Land use intensification increasingly drives the spatiotemporal patterns of the global human appropriation of net primary production in the last century

Thomas Kastner1,2 | Sarah Matej2 | Matthew Forrest1 | Simone Gingrich2 | Helmut Haberl2 | Thomas Hickler1,3 | Fridolin Krausmann2 | Gitta Lasslop1 | Maria Niedertscheider2,4 | Christoph Plutzar2,5 | Florian Schwarzmüller1 | Jörg Steinkamp1,6 | Karl-Heinz Erb2

Abstract

Land use has greatly transformed Earth’s surface. While spatial reconstructions of how the extent of land cover and land-use types have changed during the last century are available, much less information exists about changes in land-use intensity. In particular, global reconstructions that consistently cover land-use intensity across land-use types and ecosystems are missing. We, therefore, lack understanding of how changes in land-use intensity interfere with the natural processes in land systems. To address this research gap, we map land-cover and land-use intensity changes between 1910 and 2010 for 9 points in time. We rely on the indicator framework of human appropriation of net primary production (HANPP) to quantify and map land-use-induced alterations of the carbon flows in ecosystems. We find that, while at the global aggregate level HANPP growth slowed down during the century, the spatial dynamics of changes in HANPP were increasing, with the highest change rates observed in the most recent past. Across all biomes, the importance of changes in land-use areas has declined, with the exception of the tropical biomes. In contrast, increases in land-use intensity became the most important driver of HANPP across all biomes and settings. We conducted uncertainty analyses by modulating input data and assumptions, which indicate that the spatial patterns of land use and potential net primary production are the most critical factors, while spatial allocation rules and uncertainties in overall harvest values play a smaller role. Highlighting the increasing role of land-use intensity compared to changes in the areal extent of land uses, our study supports calls for better integration of the intensity dimension into global analyses and models. On top of that, we provide important empirical input for further analyses of the sustainability of the global land system.
1 | INTRODUCTION

During the 20th century, industrialization and globalization processes have greatly increased humanity’s physical imprint on the planet (Arnheth et al., 2019; Krausmann et al., 2013; Kummel et al., 2010; Steffen et al., 2015). With the industrial intensification of land use, yields could be raised by crop breeding and increasing external inputs to agricultural production, such as fertilizer, pesticides, and mechanical power, a process often described as the green revolution (Pellegrini & Fernández, 2018). These trends have driven land system trajectories in many locations in the past decades, and they have also shaped the pressures land use exerts on ecosystems and ecosystem processes (Erb et al., 2018; IPCC, 2019), including biodiversity loss (IPBES, 2019; Newbold et al., 2015; Pereira et al., 2012).

Global analyses of the effects of land use across spatial units require spatial information on the evolution of the extent of land use, but also of land-use intensity. At the global level, the time series of maps of the areal extent of different land-use types are available (Ellis et al., 2021; Hertt et al., 2020; Klein Goldewijk et al., 2017). In contrast, maps on land-use intensity are available only for selected land uses. Three dimensions of land-use intensity have been discerned recently (Erb et al., 2013; Kuemmel et al., 2013): (i) input intensity, referring to the amount of (agricultural) inputs per unit of land (e.g., fertilizer application rates), (ii) output intensity, referring to the amount of biomass outputs from the land-use activities (e.g., crop or forestry yields), and (iii) system-level intensity, i.e., the extent to which land-use alters properties of land systems such as water availability or ecosystem stocks and flows. At the global level, spatial data on the evolution of (i) and (ii) are available; however, they are largely limited to croplands, respectively, specific crops. Consistent maps of land-use intensity dynamics across land-use types are lacking.

We contribute to filling this research gap by producing consistent global maps of the spatial evolution of land use and land-use intensity during the last century (1910 to 2010). We employ the framework of the human appropriation of net primary production (HANPP), which measures the scope of human intervention into ecological carbon flows by quantifying the difference between the potential NPP and the NPP prevailing in an ecosystem after harvest (Haberl et al., 2014). HANPP provides a systemic perspective on land use that allows for analyses across all land uses, such as growing different types of crops, livestock grazing, and forestry, in a given spatial unit. HANPP has previously been mapped at the global level for the year 2000 (Haberl et al., 2007), with information on its temporal evolution available at the aggregate level of world regions and for selected countries (Chen et al., 2015; deSouza & Malhi, 2018; Kastner, 2009; Krausmann et al., 2013), and the local level (Niedertscheider et al., 2017; Pritchard et al., 2018; Qin et al., 2021).

Advancing established accounting rules and available data, we present a spatially explicit reconstruction of the temporal evolution of HANPP during the last century (1910–2010), including the following components of HANPP: (1) the NPP associated with society’s biomass harvest \( \text{HANPP}_{\text{harv}} \), including NPP lost due to deforestation and (2) the change in NPP induced by land use \( \text{HANPP}_{\text{luc}} \). In addition, we explore the role of changes in the potential NPP \( \text{NPP}_{\text{pot}} \), i.e., the NPP that would prevail in the absence of land use but with contemporary climate, which forms the baseline of measuring human impacts on NPP flows.

