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Global models of human decision-making for land-based mitigation and adaptation assessment

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Understanding the links between land-use change (LUC) and climate change is vital in developing effective land-based climate mitigation policies and adaptation measures. Although mitigation and adaptation are human-mediated processes, current global-scale modelling tools do not account for societal learning and other human responses to environmental change. We propose the agent functional type (AFT) method to advance the representation of these processes, by combining socio-economics (agent-based modelling) with natural sciences (dynamic global vegetation models). Initial AFT-based simulations show the emergence of realistic LUC patterns that reflect known LUC processes, demonstrating the potential of the method to enhance our understanding of the role of people in the Earth system.

In a world that faces continued population growth and changing consumption patterns while striving to achieve an equitable and acceptable level of human well-being, climate change and land-use change (LUC) are two of the foremost environmental challenges. They are also inseparably linked: land-use and land-cover change contribute to climate change by affecting ecosystem biogeochemical and biophysical processes[1,2], and the climate shapes the way people use land by affecting food supply and pollution impacts on ecosystems[3–5]. Nearly half of today's ice-free land surface has been converted from natural ecosystems into cropland and pastures[6]. Since around 1850, LUC resulted in an estimated release of more than 150 Pg C into the atmosphere — one third of the approximate total anthropogenic carbon emissions — and contributed 10–20% of CO_2 emissions during the late twentieth and early twenty-first centuries[1,7]. Most of the observed increase in atmospheric N_2O over the same period has been attributed to emissions from agricultural fertiliser use[8]. LUC-related climate forcing also occurs at the regional scale, either with a cooling or warming effect[2,9], arising from changes to biogeophysical processes at the land surface that control the mixing of the near-surface air, and the surface radiation and energy balances[10].

LUC will continue to contribute substantially to climate change in the future. A number of climate-change mitigation policies recognize the climate-regulating services of terrestrial ecosystems, which can be implemented through LUC[11–13]. But despite the recognized need for a better understanding of the LUC–climate interplay, LUC is still poorly represented in the current generation of global circulation models (GCMs), which limits evaluations of the sensitivity of the climate system to LUC[14]. Moreover, the potentially adverse effects of climate change mitigation arising from indirect land-use change are largely ignored[15–17].

An adaptive socio-ecological system response

People will need to adapt land-use practices in response to climate change impacts, particularly in regions where climate change has been shown to be a threat to crop and pasture yields and water supply. Examples from history demonstrate that considerable economic and societal decline, even collapses of entire civilizations, can occur because of periods of unprecedented and persistent drought[18,19]. Conversely, examples of past successful responses to climate change exist through migration or the adoption of new models of sustenance[18,20]. Although changing supplies of natural resources combined with rapid rates of climate change certainly exert pressure on societies, it seems unlikely that a single driver (that is, climate change) is the sole cause of instability in socio-ecological systems, with their mix of vulnerable, but also stabilizing, facets.

Whether or not the adaptive capacity of today's societal actors is sufficient, globally, to withstand the impacts of projected climate change over the twenty-first century and beyond is a matter of debate[21]. Land-based mitigation or adaptation options at a certain locale may cause changes elsewhere with opposing effects[16,21]. Adaptive actions that don't seem promising in the short-term might become important for adaptation over a longer time horizon, whereas others may be increasingly ineffective when longer periods of time are considered. Thus a broad temporal and spatial perspective is needed when assessing adaptation and mitigation responses to climate change.

Challenges for LUC–climate feedback models

Adaptation and mitigation are processes. However, current attempts to represent adaptation and mitigation in climate change assessments have focused on top-down statistical indicators of the capacity to adapt[22], or the capacity to mitigate[23], as proxies for these processes. It is axiomatic that statistical approaches are only valid within their calibration range and are therefore limited in their applicability under changing conditions beyond this range[24]. Most importantly, current state-of-the-art modelling tools are unable to represent human agency, which underpins individual behaviour, decision making and adaptive learning and hence is important for understanding how societies will respond to challenges such as climate and other environmental changes.

Integrated assessment models (IAMs), often combined with computable general equilibrium (CGE) models, are the most commonly applied tools for creating projections of global LUC[25]. These models combine representations of micro- and macro-economic theory with social and natural system constraints, and are widely used to project development pathways in climate change assessments[14,26,27]. IAMs and CGEs have acknowledged strengths

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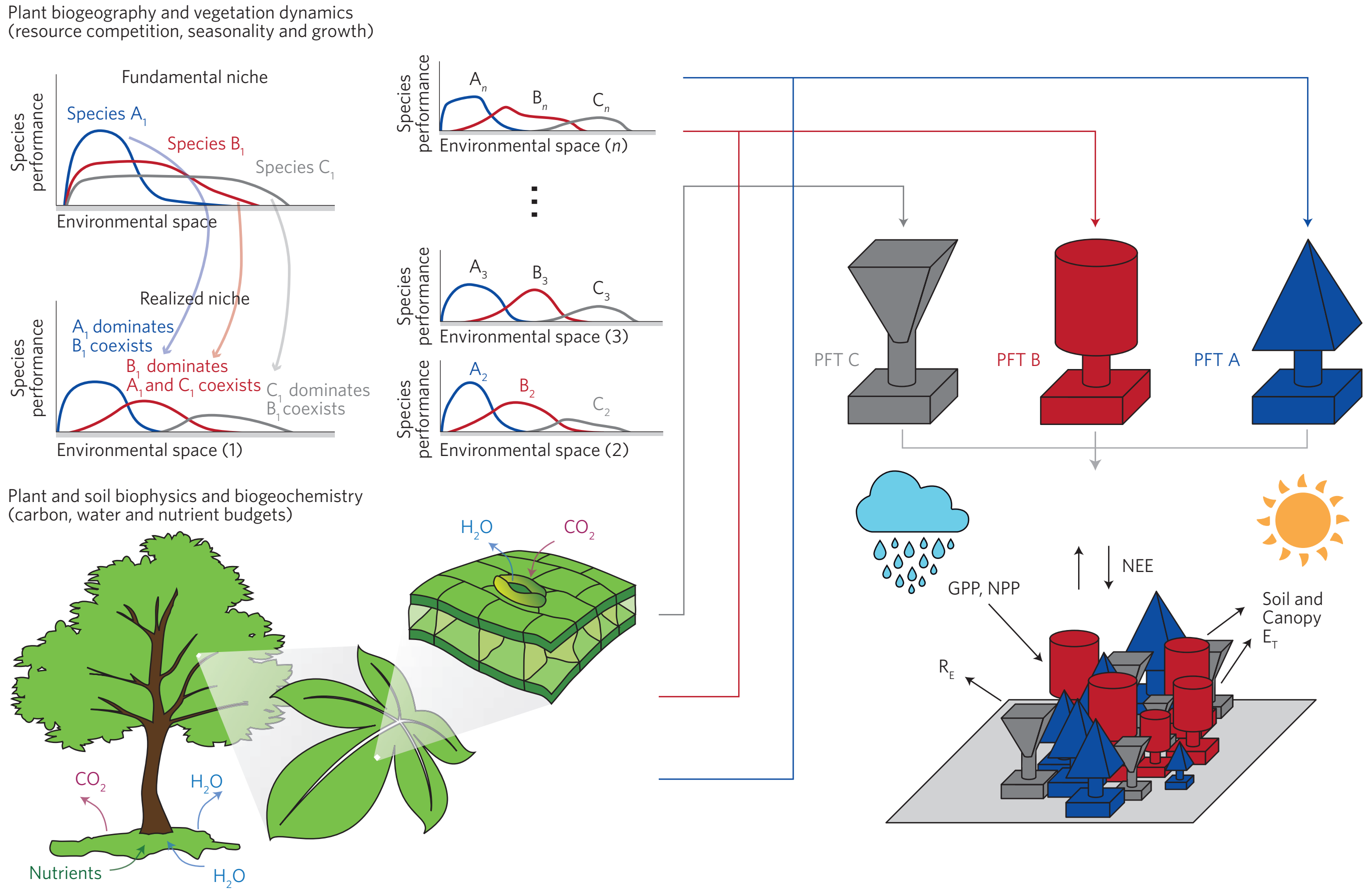

