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.

The climate-LUC interplay

In a world that faces continued population growth and changing consumption patterns, whilst striving to achieve an equitable and acceptable level of human well-being, climate change and land-use change are two of the foremost environmental challenges. They are also inseparably linked: land-use and land-cover change (LUC) contributes 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 50% of today's ice-free land surface has been converted from natural ecosystems into cropland and pastures[6]. Since ca. 1850, LUC released an estimated > 150 PgC into the atmosphere, one third of the approximate total anthropogenic carbon emissions, and contributed 10-20% of CO_2 emissions during the late 20th- early 21st century[1,7]. Most of the observed increase in atmospheric N_2O over the same time period has been attributed to emissions from agricultural fertiliser use[8]. LUC-related climate forcing also occurs at the regional-scale level, either as a cooling or warming[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 recognise the climate-regulating services of terrestrial ecosystems that can be implemented through LUC[11-13]. But in spite of the recognised policy 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 whole civilisations, can take place because of periods of unprecedented and persistent droughts[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 (i.e., climate change) in isolation is the sole cause of instability in socio-ecological systems with their mix of vulnerable, but also stabilising, 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 21st century and beyond is a matter of scrutiny and debate[21]. Land-based mitigation or adaptation options at a certain locale may cause changes elsewhere with opposing effects[16,21]. Adaptive actions that appear unpromising in the short-term might become important for adaptation over a longer time horizon, while 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-feedbacks models

Adaptation and mitigation are processes. Yet, 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 today's state-of-the art tools for 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 in providing comprehensive cross-sectoral analyses, and are an important component of a common scenario framework that bridges across climate research communities[28]. State-of-the art IAM analyses project changes in food exports or imports in response to market liberalisations, while also considering environmental aspects[29], providing estimates of the impacts of biofuel policies on LUC[30], or assessing how changes in diets 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, limits the capacity to explore adaptive learning across future scenarios[32]. Models that are based on the principles of homogenous, utility optimising 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 to 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 what a system might look like 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. Such an approach seeks to understand how a system functions at present and how these functional processes will change through 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 that account for dynamic human behaviour and decision making in order to represent adaptive learning, behavioural evolution and the emergence of new ways of doing things are complimentary to the on-going 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 that are used to simulate heterogeneous and evolving actors across different spatial and hierarchical levels[35-39]. ABMs have been applied successfully in climate-policy analyses: for instance, in understanding how human behaviour and links with carbon prices affects the success of REDD+-related activities, or how resources are used in cooperatively *vs*. competitively managed environments[40,41]. ABMs simulate the behaviour of, and interactions between, individual actors at the local scale[42,43], and these local-scale, individual decision rules are not easily transferable to the region or the globe, especially when combined with a geographically explicit domain. This arises partly from the limited availability of consistent, global socio-economic data, but also from a lack of theory about how to represent these processes over large regions.

ABMs can handle non-linear system behaviour, including the possibility of agents to look forward and/or adapt[39,42,43]. Interactions between different agents and between agents and their environment are also fundamental principles of LUC-ABMs[35,44] with feedbacks that might dampen or amplify the impacts of change. But, while 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, non-linear dynamics and/or possible surprises that might emerge in the complex global natural-socio-economic system have not yet been tackled. Up-scaling LUC-ABMs to the global-scale level would provide a methodological break-through to improve the representation of LUC processes within 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 level. First, modelling tools need to represent essential processes, at appropriate and variable space and time scales, within both natural and socio-economic systems[14,30]. Secondly, methods are needed to extend the analysis of local coupled socio-ecological systems to the global–scale level over time periods of years to decades[14,30]. Thirdly, the representation of LUC in GCMs needs to reflect how the land system modelling community understands LUC processes, so that climate effects are not attributed to LUC that arise from erroneous representation[46]. 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 to identify solutions to societal challenges[48].

A novel concept for the human-land nexus

We propose here a novel concept in developing LUC models that could overcome the issues 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 functioning of the human-land system and its sustainable use in a changing world. The ABM approaches that are applied at the local scale level are not practical for global-scale applications as they are currently formulated. With today's rapidly growing computing power a model that mimics several billion individual actors might be technically feasible (see[14], and references therein). Still, properly parameterising the attributes of millions of individuals is not possible in the absence of global socio-cultural data[49]. This implies the need for the use of a more limited set of generic agent types[49] that will also allow models to be applicable to a wide range of questions, and over long time-scales.

