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Key Points:
- We quantify massive uncertainties in global grazing intensity maps
- Grazing area, NPP, and livestock distribution contribute most to total uncertainty
- Improving data quality is key to understanding the role of livestock in GHG and nitrogen balances

Supporting Information:
- Supporting Information S1

Correspondence to:
T. Fetzel,
tamara@fetzel.eu

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Quantification of uncertainties in global grazing systems assessment

T. Fetzel[1], P. Havlik[2], M. Herrero[3], J. O. Kaplan[4], T. Kastner[1,5], C. Kroisleitner[6], S. Rolinski[7], T. Searchinger[8], P. M. Van Bodegom[9], S. Wirsenius[10], and K.-H. Erb[1]

[1]Institute of Social Ecology Vienna, Alpen-Adria Universitaet Klagenfurt, Vienna, Austria, [2]International Institute for Applied Systems Analysis, Ecosystem Services and Management, Laxenburg, Austria, [3]Commonwealth Scientific and Industrial Research Organisation, St Lucia, Queensland, Australia, [4]ARVE Research Group, Institute of Earth Surface Dynamics, University of Lausanne, Lausanne, Switzerland, [5]Senckenberg Biodiversity and Climate Research Centre (BiK-F), Frankfurt am Main, Germany, [6]Department of Geography and Regional Science, University of Graz, Graz, Austria, [7]Potsdam Institute for Climate Impact Research, Potsdam, Germany, [8]Princeton Environmental Institute and the Woodrow Wilson School, Princeton University, Princeton, New Jersey, USA, [9]Institute of Environmental Sciences, Leiden University, Leiden, The Netherlands, [10]Department of Energy and Environment, Chalmers University of Technology, Göteborg, Sweden

Abstract Livestock systems play a key role in global sustainability challenges like food security and climate change, yet many unknowns and large uncertainties prevail. We present a systematic, spatially explicit assessment of uncertainties related to grazing intensity (GI), a key metric for assessing ecological impacts of grazing, by combining existing data sets on (a) grazing feed intake, (b) the spatial distribution of livestock, (c) the extent of grazing land, and (d) its net primary productivity (NPP). An analysis of the resulting 96 maps implies that on average 15% of the grazing land NPP is consumed by livestock. GI is low in most of the world's grazing lands, but hotspots of very high GI prevail in 1% of the total grazing area. The agreement between GI maps is good on one fifth of the world's grazing area, while on the remainder, it is low to very low. Largest uncertainties are found in global drylands and where grazing land bears trees (e.g., the Amazon basin or the Taiga belt). In some regions like India or Western Europe, massive uncertainties even result in GI $>$ 100% estimates. Our sensitivity analysis indicates that the input data for NPP, animal distribution, and grazing area contribute about equally to the total variability in GI maps, while grazing feed intake is a less critical variable. We argue that a general improvement in quality of the available global level data sets is a precondition for improving the understanding of the role of livestock systems in the context of global environmental change or food security.

Plain Language Summary Livestock systems play a key role in global sustainability challenges like food security and climate change, yet many unknowns and large uncertainties prevail. We present a systematic assessment of uncertainties related to the intensity of grazing, a key metric for assessing ecological impacts of grazing. We combine existing data sets on (a) grazing feed intake, (b) the spatial distribution of livestock, (c) the extent of grazing land, and (d) the biomass available for grazing. Our results show that most grasslands are used with low intensity, but hotspots of high intensity prevail on 1% of the global grazing area, mainly located in drylands and where grazing land bears trees. The agreement between all maps is good on one fifth of the global grazing area, while on the remainder, it is low to very low. Our sensitivity analysis indicates that the input data for available biomass, animal distribution, and grazing area contribute about equally to the total variability of our maps, while grazing feed intake is a less critical variable. We argue that a general improvement in quality of the available data sets is a precondition for improving the understanding of livestock systems in the context of global environmental change or food security.

1. Introduction

Many sustainability challenges relate to global livestock production systems. Livestock provides 17% of the global energy provision to humans and builds the basis of livelihood for many in developing countries [*Herrero et al.*, 2009]. Moreover, grazing systems, i.e., ecosystems subject to grazing like grasslands and shrublands where ruminant livestock species feed predominantly from grazing land borne biomass, cover about 40% of the global terrestrial ice-free land surface [*Reid et al.*, 2005; *Erb et al.*, 2007] and are responsible for one third of the total ecological energy flow appropriated by humans [*Haberl et al.*, 2007]. Intensive grazing and livestock production is often associated with ecological detriments, from greenhouse gas emissions (livestock contributes for 12% of the total anthropogenic GHG emissions [*Gerber et al.*, 2013]) to overgrazing, degradation, and environmental pollution [*Steinfeld et al.*, 2006; *Herrero et al.*, 2015].

Despite the importance of the ruminant livestock sector for food security and global change, the scientific community agrees that uncertainties and data gaps prevail [*Ramankutty et al.*, 2008; *Kümmerle et al.*, 2013; *Petz et al.*, 2014; *Erb et al.*, 2016], yet their magnitude is not well known. These knowledge gaps hamper the analysis and understanding of the role of grazing systems in the Earth system as well as assessments of their contribution to human well-being. In the light of future sustainability challenges like population growth, dietary changes, climate change, and the objective of substituting fossil fuels with biomass, it is essential to improve our understanding and knowledge on the magnitude of uncertainties.

A range of indicators exists that allows analysts to describe the environmental impact of grazing. These include percent utilization of available biomass for grazing, forage standing biomass at the end of the grazing period, sward height, litter amount, availability of old standing biomass, stocking rate/density, or the heterogeneity of grazing [*Holechek et al.*, 1998; *Allen et al.*, 2011]. Unfortunately, data on most of these indicators are rare at local scale and even more globally. In addition, these indicators can only serve as a proxy for the land use impact of grazing, because livestock feed often contains other sources of feed such as crop residues, byproducts, or forage crops [*Schader et al.*, 2015]. Assessing the impacts of grazing at large scales is thus generally limited to simpler statistics, such as grazing intensity (GI), defined as the amount of grazing per unit of primary productivity (i.e., percent utilization per available net primary production (NPP; [*Bouwman et al.*, 2005; *Haberl et al.*, 2007; *Petz et al.*, 2014]). To account for the impact of natural and anthropogenic disturbances on the availability of NPP, we apply estimates of actual (currently prevailing) NPP. Focusing on NPP as a reference measure, in contrast to livestock density or grazing harvest per unit area, has the advantage that it introduces an unambiguous baseline that is purely dependent on natural conditions. Thus, using NPP for calculating GI allows researchers to account for differences in climate and soils, which vary widely in natural grasslands, and so to provide a meaningful measure for grazing pressures on ecosystems [*Bouwman et al.*, 2005; *Haberl et al.*, 2007; *Petz et al.*, 2014; *Erb et al.*, 2016].

