent-based model (ABM), real-world actors are represented as virtual agents (An, 2012) that make decisions based on their attributes and their interaction with other agents as well as their environment. In ABLUM agents typically represent land managers, such as farmers or foresters, but they are also used to represent residential households, businesses and institutions (Brown et al., 2017). By capturing the processes and decisions associated with land-use change, ABLUMs facilitate a stronger mechanistic understanding of land-use change, particularly the role of human decision-making in these processes (Meyfroidt, 2013). As process-based models, ABLUMs can respond to a much wider range of land-use change perturbations and scenarios than statistical models, which subsequently provides a broader range and richer understanding of plausible land-use futures. The heterogeneity in agents is important because variation in agent attributes and subsequent decisions can yield different outcomes than when a model represents an average actor or population of actors (Kirman, 1992). Furthermore, the interactions between actors and their environment enable the generation of system-level outcomes that are not analytically tractable and are particularly important to simulating spatial processes, such as innovation diffusion (Hägerstrand, 1967) and neighbourhood effects (Krebs et al., 2013).

Despite the benefits associated with ABLUMs, their site-specific application can be data intensive and challenging given the need for behavioural data. The challenge becomes even greater as researchers seek to apply ABLUMs across large spatial extents (e.g. regional, national or global). These types of applications require data about the relevant actors, in addition to the spatial data that is used as input in other types of land-use models. The availability of spatial data, such as land cover data, digital elevation models, transportation networks and climate data, has increased considerably over the past decades. Numerous satellites and satellite programs provide data at different spatial and spectral resolutions (e.g. SPOT, Sentinel, Landsat, MODIS) and an increasing number of derivative datasets (e.g. Fick & Hijmans, 2017; Kummu et al., 2018; Siebert et al., 2015). However, the large resources spent on the production of spatial data, for example by public bodies such as the National Aeronautics and Space Administration and the European Space Agency, dwarf efforts to systematically collect data about the relevant actors, their characteristics and their decisions, especially across large geographic extents. The limited availability of data about land-use actors renders land-use change modelling underutilised, and restricts its potential for scenario studies and assessment of land-related policies. Here, we argue that to advance the mapping and forecasting of LULCC across large spatial extents with land-use models, more effort is needed to collect data about relevant actors, their characteristics and their decision-making.

In the next section we explore the challenge of parameterising ABLUMs in more detail. Section 5.3 identifies a number of data acquisition approaches that can help overcome these challenges. We conclude by summarising the current state of ABLUMs and note the need for coordinate data collection if large-scale behavioural models are to be able to represent human behaviour across large spatial extents.

5.2 Agent types as a way to apply agent-based models to large geographic extents

Before discussing the challenge of parameterisation of ABLUMs, it is important to acknowledge that some of the most impactful ABMs are void of data and offer a proof of existence that certain types of agents and their interactions can give rise to system-level properties of interest. Therefore we find a number of ABLUMs that use synthetic data to initiate their agent populations (e.g. Brown et al., 2014; Filatova et al., 2011) in a stylised world. The benefit of this approach is that the entire system and all data are known and therefore the model can be treated as a controlled experimental laboratory to investigate the impacts of system properties and processes on outcomes. An early and well-documented example of a spatially explicit ABM based on synthetic data is Sugarscape (Epstein & Axtell, 1996). Agents in this model reside in a gridded and torus landscape, and agents and their characteristics do not necessarily resemble a particular area or people. While these synthetic applications have proven very useful to study specific social and socio-ecological systems, they do not typically represent specifics about real-world land-use dynamics (Arneth et al., 2014; Rounsevell et al., 2014).

Existing real-world applications of ABLUMs mostly use case studies to gather data to initiate and parameterise agents, for example using participatory observation, surveys, interviews and role-playing games (Robinson et al., 2007; Smajgl et al., 2011; Zagaria et al., 2021). These methods can be utilised to establish the characteristics of the relevant actors, such as their age, financial status, land they own, social network and, crucially, their motivations and preferences. However, such case studies are resource-intensive, and the required resources relate closely to the number of actors that are being assessed this way. Therefore real-world applications of ABLUMs often target small study areas that allow for a case study approach (e.g. Bakker et al., 2014; Kiruki et al., 2019).