The plant functional type (PFT) concept applied in dynamic global vegetation models (DGVMs) is used here as a template for how to develop 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 (Figure 1), hence using theory, rather than empiricism, as the starting point. By contrast to how large-scale typologies are created in e.g., marketing[50], the derivation of PFTs is fully transparent. For the analysis of socio-ecological or economic systems, the concept of theoretically-grounded agent types has been proposed before, conceptually, but not explicitly for global scale applications[39,49-52]. The PFT approach is one of the few (perhaps only) examples of the successful upscaling of individuals (here plant species) to create global models. Hence it is reasonable to learn as much as possible from this experience, especially where the goal of the modelling is the up-scaling.

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. The AFT approach underpins a theoretically-informed typological approach that might help achieve the goal of ABM upscaling. Other papers have demonstrated the value of the theoretical approach in specific, local contexts[52], and so through this discussion we aim to challenge the LUC modelling community in extending these approaches to the global context. In the following we develop this logic further by briefly summarising the PFT concept (Figure 1) and exploring how AFTs might be constructed along analogous principles (Table 1, Figure 2).

A short overview of the PFT concept

An assemblage of observable properties (traits) can be linked to plant biophysical and biogeochemical mechanisms that enable different plant 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] (Figure 1, Table 1). Today's DGVMs aim to represent plant species performance by combining climatic limits to growth, with a strong footing in ecological theory and physiological mechanisms, so as to model the dynamics of plant-environment interactions.

DGVMs typically define in the order of 5 to 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 compute biomes to form and reform in response to changing environments, as well as reproducing patterns of terrestrial carbon and water fluxes[53,56]. Thus far, most of the DGVM applications have not accounted explicitly 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 model systems could be employed 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, since they learn and evolve and in so doing update their decision strategies and individual goals[60]. Typologies allow generalisations 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 data representing human attributes[39,61,62].

Humans are not plants, but AFTs as an analogy of PFTs (Table 1, Figure 2) allow generalisations to be made about human-environment interactions within socio-ecological models for application at global scale levels[45,63]. A land-user AFT is based on two primary characteristics: roles (e.g. forester, farmer, urban resident, etc.), and behaviour (e.g. risk averse, imitator, conservative, etc.) that underpins 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 could not replace specialised 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, behaviours) that hold across very diverse individuals, groups or communities and therefore are useful in indentifying robust, but large-scale, patterns[49,65].

The presence of an AFT at a given geographic location depends on the attributes of all of the possible AFTs, and the attributes of the location (Figure 2, Table 1). For PFTs, the attributes of a location depend on resource availability (e.g. light, water, nutrients and space). For AFTs, resource availability can be conceptualised in terms of capital availability (financial, human, social, natural and infrastructure) that provide 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 (e.g. potential for investment, availability of finance), human capital refers to the attributes of individuals (e.g. education, skills, training), social capital to how individuals interact with one another through networks (e.g. family units, associations/organisations, governance structures reflecting access and control), natural capital indicates the productive potential of a location (e.g. crop or timber yields, or conservation value) and infrastructure represents the physical means of exploiting a location (e.g. transport networks, supply chains). So, in simple terms, a rural location that is well endowed with all of the capitals would tend to be exploited by an intensive agriculturalist using high input production techniques, rather than a subsistence farmer. Conversely, a location with poor natural resources (for agriculture), little access to financial capital and no infrastructure would likely favour a subsistence farmer. As for PFTs, we can conceptualise the competitive interactions between AFTs with response curves (Figure 2). The parameterisation 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 acknowledged also in the use of behavioural types described as, for example, 'innovative', 'imitative' or 'conservative' in a number of land use ABMs[68]. Recognition is currently growing that generalised factors and processes can be used to characterise the behaviour of a wide range of different real-world actors.