Calculating GI requires spatially explicit information for supply of biomass and demand for forage. Supply is a function of the extent of grazing land and its productivity. At the demand side, estimates on the biomass harvested directly by ruminants or by mowing are required. This can be calculated, for instance, as the product of livestock numbers and forage demand per animal in a given area.

Robust data on a key indicator such as GI are a requirement to reliably assess the impacts of grazing on ecosystems, analyze potentials for food production or greenhouse gas mitigation, and are thus essential to formulating effective policies. Yet due to large uncertainties, most available data related to grazing are deemed inappropriate for informing policies or investment decisions that aim at improving the efficiency of the livestock sector [*World Bank*, 2014; *Petz et al.*, 2014]. For example, estimates of global land area used for grazing range from 27 to 47 Mio km^2; a similar range of estimates can be found for other metrics, such as biomass grazed by livestock and NPP available for grazing. Specific maps are usually prepared by different institutions and often based on different classification methods and input data [*Fritz and See*, 2008; *Verburg et al.*, 2011], which hampers comparability. The choice of database is thus decisive for study results [*McCallum et al.*, 2006; *Fritz and See*, 2008], and the lack of information on the underlying uncertainties and/or robustness of data is aggravating this difficulty [*Verburg et al.*, 2011; *Hunter*, 2005]. This calls for a better understanding of how uncertainties related to input data propagate in the modeling process and how this influences global GI estimates.

Here we present a systematic and comprehensive uncertainty and sensitivity analysis for calculating and mapping GI globally. By combining a range of data on (a) global grazing area, (b) NPP, (c) grazing feed intake of ruminant livestock, and (d) data on livestock distribution, we derive 96 maps of GI. We identify geographic hotspots and potential sources of uncertainties for different input data products and discuss possible ways for improvement. Our results aim at providing background information for prioritization efforts for future research activities that allow to narrow the uncertainty ranges related to the amount and pattern of global GI, and we discuss how these uncertainties impact the assessment of global GHG balances.

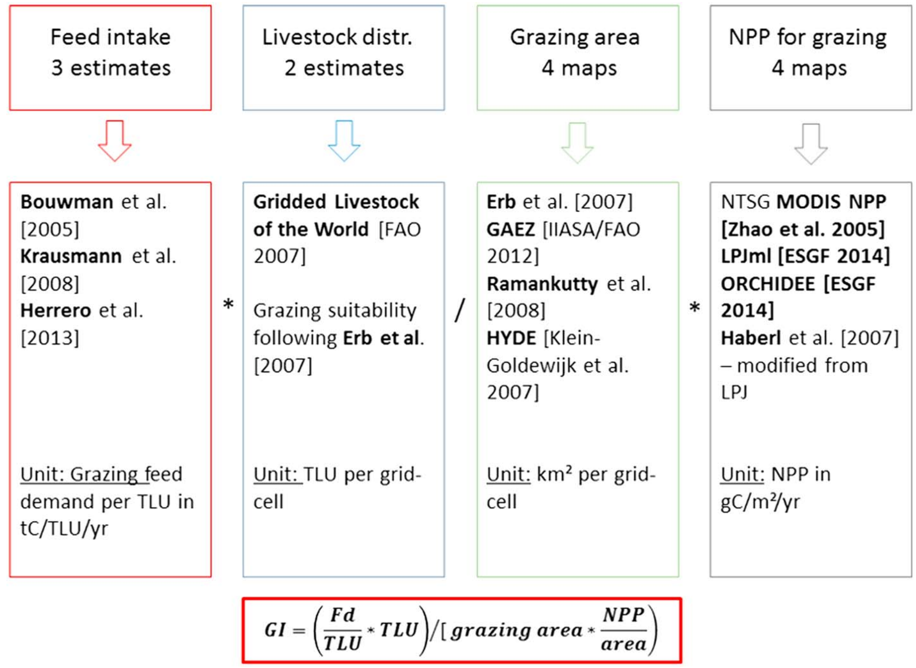

Figure 1. Schematic representation of the calculation procedure for assessing grazing intensity (GI). Fd = grazing feed demand, TLU = tropical livestock units per grid cell, NPP = aboveground NPP.

2. Methods

2.1. Grazing Intensity Model

We here define grazing intensity (GI) as the ratio of grazed biomass per unit of aboveground NPP [*Bouwman et al.*, 2005; *Haberl et al.*, 2007; *Petz et al.*, 2014; equation (1)]. Because grazed biomass and NPP can be measured in the same biophysical units, e.g., gC m^{-2} yr^{-1}, GI represents a ratio, expressed in percent [%]. Four individual input data sets are required to calculate GI: (i) feed intake, calculated as the amount of biomass consumed by livestock in a region, usually available at the country level; (ii) the spatial pattern of biomass grazing/livestock distribution; (iii) the extent and pattern of grazing land; and (iv) the NPP available for grazing in a grid cell:

$$\mathrm{GI} = \left(\frac{\mathrm{Fi}}{\mathrm{TLU}}{}^{*}\,\mathrm{TLU}\right) \Big/ \left(\text{grazing area}^{*}\,\frac{\mathrm{aNPP}}{\mathrm{area}}\right) \tag{1}$$

where Fi = biomass feed intake, TLU = Tropical livestock units per grid cell (one TLU is equivalent to 250 kg live weight), area = grazing area per grid cell, and aNPP = aboveground NPP available for grazing in a grid cell.

Figure 1 shows a flowchart of the GI map calculations and the various data sources used. As a first step, national data on grazing demand following three different literature sources were converted into grazing demand per TLU [*Bouwman et al.*, 2005; *Krausmann et al.*, 2008; *Herrero et al.*, 2013]. Grazing demand relates to the following livestock species: cattle, buffalo, sheep, and goat which make up for approximately 90% of the total estimated feed demand of all domestic livestock as reported by FAO statistics including horses, camels, asses, mules, etc. We established a map of grazing feed intake based on two different data sets for the spatial distribution of grazing demand [*FAO*, 2007; *Erb et al.*, 2007]. The resulting spatially explicit grazing feed intake is then related to estimates of aNPP of grazing land, calculated by combining four sources for grazing area [*Erb et al.*, 2007; *IIASA and FAO*, 2012; *Ramankutty et al.*, 2008; *Klein Goldewijk et al.*, 2011] and four NPP estimates [*ESGF*, 2014; *Sitch et al.*, 2003; *Gerten et al.*, 2004; *Zhao et al.*, 2005]. The combination of all available data sets resulted in the calculation of 96 spatially explicit GI maps.

