Measuring agricultural land-use intensity - A global analysis using a model-assisted approach

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Abstract

Human activities such as research & development, infrastructure or management are of major importance for agricultural productivity. These activities can be summarized as agricultural land-use intensity. We present a measure, called the τ-factor, which is an alternative to current measures for agricultural land-use intensity. The τ-factor is the ratio between actual yield and a reference yield under well defined management and technology conditions. By taking this ratio, the physical component (soils, climate), which is equal in both terms, is removed. We analyze global patterns of agricultural land-use intensity for 10 world regions and 12 crops, employing reference yields as computed with a global crop growth model for the year 2000. We show that parts of Russia, Asia and especially Africa had low agricultural land-use intensities, whereas the Eastern US, Western Europe and parts of China had high agricultural land-use intensities in 2000. Our presented measure of land use intensity is a useful alternative to existing measures, since it is independent of socio-economic data and allows for quantitative analysis.

Keywords: agriculture, land-use intensity, land-use, agricultural productivity, yield growth

1. Introduction

Future demand for agricultural products will increase over the coming decades, driven by population growth and changing dietary habits (Pingali, 2007; von Braun, 2007), which means that agricultural production will have to increase. The two basic options for this are expansion of the land area under agricultural production, and agricultural land-use intensification (for definitions see Table

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concept	description
yield	a measure of the output per unit area
human activity	any kind of human interaction influencing yields (e.g. management or R&D)
physical environment	natural circumstances under which production takes place (soil, climate, terrain)
agricultural land-use intensity α	degree of yield amplification caused by human activities
τ-factor	measure proportional to agricultural land-use intensity

Table 1: Concepts and terms used in this paper

1). Because land expansion is limited (Lambin and Meyfroidt, 2011), intensification has been and will increasingly become more important in the future (Ewert et al., 2005). To assess further long-term yield growth and for projections of future land-use developments it is essential to quantify current levels of agricultural land-use intensity, assuming that further improvements are more difficult to achieve in systems operating at the forefront of intensity levels than for systems at lower intensity levels (e.g. spillover).

Literature provides two different concepts for analyzing agricultural performance: yield gap analysis and analysis of land-use intensities[1]. Yield gap analyses assume that each location has an upper yield boundary, called either "potential yield" (Ittersum and Rabbinge, 1997) or "technology frontier" (Nishimizu and Page, 1982), which is determined by present physical conditions and available technologies. Observed or actual yields may be lower than the potential yield due to the ineffective application of inputs and available technologies. Regions with strong discrepancies between actual and potential yield have strong potentials for further yield increases, whereas regions at the technology frontier are not able to increase their yields any further (Färe et al., 1994; Coelli and Rao, 2005; Neumann et al., 2010). This approach can be seen as a short-term analysis of agricultural potentials, since it focuses on agricultural inputs and management, which can be changed and optimized within years. However, it excludes productivity changes induced by Research & Development (R&D) (Licker et al., 2010; Johnston et al., 2011), which typically have a time lag of around 10-30 years (Alston et al., 1995, 2000).

The concept of agricultural land-use intensity as followed in this paper does not measure the distance to a technology frontier or potential yield. Instead, it is a productivity measure which takes only the human-induced productivity into account (Brookfield, 1993; Kates et al., 1993; Netting, 1993), explicitly including those that affect the technology frontier like the development of new varieties as during the so-called green revolution (Evenson and Gollin, 2003).

[1]In this paper we use the term land use intensity analysis contrasting to yield gap analysis rather than a generic term for agricultural potential analysis as it is sometimes used in literature. For further explanations for this choice check Appendix D

Although, both measures can be calculated in similar ways, their meaning is different: Yield gap measures the distance to the currently best practice, typically excluding possible changes in best practices, whereas land-use intensity measures all those parts of agricultural productivity, which cannot be explained by the physical environment (soils, climate). This difference becomes eminent when comparing values at different time steps. A farm not adopting any technological progress will show an increasing yield gap, but constant land-use intensity. This is, because the technology frontier moves in this case, but not the productivity level (see Appendix D for more details on this example and more explanations about the crucial differences between yield gap and land use intensity). As the position of the technology frontier cannot be assumed to be constant over decades, measures of land-use intensity are more adequate tools for assessing long-term developments in agriculture (time horizons of several decades). Due to its more comprehensive definition with respect to yield increasing activities, land-use intensity is also more appropriate as a surrogate for the general state of agricultural development.

The concept "land-use intensity" is less clearly defined than that of yield gap analysis. Sometimes the term is used in the sense of an overarching definition, including yield gap analysis as some part of it, in other cases it is used more narrowly as in our definition. We only found explicit definitions for the term "land-use intensification", but none for "land-use intensity". Brookfield (1993) describes intensification as 'in relation to constant land, the substitution of labor, capital or technology for land, in any combination, so as to obtain higher long-term production from the same area'. Kates et al. (1993) and Netting (1993) use the formulation that intensification is 'a process of increasing the utilization or productivity of land currently under production, and it contrasts with expansion, that is, the extension of land under cultivation'. Shriar (2000) uses the formulation that 'agricultural intensification is a process of raising land productivity over time through increases in inputs of one form or another on a per unit area basis'.

Land-use intensity can be measured either in an output-oriented or input-oriented way using inputs as surrogates for increases in productivity (Lambin et al., 2000). When the focus is on output, intensity can be measured in production units (calories, tons, monetary value,...) per area per time unit (Turner and Doolittle, 1978). In an input-oriented approach the amount of inputs is measured and weighted with their assumed increase in production (Shriar, 2000; Turner and Doolittle, 1978) or single input characteristics are used as a surrogate for land-use intensity, for instance, cultivation frequency (Boserup and Kaldor, 1977).

Comparing all these definitions and measures we find general agreement in two respects: (1) intensification means increases in productivity and (2) intensification can be achieved by a broad spectrum of options which are all induced by humans. Changes in productivity due to environmental reasons, such as climate change, are generally excluded. Based on this consensus we here define intensification and intensity as:

1. agricultural land-use intensification is the increase of land productivity due to human activities
2. agricultural land-use intensity is the degree of yield amplification caused by human activities.