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 and 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 upscale the ABM approach to global scale levels. 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 other ways, beyond competition for resources. Trade flows including supply and demand trends connect distant agents, as do flows in knowledge or information and through migration. We can conceptualise supply and demand through the ecosystem service concept[69], in which services are demanded by a population (society) and supplied by AFTs. And although the discussion thus far has concerned the role of AFTs perceived as individuals, we can also envisage agent types that reflect the collective organisation of individuals, e.g. through institutions. Institutional agents[39] would operate at different scale levels within a hierarchy of interacting agents so, for example, a policy institution would operate over regions and/or nation states, and influence 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 minimise disservices) between AFT suppliers and the population (societal) demanders. The capacity for higher-level organisation such as institutions has no analogy 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 shown 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 USA over the past 50-60 years (e.g.[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 regionalisation strategies in failing to achieve globally optimal outcomes in the economy-energy climate system[35, 40]. It is important to note that whilst panel d in Figure 3 shows what are apparently random spatial patterns, these are derived deterministically and as such the processes causing these patterns can be understood; 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 because of the effects of time-lags in crop uptake, which may be of the order of 20 years[71]. Magliocca et al.[52] have also 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 non-linearities 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, nor are they able 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 here for a deductive approach to the theoretical construction of AFTs, rather than the more commonly used inductive approach based on empiricism. This is not to criticise empirical approaches, but rather to highlight that different methods are required to upscale beyond the traditional ABM domain of landscapes to higher-scale levels (e.g. the Earth system). We propose a coherent method that is based on precedent in another discipline. This provides structure, and serves as basis for further development and testing. The successes and failures in experimenting with this approach will be also 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 review (psychological sciences, economics, game-theory) and expert elicitation, amongst others.

So, how many AFTs would be needed? As a best guess, probably more than the 5-15 PFTs in DGVMs, but fewer than 100, in order to be able to specify AFTs roles and behaviours. While this indicates a slightly more complex model system compared to those representing the plant-world it is still many fewer than 8 to 9 billion individuals. Parameterising AFTs is a formidable task, but one that is achievable. The plant ecology and DGVM community, for instance, has demonstrated that it is possible to gather thousands of empirical studies into a single data-base that is accessible to the scientific community to synthesise trait-relationships for the improvement of DGVMs[75]. Similar efforts have already been initiated by the LUC community, via a number of socio-economic data portals[76] and by providing exemplars of classifying large data-sets into clusters[77]. In particular, Qualitative Comparative Analysis[78] has potential for meta-analysis of case studies. While development of these approaches is still in their early stages, 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 LUC-climate change interplay 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 models of similar paradigms and spatial explicitness. For example, coupling AFT-based LUC models with DGVMs that account for LUC, would allow fundamental processes to be endogenised that are known to operate in real socio-ecological systems. A bi-directional information flow would enable agents (including institutions; i.e. decision makers) to respond to changing vegetation and landscape characteristics (i.e. adaptive learning), and hence to deal with feedbacks, time-lags and non-linearities in the system response through time. 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.

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

Conceptual principle	**PFT**	**AFT**
Grouping of types motivated mainly by:	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:	Available of location-specific resources (e.g., H_2O, light, nitrogen), disturbances	Availability of different location-specific capitals (financial, social, human, natural, infrastructure)
Guiding process:	Physiology of plant carbon, water, nitrogen balance, allocation and growth strategies	Agent roles and behaviours
Interactions defined by:	Competition between PFTs or between age-cohorts of a PFT; no mutualism	Competition, market interactions, capital consumption & transfer
Plastic response strategies to pressure:	Acclimation of process or growth response to local environment	Experimentation, imitation, learning
Dynamically emerging larger units:	Ecosystems & biomes	Societies, social networks and institutions
Unit of simulation (space):	Point-scale, representative for grid-cell (e.g., 10' or 0.5^o)	Grid cell and administrative unit
Unit of simulation (time):	Hourly or daily, some processes annually	Annual
Land use/ management represented by:	Crop functional types as an extension to natural vegetation PFTs	Agent roles that are types of land uses within grids

Figure Captions:

Figure 1:
Niche theory underpins plant distribution modelling along environmental gradients in DGVMs (top left of figure). The realised niche is differentiated from the fundamental niche in that it reflects interactions with environmental filters and other plants, modifying a species' relative abundance within an area or within varying developmental stages of the ecosystem (e.g., over time). Vegetation dynamics are represented through a limited number of plant functional types. 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 of figure; see also Table 1). At a given location, a mix of plant functional types interacts with the atmosphere and soils (and, more recently, humans). This mix can change in response to the ageing of the ecosystem, disturbance and environmental trends (bottom right of figure). Typical (example) outputs of DGVMs are carbon and water fluxes (net ecosystem exchange, NEE; gross and net primary production, GPP, NPP; respiration, R_E; evapotranspiration, E_T).

Figure 2:
Human agency underpins the decisions of heterogeneous and interacting agents that are represented through AFTs (see also Table 1). Whilst the decision process is individually-based, reflecting a number of factors that influence decisions such as experience, communicating, deliberating and acting (bottom left of the figure), competition between individuals for available resources or capitals (top left of the figure) leads to some AFTs (top right of the figure) occupying specific geographic locations (bottom right of the figure). Hence the approach combines the heterogeneity of individual behaviour and decision making with the heterogeneity of geographic space leading to complex patterns of land use. Land use dynamics (LUC) 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 incentivising ecosystem service supply (bottom right of the figure).

