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Challenges and opportunities in mapping land use intensity globally

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Future increases in land-based production will need to focus more on sustainably intensifying existing production systems. Unfortunately, our understanding of the global patterns of land use intensity is weak, partly because land use intensity is a complex, multidimensional term, and partly because we lack appropriate datasets to assess land use intensity across broad geographic extents. Here, we review the state of the art regarding approaches for mapping land use intensity and provide a comprehensive overview of available global-scale datasets on land use intensity. We also outline major challenges and opportunities for mapping land use intensity for cropland, grazing, and forestry systems, and identify key issues for future research.

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Introduction

Unless fundamental changes in consumption occur, land-based production of food, feed, fiber, and bioenergy will have to increase substantially to meet humanity's surging demands [1,2••]. As land resources are becoming scarcer [3••] much of this rise in production must come from sustainably intensifying existing production systems [4]. Yet, land use science has so far mainly focused on broad land cover conversions while the spatial patterns in the intensity of cropland, grazing, and forestry systems remain highly unclear for most world regions.

The lack of datasets to adequately assess land use intensity and changes therein is particularly apparent at the global scale, where existing data on land use intensity are either coarse in scale (e.g. national-scale statistics) or connected to considerable uncertainties [5•,6••], or both. Existing data gaps translate into large uncertainties when assessing the world's potential for increasing land-based production, for minimizing the environmental trade-offs of land use, or for assessing the outcomes of alternative land use pathways such as expansion versus intensification. Moreover, data gaps are particularly in developing countries, which sometimes lack consistent data collection and sharing frameworks, yet where land systems change is extensive.

Three reasons explain the scarcity of global-scale land use intensity datasets. First, land use intensity is a complex and multidimensional phenomenon. Land use intensity can refer to the land area farmed, the frequency of cultivation [7], the amount of capital-related inputs (e.g. fertilizer [8], irrigation [9], technology [10], or mechanization [11]), the crop yields from a particular area [12,13], or the share of ecosystem productivity that is appropriated by humans [14]. Second, indicator definitions may vary between disciplines or countries. Finally, adequate approaches for measuring land use intensity and for integrating various data sources are often missing (see Erb *et al.*, this issue).

Despite these issues, new opportunities are arising to fill the existing data gaps and to derive new land use intensity indicators. Data availability is rapidly improving, and new algorithms and computer processing capacities allow for better use of these datasets. Here, our goals here are to:

(a) Review approaches to measure and map land use intensity at the global scale,
(b) Provide an overview of spatially explicit datasets on land use intensity, and
(c) Outline research gaps and opportunities for mapping land use intensity globally.

Measuring and mapping land use intensity

Conceptual framework

Our conceptual framework of land use intensity follows Erb *et al.* (this issue), which refers to land-based production in a broad sense, including agriculture, grazing, and forestry. In short, Erb *et al.* argue that adequately addressing land use intensity and its impact on society and the environment requires considering the different dimensions of land use intensity in a systemic way. Land use activities take place in production systems, which are defined as integrated socio-ecological systems with both biophysical (e.g. soils, climate, topography) and socio-economic properties (e.g. institutions, market integration, population). Land-based production then encompasses all activities that convert some combination of inputs into outputs, dependent on the properties of the system (Figure 1). Inputs in the classical sense refer to the land area utilized, to capital (e.g. technology, mechanization, agrochemicals applied), and labor (e.g. the amount of labor, knowledge) [15]. Outputs refer to the production itself (e.g. harvests). Beyond outputs, land-based production impacts a range of ecosystem functions and services, as well as biodiversity, human, social, and natural capital, as well as land system resilience. These, usually unintended, impacts are here referred to as the outcomes of land-based production. Measuring and mapping outcomes, as well as the trade-offs between production output and outcomes (e.g. food versus carbon storage or biodiversity loss), are at the heart of sustainability science, but beyond the scope of this manuscript.

Here, we focus on three types of metrics that provide a quantitative, spatially explicit measure of land use intensity itself and thus allow ranking land use systems or places according to their intensity (Figure 1):

(1) Input metrics measure the intensity of land use along input dimensions (e.g. fertilizer, cropping frequency, rotation lengths).
(2) Output metrics relate outputs from the production system to inputs (e.g. yields, capital productivity, or residue/felling ratios in forestry).
(3) System metrics relate the inputs or outputs of land-based production to system properties (e.g. yield gaps (actual versus potential yield), human appropriation of net primary production (HANPP), or wood felling in relation to wood increment).