These definitions are quite similar to former ones but highlight that any kind of human interaction with agriculture that affects productivity also affects land-use intensity whereas no kind of environmental interaction has any influence on it.

To capture agricultural land-use intensities as defined in this paper we introduce a new measure τ. It is the ratio between an actual yield (observed yields) and a reference yield (a yield that would be achieved under spatial and temporal constant land-use intensity). Actual yields can be directly observed, whereas reference yields can either be derived by models or statistical analysis, for which a global crop-growth model, the "Lund-Potsdam-Jena dynamic global vegetation model with managed Land" (LPJmL) (Bondeau et al., 2007).

2. Methods

2.1. Agricultural land-use intensity and τ-factor

Crop yields are useful parameters in assessing agricultural land-use intensity. The yield of a region itself already provides a rough estimate of it. However, this measure is still distorted because of its dependence on the physical environment. Hence, a high yield could either indicate high agricultural land-use intensity or favorable physical conditions. Applying the concept of partial factor productivity (Nin et al., 2003), a yield $Y(c,j)$ (of crop c at place j) can be described as the product of two factors: a base yield $Y_0(c,j)$ and an amplification factor $\alpha(c,j)$ (Equation 1).

$$Y(c,j) = \underbrace{\alpha(c,j)}_{\text{land-use intensity}} \cdot \underbrace{Y_0(c,j)}_{\text{base yield}} \tag{1}$$

The base yield depends only on the physical environment and is free of any human influences except sowing and harvesting, which are essential cropping activities. The amplification factor α is independent of the physical environment and represents only the amplification of yields due to human activities. Thus, α is the agricultural land-use intensity as followed in this paper.

Since a base yield in agriculture without any management is a rather theoretical entity, we here use a reference yield Y_{ref}, which represents yields under clearly defined management settings. Consequently, it is a combination of physical environment and human activity. The physical environment component, however, is eliminated by dividing the actual yield Y_{act} by this reference yield Y_{ref} (Equation 2). The ratio τ of the actual yield Y_{act} and the reference yield Y_{ref} is therefore our measure for land-use intensity.

$$\tau(c,j) = \frac{Y_{act}(c,j)}{Y_{ref}(c,j)} = \frac{\alpha_{act}(c,j) \cdot Y_0(c,j)}{\alpha_{ref} \cdot Y_0(c,j)} = \frac{\alpha_{act}(c,j)}{\alpha_{ref}} \quad (2)$$

τ is independent of the physical environment, since Y_0 is equal in both the reference and the actual yields. It is proportional to the agricultural land-use intensity α_{act} but easier to calculate since it does not require a full separation of physical environment and human activities. While actual yields can be measured directly, reference yields Y_{ref} need to be deduced. We therefore employ the crop growth model LPJmL (Bondeau et al., 2007) to compute spatial patterns of crop yields under static assumptions on management. Static assumptions on management in the simulations of the reference yield ensure that τ is proportional to the land-use intensity α, as reference yields are thus comparable over both time and space, as needed (Equation 2).

τ is not a direct measure of land-use intensity but can be used as a surrogate, representing land-use intensity, scaled with $1/\alpha_{ref}$, which is a constant. Relative changes in τ are directly proportional to relative changes in α_{act}. Accordingly, τ doubles if crop yield double owing to improved management, technological development or any other human activity. If crop yields change owing to changing environmental conditions (like climate change), τ and α_{act} remain unaltered. For analyzing land-use intensity patterns, we can use τ as it is. However, we have to consider its scaling factor, when comparing different τ estimates with each other. A τ-factor in one region A that is twice as high as the τ-factor in another region B can be interpreted as such: if both regions have the same physical conditions, region A will have twice the yield of region B due to a higher agricultural land-use intensity. If, on the contrary, physical conditions in region A are half as good as in region B, yields in region A and B would be equal. Thus, the τ-factor not only ranks regions, but also delivers quantitative information about yield differences between regions due to differences in human activity (agricultural land-use intensity).

Accurate estimates of land-use intensity are dependent on the quality of observations of actual yields. Actual yield data is available at national (FAOSTAT, 2009) or even sub-national level (Monfreda et al., 2008) and are subject to some uncertainty, while reference yield data have to be deduced theoretically, e.g. by means of crop models. However, especially global models typically suffer from systematic errors and biases caused by the high complexity of the modeled system. To reduce the error caused by these biases in τ, consistency between actual yield Y_{act} and reference yield Y_{ref} is of eminent importance. Therefore, we use the same model for both, simulating reference yields and model-based downscaling of national FAOSTAT data as spatial patterns of actual yields. By doing so impacts of model biases on τ do not vanish but are reduced, since they are part of both the numerator Y_{act} and denominator Y_{ref}.

2.2. The LPJmL model and simulations of yields

For calculations we use the "Lund-Potsdam-Jena dynamic global vegetation model with managed Land" (LPJmL). LPJmL is a process-based ecosystem

