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Mapping global land system archetypes

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ABSTRACT

Land use is a key driver of global environmental change. Unless major shifts in consumptive behaviours occur, land-based production will have to increase drastically to meet future demands for food and other commodities. One approach to better understand the drivers and impacts of agricultural intensification is the identification of global, archetypical patterns of land systems. Current approaches focus on broad-scale representations of dominant land cover with limited consideration of land-use intensity. In this study, we derived a new global representation of land systems based on more than 30 high-resolution datasets on land-use intensity, environmental conditions and socioeconomic indicators. Using a self-organizing map algorithm, we identified and mapped twelve archetypes of land systems for the year 2005. Our analysis reveals similarities in land systems across the globe but the diverse pattern at sub-national scales implies that there are no 'one-size-fits-all' solutions to sustainable land management. Our results help to identify generic patterns of land pressures and environmental threats and provide means to target regionalized strategies to cope with the challenges of global change. Mapping global archetypes of land systems represents a first step towards better understanding the global patterns of human–environment interactions and the environmental and social outcomes of land system dynamics.

1. Introduction

Not only is the world experiencing rapid changes in climate and biodiversity patterns, but increasing consumption of goods and services is placing an enormous pressure on natural ecosystems and the resources they harbour (Butchart et al., 2010; Foley et al., 2005). Particularly, land use has become a major driver of global change because human populations drastically alter land in order to satisfy their basic needs for food, fibre, energy and housing. Human utilization of the biosphere has reached such a magnitude that now more than 75% of ice-free land shows evidence of marked human alteration (Ellis and Ramankutty, 2008) and almost 30% of global terrestrial net primary production is appropriated for human use (Haberl et al., 2007). Current land-use practices result in changes in the Earth's biogeochemical cycles and ultimately in the ability of ecosystems to deliver services critical to human well-being (MEA, 2005). While land use is essential for human societies, it is also becoming increasingly clear that the current global land-use system is unsustainable. Transitioning to sustainable land-use systems that would balance growing resource demands with the conservation of ecosystems and biodiversity is therefore a central challenge for science and society (Foley et al., 2007).

Land-based agricultural production is expected to increase further to meet future demands for food and other commodities, such as biofuel or fibre (Kearney, 2010; Kiers et al., 2008). However, as fertile land resources are getting scarcer and ecosystem functions and services degraded, further agricultural expansion becomes hardly acceptable. Future production increases will have to be, to a large part, achieved via intensifying existing production systems in order to reach global food security and environmental sustainability (Tilman et al., 2011, 2002). Whereas the distribution of agricultural expansion is relatively well mapped (DeFries et al., 2010; Klein Goldewijk, 2001; Klein Goldewijk et al., 2011; Ramankutty et al., 2008, 2002), the patterns of land-use intensity remain poorly understood at the global scale. To identify the potential for sustainable intensification and to better understand the environmental and

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social trade-offs, constraints, and opportunities connected to it, we urgently need to move beyond mapping broad agricultural classes towards mapping land use systems (DeFries and Rosenzweig, 2010).

Traditional models of land systems focus on broad-scale representations of land cover with limited consideration of human influence or land-use intensity (GlobCover, Arino et al., 2007; GLC 2000, Bartholome and Belward, 2005). However, the recent surge in global-scale geospatial data pertaining to land management, such as cropland densities (Ramankutty et al., 2008), fertilizer use (Potter et al., 2010), or soil erosion (Van Oost et al., 2007), provide opportunities to incorporate indicators of land-use intensity. Mapping land systems, and thereby incorporating the multidimensional aspects of land-use intensity and land management practices, can help us to (i) better understand the interactions and feedbacks among different biophysical and social components, (ii) measure impacts that are currently difficult to quantify (e.g. effects of changing land use intensity on biodiversity or social implications of land system transitions), (iii) address global trade-offs and distant impacts of land-use change (Seppelt et al., 2011), and (iv) develop better policies and spatially explicit solutions adapted to regional conditions (Foley et al., 2011). These efforts require a global analysis of land systems that would help identify both the intensity and geographical manifestation of human–environment interactions.

Several new studies made critical strides towards better integrating land management patterns in global representations of the earth's surface. For instance, Ellis and Ramankutty (2008) suggested a new classification of anthropogenic biomes as an innovative view of the human-dominated biosphere. These anthromes are based on empirical analyses of global land cover, irrigation and population data, assuming that population density is a sufficient indicator of sustained human interactions with ecosystems. The anthrome concept was developed further by Letourneau et al. (2012) who proposed a classification of global land-use systems based on additional data on irrigation, livestock type and market accessibility. Most recently, van Asselen and Verburg (2012) improved the representation of land systems by including fractional land cover, livestock density and the efficiency of agricultural production for wheat, maize and rice. These studies used either indirect or a few direct indicators of land-use intensity. They also applied top-down approaches to define land system classes based on expert's rules or a priori classification. To complement these efforts and reduce the level of subjectivity in the classification, an alternative approach is needed that would account for the multiple dimensions of land-use intensity and provide a typology of land systems driven mostly by data rather than by predefined assumptions. Such analysis may help us better understand the global patterns of human–environment interactions and land use intensity and examine the social and environmental outcomes of land system dynamics.

In this study, we propose a new approach for representing human–environment interactions as global archetypes of land systems, which we define as unique combinations of land-use intensity, environmental conditions and socioeconomic factors, with patterns that appear repeatedly across the terrestrial surface of the earth. We aim to move beyond the abovementioned representations by explicitly addressing the multidimensional aspects of land-use intensity and both the drivers of land use and its impacts. Our analysis takes advantage of globally continuous, high spatial resolution datasets on more than 30 indicators of land systems and adopts a bottom-up approach driven solely by the data. We hypothesize that (1) land systems can be clustered in consistent groups based on the similarity of available indicators of global land-use and that (2) the same land system archetypes (LSAs) can be identified across the globe, while diverse patterns can be found at the sub-national scale. By mapping LSAs, we offer a broad view of the most relevant characteristics of human–environment interactions while still preserving local context

Table 1
Datasets used for classification of land system archetypes.