Figure 1 | Concept of plant functional types in dynamic global vegetation models (DGVMs). The realized niche is differentiated from the fundamental niche because it reflects interactions with environmental filters and other plants, modifying the relative abundance of a species within an area or within varying developmental stages of the ecosystem (for example, over time). Vegetation dynamics are represented through a limited number of plant functional types (PFTs) that group species with similar characteristics, growing in ecosystems of a similar type, even though these might be found in geographically very different locations (illustrated by the similar performance curves for species found in *n* environmental spaces, top centre). The biogeography and growth-components of a PFT are combined with process-based algorithms for plant and soil carbon, water, energy and nitrogen cycling (bottom left; see also Table 1). At a given location, a mix of PFTs interacts with the atmosphere and soil (and, more recently, humans). This mix can change in response to the ageing of the ecosystem, disturbances and environmental trends (bottom right). Typical outputs of DGVMs are carbon and water fluxes: net ecosystem exchange (NEE), gross primary production (GPP), net primary production (NPP), respiration (R_E) and evapotranspiration (E_T).

in providing comprehensive cross-sectoral analyses, and are an important component of a common scenario framework that bridges climate research communities[28]. State-of-the-art IAMs analyse project changes in food exports or imports in response to market liberalisation, by considering environmental aspects[29]. IAMs can provide estimates of the impacts of biofuel policies on LUC[30], or assess how changes in diet may affect agricultural greenhouse gas emissions[31]. But, such comprehensive cross-sectoral approaches come at the expense of simplifying the heterogeneity of human agency and human socio-cultural attributes. Assuming that the extant structural and functional relationships between people and their environment remain static, the capacity to explore adaptive learning across future scenarios is limited[32]. Models that are based on the principles of homogenous, utility-optimizing decision-making under equilibrium conditions[14] tend to generate spatial patterns of land-use that conform to the underlying patterns of natural resources (see example in Box 1). They also generate outcomes that are very different when compared with models that have been developed and calibrated at regional scales[33].

There are two fundamental, but somewhat different objectives for using models to analyse global environmental change. One is to evaluate the consequences of a range of environmental change drivers, including the effects of policies, in a scenario-based approach. Such an approach would typically assess the state of a system at some point in the future. The other objective is to explore the dynamics and alternative representation of interacting processes in complex socio-ecological systems. This approach seeks to understand how a system functions at present and how these functional processes will change over time[34]. The predictive approach is necessary when assessing future environmental change, whereas the process-based approach is vital in supporting the continued development of predictive models. Thus, new methods to represent adaptive learning, behavioural evolution and the emergence of new ways of doing things, which account for dynamic human behaviour and decision-making, are complimentary to the continuing development and application of IAMs.

Agent-based models (ABMs) translate empirical, social survey data about human behaviour and decision-making strategies into computer-based representations of interacting agents. They are used to simulate heterogeneous and evolving actors across different spatial and hierarchical levels[35–39]. ABMs have been successfully applied in climate-policy analyses: for example, in understanding how human behaviour and links with carbon prices affect the success of activities related to REDD+, and how resources are used in cooperatively or competitively managed environments[40,41]. ABMs simulate the behaviour of, and interactions between, individual

Table 1 | Concepts of plant functional types (PFTs) used in today's dynamic vegetation models[53,54,56] and their analogue in the agent functional type (AFT) approach.

Conceptual principle	PFT	AFT
Motivation for the grouping of types	Specified bioclimatic limits and representation of a select number of observable functional and structural traits	Typology of agent roles and attributes/behaviour
Primary determinants at the regional-global scales	Availability of location-specific resources (H_2O, light and nitrogen) and disturbances	Availability of location-specific capitals (financial, social, human, natural and infrastructure)
Guiding process	Physiology of plant carbon, water, nitrogen balance, allocation and growth strategies	Agent roles and behaviours
Definition of interactions	Competition between PFTs or between age-cohorts of a PFT; no mutualism	Competition, market interactions, capital consumption and transfer
Plastic response-strategies to pressures	Acclimation of process or growth response to local environment	Experimentation, imitation and learning
Dynamically emerging larger units	Ecosystems and biomes	Societies, social networks and institutions
Unit of simulation (space)	Point-scale, representative for grid-cell (for example, 10 minutes or 0.5 degrees)	Grid cell and administrative unit
Unit of simulation (time)	Hourly or daily, some processes annually	Annual
Land-use and management representation	Crop functional types as an extension to natural vegetation PFTs	Agent roles that are types of land-uses within grids

This comparison is not intended to convey that plants and humans are similar, but rather to outline mapping strategies for translating typologies in the plant world into analogous approaches that would work for AFTs.

actors at the local scale[42,43], which are not easily translatable to a regional or global scale, especially when considering a geographically explicit domain. This is partly due to the limited availability of consistent, global socio-economic data, but is also because of a lack of theory about how to represent these processes over large regions.

ABMs can handle nonlinear system behaviour, including the possibility of agents to plan and/or adapt[39,42,43]. Interactions between different agents and between agents and their environments are fundamental principles of LUC ABMs[35,44], which provide feedbacks that can dampen or amplify the impacts of change. Although ABMs have shown promise as land-system models that incorporate dynamic human decision-making in response to environmental and socio-economic change[45], the tele-connections, nonlinear dynamics and possible surprises that might emerge in the complex global socio-economic system have not yet been tackled. Scaling-up LUC ABMs to the global scale would provide a methodological breakthrough to improve the representation of LUC processes in Earth-system models and make the role of human decisions explicit in assessments of climate change adaptation and mitigation.