Approaches for mapping land use intensity

Approaches for deriving global-scale metrics of land use intensity at fine resolutions (i.e. 0.5° or finer) can be broadly grouped into approaches based solely on remote sensing image analysis, and methods that combine satellite observations with ground-based inventory data to derive grid-level land use intensity metrics (Table 1).

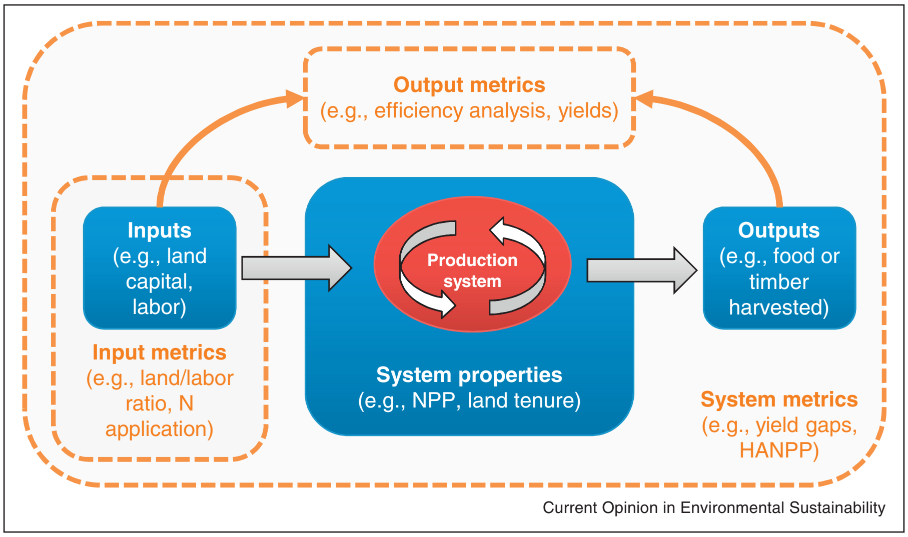
Satellite remote sensing

Remote sensing is arguably the most important technology available for mapping land use and land cover dynamics across broad geographic extents. Image access has surged over the last few decades, the spatial, spectral, and temporal resolution of observations have increased, and data archives cover increasingly longer time periods, altogether allowing for more detailed assessments of land use changes than ever before. Strong advantages of remote sensing include the systematic acquisition setup, the spatially explicit nature of measurements, and their consistency across political borders. Yet, land use intensity changes are often related to subtle spectral changes, and are thus notoriously hard to separate from the background variability in the system (e.g. phenology, atmospheric or topographic effects). Apart from a few notable exceptions (see below), satellite-based methods do not generally provide direct measurements of land use intensity.

In terms of input metrics, remote sensing provides crucial information on the extent of land use, for example the global extent of agriculture (see [6]). Furthermore, satellite image time series allow in some cases for determining cropping cycles (e.g. [16,17]), the extent of fallow land [18•], or the frequency of fallow periods [19]. Mapping grazing pressure and forest management effects across broad geographic extents remains a challenge, although some promising applications exist [20,21]. Advances have also been made regarding mapping individual crop types [22–24] or for distinguishing irrigated from rainfed agriculture (e.g. [25,26]). Finally, remote sensing can provide some information on the spatial configuration of land use, such as field size ([27] see Figure S1), which can be important for mapping capital and labor intensity (e.g. large fields as indicator of agri-business farming).

Remote sensing can also help to derive output metrics. Examples include yield estimates [28,29] or timber volumes extracted [30], although global applications of this kind are still lacking. Likewise, satellites can assist in

Figure 1



Schematic overview of land use intensity metrics. Metrics (orange boxes) are quantitative, spatially explicit measures of land use intensity derived by relating different dimensions to each other. Input metrics measure the intensity of land use along different input dimensions (e.g. fertilizer/land, labor/land). Output metrics relate outputs from the production system to inputs (e.g. yields, residue/felling ratios in forestry). System metrics relate the inputs or outputs of land-based production to system properties (e.g. actual/potential yield ratios (i.e. yield gaps), wood felling to wood increment ratios).