Applying ABLUMs to real-world cases with large geographical extents thus poses some challenges. First, as explained above, case study approaches are resource-intensive and localised, which makes it difficult to scale them up. Second, although many data are available for large areas, these data are typically reduced to averages over administrative units, such as counties, provinces or countries (e.g. census data). However, representing the heterogeneity within a population is a particular strength for agent-based modelling and results have shown that variation leads to significantly different results than averages or categorisation (Brown & Robinson, 2006). Case studies that have original social survey data do not face this problem.

In response to these challenges, several models (e.g. SOME, DEED, Brown et al., 2008; CRAFTY, Murray-Rust et al., 2014) have relied on the use of agent typologies, which render decision-making processes tractable, as well as computationally feasible (e.g. Arneth et al., 2014; Murray-Rust et al., 2014). Key commonalities between behavioural theories (Ajzen, 1991; Grothmann & Patt, 2005; Meyfroidt, 2013) provide directions for the design of agent types. These include the social contexts within which agents make decisions, personal values and preferences, access to resources and peer-relations. A model based on agent types does not require data on individual actors, but instead uses information about the class of actors represented as an agent type. For example, with the numbers of different types of agents, measures of central tendency and spread of different attributes, distributions of agent types and their proportion of the population can be acquired and used. Consequently, while case study approaches might not be practically applicable to parameterise large-scale ABLUMs, agent types can be defined and characterised using alternative data collection methods, which have greater potential for upscaling. Indeed, a great deal of existing data could be better utilised, and complemented by new approaches to data gathering and sharing.

5.3 Data acquisition for models based on agent types

While the extension of case study data to other regions has limitations, a large number of case studies can be analysed to identify generalities among them. Several metastudies have synthesised collective knowledge across case studies to advance our understanding about land-use change processes (van Vliet, Magliocca, et al., 2015). Although few existing metastudies have explicitly investigated the role of actors in land-use change processes, this approach could yield valuable information for the design of agent types and the identification of agent attributes that should be represented (Magliocca et al., 2015). An example of such a metastudy is provided by van Vliet, de Groot, et al. (2015) who analysed case studies of agricultural land-use change in Europe to elucidate the role of farmers as moderators between underlying drivers and observed agricultural land-use changes. Results revealed the importance of the presence of a successor, farmers' attitudes towards environmental values as well as their view on the role of farming as important factors in their decision-making. In another study Malek et al. (2019) reviewed studies of land-use decision-making, globally, to identify different types of land managers. These results reveal the clearly different motivations underlying these types of decision-making, ranging from subsistence to environmental attitudes. Like many scaling approaches seeking to represent behaviour in models covering large spatial extents, the challenge is that even with metastudies, there is a lack of detail and depth to parameterise behaviour in ABLUMs. Therefore the potential contribution of metastudies for ABLUM applications is in the design of agent types and they require fusion with other data sources to empirically inform behaviour parameters.

An obvious source of data for parameterisation of large-scale behavioural models resides in the use of Census data. Censuses provide information about the total population and age structure in a specific region and are repeated in many areas on a regular or irregular basis (e.g. Fontaine et al., 2014). Similarly, agricultural censuses collect data about farm production as well as additional information on farm households (Aalders & Aitkenhead, 2006). On a European scale, the Farm Accounting Data Network systematically collects data on the structure and income of a large sample of the agricultural holdings (Klein et al., 2012). For privacy reasons and by the nature of their collection mechanism, these data are only available as averages for larger areas. However, given the representation of census data at multiple scales, they can be used in combination with other data to derive finer resolution information and distributions of census data. For example, census count data and land cover data were resolved for census units in Koper, Slovenia to identify the number of housing units associated with land-use pixels (Robinson et al., 2012).