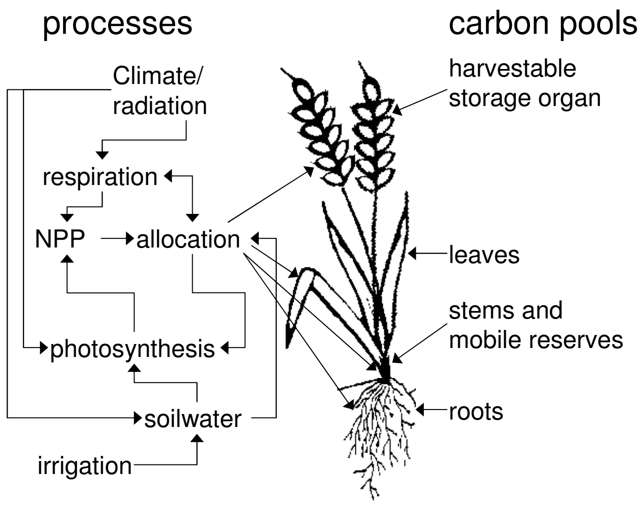

Figure 1: Conceptual diagram of the plant processes and pools in the LPJmL model

model which simulates the growth, production and phenology of 9 plant functional types (representing natural vegetation at the level of biomes; Sitch et al. (2003)) and of 12 crop functional types[2] (CFTs) and managed grass (Bondeau et al., 2007). Carbon fluxes (gross primary production, auto- and heterotrophic respiration) and pools (in leaves, sapwood, heartwood, storage organs, roots, litter and soil) as well as water fluxes (interception, evaporation, transpiration, soil moisture, snow melt, runoff, discharge) are modeled accounting explicitly for the dynamics of natural and agricultural vegetation. The photosynthetic processes are modeled according to Farquhar et al. (1980) and Collatz et al. (1992). The phenology and management dates (sowing and harvest) of the different crop types are simulated dynamically based on crop-specific parameters and past climate experience, allowing for adaptation of varieties and growing periods to climate change (Waha et al., 2012). All processes are modeled at a daily resolution and on a global $0.5° \times 0.5°$ grid. For agricultural crops, assimilated biomass from photosynthesis is allocated at daily steps to four carbon pools: leaves, roots, harvestable storage organs (e.g. grains for cereals), and a pool representing stems and mobile reserves (see Figure 1). At harvest, the biomass fraction of the storage organs represents the harvested yield. For more details see Bondeau et al. (2007)

The suitability of the model (and its predecessor LPJ that did not include cropland) for vegetation/crop and water studies has been demonstrated before by validating simulated phenology and yields (Bondeau et al., 2007; Fader et al., 2010), river discharge (Biemans et al., 2009; Gerten et al., 2004), soil moisture

[2]wheat, maize, rice, millet, sugar beet, cassava, sugar cane, rapeseed, groundnut, soybean, field peas, sunflower

(Wagner et al., 2003), evapotranspiration (Gerten et al., 2004; Sitch et al., 2003) and irrigation water requirements (Rost et al., 2008).

Agricultural intensity is represented in LPJmL via three parameters: (1) the maximum Leaf Area Index (LAImax), an index that depicts the ratio of leaf surface to covered land surface at maximum green-leaf development and affects the overall productivity of the plant via the fraction of absorbed photosynthetically active radiation (fpar), (2) a scaling factor from simulated leaf-level photosynthesis to field scale (alphaa, representing the homogeneity of a field), as well as (3) the harvest index (HI), assuming that intensive systems grow high yielding varieties and extensive systems grow more robust but lower-yielding varieties (Gosme et al., 2009). All three factors are directly linked: highly developed systems are parameterized with a high LAImax value, high alphaa, and high HI (Fader et al., 2010). High agricultural land-use intensity is represented by high LAImax, alphaa, and HI which leads to simulation of high yields.

The reference yield Y_{ref} in our study is computed by using static values for LAImax, alphaa, and HI, representing static agricultural land-use intensities, as needed for computing τ (see Equation 2). In order to reduce model-based errors, we here do not use a single static assumption on agricultural land-use intensity but the mean of seven different settings. Methodologically, this choice does not affect the results as it is also possible to use only one single level of agricultural intensity. However, using the mean of several settings increases the signal-to-noise ratio of the simulated data and contributes to the robustness of our τ estimates.

Actual yields could be taken directly from observations, such as the FAO statistics. Here, we also use model-based representations of observed yields to avoid model-based distortions of actual and reference yields. For downscaling of actual yields to sub-national level, agricultural intensity of each crop in each country was chosen in a way to best match observed national yield levels as reported by FAOSTAT (2009). Grid cell level yields were aggregated to national yields using a global land-use data set (Portmann et al., 2010) as modified by Fader et al. (2010). For details of scaling to observed national yield levels see Fader et al. (2010). The goodness-of-fit between simulated actual yields Y_{act} and FAOSTAT data is shown by the Willmott coefficient (Willmott, 1982), which ranges between 0 (no relationship) and 1 (perfect agreement) (see Appendix A). Results between 0.74 and 0.98 indicate good agreement. Since information on the spatial distribution of multiple cropping systems is lacking and FAOstat only delivers data on harvested yields we related all our calculations to area harvested rather than physical area. This approach excludes multi-cropping as an indicator for favorable physical conditions as well as a source of intensification but marks the best alternative under absence of reliable spatial data on multiple cropping systems.

2.3. Aggregating the τ-factor

For our analysis of agricultural land-use intensity, we analyse the spatial patterns of agricultural land-use intensity as well as the rankings of world regions. The aggregation of τ computed at grid cell level j to larger spatial units i is computed as the ratio of aggregated actual yield Y_{act} and aggregated reference yield Y_{ref} (Equation 3).

$$\overline{\tau}(c,i) = \frac{\overline{Y_{act}}(c,i)}{\overline{Y_{ref}}(c,i)} = \frac{\sum\limits_{j \in i} \overbrace{\frac{Y_{act}(c,j)}{Y_{ref}(c,j)}}^{\tau(c,j)} \cdot \overbrace{Y_{ref}(c,j) \cdot A(c,j)}^{X_{ref}(c,j)}}{\sum\limits_{j \in i} \underbrace{Y_{ref}(c,j) \cdot A(c,j)}_{X_{ref}(c,j)}} \tag{3}$$

Since both aggregates of Y_{act} and Y_{ref} need to be weighted by crop area $A(c,j)$ equation 3 can be simplified to a weighted mean of τ with weight X_{ref} (Equation 4).

$$\overline{\tau}(c,i) = \frac{\sum\limits_{j \in i} \tau(c,j) \cdot X_{ref}(c,j)}{\sum\limits_{j \in i} X_{ref}(c,j)} \tag{4}$$

The weight X_{ref} is a product of crop area $A(c,j)$ and reference yield $Y_{ref}(c,j)$ (Equation 5) and represents production under reference conditions.

$$X_{ref}(c,j) = Y_{ref}(c,j) \cdot A(c,j) \tag{5}$$

The aggregation of several crop-specific τ is complicated by the fact that τ is a scaled representative of agricultural land-use intensity α (see above). Because crop parameters used for the 12 crops studied here in the LPJmL model also represent different crop varieties, reference yields of different crops are not directly comparable to each other, as also the selection of crop varieties (and their breeding) is an integral part of agricultural land-use intensity. In order to make them comparable, we normalize crop-specific τ values so that the global area-weighted mean of each crop-specific τ is equal to 1.0 before combining crop-specific τ values to one overall τ. More information on the aggregation of crop-specific τ values to a general τ factor and how this aggregation produces information on the sub-national level is given in Appendix C.