Applying the HANPP framework for time-series analyses is well suited to investigate changes in land-use intensity, as it covers two of the three land-use intensity dimensions introduced above, namely output intensity (via \( \text{HANPP}_{\text{harv}} \) per unit land) and a system-level metric, i.e., the effect of land use on overall NPP flows in ecosystems (via HANPP as a percentage of \( \text{NPP}_{\text{pot}} \)). In addition, the HANPP framework is consistently applicable across different land-use types (such as cropping, livestock grazing, and forestry) and its results are expressed in units that can straightforwardly be linked to ecological and socio-economic processes. Next to investigating changes in land-use intensity, the HANPP framework can also quantify the impact of other major drivers of land system change, namely the effects of e.g., expansion or contraction of areas under human use, and the impact of changes in the efficiency of societal biomass appropriation (e.g., via asking how much biomass harvest is generated per unit of overall HANPP). Using \( \text{NPP}_{\text{pot}} \) as the reference level, the framework is well suited to explore how changes in potential vegetation productivity through environmental change have affected the dynamics of the indicator. In addition, spatially explicit maps of the temporal evolution of HANPP allow going beyond analyzing national-level trends and enable assessing how HANPP has changed across any socio-economically or biogeographically defined region.

We address the following research questions: How have spatial patterns of HANPP and its components evolved during the 20th century? How did the patterns change across the world’s major biomes? What were the proximate drivers of these changes, such as the role of land-use expansion, specific elements of land-use intensity, and changes in natural productivity? Finally, how large are the uncertainties of the spatial evolution of HANPP, and which set of input data and assumptions contributes most to these uncertainties?

2 | MATERIALS AND METHODS

Following Haberl et al. (2014), HANPP is defined as the amount of NPP appropriated by societal activities in a given year through harvest \( \text{HANPP}_{\text{harv}} \) or land-use change \( \text{HANPP}_{\text{luc}} \):

\[
\text{HANPP} = \text{HANPP}_{\text{harv}} + \text{HANPP}_{\text{luc}}
\]
HANPP is the aggregate of biomass harvested that enters socioeconomic processes (including biomass grazed by livestock) and biomass compartments that are destroyed during harvest but do not enter socioeconomic processes such as unused crop and forestry residues or biomass destroyed through deforestation. Due to high uncertainties in the deforestation term, we present results for this part separately and refer to this compartment as HANPP\_defo and label the sum of all other HANPP\_harv flows HANPP\_harv*, i.e.,

\[
\text{HANPP}_{\text{harv}} = \text{HANPP}_{\text{harv}}^* + \text{HANPP}_{\text{defo}}
\]

HANPP\_lc denotes the difference between the NPP of the potential natural vegetation (NPP\_pot) and the NPP of the vegetation prevailing in the studied year (NPP\_act). HANPP\_lc can be positive, if land-use practices lower ecosystem productivity, or negative in cases where they increase ecosystem productivity, for instance, through irrigation in drylands, and is calculated as:

\[
\text{HANPP}_{\text{lc}} = \text{NPP}_{\text{pot}} - \text{NPP}_{\text{act}}
\]

We assessed HANPP as the annual flow of carbon and as a percentage of NPP\_pot. We calculated HANPP components at a resolution of five arcminutes for the years 1910, 1930, 1950, 1960, 1970, 1980, 1990, 2000, and 2010. To tackle the uncertainties in the spatial distribution of HANPP, we modulated six central input datasets and assumptions (Table 1). This way, we calculated a total of 216 global maps of the HANPP indicator for each year studied.

The starting point for the calculations was the compilation of consistent land-use reconstructions for each year, discerning six major land-use types. Each grid cell contains information on the fractional cover, i.e., the share of the respective land use in the total land area of the grid cell, of the discerned land uses. For this, we used state-of-the-art reconstructions of historical trends in land use and land cover (Klein Goldewijk et al., 2017; Ramankutty & Foley, 1999; Ramankutty, personal communication, 2018) and processed them in order to achieve full fractional cover for the sum of all land-use layers. This way, summing up across land uses will consistently equal the total land area of each grid cell. We prioritized the different input maps and reduced fractional cover of the land uses with lower priority, in cases where inconsistencies between data sets exist, i.e., summing up the different land uses would exceed the available land area. A detailed account of how the land use data were constructed can be found in Supplementary Method Note S1. Using different input data on the distribution of cropland areas, we arrived at three modulations for the land-use reconstructions used in our assessments (Table 1). The resulting land-use datasets distinguish six land-use categories at a resolution of five arcminutes: cropland, grazing land, forestry land (i.e., forests that we considered to be used for forestry), infrastructure areas, wilderness areas, and non-productive lands.

For each of these land-use categories, we separately calculated and mapped HANPP and its components and arrived at the overall HANPP by summing across each pixel of these maps. NPP\_pot served as a reference level from which the human appropriation of NPP was calculated. We considered three modulations of this input data set (Table 1). Two of them were derived from the global dynamic vegetation model (DGVM) LPJ-GUESS (Smith et al., 2014) and one from the DGVM JSBACH (Lasslop et al., 2020). In all cases, we ran the models without land-use information but with historical climate forcing for the years 1901 to 2015. LPJ-GUESS version 4.0.1 was used in its standard configuration and forced by the CRU-NCEP (Harris et al., 2014; Viovy, 2018) climate data aggregated from 6-hourly to monthly fields. In addition, we performed an LPJ-GUESS simulation with nitrogen limitation disabled to ensure consistency with the previous studies (e.g., Haberl et al., 2007; Krausmann et al., 2013), and comparing these different model runs enabled us to identify the diverging spatial patterns and temporal trends of NPP induced by nitrogen limitation (Friedlingstein et al., 2014; Smith et al., 2014; Wärnund et al., 2014). We used the model output of NPP per year and unit area in terms of grams of carbon per m² and year, which was available at a spatial resolution of 30 arcminutess. We built decadal averages of this output around the years included in our assess- ment, downcaled the resulting maps to five arcminutes to match the resolution of the land-use data, using bilinear interpolation, and removed values below zero. To avoid biases, we only used the two LPJ-GUESS runs in the presentation of the results and included the JSBACH model only in the uncertainty assessment. This is because the NPP values derived by JSBACH are at the very high end of global estimates of NPP, whereas the LPJ-GUESS runs are positioned at the center of the current estimates (Ito, 2011; Yu et al., 2018).