Besides government-led data collection activities, there are a large and increasing number of other organisations that collect data about specific groups of individuals. For example, many commercial organisations monitor the behaviour and characteristics of their clients, to improve their service (i.e. customer relationship management systems). While not all retail information is directly relevant for modelling land-use changes, some organisations are certainly relevant. Tourist organisations, for instance, collect information about the amount and spatial distribution of farm-based tourism, which affects land management decisions of the involved farmers (Sharpley & Vass, 2006). Similarly, professional organisations, such as farmers' and foresters' organisations, maintain extensive databases about their members. Excerpts of such databases can provide information about the distribution of land management practices, which is an important aspect of land-use change but very hard to detect otherwise (Kuemmerle et al., 2013). These data sources are not normally publicly accessible, but by providing distributions of actor characteristics over larger geographic areas, rather than data of individuals, these databases can provide valuable information for modelling while privacy as well as potential commercial interests remain protected.

Technological applications, such as mobile phones, apps and social media, allow the direct involvement of citizens in the collection of data through crowdsourcing. While these data can incur a number of limitations (e.g. a lack of standardisation, completeness, consistency and geographic accuracy; Senaratne et al., 2017), they can be used as a passive data source, that is by analysing 'big data' that can be harvested online, or actively, by asking citizens directly for the desired information. An example of the former is presented in García-Palomares et al. (2015), who analyse data from photo-sharing services in a spatially explicit way to find hotspots for tourism. In fact social media data can further reveal relationships between land use and ecosystem services (Lee et al., 2019; Yoshimura & Hiura, 2017), with targeted reviews used to understand the processes that affect supply and demand for these services (Díaz et al., 2018; Feurer et al., 2019; Burton et al., 2018). Crowdsourcing can complement these methods, as a tool for data analysis as well as gathering (Fritz et al., 2017; Sturn et al., 2018).

A potential application would be to use such data to find the use of built-up areas, which cannot be derived easily from land cover data due to tree canopy overlap and other issues. However, tweets, pictures and movement patterns at specific times provide ample information to distinguish between residential areas, recreation areas and places where people work. An example of the latter is the Geo-wiki project (Fritz et al., 2012, 2017), in which users are asked to provide land cover information for the validation of remote sensing–based land-cover products. This effort can relatively easily be extended to derive the land use of specific locations, such as the usage of built-up land, the preference for recreation sites, agricultural land management practices or even field sizes (Sturn et al., 2018). However, while techniques to take advantage of 'the crowd' have been available for some time, the challenge remains to keep users sufficiently enthusiastic to provide the data that are needed (Heipke, 2010). Furthermore, efforts are required to ensure the representativeness of crowdsourced data, which is especially crucial when they are about land mangers' decision-making.

5.4 Conclusion

ABLUMs offer great opportunities to better understand land-use change processes as well as to generate plausible future land-use change trajectories.

However, this potential is currently limited by the availability of data for the design, initiation and parameterisation of agent behaviours. To advance land-use modelling, there is a need for data that describes relevant actors, their characteristics, their behaviour and their interaction with other actors and their environment. We have highlighted a number of challenges and approaches to assist with the design and parameterisation of large-scale ABLUMs, including systematic reviews, censuses and large-scale surveys, collaboration with underutilised data collection efforts from commercial and other parties and crowdsourcing. Existing modelling frameworks already enable the simulation of land-use changes for a very large number of agents, for example the number of farmers in the European Union (Brown et al., 2014; Murray-Rust et al., 2014), and therefore allow leveraging these new data. Ultimately, the added value of actor data for ABLUM has to be confirmed by the model application, and whether such an application is considered a success depends on the objective of the model. An application might provide a better understanding of the relevant land-use change processes, yet the accuracy could be insufficient for meaningful projections of future land-use change. Individual research projects can apply the approaches identified above. However, we also emphasise that there is a role for institutions and funding bodies to encourage the collection and dissemination of these data, for example through data repositories and coordinated actions across larger geographical areas.

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