2.2. Input Data

2.2.1. Feed Intake

We use three estimates for the global feed demand of ruminant livestock from *Krausmann et al.* [2013], *Bouwman et al.* [2005], and *Herrero et al.* [2013], respectively. These data sets estimate the daily animal feed demand at the national and regional levels approximately for the year 2000; the latter two further distinguish livestock production systems. All three approaches follow the so called "grazing gap method" (see, e.g., *Krausmann et al.* [2008]), which calculates total feed intake (for instance, as a function of milk and meat output or of milk yield or slaughter weight per animal) and subtracts the amount of market feed, fodder crops, and crop residues used as feedstuff. Statistics, such as the FAO [*FAOSTAT*, 2015], report on the amount of market feed (e.g., on cropland products or residues from food processing), as well as the amount of fodder crops produced at the country level. No statistical data are available for cropland residues (e.g., straw) used as feedstuff, but national and regional level estimates exist [e.g., *Wirsenius*, 2000; *Herrero et al.*, 2013]. The difference between total feed intake and all known feedstuff is assumed to originate from grazing lands.

The approach by *Krausmann et al.* [2013] is based on linear correlations between intake per head and milk yield or carcass weight for cattle and buffaloes and region-specific factors for sheep and goats and estimates of grazed biomass at the spatial resolution of countries. This data set does not distinguish individual livestock systems. *Bouwman et al.* [2005] assess feed intake for two aggregated groups of ruminants (cattle and buffaloes; sheep and goat) and provide data on animal feed demand covered through roughage and feed crops based on output of meat and milk. Feed-demand for buffaloes is included in the estimate for cattle. The data by *Bouwman et al.* [2005] distinguish pastoral and mixed livestock systems based on the Livestock Production Systems data product from *Seré and Steinfeld* [1996] at the level of world regions (17 regions, which we aggregate to 11; see supporting information). *Herrero et al.* [2013] estimate biomass consumption of ruminants (sheep and goat; cattle and buffaloes) based on information on feed composition (grains, occasional, stover, and grass) obtained from comprehensive literature research and calculated by the RUMINANT model. The authors use information on the availability of grass based on EPIC model results for humid and temperate regions and rain-use efficiency concepts in drylands, data on the availability of grains for livestock feeding from FAO, and the use of crop residues and stover (estimated using harvest indices and literature-derived coefficients). The data are available for eight livestock production systems [*Robinson et al.*, 2011] and at a spatial resolution of 28 world regions.

All data on grazing feed demand have been converted to feed demand per TLU by dividing the absolute feed demand by the total number of TLU per world region. Using livestock units essentially enables the comparison of different types of livestock (e.g., sheep, cattle, goats, and buffaloes) and allowed us to easily downscale feed intake from the national level to the grid, using gridded livestock information (see below).

2.2.2. Animal Distribution

The spatially explicit allocation of national or regional grazing demand data was performed using two different approaches. Both reproduce official FAO livestock numbers for the year 2000 at the national level.

Based on information on TLU numbers per livestock species and the Gridded Livestock of the World maps [*FAO*, 2007] for the distribution of cattle, buffaloes, sheep, and goats, we calculated a map of TLU per grid cell. The gridded livestock map applies a wide range of auxiliary variables in a multiple regression analysis to allocate animal numbers to a certain grid cell, which introduces uncertainty. One of those auxiliary variables is the Normalized Difference Vegetation Index. Some authors [e.g., *Petz et al.*, 2014] argue that it is not straightforward to combine this data set with data on NPP. We apply the data product regardless of those critiques because Normalized Difference Vegetation Index is only one variable among a large list of indicators used in the underlying modeling process. In addition, an exploratory analysis indicated that the actual correlation between the Gridded Livestock of the World data and NPP layers is very weak. This map is the basis for the calculation of the animal feed intake, which is calculated by multiplying the number of TLUs per grid cell with the estimated feed intake per TLU.

The second approach is based on the method outlined in *Haberl et al.* [2007], allocating national level grazing feed demand estimates to individual grid cells based on an aboveground NPP and a grazing land quality map [*Erb et al.*, 2007]. This approach follows the notion by *Oesterheld et al.* [1992] that highly suitable land is more intensively grazed than less suitable land [*Haberl et al.*, 2007; *Oesterheld et al.*, 1992]. The approach assumes that all grazing land is subject to grazing, but not proportionally to its actual production but rather with decreasing intensity from highly suitable to least suitable grazing land classes. A suitability map for grazing land is constructed by using a combination of data on aNPP and land cover and management information from the Global Land Cover 2000 map (GLC2000 [*Bartholomé and Belward*, 2005]). Areas identified as being managed by the GLC2000 including cultivated and managed areas, mosaics of cropland/shrub and or grass, and mosaics of cropland/tree cover and other natural vegetation or natural grasslands or natural grasslands with a productivity above 200 gC m^{-2} yr^{-1} are labeled highly suitable. Areas that bear tree cover or grass-tree mosaics above 200 gC m^{-2} yr^{-1} are defined being of medium suitability, areas with the same land cover but a productivity below 200 gC m^{-2} yr^{-1} of low suitability and areas where shrub cover or sparse herbaceous cover is the dominant land cover according to the GLC and where productivity is below 200 gC m^{-2} yr^{-1} as very low suitability [*Erb et al.*, 2007]. To distribute animal numbers, we first extracted the NPP available for grazing for each of the suitability classes and, second, distributed the estimated feed intake to the classes by applying weights (e.g., highest suitability class first, followed by medium, low, and very low suitability—weights are 10, 6, 3, and 1) and utilization limits for the individual grazing suitability classes (75%, 70%, 70%, and 55%). The suitability limits are taken from *Erb et al.* [2007], who based their assumptions on a profound literature research. Naturally, this approach results in a higher correlation of available aNPP for grazing and animal distribution/grazing intensity because aNPP is used to assign feed demand to the grid cell. Yet, in contrast to the other approach, the resulting GI maps show that a much more homogeneous picture and hotspots of very high GI are much less dominant.

2.2.3. Grazing Area

We use four maps on the extent of grazing land in the year 2000: (a) *Erb et al.* [2007], (b) HYDE—*Klein Goldewijk et al.* [2011], (c) *Ramankutty et al.* [2008], and (d) GAEZ from *IIASA and FAO* [2012]. All maps are available at a spatial resolution of 5 arc minutes (approximately 10 × 10 km at the equator) but differ strongly due to differences in the underlying methodology [*Erb et al.*, 2016]. The maps by *Erb et al.* [2007] and GAEZ are based on a similar methodology, both employing a “subtractive approach”: In each grid cell, all known land uses (cropland, forestry, and infrastructure as well as untouched, unused land) are subtracted from the total area, resulting in a remainder area which is defined as being predominantly used for grazing. Naturally, this includes a wide range of ecosystems (e.g., grasslands, steppe, savannas, shrubland, and forest) and hence constitutes an inclusive estimate. A noteworthy difference relates to the exclusion of areas void of land use. The map by *Erb et al.* [2007] excludes areas with an aboveground productivity below 20 g dm/m^2/yr (based on a dynamic vegetation model, LPJ-DGVM [*Gerten et al.*, 2004; *Sitch et al.*, 2003]) and wilderness areas using information from *Sanderson et al.* [2002], while the GAEZ map only excludes water bodies, barren lands as well as areas where productivity is below 10 g dm/m^2/yr. In contrast, the maps from HYDE and *Ramankutty et al.* [2008], refer to permanent pastures only and represent thus exclusive estimates. Both maps are based on a combination of national level statistics and remote-sensing derived proxies on the extent of permanent pasture, and both exclude areas beyond 50° north. The map by *Ramankutty et al.* [2008] uses detailed statistical information on 16,000 spatial units and corrects for obvious errors of the FAO data set (e.g., Saudi Arabia; see section 4), while the HYDE data set uses only national level data on permanent pastures from FAO.