The land-use and NPP\_pot datasets provided the starting point for downscaling data on HANPP\_harv and HANPP\_lc from the national level to the grid. For the first three years in our study (1910, 1930, and 1950), we relied on HANPP\_harv reconstructions from a previous study (Krausmann et al., 2013), adapted to national borders of 1960 (Supplementary Method Note S3). For the years from 1960 onwards, we calculated HANPP\_harv at the national level based on the data from FAOSTAT (FAO, 2020), using 3-year averages around the respective base year. Table 2 gives a brief summary of the main data sources for calculating the HANPP components (HANPP\_harv* and HANPP\_lc) and on the calculation approach according to the land-use type. In the Supplementary Method Note S2, we outline the calculation procedures in detail. On all land-use types, NPP\_pot was calculated by multiplying the per-unit area values of NPP\_pot with the land area of the respective land-use types in each grid cell. The spatially explicit land use data set in time series also allowed for calculating HANPP\_harv associated with deforestation (HANPP\_defo). For this, we checked where cropland, grazing areas, or infrastructure land encroached into forests or other carbon-rich ecosystems. For details on the calculation of this component, refer to the Supplementary Method Note S2.

### 2.1 Uncertainty assessment

Table 1 summarizes the modulations performed in this study. In total, we calculated 216 versions of HANPP for each year investigated. Note that the main results are based on 144 of this 216 version only (see above). We used all 216 versions to perform a comprehensive assessment of spatial uncertainty and to identify which of the
TABLE 1 Overview of the different modulations performed in the study to assess the uncertainty in spatial patterns

| Parameter | Rationale for modulating input parameters | Specific modulations performed |
|-----------|------------------------------------------|-------------------------------|
| Land use  | High uncertainties exist in the historical extent of land use. We explore this using different layers for the extent of croplands, which also affects the estimates for the extent of the other land use types (Supplementary Note S1) | Cropland reconstruction from HYDE 3.2 (Klein Goldewijk et al., 2017) Cropland reconstruction from Ramankutty and Foley (1999; Ramankutty, personal communication 2018) A combination of the two above, calibrated to match the totals for cropland extent in Krausmann et al. (2013) |
| Productivity of the potential natural vegetation NPP_{pot} | NPP_{pot} is the baseline for the HANPP framework. Different global vegetation models provide varying estimates for NPP_{pot}, both in the overall magnitude and in spatial and temporal patterns | Global vegetation model LPJ-GUESS with nitrogen limitation of NPP (Smith et al., 2014) Global vegetation model LPJ-GUESS without nitrogen limitation of NPP (Smith et al., 2014) Global vegetation model JS BACH (Lasslop et al., 2020) (included for the uncertainty assessment only) |
| Amount of biomass harvest on croplands | Estimates of harvest volumes at the national level are subject to uncertainties. To cover these uncertainties, we rely on published estimates on ranges of HANPP_{harv} (Krausmann et al., 2018) | Low estimate Medium estimate High estimate |
| Allocation of biomass harvest on croplands | Different allocation rules were explored, as historical data on spatial distribution of crop harvest are not available | Harvest follows patterns of NPP_{pot}, in line with the previous work (Haberl et al., 2007) Harvest follows patterns of NPP_{pot} and synthetic nitrogen fertilizer inputs (Nishina et al., 2017) |
| Allocation of biomass harvest on grazing lands | Different allocation rules were explored, due to large uncertainties on spatial distribution of grazing pressures (Fetzel et al., 2017) | Grazing pressure is more concentrated in regions of higher productivity Grazing pressure is more evenly spread out across grazing lands |
| Extent of land degradation in drylands | The effect of land degradation on NPP is highly uncertain and we used published estimates (Zika & Erb, 2009) on plausible ranges of this process in drylands | Low estimate High estimate |

In total, we perform 216 calculations per year, i.e., all possible combinations of the outlined modulations.

TABLE 2 Data sources and calculation approach for the HANPP calculations, according to land use type

| Land-use type | Main data sources | Calculation approach |
|---------------|-------------------|----------------------|
| Infrastructure land | Assumptions follow Haberl et al. (2007) | HANPP_{harv} is estimated at 1/6th of NPP_{pot} HANPP_{luc} is estimated at 2/3rd of NPP_{pot} |
| Cropland | FAO, 2020; Klein Goldewijk et al., 2017; Krausmann et al., 2013; Nishina et al., 2017 | National level crop harvest statistics are extrapolated with crop and country-specific factors to estimate HANPP_{harv} and HANPP_{luc}. Spatial allocation is based on NPP_{pot} patterns (removing water limitations on irrigated lands) and on patterns of fertilizer application |
| Non-productive lands | — | Excluded from the assessment |
| Wilderness | Assumptions follow Haberl et al. (2007) | HANPP assumed to be zero |
| Grazing lands | FAO, 2020; Fetzel et al., 2017; Krausmann et al., 2013; Lassaletta et al., 2014; Zika & Erb, 2009 | National level livestock feed demand is calculated based on data on livestock populations and feed requirements. Feed availability from non-grazing-land sources is estimated based on feed use statistics and assumptions on non-market feed sources. The difference between feed demand and feed availability from non-grazing land sources is assumed to be HANPP_{harv} on grazing lands. HANPP_{luc} is assessed based on information on potential vegetation cover of grazing lands and on land degradation in dryland areas. Spatial allocation is based on modelling NPP available for grazing per pixel |
| Forestry land | FAO, 2020; Krausmann et al., 2013; Schulze et al., 2012 | National level wood harvest statistics are extrapolated to estimate HANPP_{harv}. Spatial allocation follows NPP_{pot} patterns and patterns of fertilizer application. Spatial allocation is based on NPP_{pot} patterns. HANPP_{luc} is assumed to be zero. |