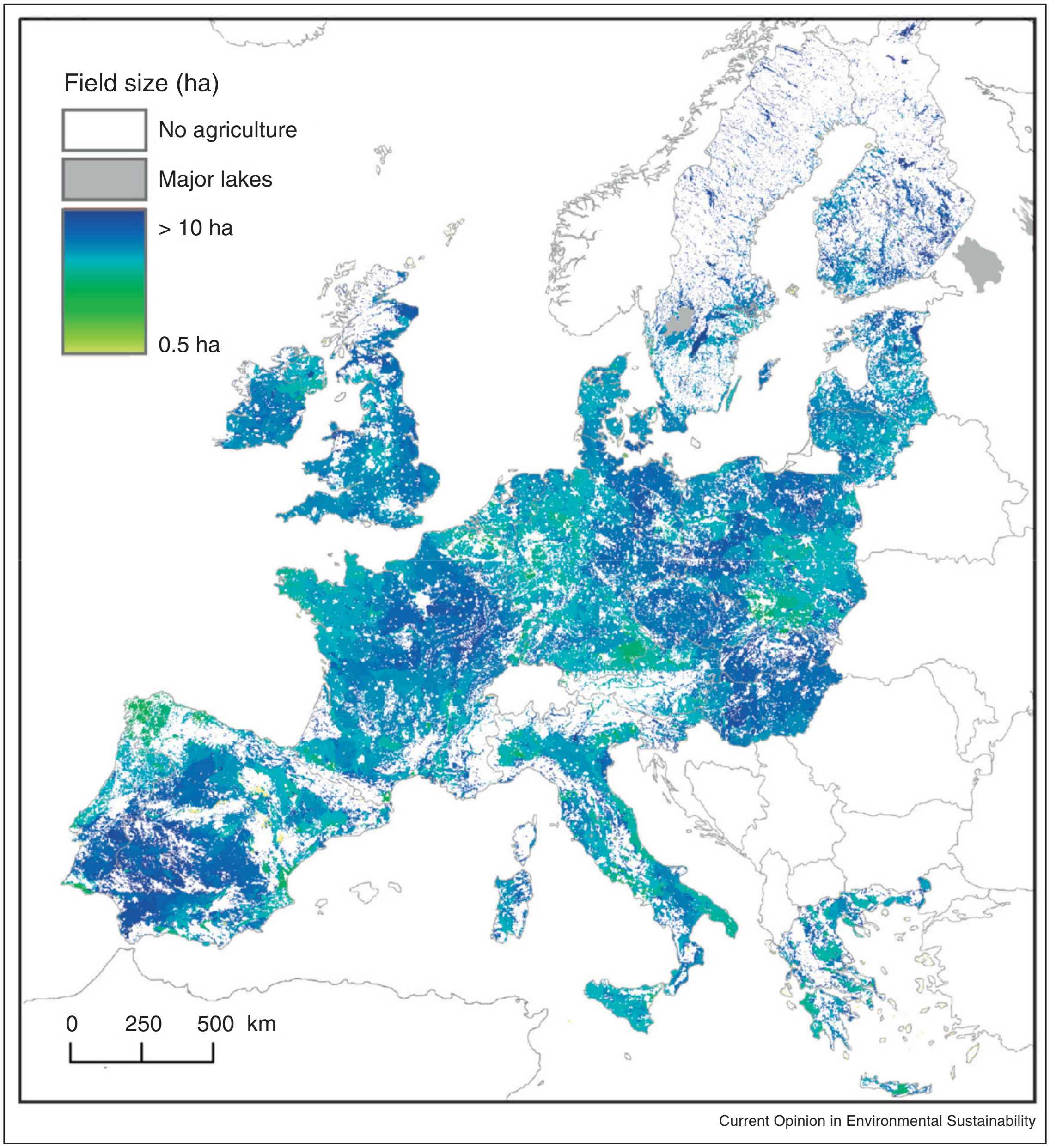
generating land use intensity system metrics, for example by measuring reference states and changes in ecosystem properties such as net primary production [31], carbon stocks [30] or forest tree species composition [32,33], although many of these approaches are still experimental and cannot readily be applied across broad geographic extents. Despite these promising developments though, algorithms for mapping outputs and system metrics are not mature enough to be routinely applied to map larger regions.