Archetype factor	Spatial resolution	Unit	Source
Land-use intensity factors			
Cropland area	5 arc-minutes	km^2 per grid cell	Klein Goldewijk et al. (2011)
Cropland area trend	5 arc-minutes	km^2 per grid cell	Klein Goldewijk et al. (2011)
Pasture area	5 arc-minutes	km^2 per grid cell	Klein Goldewijk et al. (2011)
Pasture area trend	5 arc-minutes	km^2 per grid cell	Klein Goldewijk et al. (2011)
N fertilizer	0.5 arc-degrees	$kg\,ha^{-1}$	Potter et al. (2010)
Irrigation	5 arc-minutes	Ha per grid cell	Siebert et al. (2007)
Soil erosion	5 arc-minutes	$Mg\,ha^{-1}\,year^{-1}$	Van Oost et al. (2007)
Yields (wheat, maize, rice)	5 arc-minutes	$t\,ha^{-1}\,year^{-1}$	http://www.gaez.iiasa.ac.at/
Yield gaps (wheat, maize, rice)	5 arc-minutes	1000 t	http://www.gaez.iiasa.ac.at/
Total production index	National level	Index	http://faostat.fao.org/
HANPP	5 arc-minutes	% of NPP_0	Haberl et al. (2007)
Environmental factors			
Temperature	10 arc-minutes	$^{\circ}C \times 10$	Kriticos et al. (2012)
Diurnal temperature range	10 arc-minutes	$^{\circ}C \times 10$	Kriticos et al. (2012)
Precipitation	10 arc-minutes	mm	Kriticos et al. (2012)
Precipitation seasonality	10 arc-minutes	Coeff. of variation	Kriticos et al. (2012)
Solar radiation	10 arc-minutes	$W\,m^{-2}$	Kriticos et al. (2012)
Climate anomalies	5 arc-degrees	$^{\circ}C \times 10$	http://www.ncdc.noaa.gov/cmb-faq/anomalies.php#grid
NDVI – mean	4.36 arc-minutes	Index	Tucker et al. (2005)
NDVI – seasonality	4.36 arc-minutes	Index	Tucker et al. (2005)
Soil organic carbon	5 arc-minutes	$g\,C\,kg^{-1}$ of soil	Batjes (2006)
Species richness	Calculated from range polygons	# of species per grid cell	http://www.iucnredlist.org/technical-documents/spatial-data
Socioeconomic factors			
Gross domestic product	National level	$ per capita	http://faostat.fao.org/
Gross domestic product in agriculture	National level	% of GDP	http://faostat.fao.org/
Capital stock in agriculture	National level	$	http://faostat.fao.org/
Population density	2.5 arc-minutes	$persons\,km^{-2}$	CIESIN (2005)
Population density trend	2.5 arc-minutes	$persons\,km^{-2}$	CIESIN (2005)
Political stability	National level	Index	http://www.govindicators.org
Accessibility	0.5 arc-minutes	Minutes of travel time	http://bioval.jrc.ec.europa.eu/products/gam/index.htm

needed for place-specific solutions to global challenges of land use and sustainability.

2. Materials and methods

2.1. Data sources and preparation

Global patterns of land system archetypes were identified based on 32 indicators characterizing land-use intensity (covering input and output intensity factors), environmental factors and socioeconomic factors (Table 1). We hypothesized these variables would well represent the multidimensional aspects of human–environment interactions, while many of these factors function both as drivers and consequences in the complex land systems. While some variables were not completely independent from each other, as they were created by a combination of several datasets or models, we inspected Pearson correlations between all variables to avoid redundancy in the input information (Table A1). Our final set of input data included only those variables with $|r| < 0.7$ (Dormann et al., 2013). All datasets on the current land-use status were derived for the period around the year 2005 and were aggregated prior to the analysis to 5 arc-minutes ($\sim$9.3 $\times$ 9.3 km at the equator) spatial resolution. In addition, we included several indicators of temporal trends to account for legacies and transient dynamics of LSAs. The Arctic and Antarctic regions were excluded from the analysis.

2.1.1. Land-use intensity factors

Land-use intensity is a multidimensional issue and we therefore used indicators that characterize land-use intensity in terms of inputs, outputs and system properties (Kuemmerle et al., 2013). Data on cropland and pasture cover were obtained from the HYDE 3.1 database (Klein Goldewijk et al., 2011), an updated version of the standard data source for investigations of human-induced land change (Ellis et al., 2010; Hurtt et al., 2006). The HYDE model combines agricultural statistics with remote sensing data and allocation algorithms to produce spatially explicit maps of agricultural intensity (Klein Goldewijk, 2001; Klein Goldewijk et al., 2011). In addition to the status for 2005, we included temporal trends in cropland and pasture densities over the last 50 years. These trends were calculated as the difference between the values in 2005 and 1955, so the variables describe overall increase or decrease of the factors in the 50-year period. The amount of fertilizer applied and area under irrigation were used as additional indicators of land-use intensity. We acquired spatially explicit estimates of nitrogen (N) and phosphorus (P) inputs resulting from global fertilizer application and manure production (Potter et al., 2010). We used only the N fertilizer variable in the final analysis due to its high correlations with P fertilizer (Pearson correlation $>$ 0.9). Irrigation data were obtained from the Global Map of Irrigation Areas version 4.0.1 which shows the area equipped for irrigation estimated by combining subnational statistics with geospatial information on the position and extent of irrigation schemes (Siebert et al., 2007). As large-scale soil erosion is a major consequence of industrial agriculture and an indicator of land degradation (Boardman, 2006), we also acquired data from Van Oost et al. (2007) who simulated global distribution of soil erosion caused by water and tillage. The estimates were based on mechanistic models that quantitatively described the relationship between sediment erosion and land use, topography, climate and soils as controlling factors.

As an indicator of the intensity and efficiency of land-based production, we acquired data on yields and yield gaps for wheat, maize and rice from the GAEZ v3.0 database (IIASA/FAO, 2012). These data were developed by downscaling the national and subnational crop production statistics (Monfreda et al., 2008) and allocating them to cultivated land. Yields were calculated for both rain-fed and irrigated croplands in t ha^{-1} year^{-1} and yield gaps represented the difference between actual production and potential agro-ecological productivity. We also included one country-level indicator of land-based production: the total production index (TPI) which represents the relative level of the aggregate volume of agricultural production in comparison with the base period 1999–2001. As an additional indicator of land-use intensity and human pressure on land, we used data on the human appropriation of net primary production (HANPP) that represents an aggregate impact of land use on biomass available in ecosystems (Haberl et al., 2007). HANPP accounts not only for biomass withdrawn from ecosystems through harvest but also for NPP losses due to biomass being destroyed during harvest and due to decreased productivity of human-dominated ecosystems as compared to productivity of natural ecosystems (Erb et al., 2009).