For details please refer to Supplementary Method Note S2.
modulated input factors contributed most to the observed variance. We did this by calculating the variance between modulations of a single parameter and comparing it to the overall variance in each pixel. We assumed a linear model between the values of HANPP and the different parameter modulations and used an ANOVA to quantify individual and overall sums of squares (SSq). The ratio between the parameter SSq and the overall SSq gave the variance contribution of the parameter. This variance decomposition was performed for every pixel, which allowed us to investigate the spatial differences in the most critical parameters. In addition, we provide additional maps showing the standard deviation of the components of the HANPP framework in the supplementary material (Figures S3 and S5).

2.2 | Decomposing HANPP to investigate the contribution of major land-system change drivers across biomes

To quantify how different drivers contribute to the land-system change throughout time, we employed the additive implementation of the log mean divisia index (LMDI) decomposition approach (Ang, 2005). A mathematical formalization of this approach and an elaboration of its strengths compared to the other index decomposition approaches can be found in Ang (2005). In index decomposition approaches, the variable of interest (in our case HANPP as a share of NPP\textsubscript{pot}) is split into meaningful terms, constructing a mathematical identity. The method then quantifies the contribution of each of these terms to the change in the variable of interest. Summing up the individual contributions will give the change in the variable of interest. We employed an approach that decomposes changes in HANPP through the following identity, modified from Gingrich et al. (2015):

\[
\text{HANPP}_{\text{b}}\% = \sum_{i=1}^{n} A_{b,li} \times \frac{\text{HANPP}_{\text{harv,li}}}{A_{b,li}} \times \frac{\text{HANPP}_{b,li}}{\text{HANPP}_{\text{harv,li}}} \times \frac{1}{\text{NPP}_{\text{pot,li}}} \quad (4)
\]

We performed a decomposition analysis at the level of seven ecological biomes (b, for definitions, see Supplementary Method Note S4) and for the global total, to assess the changes in HANPP\% (HANPP as a share of NPP\textsubscript{pot}) for each land-use type, li, individually (i.e., infrastructure land, cropland, grazing land, forestry land, and wilderness). Summing up across land-use types, this method enables us to quantify the following drivers’ contribution to overall changes in HANPP%:

- Changes in area mix, A, expressed in km\textsuperscript{2}. Agricultural expansion typically results in changes toward more HANPP-intensive land uses and will drive HANPP\% upwards, contraction of intensely use lands, e.g., cropland abandonment, will decrease HANPP\%.
- Changes in harvest intensity, \(\frac{\text{HANPP}_{\text{harv}}}{A}\), expressed in tons of carbon per year and km\textsuperscript{2}, i.e., the amount of harvested biomass per unit area. Increases here will increase HANPP\%. This driver represents an indicator of the output intensity of land use.
- Changes in HANPP intensity, \(\frac{\text{HANPP}}{\text{NPP}_{\text{pot}}}\), expressed in tons of carbon per year and km\textsuperscript{2}, i.e., HANPP per unit harvested biomass; this value is high if \(\text{HANPP}_{\text{harv}}\) is high, i.e., a large part of HANPP is not harvested biomass. Decreases in \(\text{HANPP}_{\text{harv}}\) will decrease HANPP\%. Therefore, this measure indicates the ratio between the system-level intensity and output intensity and can be interpreted as (the inverse) of a measure for the efficiency of societal biomass appropriation.
- Changes in natural productivity, here considered as \(\frac{1}{\text{NPP}_{\text{pot}}}\), expressed in tons of carbon per year and km\textsuperscript{2}, i.e., the inverse of NPP\textsubscript{pot}: if NPP\textsubscript{pot} increases due to changing environmental conditions (e.g., longer vegetation growing seasons in the north or increased CO\textsubscript{2} levels in the atmosphere) HANPP\% will decrease.

2.3 | Presentation of the results

For the presentation of the main results, we use the mean of 144 of the 216 runs, excluding the runs relying on JSBACH for NPP\textsubscript{pot} (see above). For the uncertainty assessment, we include all 216 versions. For the panel figures showing maps (Figures 1 and 2), we include versions based on all 216 runs in the supplement (Figures S2 and S4). In addition, we include high-resolution versions of the individual maps in Figures 1 and 2 in the data repository accompanying this article. We distinguish three periods for the presentation of results: 1910–1950 (period I), 1950–1990 (period II), 1990–2010 (period III), and accordingly, only show a subset of the maps available in our data- sets. The periodization follows the rationale that different dynamics of land-use change prevailed in the different periods (Jepsen et al., 2015, for Europe; Krausmann et al., 2013). In 1910–1950, the land-use intensification was constrained by agrarian conditions in most parts of the world. 1950–1990 was the period of the green revolution spreading from the Global North to the rest of the world, and the most recent period 1990–2010 is characterized by a moderate “extensification” of land uses in many Northern countries, for environmental, or economic or political reasons (including the collapse of the Soviet Union).