Table 1

Data sources characterizing land use intensity across broad spatial extents

Data source	Description	Extent	Unit of observation	Examples
Satellite imagery	Measurements of the spectral properties of land surfaces	Variable (local to regional to global coverage, depending on the sensor system)	Pixel	Land cover (e.g. cropping area), land cover change (e.g. logged area), vegetation indices, NPP, albedo, surface temperature
International statistics	Reconciled national statistics from various sources	National (global coverage)	Nations (sometimes subnational)	FAO (e.g. labor, capital, pesticide use, agricultural production, land use area, forestry use), FAO Forest Resource Assessments
Census (total population)	Agriculture or forestry statistics (usually based on questionnaires)	National/subnational	Administrative units	Population and housing census, tax reports
Survey (sample of population)	Agriculture or forestry statistics (usually based on questionnaires or interviews of a stratified sample of the population)	National/subnational	Individual, household, plot	LUCAS database; living standard surveys, national forest inventories
Cadastre data	Land property boundaries and ass ociated information	Individual properties	Property boundaries	Land tenure, national land registers

Figure 2



Map of cropland field sizes for Europe derived from interpolating ground-based survey data from the Land Use/Cover Area Frame Survey (LUCAS) of the European Union using an ordinary Kriging approach.
Source: LUCAS primary data 2009, http://epp.eurostat.ec.europa.eu/portal/page/portal/lucas/data/lucas_primary_data_2009.

Combining satellite data and ground-based inventory data

A range of land use intensity metrics primarily rely on ground-based inventory data, often combined with remote sensing information. Three approaches are frequently used to translate inventory data into spatially explicit land use intensity metrics.

First, interpolation techniques can derive maps from point-based measurements such as national forest inventories [34], the Land Use/Cover Area Frame Survey (LUCAS) of the European Union [35], or national farm-level surveys. A wide array of deterministic and geostatistical interpolation techniques can be used to derive grid-based land use intensity metrics from such point datasets (for a review see [36]). The potential of these techniques is illustrated by advances in mapping tree species [37,38] or age-class distributions [39] based on forestry inventory data, or maps of field size and agricultural landscape patterns derived from the LUCAS data

(Figure 2). Despite this potential though, no global ground-observation dataset which would allow for interpolating broad-scale land use intensity metrics currently exists to our knowledge.

A second group of methods disaggregates spatially aggregated data. Most datasets containing land use intensity information are available in aggregated form, because microdata (e.g. farm-level surveys, tax records) cannot be made available widely due to privacy issues, are difficult to interpret (e.g. individual forest inventory plots), are often not geocoded, or were only gathered for administrative units (e.g. timber harvests). Disaggregation techniques commonly combine harmonized land use statistics with high-resolution land cover information, for example to map forest growing stock [40] or the extent of different crops [13,41]. More complex disaggregation techniques use a wider range of ancillary data, for example crop-type maps to produce global N and P fertilizer application maps [8], or census data and land cover maps to produce rainfed and irrigated agriculture maps [9,42•,43], which can then be used to map the cropping intensity of agriculture [44]. Similarly, livestock patterns in Europe [45] and globally [46] were mapped by disaggregating livestock statistics.

A third group of land use intensity metrics combines measurements, either from satellites or on the ground, with model outputs. This is particularly important regarding system metrics, which typically rely on a reference value that is less straightforward to measure than inputs and outputs alone. For example, global yield gaps [47,48•] were mapped by first deriving efficiency frontiers using econometric modeling, and then calculating the gap between actual and potential yields at the grid level [10]. Another example is HANPP [14], which is defined as the difference between the fraction of actual NPP remaining in an ecosystem after harvest (e.g. determined with methods that combine ground-based and remote sensing data) and potential productivity from dynamic global vegetation models.

Available global metrics and data gaps

A review of available global-scale, gridded land use intensity metrics reveals that a number of such metrics are already available, but large data gaps remain in terms of dimensions and sectors covered (Table S1).