Three significant hurdles exist when assessing land-based societal adaptation and mitigation options in complex systems at the global-scale. First, modelling tools need to represent essential processes, with appropriate and variable space- and timescales, within both natural and socio-economic systems[14,30]. Second, methods are needed to extend the analysis of local coupled socio-ecological systems to the global-scale over time periods of years to decades[14,30]. Third, the representation of LUC in GCMs needs to reflect how the land-system modelling community understands LUC processes to correctly attribute the climate effects of LUC. Tackling these challenges requires a common analytical framework to accommodate disparate methodologies and research paradigms across the physical and socio-economic sciences[47], thus providing the conditions needed to identify solutions to societal challenges[48].

A novel concept for the human–land nexus

We propose a novel concept for developing LUC models that could overcome the difficulties outlined above. We focus on LUC because of its impact on climate change at the global and regional scales, the variety of land-based mitigation policies and the clear need for land-use adaptation to climate change. The concept is, however, sufficiently generic to be adopted in addressing other questions and interactions within broader socio-ecological systems. We argue for a new generation of global LUC models that are explicit about the role of human behaviour and decision making; models that can be linked to terrestrial ecosystem models to advance our understanding of the human–land system and its sustainable use in a changing world. Current ABM approaches that are applied at the local-scale are not practical for global-scale applications. Owing to rapidly increasing computing power, a model that mimics several billion individual actors might be technically feasible[14] but properly parameterizing the attributes of billions of individuals is not possible in the absence of global socio-cultural data[49]. This implies the need for a more limited set of generic agent types[49] that will also allow models to be applicable to a wide range of questions over long timescales.

The plant functional type (PFT) concept applied in dynamic global vegetation models (DGVMs) is used here as a template for developing typologies that operate at large spatial scales[48,49]. The basic principles that define PFTs are well grounded in fundamental ecology, plant physiology and biogeography (Fig. 1). Hence theory, rather than empiricism, is used as the starting point. In contrast to how large-scale typologies are created in, for example, marketing[50], the derivation of PFTs is much more transparent. Although concepts of theoretically grounded agents have been proposed before for the analysis of socio-ecological or economic systems, none of these concepts are explicitly for global-scale applications[39,49–52]. The PFT approach is one of the few (perhaps the only) examples of the successful scaling-up of individuals (here plant species) to create global models. Thus, it is reasonable to learn as much as possible from this experience.

The diversity that exists in human systems could be represented by meaningful approximations that make use of agent functional types (AFTs) in analogy to the use of PFTs. AFTs underpin a theoretically informed typological approach that might help achieve the goal of scaling-up ABMs. Other papers have demonstrated the value of the theoretical approach in specific local contexts[52], and we aim to encourage the LUC modelling community to extend these approaches to a global context. In the following, we further develop this idea by briefly summarizing the PFT concept (Fig. 1) and exploring how AFTs might be constructed using analogous principles (Table 1 and Fig. 2).