3 | RESULTS

Our results reveal global spatiotemporal patterns of HANPP and its components in the period 1910–2010 (Figure 1). In 1910, HANPP was already at high levels in much of Europe and the Indian subcontinent, in eastern China and in the eastern US. The temporal and spatial dynamics of these increases become clearer in the change maps (Figure 2). In the course of the century, strong increases in HANPP were observed in parts of South America, in Western and Eastern Africa, and in much of Southeast Asia. HANPP slightly decreased in Europe between 1910 and 1950 (period I) and increased in most parts of the world between 1950 and 1990 (period II). In the most recent period III (1990–2010), there were marked decreases in HANPP in Central Asia and in eastern China.
Figure 1: HANPP, its components, and NPPpot for 1910, 1950, 1990, and 2010. Values are means of 144 runs and in grams of carbon per square meter and year.
FIGURE 2  Changes in HANPP, its components, and NPPpot, from 1910 to 2010 for three subperiods and for the entire period (mean of 144 runs). Values show the average annual change in grams of carbon per square meter and year.
Trends and patterns in HANPP were dominated by the effect of $\text{HANPP}_{\text{harv}}$, i.e., NPP destroyed through harvest, grazing, and deforestation. $\text{HANPP}_{\text{harv}}$, i.e., $\text{HANPP}_{\text{harv}}$ without the deforestation component, showed continuous increases over the whole century in virtually all world regions (Figure 1). These increases also accelerated in most regions, except Europe and especially the former Soviet Union, where $\text{HANPP}_{\text{harv}}$ even slightly declined in the last period (Figure 2). In comparison to the other components, $\text{HANPP}_{\text{defo}}$ exhibited lower values throughout the century, with no clear trends, but substantial local changes over the century, e.g., recent decreases in large parts of China and increases in Sub-Saharan Africa.

The second major component of HANPP, $\text{HANPP}_{\text{luc}}$, shows more diverse temporal dynamics than $\text{HANPP}_{\text{harv}}$. $\text{HANPP}_{\text{luc}}$ was substantial in the Indian subcontinent and Europe already in 1910 (Figure 1), indicating the effect of non-industrialized agriculture on NPP. Over the study period, $\text{HANPP}_{\text{luc}}$ has increased in South America (period II), Southeast Asia (periods II and III), and much of sub-Saharan Africa (especially period III, see Figure 2). However, the main trends here were decreases of this component, brought about by productivity gains in the agroecosystems. Decreases in $\text{HANPP}_{\text{luc}}$ occurred in period I in Europe, the eastern US, and China. They picked up speed during the century and were the dominating changes in period III in many regions (Figure 2). This led to a situation where overall $\text{HANPP}_{\text{luc}}^*$ became substantially negative in many temperate regions by 2010 (Figure 1), indicating that land management resulted in an increase of NPP beyond $\text{NPP}_{\text{pot}}$ in these regions.

Natural productivity ($\text{NPP}_{\text{pot}}$) is highest in the tropics and values increased over time around the globe (Figure 1). While the average annual changes have been relatively small in period I, they have picked up in period II and were largest in the most recent period III. Changes were not uniform across the globe and in all periods individual regions experienced declines in $\text{NPP}_{\text{pot}}$. However, over the whole period, a strong and increasing upward trend was observed in all regions of the world.

Figure 3 presents the aggregated results across the world’s major biomes as well as the global totals. According to the mean of all 144 model runs, HANPP as a share of $\text{NPP}_{\text{pot}}$ has increased from 13.5% in 1910 to 20.7% in 2010 (shown as the black line in Figure 3 scaled to the secondary y-axis). With two exceptions, 1960 to 1970 and 1990 to 2000, this increase has been continuous. The highest levels of HANPP were observed in the temperate forest biome. At the same time, in the temperate forest biome, a reduction of HANPP levels was observed, with a decline from 40.1% in 1910 to 36.9% by 2010, caused by a steep decrease in $\text{HANPP}_{\text{luc}}^*$ that, together with an increase
in \( NPP_{pot} \) counterbalanced a strong growth in \( HANPP_{harv} \). The strongest increases were observed in the tropics, with an increase of around 10 \( HANPP\% \) points in both tropical biomes. The lowest overall levels of \( HANPP \) were observed in the boreal and polar biomes, which are dominated by the largest remaining wilderness areas. With the exception of these biomes, \( HANPP_{harv} \) was increasing in all biomes, at an accelerating pace (Figure 3). At the same time, the contribution of \( HANPP_{harv} \) to overall \( HANPP \) has declined, with the notable exception of the tropical forest biome, where this component has grown throughout the century due to continued expansion of agriculture with relatively low output per unit area. \( HANPP_{deg} \) is the smallest component throughout the time series, displaying a peak around 1960 in the tropical and subtropical biomes.

Decomposing our results sheds light on how major determinants drove aggregate changes in \( HANPP \) (Figure 4). The factor that contributed most to increases in \( HANPP \) during the 20th century was an increase in harvest intensity, i.e., \( HANPP_{harv} \) per unit area, pointing to the major impact of increasing output-intensity of land use on \( HANPP \) dynamics. This effect was the highest on croplands but also substantial on grazing land and forestry areas. The harvest intensity effect was markedly larger in the two more recent periods in all biomes, highlighting how agricultural intensification has become a dominant land-system driver around the world since the green revolution. While the scale of this effect differed across biomes and the three periods, it was the main driver of increased \( HANPP \) values across all biomes.