Cropland systems

The data situation is arguably best in terms of cropland intensity metrics. A range of maps depict global cropland area, crop distribution, cropping frequency, and the extent of irrigated as well as fallow cropland. Several maps also depict the amount of organic and mineral fertilizer applied. Fewer datasets capture output or system metrics, the most notable of these are a comprehensive yield dataset and several global yield gap maps. Moreover, time series for some metrics (e.g. cropland area) exist (Table S1). Although a comparatively high number of cropland intensity datasets exist, it should be noted though that these datasets are often connected to considerable uncertainty.

Data gaps exist particularly with regard to capital-related inputs (e.g. spatially explicit datasets on mechanization, pesticide application, or investment in agriculture) and labor inputs (e.g. the number, share, and skill-level of the agricultural workforce). We also currently lack detailed information on the extent and pattern of agroforestry, crop rotations, shifting cultivation systems, and organic versus conventional cropping. Finally, the quality of many of the existing cropland intensity metrics could be improved further.

Grazing systems

Global data on grazing systems are particularly scarce (Table S1). While indicators of livestock densities and major livestock products (meat, milk, eggs) exist, considerable gaps relate to the extent of grazing land and the amount and types of biomass grazed. Likewise, information on other input indicators is missing, particularly regarding the spatial pattern of feed and forage production and consumption, fertilizer applied to pastures, grassland drainage, and the patterns of labor and capital inputs connected to livestock systems.

Forestry systems

Very few global forestry intensity metrics exist (Table S1). A number of datasets provide information on the current extent, biomass, and growing stock of forests, and the area of forest management can be approximated via the exclusion of wilderness areas [49]. However, major gaps include a better understanding of the characteristics of forests (e.g. tree species composition, age-class or diameter-class distributions, increment), the spatial patterns and types of forest management (e.g. close-to-nature versus monoculture, rare versus frequent management), and the inputs (e.g. fertilizer, labor, mechanization) and outputs (e.g. timber volumes extracted, non-timber goods) of forestry.

Discussion

Challenges for mapping land use intensity globally

Despite considerable recent progress, the mapping of global land use intensity continues to face major challenges. First, fine-scale land use intensity data with global coverage remains scarce, particularly regarding grazing and forestry systems. Statistical data are frequently only available at the national scale, systematic ground-based data collection covers only a few regions, and remote sensing struggles to capture the often subtle spectral effects of land use intensity changes. Data gaps are unfortunately largest in developing countries, many of which experience rapid land use change, and are thought

Table 2

Research priorities for global-scale, spatially explicit datasets needed to improve and extend the existing set of land use intensity metrics