2.2.4. Net Primary Production

Four different estimates of actual NPP for the year 2000 were used: (a) the Remote-sensing derived, MODIS-based NPP map by *Zhao and Running* [2010], the model outputs of (b) LPJmL and (c) ORCHIDEE, both Dynamic Global Vegetation Models (DGVMs), and (d) the map from *Haberl et al.* [2007]. MODIS NPP data are based on a large number of satellite-derived indicators like fraction of photosynthetically active radiation and Leaf Area Index, temperature, solar radiation and vapor pressure data, MODIS land cover classification, and a lookup table for biomes [*Zhao et al.*, 2005]. The ORCHIDEE model [*Krinner et al.*, 2005] models carbon, water, and energy fluxes based on 12 plant functional types (PFTs) including agricultural C3 and C4 grasses. The LPJmL model simulates the dynamics of natural and agricultural vegetation for 13 crop functional types including pasture and 12 PFTs [*Bondeau et al.*, 2007]. LPJmL is a more comprehensive version of the LPJ-DGVM [used in the *Haberl et al.*, 2007, study) and includes agricultural land use and management such as irrigation [*Sitch et al.*, 2003; *Gerten et al.*, 2004; *Aus der Beek et al.*, 2010], but the simulation of the natural PFTs is based on the original LPJ-DGVM [*Sitch et al.*, 2003]. The estimate by *Haberl et al.* [2007] is based on an LPJ-DGVM derived map for potential NPP (i.e., the NPP assumed to prevail in the absence of land use [*Haberl et al.*, 2014] and applies assumptions on the reduction of NPP due to land conversion (e.g., a change from forests to grazing land) for NPP increases due to fertilization and irrigation as well as for NPP decreases due to land degradation [*Zika and Erb*, 2009]. For all four NPP maps, we only consider the aboveground fraction of total NPP (aNPP) by assuming an aboveground to total NPP proportion of 60% [*House and Hall*, 2000]. We do not consider spatial changes because applying the available data would introduce further uncertainty and would not impact the uncertainties prevailing between data products. All NPP data were converted

Table 1. Variations in Relevant Input Data: Arithmetic Average of aNPP, Grazing Area, and Feed Intake and Variation in % From the Mean[a]

	NPP Tg C/yr	NPP gC/m^2/yr	Area 10^6 km^2	Feed intake Tg C/yr	Feed intake Mg C/yr/TLU	TLU/km[b]
Central Asia and Russia	902 (−45/+67%)	180	5.0 (−37/+36%)	28 (−28/+31%)	0.9	6.3
Eastern & South Eastern Europe	140 (−40/+70%)	337	0.4 (−24/+31%)	31 (−42/+34%)	1.0	75.7
Eastern Asia	876 (−53/+64%)	196	4.5 (−20/+18%)	136 (−16/+21%)	1.1	28.9
Latin America	2685 (−27/+71%)	418	6.4 (−23/+22%)	346 (−37/+48%)	1.4	39.5
Northern Africa & Western Asia	152 (−58/+59%)	95	1.6 (−34/+53%)	34 (−35/+35%)	0.9	22.5
Northern America	855 (−43/+71%)	215	4.0 (−39/+62%)	131 (−18/+11%)	1.2	28.1
Oceania	672 (−42/+79%)	171	3.9 (−29/+33%)	77 (−18/+15%)	1.6	12.5
South Eastern Asia	349 (−30/+81%)	526	0.7 (−90/+101%)	37 (−20/+38%)	0.7	76.2
Southern Asia	187 (−101/+58%)	127	1.5 (−35/+83%)	236 (−39/+24%)	0.7	214.7
Sub-Saharan Africa	3082 (−38/+62%)	325	9.5 (−25/+25%)	215 (−20/+26%)	1.4	16.3
Western Europe	285 (−17/+82%)	342	0.8 (−48/+41%)	111 (−19/+30%)	1.2	112.6
World	10,185 (−37/+68%)	266	38.3 (−39/+23%)	1382 (−13/+27%)	1.1	32.9

[a]See supporting information for more detailed information.
[b]For TLU per square kilometer, only one estimate is available.

to dry matter biomass applying a carbon content factor of 50% [*Haberl et al.*, 2007; *Gibbs*, 2006; *Mackey*, 2008].

2.3. Sensitivity Analysis

Based on a sensitivity analysis, we examine the importance of each input parameter for the total output variation (variance of GI [*Saltelli*, 2003; *Saltelli et al.*, 2010]). Sensitivity analysis analyzes and quantifies the statistical variance resulting from varying the respective input parameters [*Marino et al.*, 2008; *Thiele et al.*, 2014]. We present the results of the total effect sensitivity indices, which describe the fraction of total variance that can be explained by the variation in the respective parameter and its interaction with other parameters [*Saltelli*, 2003; *Monod et al.*, 2006].

All results are provided for 11 world regions including Central Asia and Russia (CA&RUSSIA), Eastern- and South-Eastern Europe (E&SE EUR), Eastern Asia (EA), Latin America (LAM), Northern Africa and Western Asia (NAWA), Northern America (NA), Oceania (OCE), Southeast Asia (SEA), Southern Asia (SA), Sub-Saharan Africa (SSA), and Western Europe (WEUR).

3. Results

3.1. Variability in NPP, Grazing Area, and Feed Intake

The input data for modeling global GI show large variations, not only locally but also at the aggregated level. Large differences between the individual approaches prevail for grazing area, feed demand, and available NPP (Table 1). Area varies between +23% and −39% from the arithmetic average, feed demand by +27% and −13%, and estimates of available NPP by 68% and −37%. The available NPP per area on average is highest for South-Eastern Asia (526 gC m^{-2} yr^{-1}) and lowest in Northern Africa and Western Asia (95 gC m^{-2} yr^{-1}). Feed intake at the regional level lies clearly below the available NPP in almost all regions with the exception of Southern Asia, which also shows the highest number of TLU per square kilometer (214.7). We do not present numbers on animal distribution here, because both methods reproduce the same FAO figures at the national level and hence do not show any variation.

3.2. GI Estimates

The global median of our 96 GI maps is 15% and ranges from 6% to 30%, with inner quartiles between 11% and 19% (Figure 2b). Yet the spatially explicit distribution (Figure 2a) reveals that GI is below 5% on more than half of global grazing lands (20.5 Mio km^2 of 38 Mio km^2) and between 5% and 10% on another 17% (6.4 Mio km^2). On only 1% of grazing lands, median GI is higher than 70%.