While being the major gross driver, the harvest intensity effect was countered by changes in \( HANPP \) intensity, implying a reduction in \( HANPP_{lac} \) per unit \( HANPP_{harv} \) partly offsetting the effect of higher harvest per unit area, when looking at overall \( HANPP \) levels. These counteracting trends emerge because increasing output intensity diminished the difference between \( NPP_{pot} \) and \( NPP_{act} \), especially on croplands. The net effect of changes in harvest intensity and \( HANPP \) intensity was universally positive (Figure 4).

The area-mix effect drove up \( HANPP \) in most regions and periods, albeit at very different rates, pointing toward the role of land conversion toward more \( HANPP \) intensive land uses, i.e., agricultural expansion and urbanization. In all biomes except in tropical forests and tropical non-forests, the contribution of area changes was highest in the first period. In many cases, the effect was nil or, as in the case of the temperate biomes, even assumed negative values in the last period. The tropical regions were an important exception to this trend, again indicating ongoing or even accelerating agricultural expansion into unused or less intensively used lands (e.g., Laurance et al., 2014). Here, the effect of the area changes increased to its largest contribution in the most recent period.

**Figure 4** Decomposition of changes in \( HANPP \) into the contribution of drivers of change across the world’s major biomes and for the global total. The dots present the aggregate net effect, i.e. the actually observed change rates for the respective periods. Unit: change in \( HANPP \) as percentage points of \( NPP_{pot} \), averaged over a 10-year period (mean of 144 runs). Note that the biome classification refers to potential forest cover, not current forest cover, for details see Supplementary Method Note S4. For an explanation of the drivers of change, refer to equation 4 and accompanying elaborations.
NPP\textsubscript{pot} increased during the study period in all biomes and at the global level at an accelerating pace (Figure 4). The average global increase for the entire period was 18%, but in some areas, NPP\textsubscript{pot} also declined according to the model (Figure 2). The overall increase implies that the same amount of HANPP in mass terms results in a lower HANPP value when expressed as a share of NPP\textsubscript{pot}. In the most recent period, this effect lowered HANPP levels by about 1 percent point per decade, which is substantial compared to the overall net increase of about 0.5 percent points in that period.

Figure 5 presents the results of the uncertainty assessment for 2010, for both HANPP as flows of carbon per unit area (left) and as a share of NPP\textsubscript{pot} (right). The former perspective displays consistently higher uncertainty values than the latter. The main reason for this difference is the large contribution of the NPP\textsubscript{pot} modulations to uncertainty when expressing HANPP as an annual flow of carbon. Here, the variation between the input data in the NPP\textsubscript{pot} values is the dominant source of uncertainty in virtually all world regions and biomes except for the temperate forest biome in Europe and Asia. When expressed as a share of NPP\textsubscript{pot} uncertainty is much lower in general, with areas of good agreement accounting for over 80% of the overall HANPP. The modulations that contribute most to uncertainty in this perspective are those related to the land-use data, which rank second in the other perspective. The other modulations are dominant sources of uncertainty only in a limited number of pixels, especially when weighing the results by the amount of HANPP occurring in these areas (Figure 5a and b).

4 | DISCUSSION

The key finding of our study is that dynamics of land-use intensification played a major and over time increasing role in altering land systems in the last century. At the pixel level (Figure 2), we observe an acceleration and polarization of HANPP components, i.e., in many settings HANPP\textsubscript{harv} and NPP\textsubscript{pot} are increasing at an accelerating pace, while HANPP\textsubscript{luc} is decreasing. At the biome level, we see that increasing output intensity of land use (harvest intensity) was the most striking driver of change in HANPP observed across biomes, counteracted by declines in HANPP intensity of harvest (Figure 4). Our analysis suggests that these dynamics appear to be a global phenomenon showing consistent trends across different dimensions.
of land-use intensity while taking off at different points in time in different world regions and reflecting how the green revolution has been spreading around the globe.

The crucial relevance of land-use intensity for understanding land-use patterns and their implications is increasingly acknowledged in the literature (e.g., Beckmann et al., 2019; Dullinger et al., 2021; Felipe-Lucia et al., 2020; Friedlingstein et al., 2020; Hong et al., 2021; Kuemmerle et al., 2013). Our results further corroborate these statements and clearly show that without appropriate consideration of the dynamics of land-use intensity, assessments, and models, such as integrated assessment models, will increasingly miss the major changes in land systems and might result in biased and incomplete interpretations (Erb et al., 2018; Pongratz et al., 2018). For instance, as net rates of land-use change have declined in many parts of the world, ideas like “peak land use,” i.e., the outlook that pressures on land in terms of used areas stabilize and eventually decline in the near future (Ausbubel et al., 2013; Seppelt et al., 2014), have to be critically reflected upon when considering the increasing role land-use intensity changes play in driving overall land system change.