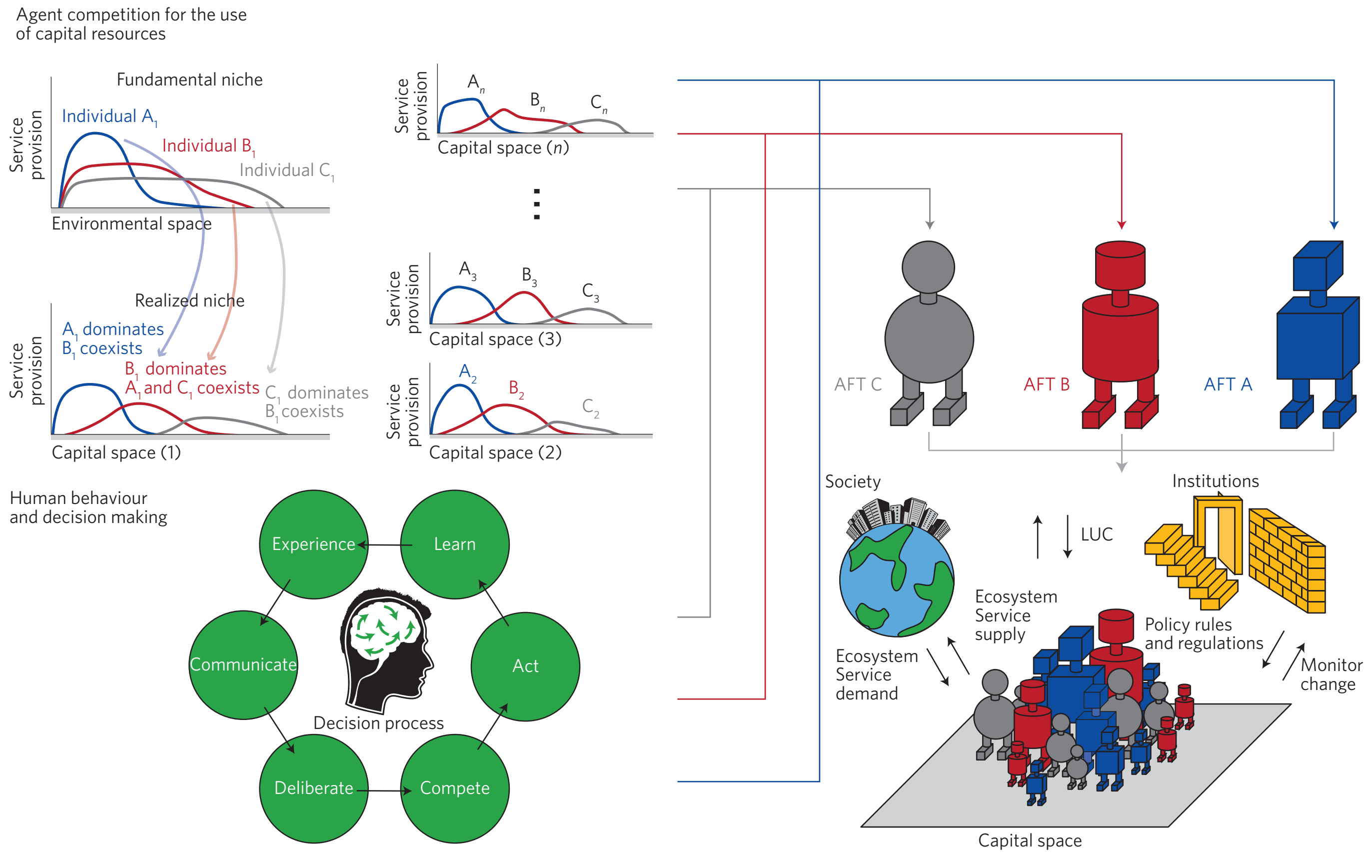

Figure 2 | Concept of agent functional types in global agent-based models. Human agency underpins land-use change modelling along capital gradients in agent-based models (top left). For a given agent, the realized niche is differentiated from the theoretically possible one due to interactions with capitals (human, social, financial, natural and infrastructure) and with other agents, modifying an agent's relative abundance within an area or over time. Human behaviour and decision making can be represented through a limited number of AFTs that group agents with similar characteristics, occurring at locations with similar attributes, even though these might be found in geographically very different places (illustrated by the similar performance curves for agents found in multiple capital spaces, top centre). The behaviour of an AFT is underpinned by a number of factors that influence decisions such as experience, communicating, deliberating and acting (bottom left; see also Table 1). The mix of AFTs at a given location changes in response to endogenous perturbations to the capital space, as well as exogenous drivers such as climate or macro-economic change (bottom right). Land-use dynamics are driven by changes in societal demands for ecosystem services leading to different combinations of AFTs, moderated by the role of institutions in regulating or incentivizing ecosystem service supply (bottom right). Typical outputs of land-use ABMs are LUC types, and the changing mix of agents and their attributes.

A short overview of plant functional types

An assemblage of observable properties (traits) can be linked to plant biophysical and biogeochemical mechanisms that enable different species to cope with similar types of environment and/or competition, even when these are encountered in geographically very distant locations[53–55]. DGVMs take advantage of this feature by coining functional units, PFTs, which can be thought of as representing groups of species with a similar expression of multiple traits in response to their environment[53–55] (Fig. 1 and Table 1). Current DGVMs aim to represent the performance of plant species, and model the dynamics of plant–environment interactions, by combining climatic limits to growth with a strong footing in ecological theory and physiological mechanisms.

DGVMs typically define around 5–15 PFTs that embody the enormous variety of the Earth's plant species by collapsing diversity into the most general strategies to cope with variable sets of conditions. A universally agreed PFT scheme for global models does not exist[53–55], but by using a limited number of PFTs, DGVMs have been shown to adequately predict the formation and reformation of biomes in response to changing environments, and successfully reproduce patterns of terrestrial carbon and water fluxes[53,56]. Thus far, most DGVM applications have not explicitly accounted for human intervention in natural ecosystems, and their treatment of agricultural and forest management processes is immature. Different approaches are currently being explored[57,58] and further development of 'land-use enabled' DGVMs will facilitate the coupling of terrestrial ecosystem processes with the dynamics of human land-use systems. Eventually, such coupled models could be used to provide the scientific basis to assess trade-offs between immediate human requirements from ecosystems and the need to preserve the capacity of the terrestrial biota to supply these ecosystem services over the long term[59].

Towards agent functional types

Agent types are often used in constructing ABMs to represent real-world actors[45,49,51]. Agents are not autonomous; they operate within a socio-cultural context that involves interactions with other societal agents[60]. They are also not static, as they learn and evolve, updating their decision strategies and individual goals in the process[60]. Typologies allow generalizations of the attributes (traits) of individual actors to simplify model development and application, and to provide a more transparent representation of agent behaviour and decision processes. Typologies have been used and applied successfully in the social and economic sciences, whenever it is necessary to handle large datasets representing human attributes[39,61,62].

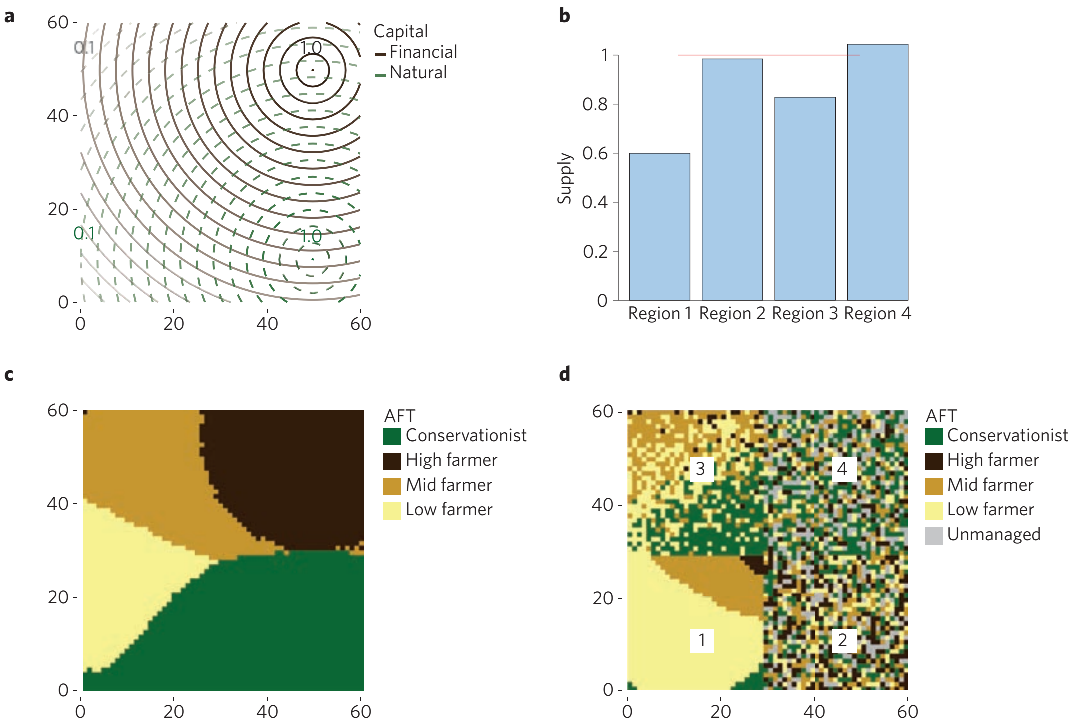

Figure 3 | Outcomes from an example simulation of an ABM application for a hypothetical region based on three farmer AFTs (high, medium and low intensity farmers) and a conservationist AFT that compete for capital resources. a, The region is divided into a 60 × 60 grid of cells, each with two capital attributes: natural capital and financial capital. The distribution of national capital and financial capital across the domain is uneven and unique for each grid cell. **b**, The calculated levels of supply per sub-region, with the red line indicating supply meeting demand (given here as unity). **c**, The modelled land use map when a global demand for food and nature is applied uniformly across the whole area. **d**, The land-use pattern that is generated when the global food demand is divided equally between four sub-regions, defined by dividing the area into four quadrants. Only the demand is spatially partitioned with the capital gradients across the whole area remaining unchanged. See Box 1 for further details.