Much of the grid-level variation is maintained at the aggregated regional level (see Figure 2b), but the upper quantile (of regional GI estimates) remains well below 50% in most world regions. Exceptions are South Asia, South-Eastern Asia, and to a much smaller extent Western Europe, where the third quantile exceeds 100%. This corresponds well with the observed interquartile range (IQR; e.g., the difference between the 75th and 25th quartiles) which is largest in Southern Asia (e.g., >400%-points) followed by South-Eastern Asia

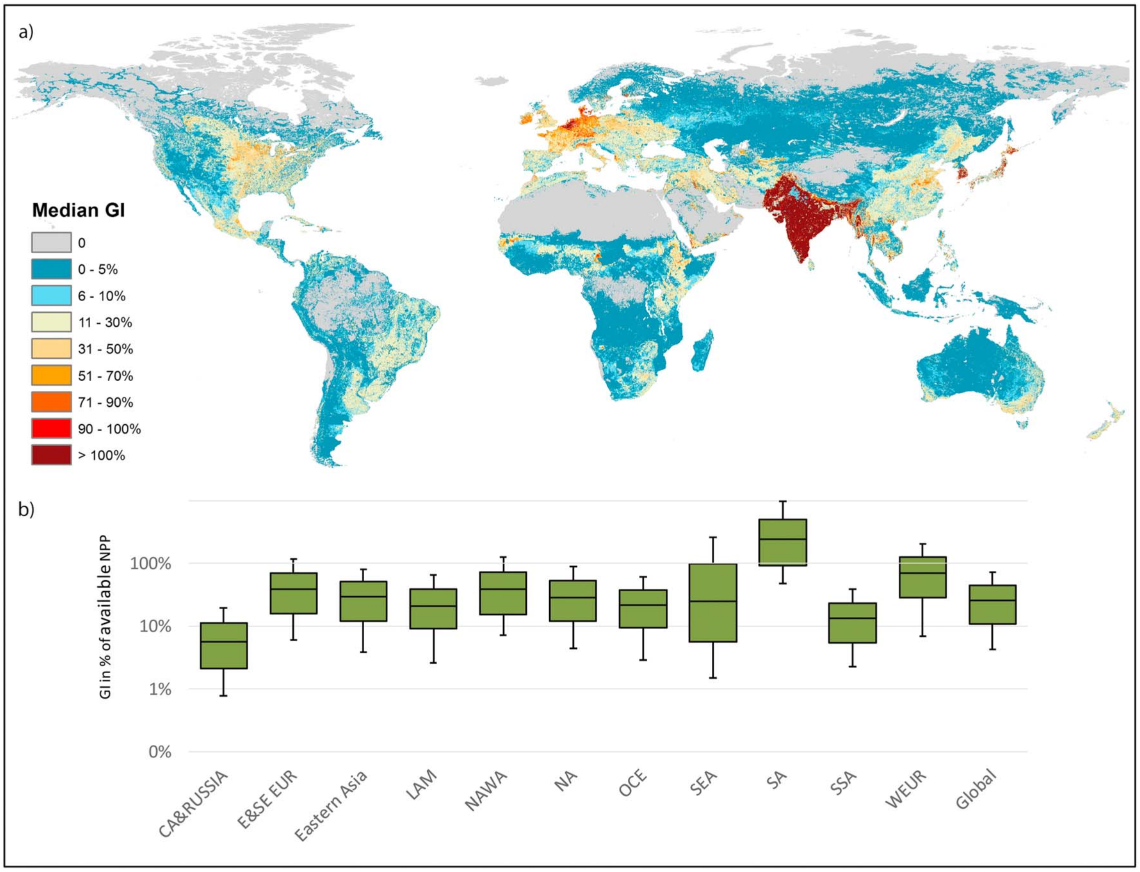

Figure 2. Spatial pattern of grazing intensity (GI): (a) spatial pattern of the median GI and grazing area, and (b) box plots of GI variation at the world region level. Note the logarithmic scale on the *y* axis. The bold line represents the median of observed GI values at the grid-cell level; boxes represent the 25th and 75th quartiles, and whiskers represent the 5th and 95th percentiles. Because GI cannot exceed 100%, values above 100% indicate areas with large uncertainties related to the input parameters. For explanation, see text.

(67%-points), Western Europe (27%-points), and Northern Africa and Western Asia (18%-points). In most other regions, the IQR lies well below 20%-points.

The variability of the 96 GI estimates in relation to the median estimate (Figure 3a), measured as the interquartile range over the median (e.g., IQR/median as a measure of spread of variables around the median, where the IQR is defined as the difference of the upper and lower quartiles), reveals a quite large variation in most regions. Up to 23% of the total grazing area shows a very large variability (e.g., IQR/median $>$ 3) of GI estimates. This includes major parts of the world's arid and semiarid regions like the Sahara, the Sahel zone, the Namib and Kalahari, the Atacama, the Arabian Peninsula, large parts of central Asia or central Australia, and areas where forest is the dominant land cover (e.g., the Amazon and Congo basin or the Taiga and boreal belt). Moderate variability (e.g., IQR/median between 1 and 3) occurs on approximately 55% of the world's grazing lands, mainly in the boreal North of Canada. A relatively high agreement (e.g., IQR/median $<$ 1) occurs on 22% of grazing land, for instance, in regions with high intensive agriculture like the prairie in North America, the Cerrado in Latin America, and the grazing land in central Europe and Asia on natural forestland.

In addition, Figure 3b shows grid cells where GI exceeds 100% in at least one of the 96 GI maps, covering 27% (or 10 Mio km^2) of the global grazing area. This happens when the estimated feed intake from grass exceeds the actually available aNPP in a grid cell. The area where this pattern is dominant (e.g., where at least one half of all GI maps exceed 100%) is much smaller and covers only 1% (or 0.35 Mio km^2) of the global grazing area, mainly in Southern Asia (India and Pakistan) and to a smaller extent in Western Europe. Of particular interest is the hotspot in Western Europe, because the variability between the maps (Figure 3a) is relatively low, yet most maps yield highly unrealistic results (e.g., GI $>$ 100%).