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, which compete for capital resources. The region is divided into 60 X 60 grid cells each with capital attributes, limited here to natural and financial capital (NC and FC). The distribution of NC and FC across the domain is uneven and unique for each grid cell, as shown in Panel a. Panel c gives the modelled land use map when a global demand for food and nature is applied uniformly across the whole area. Panel d shows the land use pattern that is generated when the global food demand is divided equally between four sub-regions (1-4) defined by dividing the area into four quadrants. Only the demand is spatially partitioned with the capital gradients across the whole area remaining unchanged. In Panel b, the corresponding calculated levels of supply per sub-region are shown, with the red line indicating supply meeting demand (given here as unity). See Box 1 for further details.

Box 1: Simulating land use change within a hypothetical region using AFTs

The results from the example simulation shown in Figure 3 are for a hypothetical region based on three farmer (high, medium and low intensity) and a conservationist AFT, which compete for capital resources in supplying ecosystem services (simplified to food and 'nature'). Conservationists only supply nature services. Farmers supply food, but also provide nature services, albeit at a lower level than conservationists, and these increase from high to low intensity farmers. The four AFTs are characterised therefore by their relative supply level of each service, and behavioural thresholds of resistance in response to stress and sensitivity to competition. Examples of behavioural parameterisations of AFTs are discussed in[81,82].

The region is divided into 3600 grid cells each with a unique combination of capital attributes, which are limited here to natural and financial capital. Natural capital (NC) for the provision of food or nature is maximised in the bottom-right of the region, as indicated on the capital gradient map above, while financial capital is maximised in the top-right (see Fig. 3a). The resulting modelled land use map when a global demand for food and nature is applied uniformly across the whole area (cf. in a fully globalised world, see Fig. 3c) basically reflects the gradients that are assumed in the distribution of NC giving the optimal distribution of land use based on resource (capital) availability. This type of outcome would be generated by utility-optimising 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 (1-4; see Figure 3d), but with the capital gradients across the whole area remaining unchanged.

In this case, sub-region 1, with low financial capital is unable to meet its food demand (Fig. 3b), and hence nearly the entire area is farmed, although only low intensity AFTs can be sustained (Fig. 3d). The high productivity sub-regions 2 and 4 can meet the sub-regional demands so some grid cells are not needed for food nor for nature supply and hence are abandoned (not-managed). 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, no land is surplus.

These example results demonstrate the basic functionality of the AFT concept, which could be applied to the global scale if parameterised 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]).

Acknowledgements

The idea for this paper was conceived at a workshop jointly sponsored by the IGBP Global Land Project, and CSIRO. The work contributes to the EU FP7 project LUC4C (grant agreement no. 603542) and the Swedish Research Council Formas Strong Research Environment "Land use today and tomorrow". AA acknowledges support from the Helmholtz Association, especially through its Initiative and Networking funds. MR and CB acknowledge funding by the European Union through the VOLANTE project (grant agreement no. 265104).

References

1 Houghton, R. A. *et al.* Carbon emissions from land use and land-cover change. *Biogeosciences* **9**, 5125-5142, doi:10.5194/bg-9-5125-2012 (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, doi: 10.1029/2009gl039076 (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, doi:10.1098/rstb.2010.0158 (2010).

4 Easterling, W. E. *et al.* in *Climate Change 2007: Impacts, Adaptation and Vulnerability* (eds. Parry, M. L. *et al.*) 273-313 (Cambridge University Press, 2007).

5 Ashmore, M. R. Assessing the future global impacts of ozone on vegetation. *Plant, Cell and Env.* **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**, doi:10.1029/2007gb002952 (2008).

7 Le Quere, C., Raupach, M. R., Canadell, J. G., Marland, G. & et al. Trends in the sources and sinks of carbon dioxide. *Nature Geosci.* **2**, 831-836, doi:10.1038/ngeo1689 (2009).

8 Zaehle, S., Ciais, P., Friend, A. D. & Prieur, V. Carbon benefits of anthropogenic reactive nitrogen offset by nitrous oxide emissions. *Nat. Geosci.* **4**, 601-605, doi:10.1038/ngeo1207 (2011).