One consequence of this trend toward an increased dynamic of land-use intensity and a decreasing role of agricultural expansion in many world regions is that HANPP, expressed as the share of NPPpot, has peaked or flattened out in the temperate, sub-tropical, and boreal biomes, where increases in harvest intensity have largely been offset by decreases in HANPP intensity (Figure 4). At the same time, we find strong continued growth of HANPP in the tropical regions, where agricultural expansion continues and where HANPPluc levels remain substantial (Figure 1) and have increased strongly in some regions in the more recent past, such as in tropical Africa (Figure 2). However, for the forest biomes, the level of HANPP in the tropics is still considerably lower than for the sub-tropical and temperate biomes, implying that the overall HANPP rates are becoming increasingly similar if these trends continue. In this context, it is important to note that the increases in pressures on terrestrial ecosystems in tropical regions such as the Amazon, the Cerrado, or Southeast Asia are driven, in part, by the consumption in world regions that have enjoyed recent declines in land-use pressures (Hoang & Kanemoto, 2021; Pendrill et al., 2019). Together with a situation where global conservation interest is also concentrated in tropical regions (Dinerstein et al., 2020; Strassburg et al., 2020), this highlights that future land-use trajectories will have to deal with competing interests and will be increasingly driven by global demand and power relations (e.g., Krausmann & Langthaler, 2019).

The trends of the ever-increasing importance of intensification also raise questions about potential limits to intensification processes. To what extent will it be possible to further increase biomass harvests per unit area and at what costs? On the one hand, demand for land-based products is expected to further increase: food and feed are needed to feed a growing and increasingly affluent global population (Tilman et al., 2011), and increased use of biomass for energy and material use is envisaged in bioeconomy strategies around the world as a central measure to curb dependence on fossil fuels (Dietz et al., 2018). On the other hand, negative consequences of intensification such as detrimental effects of nutrient leaching and pesticide use on biodiversity are becoming more and more evident (Conijn et al., 2018; Gilbert, 2017; Sharma et al., 2020). Land-systems that consistently show NPP values higher than NPPpot (i.e., negative HANPPluc), as is currently the case in, e.g., eastern China (Figure 1), are typically associated with considerable environmental externalities (West et al., 2014). These trends have led to calls for a more "sustainable" or "agroecological intensification" (Garnett et al., 2013; Thomson et al., 2019; Wezel et al., 2015), but it remains to be seen how such approaches can be operationalized at large scales, without increasing areal expansion of agriculture due to lower outputs per unit of land. Another potential way to reduce pressures on land systems that is increasingly explored relates to lowering the overall demand for land-based products, such as transitions to less resource-intensive diets, including the reduction of food waste (Hallström et al., 2015; Springmann et al., 2018; Tilman & Clark, 2014; Willett et al., 2019).

An additional major global change process is highlighted by the HANPP framework and by our results: the importance of increased vegetation productivity for land systems. Our results suggest that the productivity levels of the potential natural vegetation NPPpot have been growing at an accelerating pace at the global level. Within the HANPP framework, such increases in NPPpot imply a shift of the baseline: at constant levels of HANPP in terms of tons of carbon, such a trend will result in lower relative pressures on ecosystems, which is indicated by the increasing effect of natural productivity changes have on dampening HANPP growth in Figure 4. Output from DGVM models for NPPpot has been a central input for all assessments of HANPP at the global level. On the one hand, this is due to the required spatial and temporal scales of the data. On the other hand, this is also a conceptual issue: NPPpot is a hypothetical value, depicting values under the respective current climate conditions but without land use. NPPpot, thus, has to be modeled and cannot be straightforwardly taken from the measured data, even if they were available. Keeping this in mind, the strong increase in NPP since the beginning of the 20th century is consistent with other estimates. Ciais et al. (2012) estimated a pre-industrial gross primary production (GPP) of 80 Pg per year, which is substantially lower than the estimate for recent conditions of about 120 Pg (Ciais et al., 2013; Friedlingstein et al., 2020). Based on the records of long-term atmospheric carbonyl sulfide, another independent method, Campbell et al. (2017) estimated a GPP increase of about 31% since the early last century. GPP and NPP are strongly related, NPP being about half of GPP (Ciais et al., 2013; Yu et al., 2018). In addition, the simulated present global value of 62.4 Pg for 2010 is very similar to satellite-derived estimates from the MODerate resolution Imaging Spectroradiometer (MODIS), which also show an increase between 2004 and 2012 (Yu et al., 2018), in line with the modeled data. With regard to the robustness of our findings, it is also noteworthy that, for larger spatial scales, Krausmann et al. (2013) have highlighted that the HANPP framework is able to provide robust insights, even in the light of uncertain NPPpot trends.
The modeled and observed increases in natural vegetation productivity have been mainly attributed to increases in atmospheric CO₂ concentrations and longer growing seasons in high latitudes as a result of rising temperature levels, which, in turn, have been attributed largely to anthropogenic greenhouse gas emissions (Lucht et al., 2002; Pachauri et al., 2014; Walker et al., 2021; Zhu et al., 2016). In the context of our assessment, it is interesting to see that increases in \( NPP_{pot} \) have occurred simultaneously with strong increases in harvest intensity in many parts of the world. Our estimates for harvest intensity are independent of the used DGVM output for \( NPP_{pot} \) data and rely on agricultural and forestry statistics. The observed alignment of these trends calls for a better understanding of how much of the continued increases in output per unit area can be attributed to agronomical practices and how strong the role of such more indirect factors has been, is discussed in the literature on the effects of climate change on crop yields (e.g., Rosenzweig et al., 2014; Wang et al., 2018) and forest productivity (e.g., Pretzsch et al., 2014). Insights into this question are important, as it is far from clear that trends in increasing NPP levels will continue in a similar fashion in the future and dynamics will likely differ substantially in different biomes (Jong et al., 2012; Walker et al., 2021; Wang et al., 2020). In addition, these findings call for a more nuanced representation of such global change processes. For instance, while shifts in natural vegetation are included in current global vegetation models, the present HANPP framework does not consider such shifts. It would be interesting to explore how such changes may affect land-use patterns, as, for instance, shifts from herbaceous to woody vegetation will translate into changes in land management practices and preferences (e.g., Linders et al., 2020), which in turn will imply different HANPP patterns.