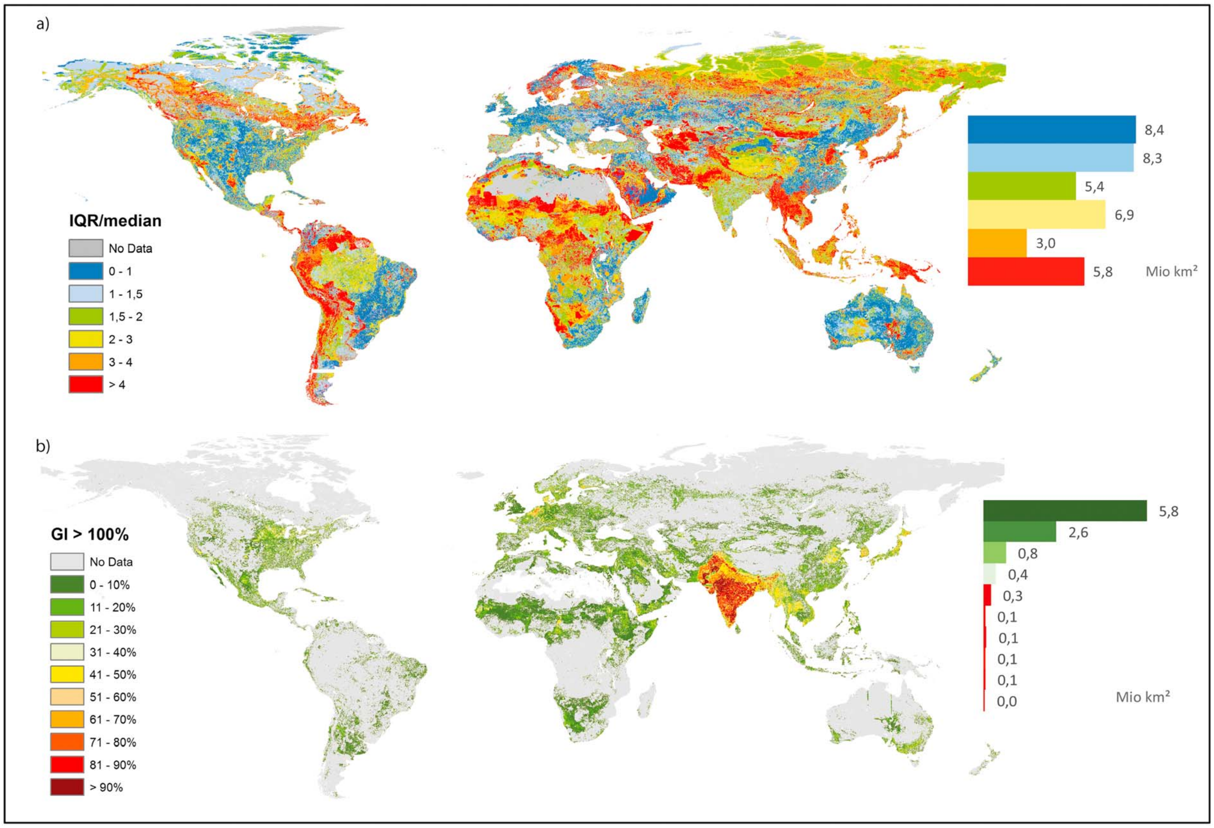

Figure 3. Spatial pattern of grazing intensity (GI) uncertainty. (a) Interquartile range (IQR)/median GI, a nonparametric measure for the dispersion of variables (e.g., GI estimates). (b) Percentage of 96 GI estimates where GI is higher than 100% and affected grazing area. This occurs in grid cells where the estimated NPP is not sufficient to cover the grazing feed demand.

3.3. Sensitivity Analysis

Figure 4 shows the contribution of each of the four input parameters to the total output variance in percent. These results do not reflect uncertainties explicitly related to the modeling process of the input data (e.g.,

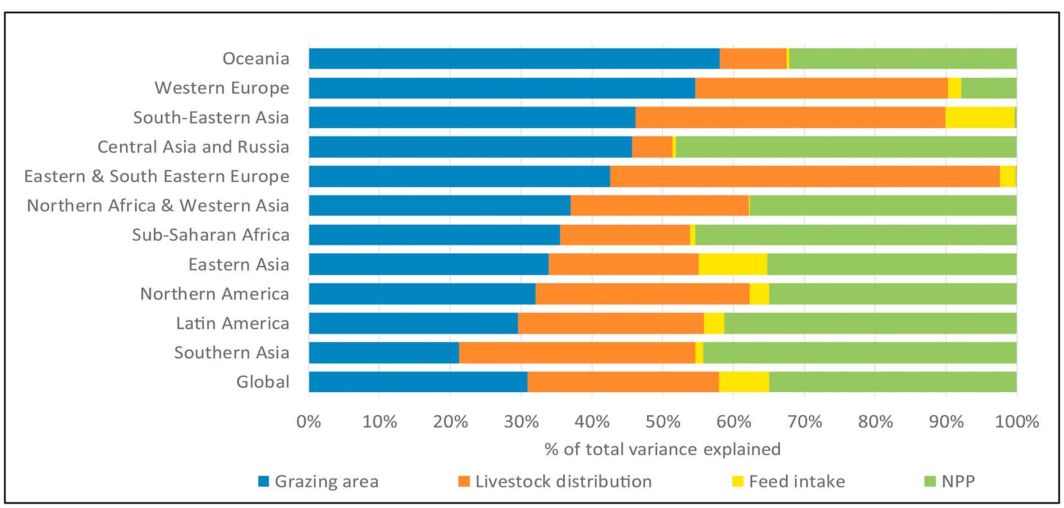

Figure 4. Total effect sensitivity indices for world regions: Coefficients represent the fraction of total variance explained by each input component (grazing area, livestock distribution, feed intake, and NPP, respectively) and its interaction with the other input variables by quantifying the statistical variance resulting from the variation of the respective input parameters using total effect sensitivity indices following *Saltelli* [2003] and *Saltelli et al.* [2010]; see supporting information.

grazing area, aNPP, etc.) but show how the observed differences between those products propagate in the modeling process and how this influences results. On the global-level NPP, area and livestock distribution are about equally important, contributing 35%, 31%, and 27%, respectively, to the total output variation (e.g., variation of all GI maps at the global level). Uncertainty of grazing feed-intake estimates, by contrast, plays a comparably minor role at the global average. Uncertainty related to area is a major contributor in Oceania (58%), Western Europe (55%), and South Eastern Europe (46%). The contribution of livestock distribution is moderate to high in most regions, with the highest contribution observed in Eastern and South-Eastern Europe (55%) followed by Eastern and South-Eastern Asia (44%). NPP plays a considerable role in Central Asia and Russia (48%), Sub-Saharan Africa (45%), and Southern Asia (44%).

4. Discussion

We find the global median GI to be 15%, but variations are large. The regional level picture reveals that on 80% of the global grazing area, median GI is found to be well below 15%. Hotspots of very high GI (>50%), which make up for only 2.5% of the world's grazing lands, are mainly located in Western Europe, central USA, Northern Africa, the Arabian Peninsula, India and Pakistan, and the Sahel and Eastern Asia. This is well in line with the results from other studies, like *Petz et al.* [2014] who find similar hotspots of high GI located in the Sahel, India, Middle East, Northern Africa, and the Arabian Peninsula. However, their estimate on the total global biomass consumption through grazing animals of 4% differs drastically from the 15% for our median GI estimate. Likely reasons for this are that their study is limited in extent (e.g., it does not cover important hotspots in Europe and Northern America) and their correction of grazing feed-demand estimates in case of insufficient biomass supply (e.g., they correct feed demand in grid cells where NPP supply is insufficient). On the other hand, our estimated 15% of biomass extraction is well in line with the results from the global study on human appropriation NPP by *Haberl et al.* [2007] who find that humans extract on average 17% of the available biomass on grasslands.