Humans are not plants, but AFTs are analogous to PFTs (Table 1 and Fig. 2); they allow generalizations to be made about human–environment interactions within socio-ecological models for application at the global scale[45,63]. A land-user AFT is based on two primary characteristics: roles (such as forester, farmer, urban resident and so on) and behaviours (such as risk aversion, imitation, conservatism and so on) that underpin decision making. This includes agents' expectations of future economic, environmental and social conditions that are known to be significant determinants of land-use change[64]. Learning could be included through, for example, past experience, access to comprehensive information, willingness to accept information or perceived importance of future conditions. Many of these characteristics are similar to those used in empirically grounded, regional-scale agent-based models of land use[49]. Global ABMs or AFT-based approaches cannot replace specialized local studies, as they will not be capable of achieving the same degree of local accuracy. Rather, the utility of AFTs depends on the identification of those theoretical characteristics (or responses and behaviours) that hold across very diverse individuals, groups or communities and therefore are useful in identifying robust, but large-scale, patterns[49,65].

The presence of an AFT at a given geographic location depends on the attributes of the location and of all possible AFTs (Fig. 2 and Table 1). For PFTs, the attributes of a location depend on resource availability (for example, light, water, nutrients and space). For AFTs, resource availability can be conceptualized in terms of the availability of capital (financial, human, social, natural and infrastructure), which provides a representation of the heterogeneity of space[66,67]. AFTs interact with one another through competition for these resources (capitals): Financial capital refers to the broad economic context of a region (such as potential for investment or availability of finance); human capital refers to the attributes of individuals (education, skills and training); social capital to how individuals interact with one another through networks (such as family units, associations and organizations and governance structures); natural capital indicates the productive potential of a location (for example, crop or timber yields and conservation value); and infrastructure represents the physical means of exploiting a location (through, for example, transport networks and supply chains). So, in simple terms, a rural location that is well endowed with all of these capitals would tend to be exploited by an intensive agriculturalist using high-input production techniques, rather than a subsistence farmer. In contrast, a location with poor natural agricultural resources, little access to financial capital and no infrastructure, is likely to favour a subsistence farmer. As in the case of PFTs, we can conceptualize the competitive interactions between AFTs with response curves (Fig. 2). The parameterization of such response curves for AFTs is non-trivial from a theoretical perspective, but some previously published concepts[51,52] provide a starting-point. This is also acknowledged in the use of behavioural types described as, for example, 'innovative', 'imitative' or 'conservative' in a number of land-use ABMs[68]. Recognition that generalized factors and processes can be used to characterize the behaviour of a wide range of different real-world actors is currently growing.

Functional typologies such as AFTs and PFTs are based on generic (functional) classes. The overall concept is based on an ontology that includes attributes of the individual classes, causal relationships between classes and between classes and the environment.

Ontologies are important in establishing the 'conceptual model', of which the types are a component part. There are similarities between AFTs and other agent typologies[51,52]. However, many agent typologies (at the regional scale of modelling) are empirically grounded, often being established using statistical, social survey data. AFTs are established theoretically, adopting PFTs as a conceptual template. Taking a theoretical approach is necessary given the overall goal of the AFT approach, which is to scale-up the ABM approach to global scale. Inevitably, reproducing large-scale patterns and emerging dynamics will mean making choices that limit the number of AFTs with associated behavioural categories[49,51].

There are cases where the AFT–PFT analogy (Table 1) does not hold. For instance, plants do not exchange resources between locations, whereas AFTs interact in more ways than PFTs, beyond competition for resources. Trade flows, including supply-and-demand trends, connect distant agents, as does migration and the flow of knowledge and information. We can conceptualize supply-and-demand through the ecosystem service concept[69], in which services are demanded by a population (society) and supplied by AFTs. Although the discussion so far has considered the role of AFTs by perceiving them as individuals, we can also envisage agent types that reflect the collective organization of individuals, for example, through institutions. Institutional agents[39] operate at different scales within a hierarchy of interacting agents. For example, a policy institution operates over regions and/or nation states, and influences the decisions of AFTs at specific geographic locations within these higher-order spatial units. The aim of an institutional agent would be to maintain the flow of ecosystem services (and minimize disservices) between AFT suppliers and the population (societal demanders). The capacity for higher-level organisation such as institutions has no analogue in the PFT concept.

Advantages of the AFT concept

Figure 3 and Box 1 present an ABM application for a hypothetical region based on three farmer AFTs and one conservationist AFT. Even though the situation is simplified, it reflects the real-world effect of trade barriers on agricultural food production. Agricultural trade barriers, combined with high levels of intensification, lead to agricultural land abandonment as, for example, has been the case in Europe and the US over the past 50–60 years[70]. At the same time, other parts of the world that are unable to meet their own sub-regional food demand, because of low natural capital, suffer from famine. Other studies have shown the effect of such regionalization strategies in failing to achieve globally optimal outcomes in the economy–energy climate system[35,40]. It is important to note that although Fig. 3d shows what are apparently random spatial patterns, these are derived deterministically and the processes causing these patterns can be understood as a typical property of complex systems.

Human behaviour has also been shown to be critical in determining the LUC time-response, for instance with respect to the cultivation of bioenergy crops. This is due to the effects of time-lags in crop uptake, which may be on the order of 20 years[71]. Magliocca *et al.*[52] used an experimental approach to LUC ABM, which, although applied to a relatively small area, is based on a theoretical construct that could be applied over larger geographic extents. There are many examples of the importance of considering a system's 'plasticity' as well as its nonlinearity, including national-level responses to economic change (partly as a consequence of expectations of future conditions)[72], and the sensitivity of ecological systems to human behaviour[64]. A number of studies have demonstrated the inadequacy of models that assume homogeneity in agent responses at a range of scales[52,73,74]. Moreover, beyond representing groups of individuals, understanding the emergence of both formal and informal governance structures requires a move away from the treatment of institutions as exogenous drivers towards representing institutional processes in socio-ecological models[14]. Current global LUC models are unable to simulate this rich and complex set of human mediated processes. By inference, therefore, they are also unable to fully encapsulate LUC feedbacks to the atmosphere and terrestrial ecosystems. Until we are able to use approaches such as AFTs to fill this methodological and philosophical gap, understanding the role of LUC in Earth-system science will progress little from its current state-of-the-art.

Ways forward for global LUC system models

We argue for a deductive approach to the theoretical construction of AFTs, rather than the more commonly used inductive

Box 1 | Simulating land-use change in a hypothetical region using AFTs.

The results from the example simulation shown in Fig. 3 are for a hypothetical region based on three farmer AFTs (high, medium and low intensity) and one conservationist AFT, which compete for capital resources that supply ecosystem services (simplified to 'food' and 'nature'). Conservationists only supply nature services. Farmers supply food and also provide nature services, but at a lower level than conservationists, and these increase from high- to low-intensity farmers. Therefore, the four AFTs are characterized by the relative level at which they supply each service, and by behavioural thresholds of resistance in response to stress and sensitivity to competition. Examples of behavioural parameterizations of AFTs are discussed in ref. 81.