Our analysis highlights the added value of a comprehensive perspective on land-use change processes, as offered by the HANPP framework. A detailed look into the dynamics of the individual HANPP components allowed disentangling processes to occur simultaneously in global land systems. By looking systematically across the different components that determine the overall magnitude of HANPP, we were able to draw up a more complete picture of land-system change, focusing in particular on the role of land-use intensity. Furthermore, through modulating central input data, we are able to provide an assessment of spatial uncertainty patterns of HANPP. While we find relatively low uncertainties across large parts of the globe, we see that the underlying land-use data and data on \( NPP_{pot} \) are central for the overall observed uncertainty patterns. Considering that we only modulated cropland areas (Supplementary Method Note S1) for which alternative historical reconstructions were available, the role land-use data play in overall uncertainties is likely even underestimated in our data. For historical periods, these uncertainties will be hard to reduce. For the most recent past and current patterns, the availability of ever-improving satellite observations has the potential to reduce uncertainties related to land use and land cover data, although the reconciliation of ground-based observation (census statistics) with satellite-derived data remains challenging. Other modulated factors had a lower relevance at the global level but might still be important regionally.

We also find that distinct uncertainty patterns emerge, depending on the unit in which HANPP is expressed (Figure 5): if expressed in absolute numbers (i.e., grams of carbon per year) \( NPP_{pot} \) data are the largest sources of uncertainty at the global level. This can be linked to the fact that current global vegetation models yield largely different global estimates of NPP as well as different spatial patterns and temporal trends. This variation is generally caused by uncertainties in process representations, parameter values, and input datasets (primarily climate data), as well as challenges in measuring and defining NPP consistently (Field et al., 1995; Ito, 2011; Roxburgh et al., 2005). Differences in temporal trends are mostly caused by uncertain plant-physiological effects of elevated atmospheric CO₂ and different model assumptions concerning nutrient limitation (Friedlingstein et al., 2014; Wårlind et al., 2014). However, if expressed as the share of \( NPP_{pot} \), the contribution of the \( NPP_{pot} \) to overall uncertainties at the global level is much smaller, highlighting that expressed in relative terms the indicator is more robust.

It is also interesting to note that for the year 2000 our estimates are by about 2–4 HANPP%-points lower than those presented in earlier studies (Haberl et al., 2007; Krausmann et al., 2013). As the main reason for this difference, we identified the fact that in our assessment HANPP\(_{del} \) and the effect of ecosystem degradation on HANPP\(_{lc} \) was estimated via spatially explicit approaches, which yielded substantially lower estimates for the year 2000. The other components were well in line with earlier assessments, with minor deviations due to refinements in the treatment of permanent cropland and the additional data limitation that FAOSTAT no longer reports the harvest of dedicated fodder crops (see Supplementary Method Note S2).

Our spatially explicit reconstruction of the development of HANPP and its components across the major land uses can provide valuable inputs for future research. For instance, the maps allow for assessing trends across spatial entities that do not align with national borders. We have presented such an assessment across the world’s major biomes, but other spatial units will be interesting to analyze as well. With HANPP being closely and mechanistically linked to biodiversity patterns and processes, it will be crucial to investigate how present global biodiversity patterns align with past land-use patterns to address the ongoing challenge of biodiversity loss. Such an analysis could scrutinize the idea that biodiversity patterns only adapt to land-use pressure with a time lag. Additionally, the maps could form a baseline for developing spatial scenarios on future land-system changes that incorporate the land-use intensity dimension, as well as contributing (along with other information) to identifying areas where further intensification is likely possible with limited negative environmental consequences. Addressing this intensity dimension will be crucial if pressing sustainability challenges in the land system, such as curbing biodiversity loss, are to be tackled in a comprehensive manner.

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DATA AVAILABILITY STATEMENT
Complete data for all included years and model runs, along with high-
resolution versions of the maps presented in Figures 1 and 2 are
available via a Zenodo repository (https://doi.org/10.5281/
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from these data. Programming code is available from the corre-
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ORCID
Thomas Kastner https://orcid.org/0000-0002-8155-136X
Sarah Matej https://orcid.org/0000-0003-4576-4189
Matthew Forrest https://orcid.org/0000-0003-1858-3489
Simone Gingrich https://orcid.org/0000-0001-7891-8688
Helmut Haberl https://orcid.org/0000-0003-2104-5446
Thomas Hickler https://orcid.org/0000-0002-4668-7552
Fridolin Krausmann https://orcid.org/0000-0002-9995-2372
Gitta Lasslop https://orcid.org/0000-0001-9939-1459
Maria Niedertscheider https://orcid.org/0000-0002-3233-5900
Christoph Plutzar https://orcid.org/0000-0003-2041-6399
Florian Schwarzmüller https://orcid.org/0000-0001-9751-0565
Jörg Steinkamp https://orcid.org/0000-0002-7861-8789
Karl-Heinz Erb https://orcid.org/0000-0002-8335-4159

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