Essays on the Challenges of Global Land Change Science

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Content Overview

Detailed Content of the Papers

List of Abbreviations

€/tCO2	Euro per tonne carbon dioxide
2FE	Two-way fixed effects
AL	Allocation factor
ALOS	Advanced land observing satellite
AMG	Augmented mean group estimator
CCEMG	Common correlated effects mean group estimator
CD	Cross-section dependence
CET	Constant elasticity of transformation
CFI	Carbon Farming Initiative
CGE	Computable general equilibirum
CHP plant	Combined heat and power plant
CO_2	Carbon dioxide
DART model	Dynamic Applied Regional Trade Model
DDGS	Dried distillers grains with solubles
dLUC	Direct land use change
DOM	Dead organic matter
EC	European Comission
EC Guidelines	European Comission´s Guidelines for the Calculation of Land Carbon Stocks
EISA	Energy Independence and Security Act
EMPRAPA	Brazilian Cooperation of Agricultural Research
EST	Emission saving threshold
ETM	Enhanced Tematic Mapper (Landsat)
ETS	Emission trading sceme
EU	European Union
EU-JRC	European Union Joint Research Centre
EU-RED	Renewable Energy Directive
FAO	Food and Agriculture Organization
FGV	Getulio Vargas Foundation
FNR	Agency for Renewable Resources
gCO2	Gram carbon dioxide
gCO2eq	Gram carbon dioxide equivilants
gCO_2eq/MJ	Gram carbon dioxide equivilants per megajoule
GDP	Gross domestic product
GHG	Greenhouse gas
GJ	Giga joule
GMM	General method of moments
GTAP	Global Trade Analysis Project
HA	Hectare
HAC	Heteroscedasticity and autocorrelation consistent covariances
HANPP	Human appropriation of net primary production
HWSD	Harmonized World Soil Database
IBGE	Instituto Brasileiro de Geografia e Estatística

ICESat-GLAS	Ice, Cloud, and Land Elevation Satellite - Geoscience Laser Altimeter System
IFPRI	International Food and Policy Research Institute
IIASA	International Institute for Applied System Analysis
iLUC /ILUC	Indirect land use change
IPCC	Intergovernmental Panel on Climate Change
IPCC Guidelines	Intergovernmental Panel on Climate Change Guidelines for National Greenhouse Gas Inventories
ISCC	International Sustainability and Carbon Certification
kha/Mtoe	Thousand hectare per mega tonne
LCA´s	Life cycle assessments
LCFS	California´s Low Carbon Fuel Standard
LIDAR	Light detection and ranging
LUC	Land use change
MEST	Minimum emission saving threshold
MG	Mean group estimator
Mha	Mega hectare
MIRAGE	Modeling International Relationships in Applied General Equilibrium (IFPRI CGE Model)
MJ	Mega joule
NGO	Non government organization
NOAA	National Oceanic and Atmospheric Administration
NPP	Net primary production
NUTS	Nomenclature of Units for Territorial Statistic
OECD	Organisation for Economic Co-operation and Development
OLS	Ordenary least squared
PALSAR	Phased Array type L-band Synthetic Aperture Radar
POLS	Pooled ordenary least squared
POME	Palm oil mill effluent
RES-D	Renewable Energy Directive
SAR	Synthetic apertur radar
TFP	Total factor productivity
UNEP_WCMC	United Nation Environmental Programm - World Conservation Monitoring Centre
UN-REDD	United Nations Collaborative Programme on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries
US	United States
VA	Value added
WtW	Well-to-weel

INTRODUCTION

Land is arguably the world's most important and mostly used natural resource (Hertel 2013a). It currently provides 6 billion people with food, fiber, water and other benefits and enables the highest global average per capita food consumption ever (Turner et al. 2007). The pace, magnitude and spatial reach of human alterations of the Earth's land surface to obtain those benefits is undeniable (Labin et a al. 2001). The dimension of human alterations can be indicated by the human appropriation of net primary production (HANPP). It denotes the aggregate share of land use in biomass availability (net primary production NPP) each year in ecosystems (Haberl et al. 2013). The aggregate global HANPP of total NPP is roughly 24% to which agriculture contributes with 78% (Haberl et al 2007). The remaining HANPP is caused by forestry, infrastructure and human induced fires (Haberl et al. 2007).