The region is divided into 3,600 grid cells, each with a unique combination of capital attributes, which are limited here to natural and financial capital. Natural capital represents the provision of food for nature and is maximized in the bottom-right of the region, as indicated on the capital gradient map (Fig. 3a), whereas financial capital is maximized in the top-right. The resulting modelled land-use map, when a global demand for food and nature is applied uniformly across the whole area (Fig. 3c), reflects the gradients that are assumed in the distribution of capitals giving the optimal distribution of land-use based on resource (capital) availability. This type of outcome would be generated by utility-optimizing approaches or models that allocate land-use based on land suitability. By contrast, a quite different pattern emerges when the global food demand is partitioned spatially by dividing the demand equally between four sub-regions (Fig. 3d), but with the capital gradients across the whole area remaining unchanged. In this case, sub-region 1, is unable to meet its food demand due to low financial capital (Fig. 3b), and hence nearly the entire area is farmed, although only low-intensity AFTs can be sustained (Fig. 3d). As the high-productivity sub-regions 2 and 4 can meet the sub-regional demands, some grid cells are not needed for food or for nature supply and are abandoned (unmanaged). In sub-region 3, with higher financial than natural capital levels, food is relatively easily produced, so agents that produce nature have a slight advantage, since their unmet demand is greater. However, in this situation, there is no surplus land.

These example results demonstrate the basic functionality of the AFT concept, which could be applied to the global scale if parameterized with real data about location attributes and agent decision making. In the given example, society consumes (demands) a fixed amount of food and nature services. In principle, it would also be useful to model consumer trends with a similar agent-based approach that could draw on market-based agent-profiling (with the caveat that not all relevant information to achieve this would be easily accessible[50]).

approach based on empiricism. This is not to criticize empirical techniques, but rather to highlight that different methods are required to scale-up beyond the traditional ABM domain of landscapes (for example, to the scale of the Earth-system). We propose a coherent method that is based on a precedent established in another discipline. This provides structure and serves as the basis for further development and testing. The successes and failures in experimenting with this approach will also be important as a learning process.

Solid relationships may not exist between generic typologies and land-use-related behaviour. However, it is important to remember that the purpose of large-scale models is to explore and develop understanding of emergent patterns and large-scale dynamics[51,52]. Theoretical characteristics designed to capture the relevant effects of a very wide range of real-world behaviours are more suitable here than in the data-driven typologies used by existing land-use ABMs. Such theoretical developments should draw on different sources, including extensive cross-disciplinary literature reviews (for example of psychological sciences, economics and game-theory) and expert elicitation, among others.

So, how many AFTs would be needed to specify all roles and behaviours? As a best guess, probably more than the 5–15 PFTs in DGVMs, but fewer than 100. Although this indicates a slightly more complex model system compared with those representing the plant-world, it still includes far fewer than the alternative — 8–9 billion individual agents. Parameterizing AFTs is a formidable task, but it is achievable. The plant ecology and DGVM researchers, for instance, have demonstrated that it is possible to gather thousands of empirical studies into a single database that is accessible to the scientific community to synthesize trait-relationships for the improvement of DGVMs[75]. Similar efforts have already been initiated by the LUC community, through a number of socio-economic data portals[76] and by providing exemplars of classifying large datasets into clusters[77]. In particular, qualitative comparative analysis[78] has potential for meta-analysis of case studies. Development of these approaches is still in early stages, but systematic data assimilation will allow the AFT approach to be applied within global-scale LUC models. Such models would be evaluated against existing observations in similar ways to LUC simulated by IAMs: using remotely sensed information on LUC, aggregated statistics from national socio-economic databases, or applying a path-dependence analysis[79,80].

Future projections of the interplay between LUC and climate change will need to deal concurrently with adaptive, plastic responses in human and biophysical systems, capturing processes in both systems that act over a wide range of time and space scales. Whether or not, and where, adaptation amplifies or dampens the system response to climate change driven by natural or socio-economic resource availability should be based on the development and application of cross-disciplinary, spatial explicit models of similar paradigms. For example, coupling AFT-based LUC models with DGVMs that account for LUC, would allow fundamental processes that are known to operate in real socio-ecological systems to be endogenized. A bi-directional information flow would enable agents (that is, decision makers) to respond to changing vegetation and landscape characteristics (through adaptive learning), and hence to deal with feedbacks, time-lags and nonlinearity in the system response. Working at a similar level of complexity within similar modelling paradigms also allows for a much clearer diagnosis of response patterns in the different systems, which is currently not possible. Such an approach would substantially enhance the capacity to assess land-based climate mitigation options and our understanding of how societies will respond to environmental change.