2.1.2. Environmental factors

Global patterns of land-use forms and processes are constrained by climate and other biophysical attributes that represent the system as a whole. To represent climate, we mapped annual means of 35 bioclimatic variables derived from the CliMond database (Kriticos et al., 2012). These interpolated surfaces were calculated from the original WorldClim variables (Hijmans et al., 2005) as historical climate averages centred on 1975. For the final analysis, we selected five bioclimatic factors with low correlation ($<$0.6) to avoid redundant information in the dataset (Table 1). In addition, we mapped mean climate anomalies reflecting 10 years (2001–2010) of anomalies in land surface temperatures measured by NOAA's Global Historical Climatology Network (Menne et al., 2009). Because the 5° aggregated data contained missing values, we interpolated them with thin plate spline algorithm (Hutchinson, 1995) to obtain global coverage. To account for biophysical factors that reflect the productivity of ecosystems, we calculated the mean and standard deviation (seasonality) of the normalized difference vegetation index (NDVI) acquired from the Global Inventory Modelling and Mapping Studies (GIMMS) available for a 25 year period spanning from 1981 to 2006 (Tucker et al., 2005). NDVI has been used extensively for investigations of global change because it correlates with primary productivity of ecosystems and is an indicator of vegetation cover and land-use practices (DeFries and Townshend, 1994; Lunetta et al., 2006; Pettorelli et al., 2005). As soil is a crucial physical constraint for plant growth and crop production (FAO, 1999), we included data on soil organic carbon from the ISRIC–World Soil Information project (Batjes, 2006). Finally, we included a measure of species diversity because biodiversity reflects both natural conditions and long-term effects of land management (Ewers et al., 2009; Green et al., 2005; Phalan et al., 2011). For the taxonomic groups of terrestrial mammals, birds, reptiles and amphibians, we obtained global range polygon data from the International Union for Conservation of Nature (IUCN) database and used overlay analysis to calculate species richness (number of species) for each grid cell.

2.1.3. Socioeconomic factors

As economic indicators of land systems, we used three statistical indices provided by the Food and Agriculture Organization (FAO) at a national level. Gross domestic product (GDP) represents the market value of all officially recognized goods and services produced within a country, and GDP from agriculture indicates the proportion of an economy's total domestic output resulting from the agricultural sector. The capital stock in agriculture quantifies investments and physical assets used in the production process covering land development, irrigation works, structures, machinery and livestock. As broad indicators of the degree of human impact on land, we used gridded data on globally consistent estimates of population density (CIESIN, 2005). Similar to the case of cropland and pasture areas, we used the status for 2005 but also calculated changes in global population density for the last 50 years. For socioeconomic indicators, we used the worldwide governance indicators (WGI) and market accessibility. WGI reports on six dimensions of a country's governance, including voice and accountability, political stability, government effectiveness, regulatory quality, rule of law and control of corruption (Kaufmann et al., 2010). We chose only one index, political stability, to represent governance indicators in the final classification, in order to avoid multicollinearity in the data. Finally, we used the global map of accessibility that measures travel time to major cities and market places (Uchida and Nelson, 2009). This dataset developed by the European Commission and the World Bank captures connectivity and concentrations of economic activities which are critical drivers of human interactions with the global environment (Verburg et al., 2011a).

2.2. Archetype classification

We adopted a multidimensional classification procedure that explicitly considers the complexity of land-use intensity to examine how this phenomenon manifests itself at a global scale. Hierarchical clustering has been previously used to delineate land cover and farming systems (FAO, 2011; Kruska et al., 2003; Letourneau et al., 2012; van Asselen and Verburg, 2012; van de Steeg et al., 2010) but these approaches required expert rules or supervised threshold selection and used relatively few variables in order to keep the interpretation of classification trees manageable. We used a self-organizing map (SOM) algorithm, an unsupervised neural network, that allows both (i) visualizing complex data sets by reducing their dimensionality and (ii) performing cluster analysis by grouping observations (grid cells in a map) into exclusive sets based on their similarity (Skupin and Agarwal, 2008). SOM is especially useful for the classification of archetypes because our exploratory aim is geared towards uncovering relevant patterns in land systems rather than confirming existing hypotheses. Also, the method preserves topology based on distances (similarity) among input vectors in the two-dimensional output space. If two high-dimensional clusters are very similar, then their position in the two-dimensional space should be very similar (Spielman and Thill, 2008).

The SOM analysis was conducted in R version 2.14.0 (R Development Core Team, 2011) using the package kohonen (Wehrens and Buydens, 2007). First, we prepared training data by randomly sampling all 32 variables with one million data points, in order to decrease the computational burden and reduce spatial autocorrelation in the variables. Second, we checked data for extreme outliers or skewed distributions. Because of their differing units, we normalized all variables by scaling them to zero mean and unit variance. This *z*-score normalization was important, as it allowed the results to be interpreted in terms of how much and in which direction the characteristic factor in each archetype deviates from the global average. Third, we selected the size and type of the two-dimensional output space. We chose a 3 by 4 hexagonal plane to provide high generalization of clusters required for the purpose of our analysis, while maintaining sufficient links among units in the neural network (for details see Skupin and Agarwal, 2008). We based our choice on a sensitivity analysis that compared different sizes and shapes of SOM output planes, ranging from 2 by 2 to 10 by 10 clusters. For each possible combination, we calculated the mean distance of samples to the codebook vector (see below) of that cluster to which the samples were assigned, normalized by the number of clusters (Wehrens and Buydens, 2007). We identified a natural break in the mean distance for the 3 by 4 SOM size, suggesting a useful trade-off between the number of clusters and their quality of data representation.

The final pattern was identified through an iterative self-organizing process which represents the core of the SOM analysis. During this process, individual input vectors were presented to the output units, the best-matching units were found and the weights of the winning and neighbouring units repeatedly modified until the algorithm converged (Skupin and Agarwal, 2008). To analyze the spatial manifestation of identified clusters, we mapped all samples back to the geographical space and created the final map of LSAs by assigning each grid cell a cluster value of its closest sample point. We evaluated the quality of the classification procedure by calculating the distance of each grid cell, mapped to a particular cluster, to the codebook vector of that cluster (i.e. the combination of variable values that best characterizes the particular cluster). A good classification should show relatively small distances for most locations in the map (Wehrens and Buydens, 2007).

3. Results

The final map of global land system archetypes revealed a clustered pattern of human–environment interactions and land-use intensity (Fig. 1). Each archetype was characterized by a specific combination of land management indicators and its spatial position in the SOM indicated its relation (similarity) to other archetypes (Fig. 2 and Fig. A2). The non-standardized values of land system determinants that best characterize each archetype were summarized in Fig. 3 and Table A2.