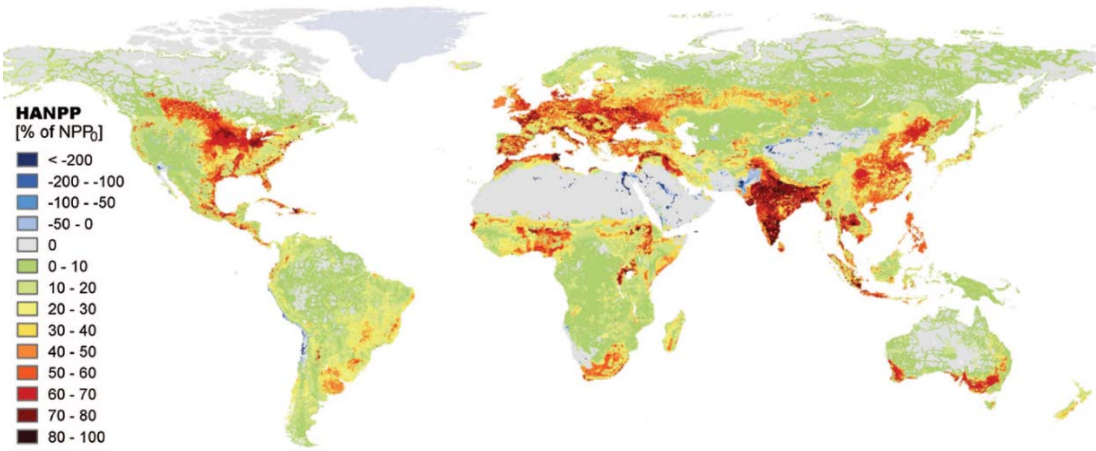

Figure 1: The global distribution of HANPP [% of NPP] in 2000

Source: Haberl et al (2007).

Figure 1 shows the global distribution of HANPP as the percentage share of total NPP in 2000. Large regional differences are visible with large parts already used intensively. There, little potential for intensifying and expanding production remains. The green and yellow areas in Figure 1 indicate the areas available for expansion and intensification of production. Major parts lie within the tropics such that an increase in production in these areas threatens other services provided by land such as carbon sequestration or biodiversity. Such threats on public goods provided by land are not new. Over the past hundred years, humans have increased the species extinction rate by as much as three orders of magnitude mainly due to habitat loss and degradation

(Millennium Ecosystem Assessment, 2005). In addition, as much as 35% of the human induced CO_2 equivalents in the atmosphere today can be traced back to the totality of land cover changes (Williams 2003).

Further land cover change for the expansion of agricultural land might be necessary nonetheless, given that by 2050 another 2 billion people need to be fed (Bloom 2011). In addition, considering potential nutrition improvements for the 2.1 billion people living of less than 2$/day, this translates into a very substantial rise in the demand for agricultural production (Hertel 2013a). The FAO forecasts that this development increases global demand by 70 percent of current production (Bruinsma 2009). The latest studies conclude that global agricultural production need to increase by 70-100% to meet the increasing demand by 2050 (Bruinsma 2009, Tilmann et al. 2011). Depending on the approach and assumptions about optimized cropping intensities and allocation of crops, studies find a potential to increase biomass production on the currently used cropland of 58-148% (Müller et al. 2012, Mauser et al. 2014). Thus, depending on the emerging intensification on the currently used cropland, further land cover changes might occur.

In order to identify potential land cover changes as a result of an increasing demand for agricultural products, an understanding of global agricultural markets is essential. Agricultural markets are increasingly globalized, disconnecting the place of consumption and production (Meyfroidt et al. 2013). This includes the dissemination of demand changes in one region to changes in land use in other regions. A prominent example of such dissemination due to globalized agricultural markets is the increase in soy production in Brazil following the BSE related ban of meat and bone meal in livestock feed in the EU (Elferink et al. 2007). The globalized agricultural markets disseminate globally price shifts following an increase in demand and so do incentives to produce more agricultural goods. As a result, the growth in global food demand in the last decades has been absorbed by few countries (Meyfroidt et al. 2013). These countries have a comparative advantage in production e.g. due to climate conditions, land availability or technology. Indonesia, for example, absorbed most of the increasing demand for vegetable oils due to favorable climate conditions and large areas of unused land. Consequently, it is likely that future demand shifts will cause land cover changes wherever agricultural production is most profitable.