3. Results

We have calculated τ-factors for 10 world regions[3] (see Table B.5 for country-to-region mapping) and 12 different commodity types for 2000 (Table 2 and Table 3). All τ-factors are normed by the corresponding global mean value. If the regional production of a crop was less than 0.1% of the global crop production the τ-factor is not computed.

[3]AFR = Sub-Sahara Africa, CPA = Centrally Planned Asia (incl. China), EUR = Europe (incl. Turkey), FSU = Former Soviet Union, LAM = Latin America, MEA = Middle East and North Africa, NAM = North America, PAO = Pacific OECD (Australia, Japan and New Zealand), PAS = Pacific Asia, SAS = South Asia (incl. India)

	total	wheat	rice	maize	millet	field peas	sugar beet
AFR	0.67	0.60	0.44	0.33	0.86	0.61	-
CPA	1.15	1.06	1.42	1.11	1.75	0.93	1.02
EUR	1.34	1.32	1.18	1.38	1.82	1.76	1.21
FSU	0.79	0.80	0.61	0.77	1.24	0.92	0.57
LAM	0.99	0.81	0.73	0.69	0.82	1.42	0.83
MEA	0.66	0.62	0.96	0.88	1.24	0.64	0.80
NAM	1.22	1.10	1.29	1.60	1.42	1.07	1.22
PAO	0.85	0.84	1.49	-	1.44	0.61	1.46
PAS	0.88	-	0.95	0.61	1.43	0.48	-
SAS	0.86	0.88	0.81	0.42	1.05	1.04	-
GLO	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 2: Crop-specific τ-factors (dimensionless) in world regions for the year 2000 (AFR: Sub-Sahara Africa, CPA: Centrally Planned Asia (incl. China), EUR: Europe (incl. Turkey), FSU: Former Soviet Union, LAM: Latin America, MEA: Middle East and North Africa, NAM: North America, PAO: Pacific OECD (Australia, Japan and New Zealand), PAS: Pacific Asia, SAS: South Asia (incl. India), GLO: World) 1/2

	cassava	sunflower	soybean	groundnut	rapeseed	sugar cane
AFR	0.88	0.94	0.75	0.60	-	0.92
CPA	1.05	1.83	0.89	1.92	0.73	1.20
EUR	-	1.20	1.15	-	1.62	-
FSU	-	0.79	0.50	-	0.68	-
LAM	1.03	1.11	1.25	0.92	-	1.10
MEA	-	0.83	-	1.42	-	1.41
NAM	-	1.10	0.90	1.97	1.13	1.40
PAO	-	1.50	0.97	-	0.82	1.33
PAS	1.30	-	0.77	1.12	-	0.82
SAS	1.78	0.69	1.21	0.80	0.72	0.86
GLO	1.00	1.00	1.00	1.00	1.00	1.00

Table 3: Crop-specific τ-factors (dimensionless) in world regions for the year 2000 (AFR: Sub-Sahara Africa, CPA: Centrally Planned Asia (incl. China), EUR: Europe (incl. Turkey), FSU: Former Soviet Union, LAM: Latin America, MEA: Middle East and North Africa, NAM: North America, PAO: Pacific OECD (Australia, Japan and New Zealand), PAS: Pacific Asia, SAS: South Asia (incl. India), GLO: World) 2/2

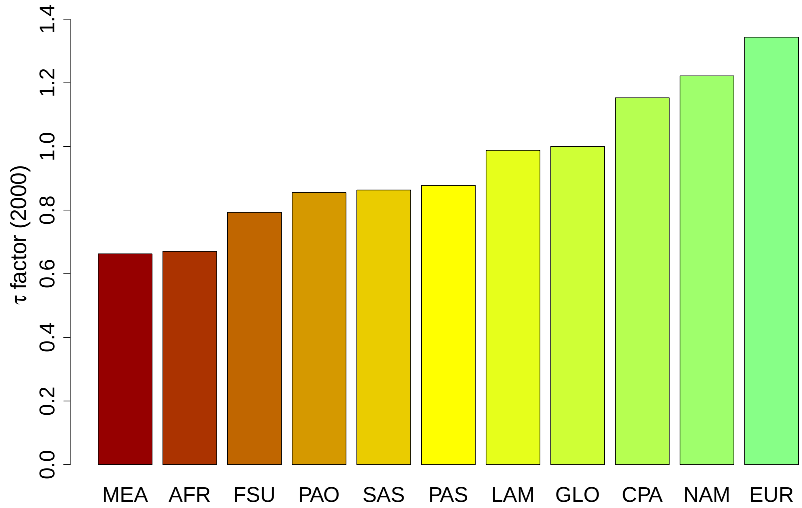

Figure 2: τ-factors in world regions & global (GLO) for the year 2000

EUR has the highest total τ-factor as well as highest crop-specific τ-factors for wheat, millet, field peas and rapeseed, NAM shows the highest maize and groundnut τ-factors, CPA the highest value for sunflower, LAM the highest value for soybean, SAS the highest value for cassava, PAO the highest τ-factors for rice and sugar beet and MEA the highest value for sugar cane. AFR has the lowest τ-factors for wheat, rice, maize, cassava and groundnut and shows only a slightly higher total τ-factor than MEA which ranks lowest in our comparison. FSU shows the lowest τ-factors for sugar beet, soybean and rapeseed, SAS the lowest value for sunflower, LAM for millet and PAS for field peas and sugar cane.