9 Arora, V. K. & Montenegro, A. Small temperature benefits provided by realistic afforestation efforts. *Nature Geosci* **4**, 514-518, doi: 10.1038/ngeo1182 (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, doi:10.1029/2010gl043010 (2010).

11 UN-REDD. Beyond Carbon: Ecosystem-based benefits of REDD+ (UNEP-WCMC, Cambridge, 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**, doi: 10.1038/nclimate1300 (2011).

14 **Rounsevell, M. D. A. *et al.* Towards decision-based global land use models for improved understanding of the Earth system. *Earth System Dynamics* 5, 117–137, doi: 10.5194/esd-5-117-2014 (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 these.

15 Melillo, J. M. *et al.* Indirect Emissions from Biofuels: How Important? *Science* **326**, 1397-1399, doi:10.1126/science.1180251 (2009).

16 Fargione, J., Hill, J., Tilman, D., Polasky, S. & Hawthorne, P. Land clearing and the biofuel carbon debt. *Science* **319**, 1235-1238, doi:10.1126/science.1152747 (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.* **8**, www.atmos-chem-phys.net/8/389/2008/ (2008).

18 deMenocal, P. B. Cultural Responses to Climate Change During the Late Holocene. *Science* **292**, 667-673, doi:10.1126/science.1059827 (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, doi:10.1029/2009jd011942 (2010).

22 Acosta-Michlik, L. *et al.* A Spatially Explicit Scenario-Driven Model of Adaptive Capacity to Global Change in Europe. *Glob. Env. 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. Env. Change* **21**, 575-591, doi:10.1016/j.gloenvcha.2010.11.003 (2011).

24 Warren, R. The role of interactions in a world implementing adaptation and mitigation solutions to climate change. *Philos. Trans. R. Soc. A* **369**, 217-241, doi:10.1098/rsta.2010.0271 (2011).
25 Hertel, T. W. The global supply and demand for agricultural land in 2050: A perfect storm in the making? *Am. J. Agricult. Econ.* **93**, 259–275, doi:10.1093/ajae/aaq189 (2011).
26 Nakicenovic, N. & Swart, R. in *Special Report on Emissions Scenarios: A Special Report of Working Group III of the Intergovernmental Panel on Climate Change* (Cambridge University Press, 2000).
27 Smith, P. *et al.* Competition for land. *Philos. Trans. R. Soc. B.* **365**, 2941-2957, doi:10.1098/rstb.2010.0127 (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. Env. Change* **22**, 21-35, doi:10.1016/j.gloenvcha.2011.08.002 (2012).
29 Schmitz, C. *et al.* Trading more food: Implications for land use, greenhouse gas emissions, and the food system. *Glob. Env. Change*, 189-209 (2012).
30 Sarofim, M. C. & Reilly, J. M. Applications of integrated assessment modeling to climate change. *Wiley Interdiscip. Rev.-Clim. Chang.* **2**, 27-44, doi:10.1002/wcc.93 (2011).
31 Popp, A., Lotze-Campen, H. & Bodirsky, B. Food consumption, diet shifts and associated non-CO_2 greenhouse gases from agricultural production. *Glob. Env. Change* **20**, 451-462, doi:10.1016/j.gloenvcha.2010.02.00 (2010).
32 Fuessel, H.-M. Modelling impacts and adaptation in global IAMs. *Wiley Interdiscip. 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? *Agriculture, Ecosystems & Environment* **114**, 121-140, doi:10.1016/j.agee.2005.11.007 (2006).
34 Giupponi, C., Borsuk, M. E., Vries, B. J. M. d. & Hasselmann, K. Innovative approaches to integrated global change modelling. *Env. Modelling & Software* **44**, 1-9, doi:10.1016/j.envsoft.2013.01.013 (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 Ecology* **22**, 1447-1459, doi:10.1007/s10980-007-9135-1 (2007).
36 Filatova, T., Verburg, P., Parker, D. C. & Stannard, C. A. Spatial agent-based models for socio-ecological systems: challenges and prospects. *Env. Modelling and Software* **45**, doi:10.1016/j.envsoft.2013.03.017 (2013).
37 Nolan, J., Parker, D. & van Kooten, G. C. An Overview of Computational Modeling in Agricultural and Resource Economics. *Can. J. Agricultural Economics* **57**, doi:10.1111/j.1744-7976.2009.01163.x (2009).
38 An, L. Modeling human decisions in coupled human and natural systems: Review of agent-based models. *Ecol. Modelling* **229**, doi:10.1016/j.ecolmodel.2011.07.010 (2012).
39 Wolf, S. *et al.* A multi-agent model of several economic regions. *Env. Modelling & Software* **44**, 25-43, doi:10.1016/j.envsoft.2012.12.012 (2013).
40 Brede, M. & de Vries, B. J. M. The energy transition in a climate-constrained world: Regional vs. global optimization. *Env. Modelling & Software* **44**, 44-61, doi:10.1016/ j.envsoft.2012.07.011 (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 and Adaptation Strategies for Global Change* **18**, 471-489, doi:10.1007/s11027-012-9370-x (2013).
42 Bonabeau, E. Agent-based modeling: Methods and techniques for simulating human systems. *Proc. Natl. Acad. Sciences* **99**, 7280-7287, doi:10.1073/pnas.082080899 (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 Ecology* **25**, 185-199, doi:10.1007/s10980-009-9380-6 (2010).