Forest systems in the tropics cover approximately 14% of terrestrial ecosystems and are determined mainly by climate conditions, namely high temperature and precipitation, which naturally correspond with primary production that is the highest among all archetypes and supports high species richness (201 species of selected taxonomic groups per grid cell). The climate conditions, however, have experienced most pronounced temperature anomalies in the recent decade. While the cropland and pasture densities are close to the global average (5 and 15% of cover, respectively), their extent has expanded in the last 50 years as a result of continuing deforestation (by 2 and 5 km^2 per grid cell, respectively). Yields for wheat, maize and rice, however, remain below 1 t ha^{-1} $year^{-1}$. These regions have low average GDP (2011 \$ per capita) but 18% of their national GDP comes from the agricultural sector. The population density varies substantially from place to place but most of the regions exhibit low political stability. These regions occur in Latin America and the Amazon basin, Central and West Africa, and in Southeast Asia.

Degraded forest/cropland systems in the tropics cover only 0.35% of terrestrial ecosystems but represent areas with the highest estimated soil erosion in the world (120 Mg ha^{-1} $year^{-1}$). This LSA exhibits a scattered pattern in locations where tropical forest had been converted to croplands with the average cropland cover of 25% that increased by 22 km^2 per grid cell in the last 50 years. Although the input of N fertilizer is approximately 9 kg ha^{-1}, the yields of the three major crops are relatively low. However, more than 39% of the net primary production is appropriated for human use. These areas have environmental and socioeconomic conditions highly similar to the forest system archetype and occur especially in Southeast Asia and Latin America.

Boreal systems of the western world (14% of terrestrial ecosystems) consist of a mixture of boreal forests and tundra. The archetype is determined by a combination of boreal climate and low human impact but advanced socioeconomic conditions. The average cover of cropland and pasture is about 6% and both indicators experienced a decreasing trend in the last 50 years. Agricultural intensity is very low with minimal potential for higher

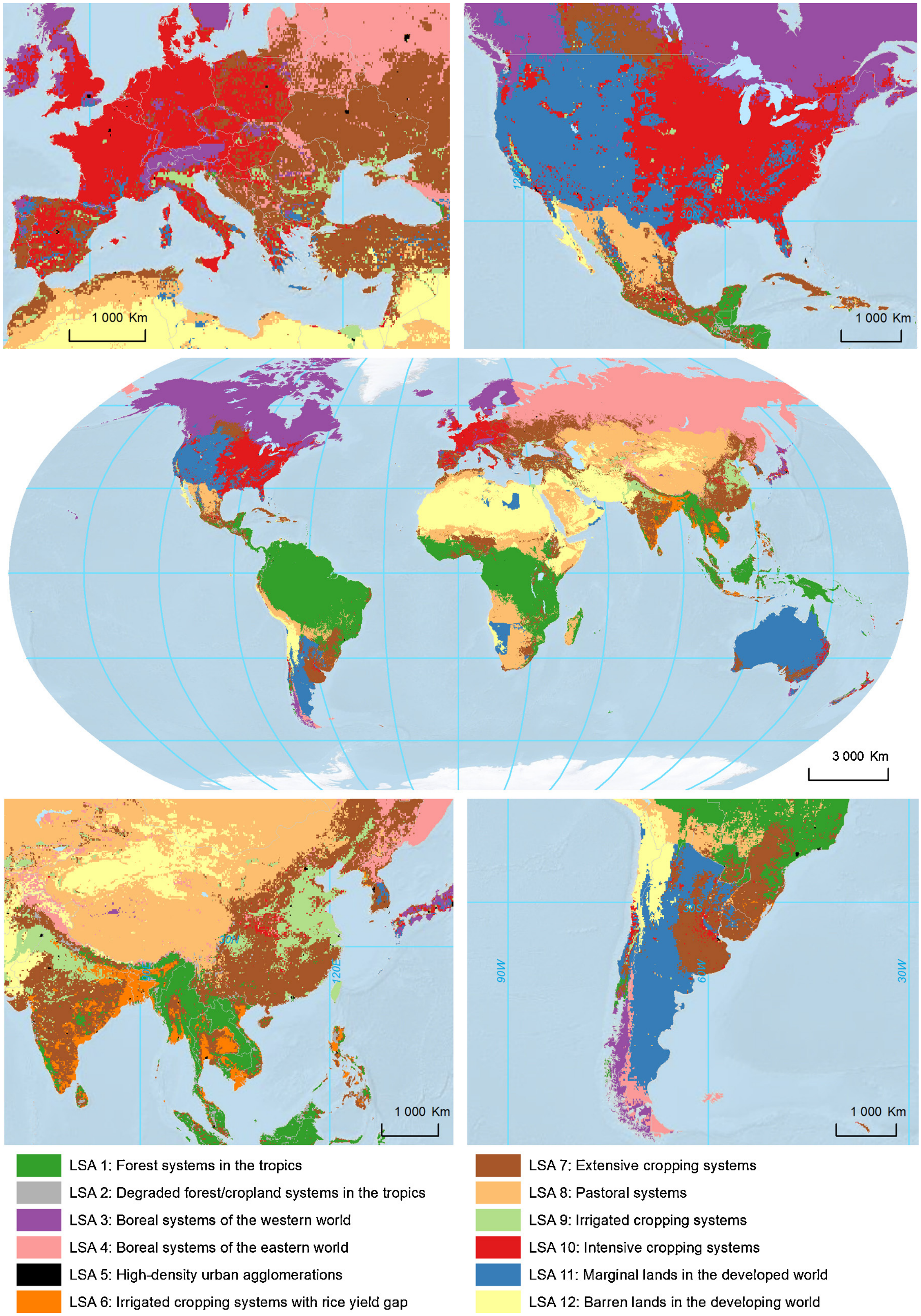

Fig. 1. Global land system archetypes: world map and regional areas. The data for this classification refer to the year 2005.

land productivity. Low and seasonally dependent NDVI corresponds to a cold and relatively dry climate that causes slow decomposition of organic material in soils and does not allow persistence of a large number of species. High GDP is a distinctive factor (average of 25,725 \$ per capita) but less than 2% of GDP originates from the agricultural sector. Boreal systems are scarcely populated (average of 5 persons per km^2), far from cities and market places (average of 2270 min of travel time) but politically