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References

1. Houghton, R. A. *et al.* Carbon emissions from land use and land-cover change. *Biogeosciences* **9,** 5125–5142 (2012).
2. Pitman, A. J. *et al.* Uncertainties in climate responses to past land cover change: First results from the LUCID intercomparison study. *Geophys. Res. Lett.* **36,** L14814 (2009).
3. Gornall, J. *et al.* Implications of climate change for agricultural productivity in the early twenty-first century. *Phil. Trans Roy. Soc. B* **365,** 2973–2989 (2010).
4. Easterling, W. E. *et al.* in *Climate Change 2007: Impacts, Adaptation and Vulnerability* (eds Parry, M. L. *et al.*) 273–313 (Cambridge Univ. Press, 2007).
5. Ashmore, M. R. Assessing the future global impacts of ozone on vegetation. *Plant Cell Environ.* **28,** 949–964 (2005).
6. Ramankutty, N., Evan, A. T., Monfreda, C. & Foley, J. A. Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. *Glob. Biogeochem. Cycles* **22,** http://dx.doi.org/10.1029/2007GB002952 (2008).
7. Le Quere, C. *et al.* Trends in the sources and sinks of carbon dioxide. *Nature Geosci.* **2,** 831–836 (2009).
8. Zaehle, S., Ciais, P., Friend, A. D. & Prieur, V. Carbon benefits of anthropogenic reactive nitrogen offset by nitrous oxide emissions. *Nature Geosci.* **4,** 601–605 (2011).
9. Arora, V. K. & Montenegro, A. Small temperature benefits provided by realistic afforestation efforts. *Nature Geosci.* **4,** 514–518 (2011).
10. Pongratz, J., Reick, C. H., Raddatz, T. & Claussen, M. Biogeophysical versus biogeochemical climate response to historical anthropogenic land cover change. *Geophys. Res. Lett.* **37,** L08702 (2010).
11. UN-REDD *Beyond Carbon: Ecosystem-based benefits of REDD+* (UNEP-WCMC, 2009).
12. IPCC *The National Greenhouse Gas Inventories Programme* (eds Eggleston, H. S., Buendia, L., Miwa, K., Ngara, T. & Tanabe, K.) (IGES, 2006).
13. Fargione, J. Energy: Boosting biofuel yields. *Nature Clim. Change* **1,** 445–446 (2011).
14. Rounsevell, M. D. A. *et al.* Towards decision-based global land use models for improved understanding of the Earth system. *Earth Syst. Dynam.* **5,** 117–137 (2014).
This paper is the outcome of a community effort that brought together the natural, economic and social sciences to provide a review of the current state-of-the art of global land-use change modelling; the main challenges and ways forward to address them.
15. Melillo, J. M. *et al.* Indirect Emissions from Biofuels: How Important? *Science* **326,** 1397–1399 (2009).
16. Fargione, J., Hill, J., Tilman, D., Polasky, S. & Hawthorne, P. Land clearing and the biofuel carbon debt. *Science* **319,** 1235–1238 (2008).
17. Crutzen, P. J., Mosier, A. R., Smith, K. A. & Winiwarter, W. N_2O release from agro-biofuel production negates global warming reduction by replacing fossil fuels. *Atm. Chem. Phys.* **7,** 11191–11205 (2007).
18. deMenocal, P. B. Cultural Responses to Climate Change During the Late Holocene. *Science* **292,** 667–673 (2001).
19. Oglesby, R. J., Sever, T. L., Saturno, W., Erickson, D. J. III & Srikishen, J. Collapse of the Maya: Could deforestation have contributed? *J. Geophys. Res.* **115,** D12106 (2010).
20. Adger, N. W., Barnett, J., Brown, K., Marshall, N. & O'Brien, K. Cultural dimension of climate change impacts and adaptation. *Nature Clim. Change* **3,** 112–117 (2013).
21. Moser, S. C. & Ekstrom, J. A. A framework to diagnose barriers to climate change adaptation. *Proc. Natl Acad. Sci. USA* **104,** 22026–22031 (2012).
22. Acosta-Michlik, L. *et al.* A spatially explicit scenario-driven model of adaptive capacity to global change in Europe. *Glob. Environ. Change* **23,** 1211–1224 (2013).
23. van Vuuren, D. P. *et al.* The use of scenarios as the basis for combined assessment of climate change mitigation and adaptation. *Glob. Environ. Change* **21,** 575–591 (2011).
24. Warren, R. The role of interactions in a world implementing adaptation and mitigation solutions to climate change. *Phil. Trans. R. Soc. A* **369,** 217–241 (2011).
25. Hertel, T. W. The global supply and demand for agricultural land in 2050: A perfect storm in the making? *Am. J. Agric. Econ.* **93,** 259–275 (2011).
26. Nakicenovic, N. & Swart, R. *Special Report on Emissions Scenarios: A Special Report of Working Group III of the Intergovernmental Panel on Climate Change* (Cambridge Univ. Press, 2000).
27. Smith, P. *et al.* Competition for land. *Phil. Trans. R. Soc. B* **365,** 2941–2957 (2010).
28. van Vuuren, D. P. *et al.* A proposal for a new scenario framework to support research and assessment in different climate research communities. *Glob. Environ. Change* **22,** 21–35 (2012).
29. Schmitz, C. *et al.* Trading more food: Implications for land use, greenhouse gas emissions, and the food system. *Glob. Environ. Change* **22,** 189–209 (2012).
30. Sarofim, M. C. & Reilly, J. M. Applications of integrated assessment modeling to climate change. *Wiley Interdis. Rev. Clim. Chang.* **2,** 27–44 (2011).