45 Rounsevell, M. D. A., Robinson, D. & Murray-Rust, D. From actors to agents in socio-ecological systems models. *Phil. Trans. Royal 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, doi:10.11029/12011JD017106 (2012).
47 Hulme, M. Meet the humanities. *Nature Clim. Change* **1**, 177-179, doi:10.1038/nclimate1150 (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, Lancaster, PA, 2013).
49 Smajgl, A., Brown, D. G., Valbuena, D. & Huigen, M. G. A. Empirical characterisation of agent behaviours in socioecological systems. *Env. Modelling and Software* **26**, 837-844 (2011).
50 Ernst, A. in *Empirical Agent-Based Modelling-Challenges and Solutions* (eds A. Smajgl & O. Barretau) 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 A. Smajgl & O. Barretau) 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**, doi:10.1371/journal.pone.0073241 (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, doi:10.1111/j.1654-1103.2009.01144.x (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, doi:10.2307/2845499 (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, doi:10.1111/j.1365-2486.2006.01305.x (2007).
58 Lindeskog, M. *et al.* Implications of accounting for land use in simulations of ecosystem services and carbon cycling in Africa. *Earth System Dynamics*, **4**, 385-407 (2013).
59 Foley, J. A. *et al.* Global Consequences of Land Use. *Science* **309**, 570-574, doi:10.1126/science.1111772 (2005).
60 **Bandura, A. Toward a Psychology of Human Agency. *Perspectives on Psychological Science* 1, 164-180, doi:10.1111/j.1745-6916.2006.00011.x (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 T. C. Kinnear) 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. Management* **17**, 580-601, doi:10.1080/09585190600581337 (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. Env. Change* **21**, 840-843, doi:10.1016/j.gloenvcha.2011.04.010 (2011).
64 Sheffer, M., Westley, F., Brock, W. A. & Holmgren, M. in *Panarchy: Understanding Transformations in Human and Natural Systems* (eds L.H. Gunderson & C.S. Holling) 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. Sciences* **101**, 13976-13981, doi:10.1073/pnas.0401545101 (2004).
66 Poritt, J. Capitalism as if the World matters. (Earthscan, London, U.K., 2005).
67 Fraser, E. D. G. in *Assessing Vulnerability to Global Environmental Change* (eds A.G. Patt, D. Schröter, R.J.T. Klein, & A.C. de la Vega-Leinert) (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. Env. Management* **110**, 226-235 (2012).
69 Carpenter, S. R. *et al.* Science for managing ecosystem services: Beyond the Millennium Ecosystem Assessment. *Proc. Natl. Acad. Sciences* **106**, 1305-1312, doi:10.1073/pnas.0808772106 (2009).
70 Rounsevell, M. D. A. *et al.* A coherent set of future land use change scenarios for Europe. *Agriculture Ecosystems & Environment* **114**, 57-68, doi:10.1016/j.agee.2005.11.027 (2006).
71 Alexander, P., Moran, D., Rounsevell, M. D. A. & Smith, P. Modelling the perennial energy crop market: the role of spatial diffusion. *J. Royal Soc. Interface*, **10**, doi: 10.1098/rsif.2013.0656 (2013).
72 Giavazzi, F., Jappelli, T. & Pagano, M. Searching for non-linear effects of fiscal policy: Evidence from industrial and developing countries. *Europ. 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. Management* **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. Agricult. Economics* **57**, 431-457 (2009).
75 Kattge, J. *et al.* TRY – a global database of plant traits. *Glob. Change Biol.* **17**, 2905-2935, doi:10.1111/j.1365-2486.2011.02451.x (2011).
76 Hertel, T. & Villoria, N. B. GEOSHARE: Geospatial Open Source Hosting of Agriculture, Resource & Environmental Data for Discovery and Decision Making. (Purdue University, West Lafayette, IN, USA, 2012).
77 Ellis, E. C. & Ramankutty, N. Putting people in the map: anthropogenic biomes of the world. *Front. Ecol. Environ.* **6**, 439-447, doi:10.1890/070062 (2008).
78 Rudel, T. K. Meta-analyses of case studies: A method for studying regional and global environmental change. *Glob. Env. Change* **18**, 18-25, doi:10.1016/j.gloenvcha.2007.06.001 (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. *Agricultural Economics* **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. Geogr. Information Science* **24**, 1829-1850, doi:10.1080/13658816.2010.490533 (2010).
81 Murray-Rust, D. *et al.* Combining Agent Functional Types, capitals and services to model land use dynamics. *Env. Modelling and Software*, in review (2014).
82 Brown, C. *et al.* Experiments in land use decision making, global trade and individual behaviour. *Ecological Economics*, in review (2014).