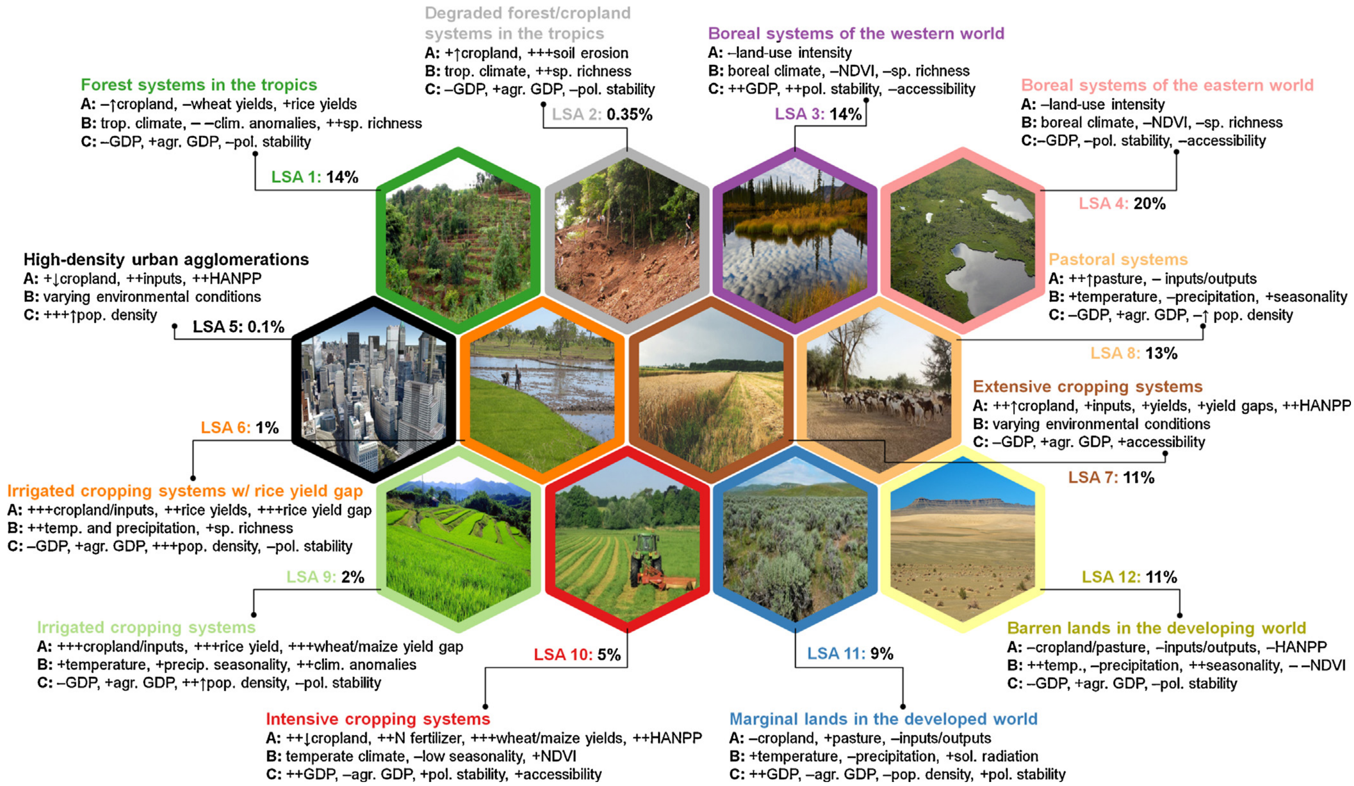

Fig. 2. Overview of land system archetypes (simplified version of Fig. A1 in the appendix), summarizing major land-use intensity indicators (A), environmental conditions (B) and socioeconomic factors (C) that best characterize each archetype. The + and – signs show whether the factor is above or below global average (+ is up to 1 s.d., ++ is 1–2 s.d., +++ is >2 s.d.); the ↑ and ↓ signs signify increasing/decreasing trends within the last 50 years; the numbers represent percentages of terrestrial land coverage. The spatial position in this self-organizing map indicates similarity among land system indicators.

highly stable. This LSA occurs predominantly in Canada and Northern Europe but also in Patagonia and the higher elevations of Japan or the Alps.

Boreal systems of the eastern world (20% of terrestrial ecosystems) closely resemble the previous archetype with the exception of several socio-economic factors. While the climate and land-use intensities are almost the same, this archetype has on average substantially lower GDP (1779 $ per capita) but a higher share of GDP (6%) comes from the agricultural sector. The population density is comparable but the regions have slightly better accessibility to cities and market places (average of 1580 min) and have lower values of governance indicators. This archetype occurs predominantly in Russia and Northeast China.

High-density urban agglomerations (0.1% of terrestrial ecosystems) are characterized by extreme values of a few land system determinants, mainly population indicators (>15 s.d.). The population density is by orders of magnitude higher than in other archetypes (average of 7138 persons km^{-2}) and in the last 50 years it increased by 4319 persons per km^2. Urban agglomerations have an average cropland cover of 13% but its decrease in the last 50 years by 22 km^2 per grid cell indicates a rapid urbanization process on fertile land. High values for N fertilizers (23 kg ha^{-1}), irrigated areas (1035 ha per grid cell) and HANPP (51%) represent a legacy of formerly cultivated land but also reflects soil sealing and NPP losses from urbanization. As urban agglomerations are scattered throughout the world, most other factors are highly variable but the travel time to market places is naturally the lowest from all archetypes. Urban areas with lower population densities, which sum up to 0.5% of the terrestrial Earth surface (Seto et al., 2012) are part of other archetypes.

Irrigated cropping systems with rice yield gap (1% of the terrestrial ecosystems) are characterized by high cropland density (49%), large extents of irrigated areas (2613 ha per grid cell) and high inputs of N fertilizers (average of 33 kg ha^{-1}). Actual yields are low for wheat and maize and higher for rice (3 t ha^{-1} year^{-1}) but the yield gap for rice due to nutrient limitation is the largest from all archetypes. Climate factors point to relatively warm climate with high precipitation amounts and seasonality. While these regions have more than 17% of their GDP resulting from agriculture, they are economically very poor (GDP of 757 $ per capita) and politically unstable. The intense land-use pressure is illustrated also by dense population (509 persons per km^2) that increased by 307 persons per km^2 in the last 50 years. These areas have relatively good accessibility to cities and market places (average of 122 min) and occur predominantly in India, Bangladesh and Southeast Asia.