31. Popp, A., Lotze-Campen, H. & Bodirsky, B. Food consumption, diet shifts and associated non-CO_2 greenhouse gases from agricultural production. *Glob. Environ. Change* **20,** 451–462 (2010).
32. Fuessel, H.-M. Modelling impacts and adaptation in global IAMs. *Wiley Interdis. Rev. Clim. Chang* **1,** 288–303 (2010).
33. Busch, G. Future European agricultural landscapes — What can we learn from existing quantitative land use scenario studies? *Agric. Ecosys. Environ.* **114,** 121–140 (2006).
34. Giupponi, C., Borsuk, M. E., Vries, B. J. M. d. & Hasselmann, K. Innovative approaches to integrated global change modelling. *Environ. Modelling Software* **44,** 1–9 (2013).
35. Matthews, R. B., Gilbert, N. G., Roach, A., Polhill, J. G. & Gotts, N. M. Agent-based land-use models: a review of applications. *Landscape Ecol.* **22,** 1447–1459 (2007).
36. Filatova, T., Verburg, P., Parker, D. C. & Stannard, C. A. Spatial agent-based models for socio-ecological systems: challenges and prospects. *Environ. Modelling Software* **45,** 1–7 (2013).
37. Nolan, J., Parker, D. & van Kooten, G. C. An Overview of Computational Modeling in Agricultural and Resource Economics. *Can. J. Agric. Econ.* **57,** 417–429 (2009).
38. An, L. Modeling human decisions in coupled human and natural systems: Review of agent-based models. *Ecol. Modelling* **229,** 25–36 (2012).
39. Wolf, S. *et al.* A multi-agent model of several economic regions. *Environ. Modelling Software* **44,** 25–43 (2013).
40. Brede, M. & de Vries, B. J. M. The energy transition in a climate-constrained world: Regional vs. global optimization. *Environ. Modelling Software* **44,** 44–61 (2013).
41. Purnomo, H., Suyamto, D. & Irawati, R. H. Harnessing the climate commons: an agent-based modelling approach to making reducing emission from deforestation and degradation (REDD)+work. *Mitigation Adapt. Strategies for Glob. Change* **18,** 471–489 (2013).
42. Bonabeau, E. Agent-based modeling: Methods and techniques for simulating human systems. *Proc. Natl Acad. Sci. USA* **99,** 7280–7287 (2002).
43. Farmer, J. D. & Foley, D. The economy needs agent-based modelling. *Nature* **460,** 685–686 (2009).
44. Valbuena, D., Verburg, P. H., Bregt, A. K. & Ligtenberg, A. An agent-based approach to model land-use change at a regional scale. *Landscape Ecol.* **25,** 185–199 (2010).
45. Rounsevell, M. D. A., Robinson, D. & Murray-Rust, D. From actors to agents in socio-ecological systems models. *Phil. Trans. R. Soc. B* **367,** 259–269 (2012).
46. Boisier, J.-P. *et al.* Attributing the impacts of land-cover changes in temperate regions on surface temperature and heat fuxes to specific causes. Results from the first LUCID set of simulations. *J. Geophys. Res.* **117,** D12116 (2012).
47. Hulme, M. Meet the humanities. *Nature Clim. Change* **1,** 177–179 (2011).
48. Roco, M. C., Bainbridge, W. S., Tonn, B. & Whitesides, G. *Converging Knowledge, Technology and Society: Beyond Convergenc of Nano-Bio-Info-Cognitive Technologies* (WTEC, 2013).
49. Smajgl, A., Brown, D. G., Valbuena, D. & Huigen, M. G. A. Empirical characterisation of agent behaviours in socioecological systems. *Environ. Modelling Software* **26,** 837–844 (2011).
50. Ernst, A. in *Empirical Agent-Based Modelling-Challenges and Solutions* (eds Smajgl, A. & Barretau, O.) 85–104 (Springer, 2014).
51. Smajgl, A. & Barreteau, O. in *Empirical Agent-Based Modelling-Challenges and Solutions Vol. 1: The Characterisation and parameterisation of empirical agent-based models* (eds Smajgl, A. & Barretau, O.) 1–26 (Springer, 2014).
52. Magliocca, N. R., Brown, D. G. & Ellis, E. C. Exploring agricultural livelihood transitions with an agent-based virtual laboratory: Global forces to local decision-making. *PLoS One* **8,** e73241 (2013).
53. Prentice, I. C. *et al.* in *Terrestrial Ecosystems in a Changing World IGBP Series* (eds Canadell, J. G., Pataki, D. E. & Pitelka, L. F.) 175–192 (Springer, 2007). **A review on the plant functional types concept, its application in dynamic global vegetation models and their application to key issues of global environmental change**.
54. Harrison, S. P. *et al.* Ecophysiological and bioclimatic foundations for a global plant functional classification. *J. Veg. Sci.* **21,** 300–317 (2010).
55. Prentice, I. C. *et al.* A global biome model based on plant physiology and dominance, soil properties and climate. *J. Biogeography* **19,** 117–134 (1992).
56. Arneth, A. *et al.* From biota to chemistry and climate: towards a comprehensive description of trace gas exchange between the biosphere and atmosphere. *Biogeosciences* **7,** 121–149 (2010).
57. Bondeau, A. *et al.* Modelling the role of agriculture for the 20th century global terrestrial carbon balance. *Glob. Change Biol.* **13,** 679–706 (2007).
58. Lindeskog, M. *et al.* Implications of accounting for land use in simulations of ecosystem services and carbon cycling in Africa. *Earth Sys. Dynam.* **4,** 385–407 (2013).
59. Foley, J. A. *et al.* Global consequences of land use. *Science* **09,** 570–574 (2005).
60. Bandura, A. Toward a Psychology of Human Agency. *Perspectives Psychol. Sci.* **1,** 164–180 (2006). **The paper summarises the important properties of human agency, including core aspects related to planning, decision making and adaptation as fundamental, endogeneous traits of people within social systems**.
61. Spiggle, S. & Sanders, C. R. in *Advances in Consumer Research Volume 11* ed. Kinnear, T. C.) 337–342 (Association for Consumer Research, 1984).
62. Dickmann, M. & Müller-Camen, M. A typology of international human resource management strategies and processes. *Int. J. Human Res. Manage.* **17,** 580–601 (2006).
63. Rounsevell, M. D. A. & Arneth, A. Representing human behaviour and decisional processes in land system models as an integral component of the earth system. *Glob. Environ. Change* **21,** 840–843 (2011).
64. Sheffer, M., Westley, F., Brock, W. A. & Holmgren, M. in *Panarchy: Understanding Transformations in Human and Natural Systems* (eds Gunderson, L. H. & Holling, C. S.) 195–239 (Island Press, 2002).
65. Rindfuss, R. R., Walsh, S. J., Turner, B. L., Fox, J. & Mishra, V. Developing a science of land change: Challenges and methodological issues. *Proc. Natl Acad. Sci. USA* **101,** 13976–13981 (2004).
66. Poritt, J. *Capitalism as if the World Matters* (Earthscan, 2005).
67. Fraser, E. D. G. in *Assessing Vulnerability to Global Environmental Change* (eds Patt, A. G., Schröter, D., Klein, R. J. T. & de la Vega-Leinert, A. C.) (Earthscan, 2009).
68. Guillem, E. E., Barnes, A. P., Rounsevell, M. D. A. & Renwick, A. Refining perception-based farmer typologies with the analysis of past census data. *J. Environ. Manage.* **110,** 226–235 (2012).
69. Carpenter, S. R. *et al.* Science for managing ecosystem services: Beyond the Millennium Ecosystem Assessment. *Proc. Natl. Acad. Sci. USA* **106,** 1305–1312 (2009).
70. Rounsevell, M. D. A. *et al.* A coherent set of future land use change scenarios for Europe. *Agric. Ecosys. Environ.* **114,** 57–68 (2006).
71. Alexander, P., Moran, D., Rounsevell, M. D. A. & Smith, P. Modelling the perennial energy crop market: the role of spatial diffusion. *J. R. Soc. Interface* **10,** 20130656 (2013).
72. Giavazzi, F., Jappelli, T. & Pagano, M. Searching for non-linear effects of fiscal policy: Evidence from industrial and developing countries. *European Econ. Rev.* **44,** 1259–1289 (2000).
73. Walters, B. B., Sabogal, C., Snook, L. K. & de Almeida, E. Constraints and opportunities for better silvicultural practice in tropical forestry: an interdisciplinary approach. *For. Ecol. Manage.* **209,** 3–18 (2005).
74. Filatova, T., Van Der Veen, A. & Parker, D. C. Land market interactions between heterogeneous agents in a heterogeneous landscape — tracing the macro-scale effects of individual trade-offs between environmental amenities and disamenities. *Can. J. Agric. Econ.* **57,** 431–457 (2009).
75. Kattge, J. *et al.* TRY — a global database of plant traits. *Glob. Change Biol.* **17,** 2905–2935 (2011).
76. Hertel, T. & Villoria, N. B. *GEOSHARE: Geospatial Open Source Hosting of Agriculture, Resource & Environmental Data for Discovery and Decision Making* (Purdue University, 2012).
77. Ellis, E. C. & Ramankutty, N. Putting people in the map: anthropogenic biomes of the world. *Frontiers Ecol. Environ.* **6,** 439–447 (2008).
78. Rudel, T. K. Meta-analyses of case studies: A method for studying regional and global environmental change. *Glob. Environ. Change* **18,** 18–25 (2008).
79. Lotze-Campen, H. *et al.* Global food demand, productivity growth, and the scarcity of land and water resources: a spatially explicit mathematical programming approach. *Agric. Econ.* **39,** 325–338 (2008).
80. Ligmann-Zielinska, A. & Sun, L. B. Applying time-dependent variance-based global sensitivity analysis to represent the dynamics of an agent-based model of land use change. *Int. J. Geo. Info. Sci.* **24,** 1829–1850 (2010).
81. Murray-Rust, D. *et al.* Combining agent functional types, capitals and services to model land use dynamics. *Environ. Modelling Software* (in the press).

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ERRATUM

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These omissions have been corrected in the HTML and PDF versions of the Perspective.