Figure 1: Concept of plant functional types in DGVMs

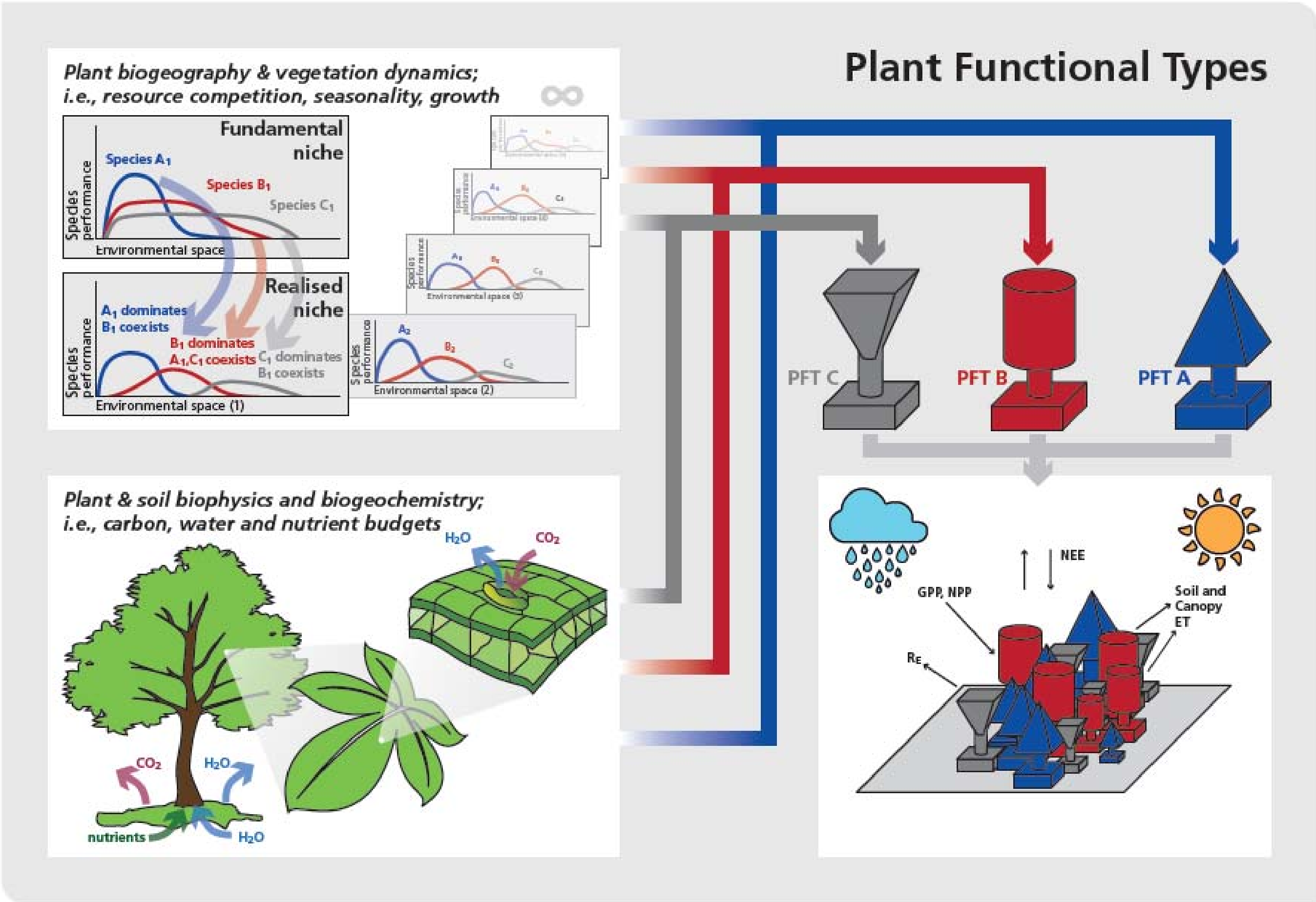

Figure 2: Concept of agent functional