Our results highlight the massive uncertainties associated with the combination of available data products. A crucial example for such uncertainties are grid cells where the combination of different demand and supply calculations results in a GI > 100%. In these grid cells, the estimated available biomass is not sufficient to cover the estimated grazing biomass feed intake (see Figures 2a and 2b). For the median GI map (median of all 96 maps), this occurs on approximately 1.2% of the total grazing areas worldwide (see Figure 2a). The analysis of all 96 maps shows that GI exceeds 100% in at least one out of the 96 GI maps on almost 27% of the total grassland area. However, it is biophysically impossible that biomass harvest exceeds biomass supply (note that our calculation procedure only takes forage from grazing lands into account, feedstuff from other sources is excluded; see section 2), because grazed biomass origins mainly from herbaceous and thus annual plant components (such as leaves). Hence, a GI > 100% is clearly the result of an accumulation of uncertainties from the various input data sets. An overestimate of harvested biomass or feed demand, or an underestimation of grazing land extent and its productivity, or both, leads to this mismatch.

Beyond those grid cells with GI > 100%, we observe a considerable variation of GI estimates in many parts of the world. Relating the interquartile range to the median GI, a nonparametric measure of spread equal to the coefficient of variation and sensitive to outliers, we observe a large variation or low agreement, particularly in arid and semiarid regions (e.g., the Atacama, the Sahel, Arabian Peninsula, and Near East), which corresponds well with the hotspots of very high GI in some cases (e.g., Northern Africa, Near East, and Western India). In contrast, agreement is relatively good in regions known for rather intensive land use around the world, e.g., the central USA, the Cerrado in Latin America, most parts of Western Europe, Eastern Asia, or Australia. Yet a high agreement (e.g., low IQR/median) does not necessarily imply that GI estimates are reliable. The agreement is for instance relatively high in prevailing hotspots of very high GI (>100%) of Western Europe (e.g., Netherlands) and Northern America. Even in India (where the most dominant hotspot of GI > 100% is located), agreement is moderate, indicating systematic error in these areas occurring in all input data, but particularly in estimates of grazing area, animal distribution, and NPP as indicated by the sensitivity analysis. This is supported by findings of other studies on GI. *Chang et al.* [2016], for instance, also find that estimated biomass supply is not sufficient to cover grazing feed demand in particular regions of India and Pakistan where the bulk of the observed deficits is located (50%), and *Petz et al.* [2014] come to a similar conclusion by locating high GIs in these regions.

One explanation for the high agreement yet implausibility of the result in the western European hotspot (e.g., Netherlands) could for instance be that most Earth System Models do not consider land use [*Quillet et al.*, 2010; *Haberl et al.*, 2007] and therefore underestimate available NPP in these regions. An example for this is increases in productivity through fertilization or the mere impacts of grazing on patterns of productivity (e.g., by promoting compensatory plant growth in the short term [*Hayashi et al.*, 2007; *Noy-Meir*, 1993]), both complex issues depending on multiple factors and facing a lack of data at the global level [*Kümmerle et al.*, 2013]. In contrast, an underestimation of the available NPP due to systematic problems in modeling approaches [*Chang et al.*, 2016] in combination with an underestimation of the fraction of other feeds (e.g., roadside grazing, household wastes and other non-reported feeds [*Bouwman et al.*, 2005]) is the most likely explanation causing the hotspots in GI in India and Pakistan.

The uncertainty we highlighted here on the GI indicator applies similarly to other important variables such as the quantification of greenhouse gas emissions and nitrogen utilization. Better understanding the root cause of these uncertainties like variations in spatial scale, methods, and definitions [*Herrero et al.*, 2016] is essential to improve current estimates, because the agricultural sector makes up for 14.5% of all human-induced emissions [*Gerber et al.*, 2013]. Uncertainty about the grassland extent, for instance, makes it inherently difficult to allocate CO_2 emissions from land use change to ruminant production although many studies, e.g., *Gibbs et al.* [2010], see in pasture expansion a key driver of deforestation. Others, e.g., *Roman-Cuesta et al.* [2016], show that the presence of deforestation dominates total uncertainty in GHG balance estimates (up to 98% of total uncertainty], which render land-use change and grassland area estimates an important factor [*Thornton*, 2010; *Herrero et al.*, 2013; *Fetzel et al.*, 2017].

The lack of sound data about management issues like the GI, timing, and length of grazing is a major source of uncertainty. Such information is essential because it influences patterns of soil carbon storage and biomass growth [*Conant and Paustian*, 2002; *Smith et al.*, 2008; *Soussana et al.*, 2013]. Uncertainty about the current grazing intensity also blurs the projections of potential intensification in the future and hence makes it difficult to estimate future pasture expansion needs, while some studies, e.g., *Popp et al.* [2017], project that grasslands will have to shrink substantially to provide the area for afforestation and biomass for energy production, both necessary for climate change stabilization. Grazing intensity not only influences carbon flows and stocks but also feed composition, a parameter that directly impacts estimates of methane emissions (CH_4) from enteric fermentation. CH_4 emissions are the most important source of greenhouse gas emissions related to ruminant production (e.g., 18% of the total anthropogenic CH_4 emissions) and depend substantially on the feed-composition [*Herrero et al.*, 2013; *Herrero et al.*, 2016]. This latter point relates also to the aNPP and grassland management because it is not only the quantity but also the quality of the forage which will impact ruminant GHG emissions and indirectly also nitrogen use linked to a particular management strategy (e.g., manure management).

Assessing the full impact of these uncertainties on GHG emission balances was beyond the scope of this study, but our results clearly highlight that attempts to estimate crucial indicators like GHG or nitrogen balances are flawed by uncertainties from currently available grazing-related data products. Future research initiatives should focus on the assessment of the impact of these uncertainties on GHG emission data and in particular on the improvement of the currently available data bases. In the following paragraphs, we discuss major drawbacks of currently available data products for modeling GI and their estimated contribution to the total output uncertainty on the basis of our sensitivity analysis.

4.1. Known Caveats Related to Input Data

Known uncertainties in animal numbers or animal distribution are related to census statistics, which are often not uniform in quality across countries [*FAO*, 2001, 2007]. In many developing countries, a lack of resources for statistical surveys results in the underrepresentation of nomadic and transhumant pastoralists (e.g., countries in Africa, Asia, and South America [*FAO*, 2007]), which can result in an underestimation of total animal numbers or influence the spatial distribution of animals because pastoralists and animals move around. Another source of uncertainty is the methodology underlying the Gridded-Livestock of the World map [*FAO*, 2007; *Robinson et al.*, 2011]. Although the map is based on a multiple regression analysis and applies a large number of predictor variables, the resulting uncertainty is high owing partly to the fact that spatial scales and census units used to spatially explicit downscale animal numbers are not constant. For instance, the size of the underlying spatial units varies according to the availability of data. In addition, the exclusion of areas deemed unsuitable for grazing (itself based on a large number of input data) introduces further uncertainty [*FAO*, 2007].