Dataset or metric needed	Potential mapping approach
Cropland systems	
Improved maps of cropland extent, especially for uncertain regions (e.g. SubSaharan Africa) and cropping systems (e.g. shifting cultivation), as well as cropland abandonment	Satellite remote sensing, at multiple scales (including images fine enough to capture land use patterns), potentially in combination with census data or local sampling surveys
Improved maps of cropping cycles, incl. fallow cycles	Analyses of satellite image time series, combined with crop calendars [61,62] and agricultural census data [44] and/or crowd-sourced information on farming practices
Labor intensity or mechanization	Disaggregation of statistical data (e.g. agricultural labor force) with ancillary data (e.g. remoteness, population density, land use systems). Harmonized collection of statistical data, preferably at subnational scale, needed. New remote sensing datasets (e.g. field size) could improve estimations
Pesticide use	Disaggregation approach similar to those used to generate global fertilizer application maps. Structured collection and access to data on pesticide use (e.g. via farm surveys) and sales (e.g. subnational statistics) needed
Capital investment and capital productivity	Structured data collection needed. Capital productivity could be mapped by relating investments to revenues (e.g. using yield maps and price estimates)
Organic farming extent	Disaggregation/downscaling of national or subnational data on organic farming extent. Close links to several of the above metrics (e.g. pesticide use)
Grazing systems	
Share of feed/forage from natural vegetation (versus cropland and permanent pastures)	Collection and homogenization of feed/forage data at the subnational scale needed, potentially in combination with crowd-sourced information on grazing practices. Such information could be used together with cropland extent and livestock density maps [63]
Extent of grazing and types of vegetation that is grazed (e.g. grasslands, forests)	Improved vegetation maps from remote sensing in combination with disaggregated livestock statistics and information on grazing practices (see above)
Forage quality	Remote sensing (vegetation structure, productivity) possibly in combination with ecosystem models, and crowd-sourced information on livestock systems
Improved maps of the share of animals in feedlots versus grazing/free-ranging animals	Collection and homogenization of such data at the subnational scale needed. Disaggregation/downscaling could be substantially improved by implementing information on grazing systems (type of vegetation grazed, forage quality)
Improved estimates of fertilizer (mineral and manure) used in grazing systems and manure transferred to cropland	Disaggregation/downscaling could be substantially improved by implementing information on grazing systems (type of vegetation grazed, feed from natural vegetation versus farmland, forage quality)
Water management on grazing land	Information on grazing extent in combination with information on irrigation equipment, climate data and satellite remote sensing
Labor or capital inputs to grazing systems	Collection and homogenization of data on labor (e.g. # persons engaged with grazing/livestock husbandry) and capital-related inputs (e.g. fences, fertilizer, vaccination) of grazing systems needed. Disaggregation/downscaling would be possible using indicators on livestock distribution and grazing practices
Forestry systems	
Forest management types (e.g. agroforestry versus plantations versus managed natural forest versus unmanaged forests)	Collection and homogenization of subnational data on the extent of plantations needed. Disaggregation/downscaling could be improved by remote sensing information (forest types, forest structure) and ancillary data (e.g. wilderness datasets)
Improved forest type maps	New remote sensing data (e.g. high-resolution, multi/hyperspectral sensors such as the upcoming Sentinel-2 sensor) or joint use of data (Lidar, radar, and optical data) may allow for moving beyond broad forest types (currently broadleaved, mixed and needle-leaved forests)
Forest harvesting rates	Disaggregation of forest harvesting statistics using forest area maps, forest management types, and market accessibility proxies (e.g. travel distance to markets, infrastructure network, terrain ruggedness)
Improve standing volume/biomass maps	Remote sensing, for example via combining information on forest types and forest structure [64•,65,66•]
Increment map and share of harvest in increment	Dynamic global vegetation models in combination with improved forest, extent, forest type, and forest harvesting maps
Age-class distributions and management frequency maps (e.g. rare versus frequent)	Collection and homogenization of national/subnational data on forest age and management cycles needed. Information could come partly from remote sensing (e.g. logging histories), survey data, or crowd-sourcing
Forestry inputs (e.g. fertilizer, labor, mechanization, drainage)	Collection and homogenization of national/subnational data on different inputs is needed. Such data could be disaggregated using maps of forestry extent and/or forest management types (see above)

to harbor major potentials for further intensifying land-based production. Second, existing datasets are often inconsistent in time (e.g. due to changes in survey methods or data processing), space (e.g. political boundary changes), or map legends, requiring substantial homogenization efforts. Third, uncertainty of existing land use intensity metrics is often high (e.g. due to positional inaccuracy, unreliable input data, or processing algorithms limitations), as highlighted by the large discrepancies of alternative global cropland extent maps [50•] or fertilizer application maps [8,51], and remain largely unquantified, because formal validation is often lacking. Where alternative maps exist, uncertainties can be reduced by combing several maps into a 'hybrid' map [52,53]. Errors may also vary substantially in space and there is a risk of error propagation in more complex datasets (e.g. land cover maps are needed to derive crop distributions, which are needed to disaggregate fertilizer statistics). Fourth, interpolation or disaggregation often relies on covariates (e.g. location factors) which may result in endogeneity problems in subsequent analyses. For example, the FAO's Gridded Livestock of the World [46] uses remote sensed vegetation measures to distribute livestock, and thus cannot be used to analyze the effects of livestock density on vegetation. This endogeneity is sometimes difficult to trace, emphasizing the need to clearly document how datasets were constructed. Fifth, global datasets are typically coarse, resulting in substantial bias in area estimates [54] or when downscaling data [55]. Finally, substantial conceptual challenges remain in order to frame land use intensity globally (see Erb *et al.*, this issue).