Extensive cropping systems (11% of terrestrial ecosystems) are characterized by high density of cropland (average cropland cover of 30%) and its high increase in the last 50 years (15 km^2 per grid cell). Although varying spatially, the extent of irrigated areas exceeds the global average and the land receives relatively high inputs of N fertilizer (approx. 13 kg ha^{-1}), while in the same time suffers from soil erosion (average of 9 Mg ha^{-1} year^{-1}). Yields of the three major cereals vary between 1 and 3 t ha^{-1} and almost 49% of NPP is appropriated for human use but there is still a substantial yield gap, especially for wheat and maize. The characteristic climate is mainly temperate but the conditions vary due to the wide spatial distribution of this LSA. GDP is below global average (4030 $ per capita) and about 12% originates from agriculture. The population density and its trend is highly variable but exceeds the global average (102 and 56 persons per km^2, respectively). Most regions are relatively well accessible, having a mean travel time of 208 min to cities and market places. This LSA occurs in Eastern Europe, India, China but also in South America and Sub-Saharan Africa.

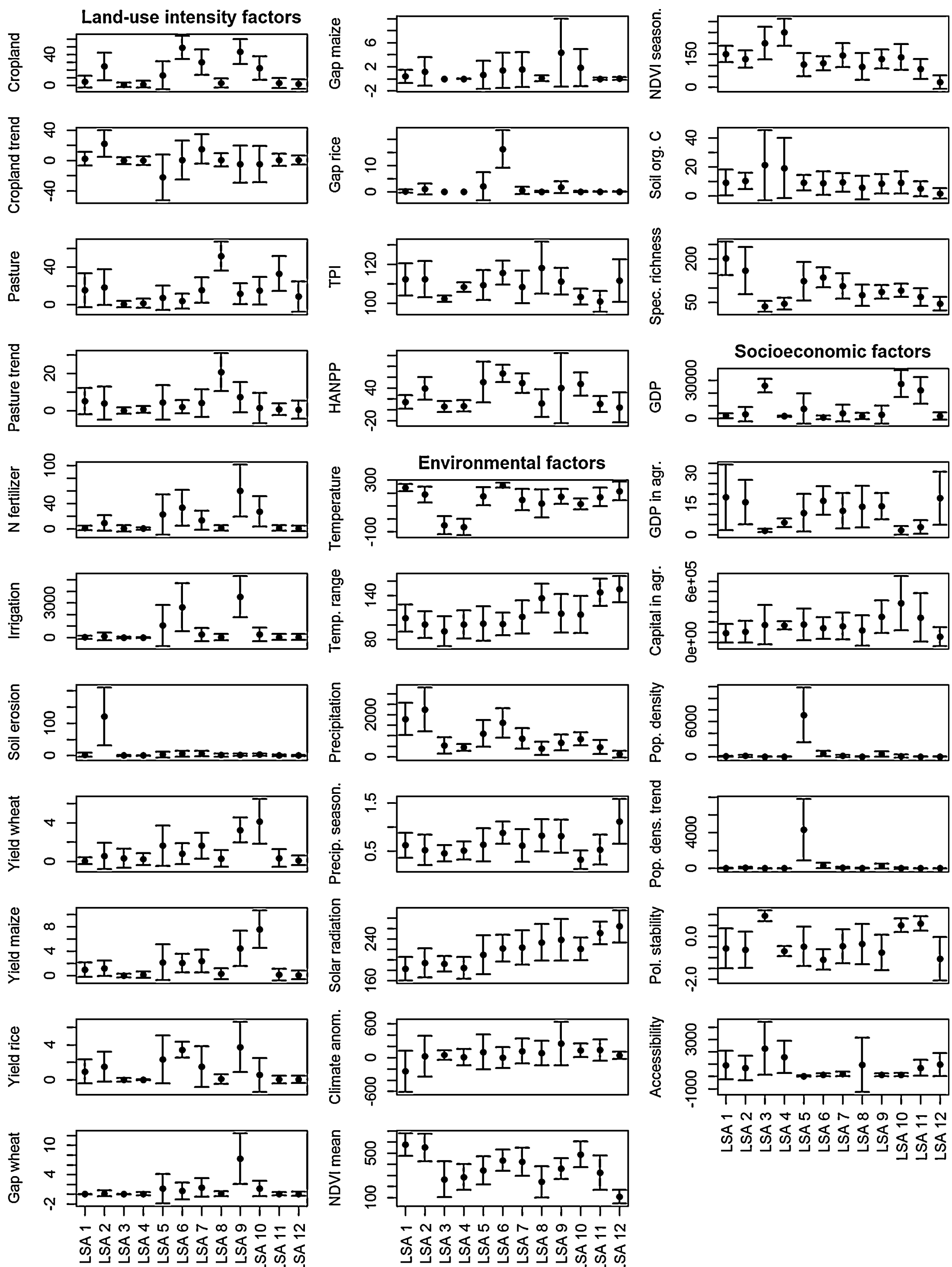

Fig. 3. Comparison of land-use input/output indicators, environmental conditions and socioeconomic factors that characterize each land system archetype. Dots represent mean values; whiskers represent standard deviations. For variable units, see Table 1.

Pastoral systems (13% of terrestrial ecosystems) are characterized especially by high densities of pastures and grasslands (average cover of 52%) and their increasing trends (average increase of 21 km^2 per grid cell). The agricultural inputs in the form of N fertilizer and irrigation are small, while the land has low actual and potential productivity. The total production index is relatively high in comparison to the base period but due to low cropland coverage, the total volume of cropland production is small. Low NDVI corresponds to drier climate but higher precipitation seasonality and diurnal temperature range. Countries that overlap with this LSA have relatively high proportion of GDP resulting from agriculture (14%), although the average total GDP is significantly lower than the global average (1772 $ per capita). These areas are scarcely populated (14 persons per km^2), although the population density has increased in the last 50 years (by 8 persons per km^2). Their accessibility is similar to the global average (945 min).

Pastoral systems occur predominantly in Central Asia but also in South and North Africa, Sahel, and in portions of Mexico and South America.

Irrigated cropping systems cover only about 2% of terrestrial ecosystems but represent managed landscapes with the highest agricultural inputs. This archetype is typical by having the largest extents of irrigated areas (3539 ha per grid cell) and extremely high inputs of N fertilizers (60 kg ha^{-1}). The cropland density is also one of the highest (average cover of 44%) but has decreased in the last 50 years by 5 km^2 per grid cell due to settlement encroachment. The yields are high for all three major cereals (3–5 t ha^{-1} $year^{-1}$) and about 39% of NPP is appropriated for human use but opportunities for agricultural intensification still exist, especially for wheat and maize. Considered climate factors point to relatively warm climate with high precipitation seasonality but the variation in climate anomalies suggests a potential threat for sustaining agricultural production. While these regions are politically unstable and economically poor (GDP of 2952 $ per capita), they have more than 14% of their GDP resulting from agriculture and relatively high capital investments in the agricultural sector. The intense land-use pressure is illustrated also by dense population (447 persons per km^2) that increased by 256 persons per km^2 in the last 50 years. Irrigated croplands have good accessibility to cities and market places (average of 116 min) and occur predominantly in India, China, Egypt, but also in Europe.