types in global ABMs

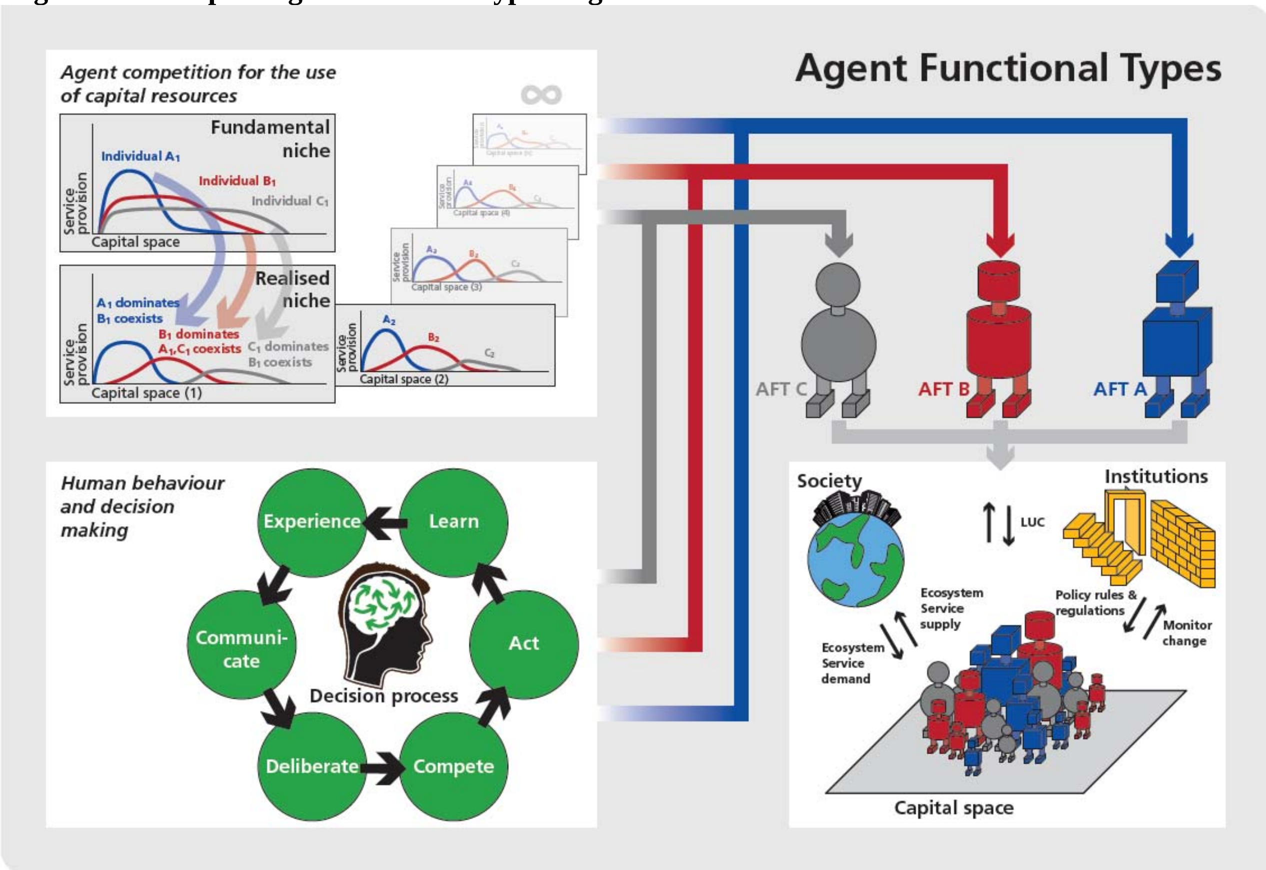

Figure 3: Outcomes from an example simulation of an ABM application