Another shortcoming is apparently related to the spatial scale of feed intake estimates, which are only available at the level of world regions, nations, and/or livestock production systems. All these assessments are based on a crude top-down grazing gap approach, which assesses the amount of grazing as the difference between ruminant feed demand and feed supply from cropland and other sources such as industry [*Bouwman et al.*, 2005; *Haberl et al.*, 2007; *Krausmann et al.*, 2013]. Such aggregated data can result in distortions, because they operate with general multipliers and thus cannot take local level variations [*Chang et al.*, 2016] (or biomass flows from other grid cells due to forage trade or moving animals) into account. Yet our sensitivity analysis suggests that this factor actually plays a rather small role when compared to other factors, also because the spatial variation is low in regional level data.

One of the most important factors driving uncertainty in GI maps is grazing area. In Oceania and Western Europe, it even makes up for more than 50% of the total variation, and in many regions, it remains unclear if grazing takes place at all. This is particularly true for remote areas, where more inclusive approaches like the *Erb et al.* [2007] maps and even more so the *IIASA and FAO* [2012] map assign grazing land, while the two maps by *Klein Goldewijk et al.* [2011] and *Ramankutty et al.* [2008] follow the strict FAO definition of permanent pastures. The difference between these two approaches makes up for as much as 12.8 Mio km^2 or approximately 10% of the terrestrial ice-free surface [*Erb et al.*, 2016] and shows that definitional issues, e.g., whether areas subject to sporadic or nonpermanent grazing should be included or not, play a key role. Other than that, the large disagreement between existing grazing maps can be attributed to variations in classification methodologies [*Fritz and See*, 2008; *Dendoncker et al.*, 2008], the use of different satellite sensors, variations in training and ground reference data as well as errors in georeferencing [*Fritz et al.*, 2011; *McCallum et al.*, 2006] and point to the fact that much room for improvement relates to the current monitoring capabilities of this key land-use type.

Our sensitivity analysis suggests that NPP is a key contributor to total output variability (Table 1) of GI estimates in Central Asia and Russia (48%), Sub-Saharan Africa (45%), and Southern Asia (44%; Figure 4). The wide range of existing approaches to estimate NPP causes large variation and large uncertainties in resulting GI maps. A comparison of modeled NPP data to satellite-derived estimates or ground level measurements reveals large variations. This seems to be particularly true for agricultural land, where a wide range of agricultural practices result in weak correlations between NPP estimates from the ORCHIDEE model and remote sensing derived FAPAR (fraction absorbed of the photosynthetically active radiation [*Maignan et al.*, 2011]). Most hotspots of high GI uncertainty are located in regions where cropland plays an important role (e.g., mixed livestock production systems; see Figure 2a). In addition, modeled NPP estimates depend strongly on assumptions underlying the modeling process, which might introduce systematic errors. One argument is for instance that many models systematically underestimate available NPP in arid areas because they do not consider water resources other than rainfall (e.g., groundwater, rivers, lakes, or irrigation [*Chang et al.*, 2016]; or place and species-specific factors such as rooting depth [*Potter et al.*, 2012]. NPP is clearly one explanation for the found hotspots of very high GI uncertainty in drylands, such as those in Southern Asia, Sub-Saharan Africa or Northern Africa, and Western Asia.

Other limitations relate to the so-called PFT modeling approach, underlying the NPP input data sets from ORCHIDEE, LPJmL, and LPJ [*Haberl et al.*, 2007], where groups of species with presumably similar characteristics (e.g., morphological, physiological, biochemical, reproductive, and demographic [*Arneth et al.*, 2014; *Yang et al.*, 2015; *Woodward and Cramer*, 1996]) are assigned to classes. Small differences between and large variation within groups [*Van Bodegom et al.*, 2012] cause overlap and hamper the definition of PFT groups. In addition, high altitude ecosystems are often poorly modeled because topography is not considered and the approach regularly fails to adequately represent local-scale competition [*Quillet et al.*, 2010]. Another issue relates to prediction of vegetation in tropical areas, which has been found to be highly uncertain because tree-grass competition and fires are often not represented well and could result in an underrepresentation of grasses [*Baudena et al.*, 2015].

A general problem related to NPP estimates not considered in this work due to the limited availability of data is that it is often not straightforward to link the NPP signal to grazing because it represents a mixture of different PFT types (e.g., trees, shrubs, grasses, etc.). Thus, not the entire aNPP is accessible to grazers. In grasslands, most feed intake includes herbaceous species only [*Havlík et al.*, 2015]. In shrub-dominated regions, shrubs are an important source of feed (up to 40–50% of the total feed demand [*Sanon et al.*, 2007]), yet, where trees are dominant (e.g., the Amazon and Congo basin or the Taiga), the inclusion of NPP from trees could result in an overestimation of biomass available for grazing, which could cause a systematic underestimation of GI in these regions. We do not include this due to data quality issues (e.g., the available data are not evenly distributed and often based on coarse assumptions). This does not seriously impact our results because it would only change the estimated relative GI but would not influence the magnitude of uncertainties between the data products.

5. Concluding Remarks

Our results highlight large uncertainties in current attempts to map GI and highlight the need to substantially improve quality of all available data products. This is an essential precondition to reliably analyzing grassland's role in future food security and sustainability challenges like the reduction of GHG emissions. The livestock sector plays an important role for food security today [*Herrero et al.*, 2013] and will continue to do so in the future [*Bouwman et al.*, 2005]. Hence, improving databases and the functional understanding of grazing, its patterns, drivers, and constraints, is key. One way forward could be to combine currently existing data products to create higher quality maps and promote the establishment of comprehensive ground measurements for validation [*Kümmerle et al.*, 2013; *Erb et al.*, 2016]. A promising approach to establish such a database is for instance the GeoWIKI project where citizen scientists help to improve land-cover data [*Fritz et al.*, 2012]. An important first step is, however, to establish a standardized validation and sampling scheme across disciplines [*Kümmerle et al.*, 2013] to ensure that available data products are reliable and of equal quality.

This is the critical prerequisite for quantifying current and future impacts as well as trade-offs but also for identifying synergies related to livestock systems and their role in the Earth system. We urgently need reliable spatial data on grassland-related topics to inform regional policies and management strategies [*Petz et al.*, 2014; *Campbell and Stafford Smith*, 2000]. GI provides essential information about the impacts of grazing on a central ecosystem variable (NPP), yet it cannot comprehensively describe impacts of grazing on the respective ecosystem and the large variations in the available data hamper the interpretability of results. Other more detailed indicators (e.g., about grazing cycles, litter, fraction of grazed and ungrazed plots, information on old/dead standing biomass, etc. [*Holechek et al.*, 1998]) could help to provide a more holistic picture and to reliably assess sustainability thresholds. Yet, in the light of our results, the improvement of the quality of the currently available data on NPP, grassland area, and livestock distribution is most urgent.

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