Intensive cropping systems (5% of terrestrial ecosystems) are characterized by a high density of cropland (cover of 22%) that has slightly decreased in the last 50 years and high inputs of N fertilizer (approx. 27 kg ha^{-1}). These inputs correspond to high yields for wheat and maize, although yield gaps for both crops still exist. The TPI has decreased in comparison to the base period but the total volume of production is higher than in other archetypes due to larger areas of harvested crops. Climate factors indicate a temperate climate with low seasonality that corresponds to productive ecosystems (high NDVI) but more than 47% of NPP is appropriated by humans. These regions are politically and economically stable (GDP of 27,287 $ per capita) and although only 2% of GDP originates from agriculture, they have the highest capital investments in the agricultural sector. Population density is on average 92 persons per km^2 and increased by 28 persons per km^2 in the last half century. Most regions are well accessible, having a short travel time (average of 134 min) to cities and market places. This LSA occurs mainly in Western Europe, Eastern USA and Western Australia.

Marginal lands in the developed world (9% of terrestrial ecosystems) are driven largely by pronounced positive socioeconomic factors and low values for indicators of land-use intensity. The average cover of pasture/grasslands is 33% but the average cropland cover is only 3% and has decreased in the last 50 years. Yields of major cereals are marginal but the conditions do not allow much potential to increase land-based production. The TPI even shows there has been a decrease in agricultural production in comparison to the base period. Temperature and precipitation indicators point to a warm and dry climate affected by frequent positive climate anomalies. These regions have similar values of socioeconomic indicators as the intensive cropping systems but the population density is only 6 people per km^2 with decreasing trend. This LSA occurs predominantly in Western USA, Australia, Argentina, but also in North and South Africa.

Barren lands in the developing world (11% of terrestrial ecosystems) consist of mostly barren and desert areas. Low densities of cropland (average cover of 2%) and pastures (average cover of 9%) allow only marginal agriculture with minimal yields and potentials for intensification. The limitation for growing crops is also emphasized by the low organic carbon content. Extremely low primary production as measured by NDVI corresponds to an extreme climate with high temperatures and their diurnal range, high solar radiation and low precipitation. The countries are economically poor (1954 $ per capita) but despite their low agricultural production and capital investments, about 18% of their GDP is generated by the agricultural sector. The population density in this archetype is only 12 people per km^2 but the settlement density varies substantially due to spatial clustering in urbanized areas. Regions in this archetype have the lowest political stability among all archetypes and include the Middle East, Saharan Africa and also deserts of Namibia, Gobi and Atacama.

4. Discussion

Identifying archetypical patterns of human–environment interactions presents a major challenge for land system science (Rounsevell et al., 2012; Turner et al., 2007). Simple approaches based on dominant land cover with limited consideration of land management are insufficient to draw a complete picture of coupled human–environment systems (Verburg et al., 2009). Integrated Assessment Models (IAMs; e.g. Bouwman et al., 2006; Schaldach et al., 2011) strive to capture interactions among biophysical and social systems but they represent land-use intensity in a simplified manner, e.g. by a single, aggregated factor of land management per world region. This represents a shortcoming for understanding the environmental impacts and socioeconomic costs of agricultural intensification. In this study, we offered an integrated view on land systems by directly accounting for the multiple dimensions of land use intensity in the context of prevailing environmental and socioeconomic conditions. Our classification identified interesting regional patterns that go beyond mono-causal analyses of a few land-use indicators. For example, the results revealed unexpected similarities in land systems across the globe (e.g. the extensive cropping archetype in East Europe, India, Argentina and China) but also showed a diversity of land systems at a sub-national scale, such as in China or India. Such findings challenge the view that land system drivers and outcomes can be modelled adequately at the national or macro-regional scales that are typical for IAMs (Bouwman et al., 2006).

4.1. Uncertainties in land system classification

As every classification scheme, LSAs represent a considerable oversimplification because land systems are inherently complex and dynamic. Still, our use of the SOM technique alleviated some of the subjective decisions needed in previous global classifications (e.g. Ellis et al., 2010; van Asselen and Verburg, 2012). Being an unsupervised data driven method, SOM allows clustering multidimensional data without the need of using expert rules or a priori classification thresholds. Moreover, SOM allows evaluating the quality of the classification procedure by calculating the distance of each grid cell in the multi-dimensional space to the mean values of the variables that best characterize the archetype. In our case, this quality assessment shows a homogeneous pattern of short distances for most locations, indicating good classification results (Fig. A2). Examples with higher distance values that require caution in interpretation are areas in the Nile Delta or in Western China. Here, some of the input variables have considerably higher or lower values than the mean values of the corresponding archetype (e.g. very large rice yield gap or poor accessibility, respectively) but are not different enough to be assigned to a different LSA. Larger distance values can be also found for many urbanized areas that do not have population densities high enough to be assigned to the LSA of high-density urban agglomerations.

While we used the best datasets on land use and environmental and social characteristics of land systems currently available, the main uncertainties in our classification stem from the quality and spatial resolution of input data. The quality of the global datasets used here was affected by (1) the techniques used to process remotely sensed data (e.g. for NDVI) or (2) the reliability of ground-based inventories (e.g. for socioeconomic data) collected by different monitoring and reporting methods (Fritz and See, 2008; Kuemmerle et al., 2013; Verburg et al., 2011b). Because remote sensing quantifies land use and environmental properties only indirectly, most variables were developed by the combination of remote sensing and inventory data, using three main approaches. First, climate or soil data were developed from point-based measurements using interpolation techniques. Second, land-use intensity data were developed by disaggregation techniques that combined statistical methods with satellite-based land-cover maps (e.g. for irrigation or yield data) or crop-type maps (e.g. for N fertilizer data) to transform national or subnational census data into grid-level metrics. Third, several datasets (e.g. soil erosion or yield gaps) linked direct remote sensing or ground-based measurements with outputs of mechanistic and simulation models. The nature of the data and applied models introduced different levels of uncertainty in the final classification. Consequently, many of the datasets were downscaled or upscaled from the original data or used directly in our classification at the national level (e.g. GDP or political stability).