Some regions have only slight variations in their τ-factors over all crops, e.g. AFR (constantly low) or EUR (constantly high), whereas other regions show strong variations between crops, as e.g. PAO or MEA.

Figure 2 shows the aggregated, normed τ-factors over all crops for all regions and at global level in 2000 aggregated using the aggregation weight described in Section 2.3. The range is between 0.66 and 1.34. Comparing e.g. Sub-Saharan Africa (AFR) and Europe (EUR), EUR would have 103% higher yields than AFR if physical environmental conditions would be identical due to its higher agricultural land-use intensity. Besides AFR which displays constantly low levels over all crops and EUR with constantly high levels, our general ranking shows a broad spectrum of regions a bit lower than the global mean of 1. Especially PAO, SAS and PAS are within a range from 0.85 to 0.88.

Figure 3 shows the global distribution of the mean τ-factors in 2000. We observe regions with homogeneous spatial distribution of τ as well as regions with strong heterogeneity. For instance, the Republic of Ireland, United King-

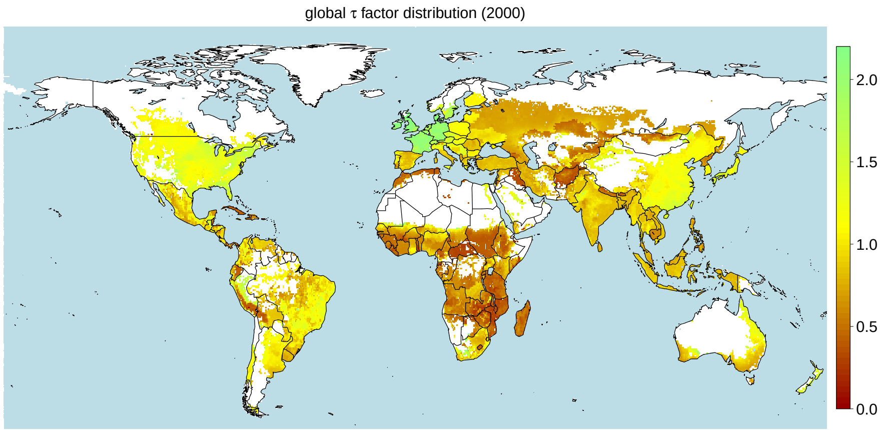

Figure 3: Global τ-factor distribution for the year 2000

dom, France, Germany and Sweden show relatively homogeneous values at a high level and Madagascar and Mozambique homogeneous values at a low level, whereas the US, Peru and South Africa seem to be more heterogeneous in their τ-factors. We observe high values in the Eastern US, Central Europe and South China, medium values in Latin America and Asia and low values in Central Africa and Eastern Europe / Russia.

4. Discussion

In this paper we present the τ-factor, a methodological extension to currently available measures for land-use intensity. The most important difference of our approach to other measures of land-use intensity is that τ determines land-use intensity by eliminating the environmental component from observed actual yields via a reference yield (see Equation 2). This procedure contrasts with input-oriented approaches which determine land-use intensity by measuring individual drivers of land-use intensity such as fertilizer use, labor use, machinery (Shriar, 2000; Turner and Doolittle, 1978; Boserup and Kaldor, 1977). Consequently, τ is by definition a comprehensive measure of land-use intensity, while input-oriented measures include only factors that have been quantified explicitly. When socio-economic data is lacking, land-use intensity can still be calculated using τ.

But τ-factor and input-oriented approaches do not only differ in terms of data requirements. Input-oriented measures deliver information about the relevance of certain inputs allowing for attributing fractions of overall land-use intensity to these inputs. In contrast, τ delivers an estimate of total land-use intensity which cannot be attributed to individual factors. However, sources of agricultural intensification do not have to be known explicitly. τ considers all determinants of agricultural intensity, except those which are explicitly excluded.

τ is defined as a factor linearly amplifying the reference yield. This linearity between τ and yield allows the direct translation of differences in τ values into differences in yields. For instance, a duplication in τ means that under fixed environmental conditions also the yield will double. On the other hand this linearity in the used definition prohibits the mapping of a τ value to a specific set of technologies. As the effectiveness of technologies typically depends on the environmental conditions the same technology will lead to different τ values at different locations.

The quality of the reference yields, which need to be derived theoretically, is an important qualification of the τ measure of land-use intensity. Currently, we use LPJmL to calculate reference yields (Bondeau et al., 2007), which leads to several unwanted disturbances in outputs: LPJmL distincts between rainfed and irrigation production and also uses a dynamic routine to set sowing dates (Waha et al., 2012). As both processes are a part of the model and cannot be switched off, intensification approaches based on irrigation and optimized sowing dates are only partially accounted for in our approach. All possible model errors and bugs also influence the calculated reference yields.

Besides the calculation of the reference yield also the availability of actual yields is a problem: FAO (FAOSTAT, 2009), our source for actual yields, reports only harvested yields, which means that multi-cropping does only lead to higher harvested areas but not to higher harvested yields. Comparing harvested yields to calculate τ, as we did, means that multi-cropping is accounted for as a natural process but not as a process for intensification. Especially, since multi-cropping was the first indicator used for land-use intensity (Boserup and Kaldor, 1977) the approach is unusual and not optimal. However, looking more into detail, multi-cropping cannot be clearly addressed to either of both sides: On the one hand, multi-cropping is, of course, an approach to intensify production and comparing two farming systems under the same, good environmental conditions the multi-cropping system will have the higher intensity. On the other hand, multi-cropping can only be applied reasonably if the environmental conditions are good enough. Therefore, it can also been seen as an indicator for the environmental conditions at a specific location.

Another problem with the FAO data is its limited resolution. Data is only available at a national level so that we are only able to calculate a single intensity per crop and country. Combined with high-resolution land-use patterns we were still able to calculate the general τ at a finer resolution, but this data is not crop-specific and has to be interpreted with care. One solution might be to use spatial-explicit data sets such as provided by Monfreda et al. (2008). However, in this case one loses the consistency between actual yields and reference yields which seemed to us more important than the use of a data set with a higher disaggregation level.