Opportunities for an improved mapping of land use intensity

Progress in data access and algorithm development provide opportunities for developing new and improved global land use intensity metrics. Advances in remote sensing are rapid, with a growing number of sensors and increasing access to image archives (e.g. the USGS Landsat archive), as well as new algorithms able to handle complex data structures (e.g. machine learning, geostatistical, or data mining tools). We see three main avenues for an improved mapping of land use intensity: First, longer and more consistent image time series which capture phenology may help to map cropping cycles and to reconstruct land use histories. Second, multi-scale applications (e.g. joint use Landsat and MODIS or Sentinel 1/2/3 images) seem promising regarding overcoming resolution-dependent limitations. Finally, merging data from different sensor systems (e.g. optical, radar, or LIDAR) may provide new insights into land use intensity.

Despite these opportunities, however, the integration of remote sensing and ground-based data will remain crucial. Although statistically rigorous, ground-based surveys are increasingly implemented, for example sampling-based national forest inventories [34] or the LUCAS survey in the European Union [35], there prevails a huge lack of high-quality, ground-based data on land management, especially for those regions where land use changes rapidly. New means for ground-based data collection are emerging though, for example crowd-sourcing could become an important source of geocoded land use data [56] and can help to validate global land use maps [50•]. Finally, new technologies for field or plot-based monitoring are also becoming available and affordable (e.g. wireless communication and solar-powered sensors) [5].

The way forward

A few general recommendations for assessing land use intensity patterns at the global scale emerge from our review. First, considerable progress can be made with already existing data, for example by combining multiple datasets from different sources and across scales. Data access is a key challenge in this context, and efforts to develop platforms and protocols to compile, share, and distribute land use datasets, such as the GEOSHARE initiative (www.geoshareproject.org), are urgently needed. Second, further standardization and harmonization of existing land use datasets as well as data collection protocols are needed, similar to efforts focusing on land cover (e.g. [57]). As ground-based data are essential for most land use intensity metrics, implementing new sampling schemes and standardizing existing national schemes are crucial. Third, there is an urgent need to validate existing global datasets and to document uncertainty, biases, and potential error propagation (i.e. uncertainty of input datasets). It is crucial, for each dataset, to transparently document the covariates used and assumptions made, so that subsequent users can avoid endogeneity problems. Fourth, better integration of observational data (from satellites or the ground) into process-based models is needed to advance the mapping of system metrics. Finally, time series for most land use variables do currently not exist, but would be important to assess past changes in land use intensity and its environmental outcomes.

Future research should focus on improving existing land use intensity metrics and on filling data gaps (Table 2), prioritizing those sectors and indicators where data deficiencies are largest. Regarding cropland use intensity, the already relatively rich set of metrics needs further improvements (e.g. global cropland extent, cropping cycles, fertilizer use), and could be extended (e.g. pesticide use). Uncertainty is generally larger regarding grazing systems, and better information on grazing extent, especially on the distribution of grazing among the different vegetation types, and feed production and consumption is urgently needed. Data gaps appear biggest regarding global forestry intensity, for which major advances could be made from maps of broad types of forestry systems (e.g. plantations, agroforestry, managed and unmanaged natural forests, as well as forest harvesting). In addition to quantitative metrics, a fruitful field for future research would be to advance the global mapping of land use systems [58,59••].

A better characterization of the spatial patterns of global land use intensity is crucial to monitor the various environmental and societal impacts of land use, and to understand the drivers of changing land use intensity. Given the multidimensional nature of land use intensity, a focus on multiple metrics within a systems perspective is needed. The metrics we discussed here provide either a quantitative measure of one aspect of land use intensity (i.e. input and output metrics), or of the aggregated effects of land use intensity (i.e. system metrics). Both types of metrics complement each other, as single metrics are relatively easy to compute and interpret, but do not provide a coherent picture of intensification, whereas system metrics, by aggregating multiple processes, hamper the understanding of the relations between different system components [60]. Ample opportunities exist to advance both types of metrics in parallel to arrive at a second generation of land use intensity metrics. Such metrics would be a major step toward confronting the sustainability challenge in global land use, but developing, harmonizing, maintaining, and sharing these datasets related will require substantially investments from scientists and funding organizations alike.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at http://dx.doi.org/10.1016/j.cosust.2013.06.002.

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- •• of outstanding interest

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