Incorporating relevant land-use intensity, environmental and socioeconomic indicators is a crucial improvement in mapping global land systems, but many influential factors were still neglected due to the lack of data. For example, data on mechanization, farm size, crop rotation, grazing intensity or feed production are unavailable at the global scale, or they are associated with large uncertainties in specific regions (e.g. Africa). Data gaps are especially large for forestry, for which developing globally consistent information on the types of forestry systems (e.g. plantations, agroforestry) and harvest intensity is a major challenge (Kuemmerle et al., 2013). In addition, national and subnational policies such as agricultural subsidies or land access restrictions may drive the demand for different land functions. Similarly, cultural factors, ownership patterns or local economies can affect the decisions made by land managers (Lambin et al., 2001). Our assessment accounted for a wider range of determinants than previous land system models, but the influence of governance and culture is notoriously difficult to capture and is not available in adequate quality across broad geographic extents (Verburg et al., 2009).

Moreover, global datasets often capture information for different points in time. We used the year 2005 as a baseline because many datasets were not available in a full coverage for later years. This limitation, however, had an obvious effect on final results. For example, a part of Libya was included in the archetype marginal lands in the developed world because socioeconomic variables for 2005 describe it as a prosperous and politically stable country, although the situation has changed dramatically in the last several years. Improving existing land-use intensity metrics and incorporating new socioeconomic and institutional data is a key priority for land system science (Rounsevell et al., 2012). Developing time series of such data would also allow us to study archetypical patterns of land-use change and societal transitions.

4.2. Interpretation and application of land system archetypes

The land system archetypes we derived in this study can be used in a variety of ways to advance our understanding of global and regional human–environment interactions. First, classification of land systems at broader scales provides opportunities to detect generic patterns of major land pressures and environmental threats, and thus to identify regions that may require similar policy responses, or highlight heterogeneity (e.g. within countries), of which decision makers should be aware. For example, we show that severe loss of soil is most pronounced in three archetypes: degraded forest/cropland systems in the tropics, irrigated cropping systems with rice yield gap and extensive cropping systems (Fig. 3 and Table A2). Although soil erosion occurs in other systems too, these regions are particularly vulnerable to the loss of soil fertility because of their high agricultural inputs, low GDP and strong dependence on agricultural production. Similarly, water scarcity threatens land systems in which water availability is limited due to high irrigation (irrigated cropping systems) or low precipitation and seasonality (pastoral systems). While the opportunities to close yield gaps exist here through nutrient and irrigation management, sustainable adaptation of production to possible water scarcity is required. The analysis also shows a general pattern of pronounced climate anomalies for the forest systems in the tropics and irrigated cropping systems (although it cannot capture local impacts of climate change). Being rich in biodiversity, but economically and politically unstable with strong dependence on cropland production, these systems are particularly vulnerable to climate variability and further land transformation.

Second, land system archetypes can provide scientific evidence and action-oriented knowledge to cope with the challenges of global change. Studying land system archetypes can help us choose between alternative land-use strategies, e.g. expansion vs. intensification, to achieve production increases, and to assess the environmental and social outcomes of such choices. Foley et al. (2011) suggested that new approaches to agriculture (e.g. halting cropland expansion, closing yield gaps and increasing cropping efficiency) should be implemented to sustain future food demands while shrinking agriculture's environmental footprint. As these strategies cannot be used in a 'one-size-fits-all' manner, analyses of land systems can help identify strategies for particular regions and support the development of portfolios of solutions relevant for particular regions or countries (Seppelt et al., 2013). Several examples from our analysis highlight the relevance of such place-based approaches. For instance, our results suggest that, while the differences between realized and attainable yields are relatively small in intensive cropping systems, considerable opportunities for yield improvements exist in the LSAs of extensive cropping systems and irrigated cropping systems. These findings are supported by Mueller et al. (2012) who showed that Eastern Europe and Sub-Saharan Africa represent 'low-hanging' intensification opportunities for wheat and maize and Southeast Asia for rice. Here, large production gains could be achieved if yields were increased to only 50% of attainable yields. We also show that a large portion of LSAs is characterized by a considerably low political stability covering 48% of the terrestrial earth surface: forest cropping systems in the tropics, boreal cropping systems in the eastern world, both irrigated cropping systems and barren lands in the developing world. Any type of land management, no matter if focusing on preserving biodiversity, adaptation to climate change or closing yield gaps, needs to consider the limitations of land-use options due to social and political constraints. Some of these regions (e.g. irrigated cropping systems) also show high and increasing population density with main threats to water supply and low GDP.

Third, our archetypes allow for identifying areas and land systems that are underrepresented in terms of knowledge and data and therefore require further case studies to investigate land change in depth. Although remote sensing and global modelling have transformed the way we observe global land-use patterns, anthropogenic systems are not directly observable from space and cannot be modelled without a grasp of how humans interact with environment locally. The synthesis of land-use case studies at local scales is thus necessary but given the unstructured and multidisciplinary nature of place-based research, there is a need to better link and share its findings. Our archetypes can serve as an operational framework for such efforts and contribute to existing initiatives, e.g. GLOBE (http://globe.umbc.edu/), that help scientists identify gaps and opportunities for future research. However, our classification should be seen as an example of possible land system typologies that should be improved as new data and knowledge from regional studies become available. Such classifications based on finely-resolved data can be more complex or hierarchical for regions but will allow us investigating how global archetypes of land systems translate in specific regions and whether different factors characterize the patterns at finer scales.

Fourth, our archetypes can serve as a way to better represent land systems in global and sub-global assessments, and thus to better understand the impact of land-use change on biodiversity and ecosystem services, as well as the feedbacks of local and regional land change to the earth system (Verburg et al., 2011b). The concept provides a blueprint for spatially explicit global assessments focusing on various options and objectives in managing limited land resources. The methodological framework gives LSAs the potential to be used as entities in land change models and to spatially examine various scenarios of land system changes based on shifts in driving factors. Using LSAs as inputs in global models of land use dynamics can help us explore (i) the interactions and non-stationarity among multiple land-use drivers and (ii) the critical thresholds causing transitions of one land system to another. In addition, the concept can be applied to different sizes of SOM topologies and thus balance the trade-off between archetype generalization and data representation. This allows analysing land systems at different scales and testing whether responses to a particular policy change follow different paths in different land systems. Systematically linking biophysical and socioeconomic drivers to land-use trajectories is a prerequisite for the development and evaluation of sustainable land management strategies.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.gloenvcha.2013.09.004. These data include a Google KML file for a map of land system archetypes and the underlying land-use intensity, environmental and socioeconomic factors.

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