Concerning the interpretation of our global analysis, it is important to realize that low agricultural land-use intensities do not necessarily imply strong yield increases in the future. Many other limiting factors have to be taken into account when projecting future yield growth. For instance, Africa shows generally low land-use intensities, but weak institutions and political conditions in many African countries are elements that could inhibit exploiting its chances. Another factor is production costs which may increase disproportionately with yield. In this case it becomes irrelevant from an economic perspective to produce at a higher land-use intensity. Typical examples for this behavior are sparsely populated regions with high wage levels, as for instance the Western US or Canada, where labor becomes more limiting and more cost-determining than land (Runge et al., 2003; Federico, 2005).

Compared to a global yield-gap analysis by Neumann et al. (2010) most regions show a similar behavior in land-use intensities (τ) and efficiencies (yield gap analysis) for maize (see appendix Appendix E for the τ-values of maize). Exceptions are Indonesia, China and Brazil, for which efficiency levels are slightly higher compared to τ land-use intensity levels. Another study (Licker et al., 2010) comes to higher values in Brazil, Indonesia and Thailand, whereas τ indicates high levels in Peru and Bolivia. The remaining regions are quite similar, ignoring the subnational heterogeneity. The general large agreement indicates, that technological advances that cannot be captured by the yield gap analysis typically occur in conjunction with advances in management practices.

In addition, our results are in good agreement with FAO/OECD yield growth projections (OECD-FAO, 2009; Bruinsma, 2003): regions with high agricultural land-use intensities, for instance EUR or NAM, have low FAO yield growth projections, whereas AFR has low land-use intensities and high FAO yield growth projections. FAO yield growth projections for SAS are significantly higher than for CPA, which is in good agreement to land-use intensities, derived in this study. As mentioned before, low land-use intensities do not imply that future development will be strong, yet it can be assumed that increases in land-use intensity are technically easier to achieve if current levels are low.

Our approach shows that Southern Europe still has significant long-term chances for yield increases whereas Western Europe is already at a high land-use intensity. Overall the highest technical long-term chances for yield increases can be found in Africa, South and Eastern Europe and Russia and also in parts of South Asia and Latin America.

5. Conclusion

The future development of agriculture is closely connected to current agricultural land-use intensities. We have proposed an output-based measure of land-use intensity applicable for global analyses. Our analysis shows that Europe, North America and parts of Asia (China, Japan) exhibit high agricultural land-use intensities whereas Africa and countries belonging to the Former Soviet Union display significantly lower land-use intensities. Concerning further yield increases we observe that parts of Asia and nearly the whole African continent show high long-term growth chances, whereas the Eastern US, Western Europe and China use their land already on intensive levels. However, whether these chances will be exploited in the future depends on various factors such as political conditions and institutional structures which are beyond the scope of this paper.

Our concept of the measure τ is an addition to currently used measures for agricultural land-use intensity. Its data requirements make it a good alternative whenever biophysical data has a better availability than socio-economic data. Furthermore, its close relationship to the yield definition allows not only qualitative but also quantitative calculations as τ behaves under constant environmental conditions like a yield.

It is a useful measure for the implementation of technological change and related R&D investments in land-use models, because it allows for relating R&D investments to overall aggregate land-use intensity (Dietrich, 2011). Changes in land-use intensity are major determinants of future yield increases, which is one of the most important factors for future developments in the agriculture sector and scenarios of food security.

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crop	willmott coefficent
cassava	0.94
field peas	0.98
groundnut	0.98
maize	0.88
millet	0.92
rapeseed	0.98
rice	0.97
soybean	0.96
sugarbeet	0.98
sugarcane	0.74
sunflower	0.97
wheat	0.99

Table A.4: Willmott coefficients of the ability of crop growth model LPJmL to reproduce national yield levels of the 12 crops represented in LPJmL

Appendix A. Willmott coefficients of LPJmL crop calibration

Table A.4 shows the Willmott coefficients of a comparison between simulated yields of the crop growth model LPJmL and reported FAO yields.

Appendix B. Country-to-region mapping

Table B.5 shows the mapping between world regions used in this paper and countries.

Appendix C. Calculation of a general τ-factor

To get a crop-unspecific, general τ-factor for each location one has to aggregate the values for the different crop-types. Figure C.4 shows this procedure for North America (NAM) and the 12 crop-types supplied by the used LPJmL version. As one can see crop-specific τ-values within a country are relatively homogeneous, caused by the country-based calibration of actual yields. Inhomogeneities within countries are primarily caused by two factors: First, outliers due to low yield levels in reference and actual yields, so that small simulation errors have a huge impact on the results. Second, general broader scale variations, which are caused by slightly different responses of the yield levels to the LPJmL management factors. However, the overall results are primarily influenced by the country-specific calibration to FAO yield levels. Aggregating these crop-specific values to the general τ-factor one gets a picture with higher variance within a country. In this case, the variance is caused by the crop-specific differences in τ-factors in combination with the underlying land-use patterns describing the spatial crop distributions. Therefore, this combination of different crop-specific τ-factors, which were calibrated with country-specific data and

AFR **Sub-Saharan-Africa**	**CPA** **Centr.-Planned Asia**	**EUR** **Europe**	**FSU** **Former Soviet Union**	**LAM** **Latin America**
Angola	Cambodia	Albania	Azerbaijan, Republic of	Argentina
Benin	China	Austria	Belarus	Belize
Botswana	Laos	Belgium-Luxembourg	Georgia	Bolivia
Burkina Faso	Mongolia	Bosnia and Herzegovina	Kazakhstan	Brazil
Burundi	Viet Nam	Bulgaria	Kyrgyzstan	Chile
Cameroon		Croatia	Moldova, Republic of	Colombia
Central African Republic		Czech Republic	Russian Federation	Costa Rica
Chad		Denmark	Tajikistan	Cuba
Congo, Dem Republic of		Estonia	Turkmenistan	Dominican Rep.
Congo, Republic of		Finland	Ukraine	Ecuador
Cote d'Ivoire		France	Uzbekistan	El Salvador
Djibouti		Germany		French Guiana
Equatorial Guinea		Greece		Guatemala
Eritrea		Hungary		Guyana
Ethiopia		Iceland		Haiti
Gabon		Ireland		Honduras
Ghana		Italy		Mexico
Guinea		Latvia		Nicaragua
Guinea-Bissau		Lithuania		Panama
Kenya		Macedonia		Paraguay
Lesotho		Netherlands		Peru
Liberia		Norway		Suriname
Madagascar		Poland		Uruguay
Malawi		Portugal		Venezuela
Mali		Romania		
Mauritania		Slovakia		
Mozambique		Slovenia		
Namibia		Spain		
Niger		Sweden		
Nigeria		Switzerland		
Rwanda		Turkey		
Senegal		United Kingdom		
Sierra Leone		Yugoslavia, Fed Rep of		
Somalia				
South Africa				
Sudan				
Swaziland				
Tanzania, United Rep. of				
Togo				
Uganda				
Western Sahara				
Zambia				
Zimbabwe				
MEA **Middle East/North Afr.**	**NAM** **North America**	**PAO** **Pacific OECD**	**PAS** **Pacific Asia**	**SAS** **South Asia**
Algeria	Canada	Australia	Indonesia	Afghanistan
Egypt	USA	Japan	Korea, Dem People's Rep	Bangladesh
Iran, Islamic Rep of		New Zealand	Korea, Rep of	Bhutan
Iraq			Malaysia	India
Israel			Papua New Guinea	Myanmar
Jordan			Philippines	Nepal
Kuwait			Solomon Islands	Pakistan
Libyan Arab Jamahiriya			Thailand	Sri Lanka
Morocco				
Oman				
Saudi Arabia				
Syrian Arab Rep				
Tunisia				
United Arab Emirates				
Yemen				

Table B.5: Country-to-region mapping

the cellular land-use patterns allow to make statements concerning sub-national land-use intensity patterns. However, its resolution and accuracy is quite limited. In the presented example of North America the combination of different crop-specific τ-factors to a general τ-factor uncovers an East-West-divide with high land-use intensities in Eastern U.S. and lower intensities in Western U.S.. Furthermore, the combination of crop-specific τ-factors leads to smoother transitions between countries compared to intensities of single crops. For instance, differences in intensities between Mexico and the U.S. are quite obvious for wheat, rice, maize and millet. However, the transition for the generalized land-use intensity is relatively smooth at the border of both countries. Same holds true for the border between the U.S. and Canada.

Appendix D. A methodological comparison of land-use intensity τ and yield gap

Analysis of land-use intensity using τ and yield gap analysis show methodologically some fundamental differences: While yield gap analysis is measuring how much improvements are still possible compared to the potential yield, a pre-defined upper bound, the τ factor is measuring how much improvements were applied so far. If the total amount of possible improvements would be time-independent and the same for any location, both measures would always measure the same. However, this is typically not the case. The following examples show some situations in which the measures will give different results.

In the following it is assumed that the inverse of the yield gap should be used as a surrogate for land-use intensity (low yield gap $\rightarrow$ high land use intensity, high yield gap $\rightarrow$ low land use intensity). Furthermore, reference yields in the given examples never exceed actual yields. This assumption is not relevant for the outcome but simplifies the shown schematics.

Appendix D.1. Not adopted technological change (temporal behavior)

The first example illustrates differences in yield gap and land use intensity measures, when technological change takes place over time (e.g. newly bred varieties or improved production means) but is not beeing adopted (Figure D.5). Assuming constant environmental conditions our measure for land use intensity τ is unaffected: The actual yield (act) does not change as the production remains unchanged as well as the environment remains stable. Accordingly, also the reference yield (ref) does not change and τ reports constant land use intensity.

The yield gap analysis on the contrary shows an increasing yield gap, as the potential yield increases but the actual yield remains unchanged. Interpreted as land use intensity that would lead to the wrong conclusion that intensity decreases, even though production and production methods remain unchanged.

The described behavior does not only exist in the temporal domain. The following example shows a similar behavior occurring in the spatial domain.

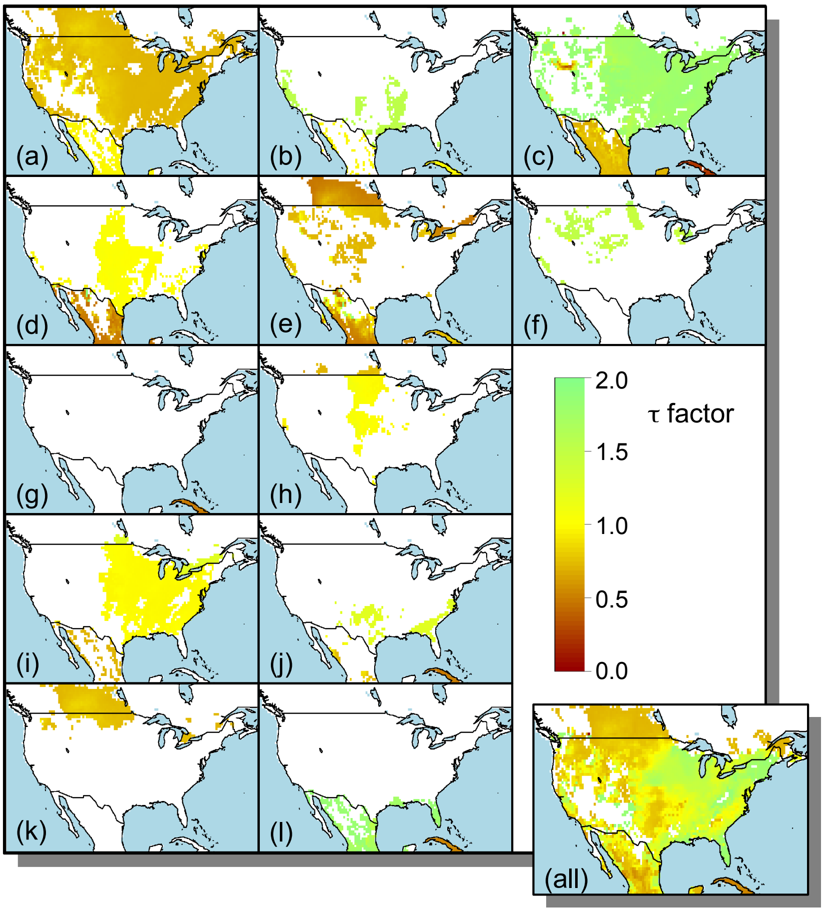

Figure C.4: crop-specific τ-factors for North America (NAM) in 2000 and their aggregate. The corresponding crop-types are: (a) wheat, (b) rice, (c) maize, (d) millet, (e) pulses, (f) sugar beet, (g) cassava, (h) sunflower, (i) soybean, (j) groundnut, (k) rapeseed, (l) sugar cane. The aggregated τ-factor, which is derived by calculating the mean over all crop-types for each cell, is marked as (all).

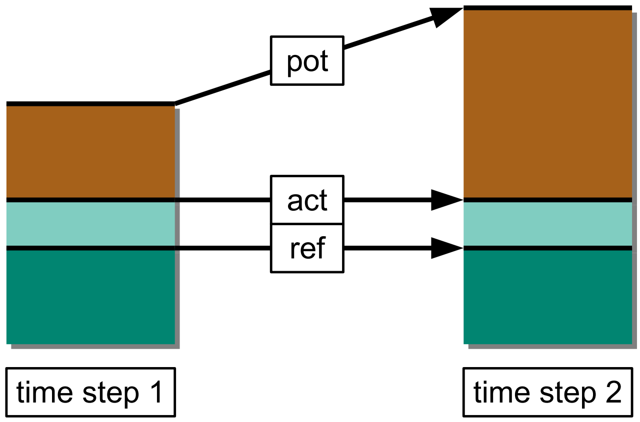

Figure D.5: Schematic evolution of reference yield (ref), actual yield (act) and potential yield (pot) over time when technological change occurs but is not adopted.

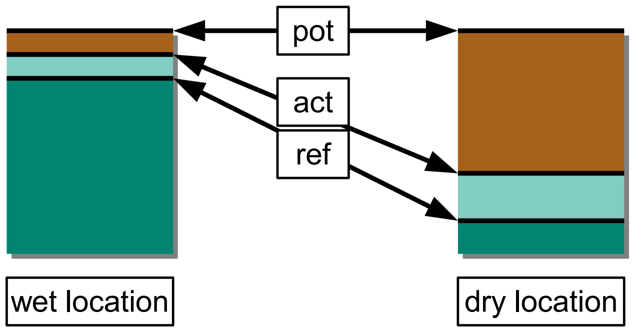

Figure D.6: Schematic comparison of reference yield (ref), actual yield (act) and potential yield (pot) on a wet and a dry location under the assumption that yields can only be increased by irrigation technologies.

Appendix D.2. A world merely equipped with irrigation technologies (spatial behavior)

This example assumes a world with agricultural yields that can only be improved by applying irrigation technologies. We compare a dry region (irrigation technologies have a major impact) with a wet region (irrigation technologies have a marginal impact) in this scenario (Figure D.6). On the wet location, there is only a small difference between potential yield and actual yield as only marginal improvements can be achieved with the available technologies, consequently the yield gap is small. As possible improvements on the location are low the difference between actual yield and reference yield is also quite low, indicating low land use intensity measured with τ.

On the dry location it is the other way around. Strong improvements are possible as irrigation technologies can significantly improve the yield: Assuming

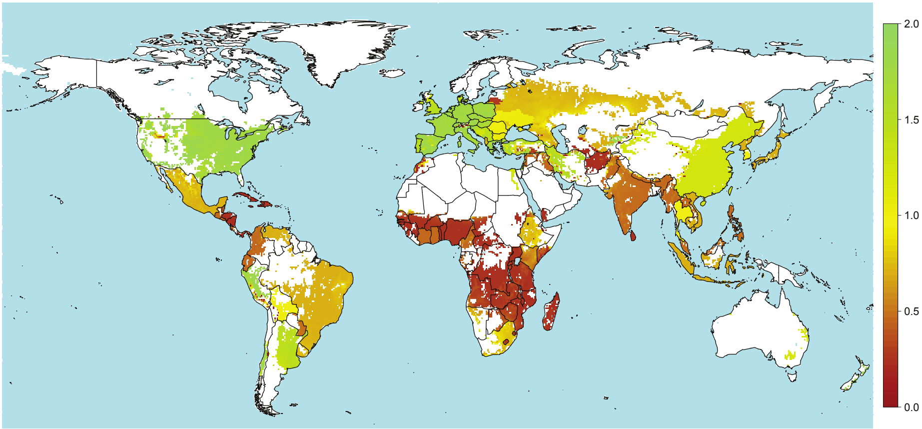

Figure E.7: Global τ-factor distribution for the year 2000 for maize

that irrigation technologies are only partially applied there is still a significant yield gap (as there is still a lot to improve) and the τ factor is relatively high (as a lot has already been done). Using the τ factor the wet location shows lower land use intensities than the dry location as there is just no possibility to intensify yields on the wet location much. At the same time yield gap analysis would report the higher intensity for the wet location not reflecting that the yields at the dry location are much stronger amplified due to intensification than on the wet location.

Yield gap analysis is a very powerful tool when it comes to comparing the current productivity levels to what is currently achievable and it is a good counterpart to an analysis with τ or another intensity measure. However, when it comes to the analysis of land use intensities in larger spatial or temporal domains (where potential yields are bound to change and very heterogeneous environmental conditions have to be considered), the yield gap analysis is less suitable than τ.

Appendix E. Agricultural land-use intensity measured with τ for maize