The expansion into the most profitable production areas potentially endangers the public goods and services provided by land. In order to protect these non-market goods and services, researchers and NGO´s claim that the potential to expand agricultural areas needs to be restricted in the wake of growing global demands (Hertel et al. 2013a). National governments can pursue two major strategies to control expansion and therefore to promote nature conservation: Land use zoning and agricultural intensification (Lambin and Meyfroidt 2011). However, the increasing globalization of markets results also in a dissemination of the effects of regional policies on global land use. Local interventions to promote sustainable land use may have unintended effects abroad owing to a displacement of land use across countries (Meyfroid et al. 2013). A protected area e.g. might induce deforestation spillovers to neighboring areas (Andam et al. 2008).

Research has only started to understand these emerging interactions and feedbacks resulting from a global dissemination of demand shifts and policies (Meyfroid et al. 2013). The globalization of agricultural markets combined with the looming competition of environmental protection and increasing agricultural production increases the complexity of future pathways of land use change (Lambin and Meyfroid 2011). The implications of these future pathways for global environmental change and sustainability represent a major research challenge for the human environmental sciences (Committee on Global Change 1999). Moreover, research is absolutely essential since demand is already continuously increasing and several land use related policies are already in place. Decision makers need to be informed about the impact of unintended and distant consequences of environmental policies and of changing consumption patterns (Meyfroid et al. 2013). This research is undertaken by various communities joining the human, environmental, geographical and remote sensing sciences in an interdisciplinary effort increasingly referred to as land change science (Turner et al. 2007)

This dissertation adds to the field of land change sciences in three ways. (1) It analyses one much discussed driver of demand increases for agricultural products and related land use effects, namely the European biofuel policies. Since the European biofuel policies include extensive sustainability regulations in order to avoid leakage effects of biofuel production, the relationship between sustainability requirements and land use change (LUC) can be investigated. (2) In addition, the dissertation picks up the claim of researchers that intensification of production is crucial to avoid further expansion of agricultural areas in the wake of rising demands. We do this by identifying local and regional deficits in agricultural development for Brazil. (3) Finally, it exploits the increasing availability of remote sensing data as potential supplements to statistic accounts. The availability results from technological developments and increasingly open data policies. We show how remote sensing data on land use can be used to derive carbon maps in order to demonstrate the local impact of carbon polices. In addition, we analyze whether night light data are a good proxy for regional economic growth when statistical data are unavailable or of bad quality.

Part one of this dissertation which includes the first three papers focuses on biofuels production and related policies. They mirror the historical development of the research on global land use and regulation which has been largely driven by the discussion about sustainable biofuel production. The idea of using biomass for energy is not new to humanity. Up to the industrial revolution, energy and land were one and the same, converging in the production of food for human labor and fodder for draft animals (Hornborg et al. 2013). Only with the emergence of fossil fuels, a substitute to land in energy production became available. A return to biofuels should therefore transform economic theory in the reverse direction (Hornborg et al. 2013). In the face of the looming peak oil but also for reasons of energy security and rural development, bioenergy policies increasingly emerged in the beginning of this century. Today, 62 countries have e.g. biofuel targets (Global Renewable Fuels Alliance 2014).

In addition, and this is new to land related policies, biofuels are promoted for their contribution to climate change mitigation (Hertel 2013a). This is due to the fact that biofuel feedstocks sequester carbon while growing and therefore possess a neutral emission balance when burning the final fuel. Indeed, as recently as 2006, the consensus of the scientific community was that corn ethanol, in particular, could contribute significantly to greenhouse gas (GHG abatement (Farell et al. 2006). In this context, the European Commission put forward its first Renewable Energy Directive (Directive 2003/30/EG) in 2003 seeking to achieve a minimum target of 10% renewables in the transport sector by 2020. However, from around 2007 onwards, the research community started to question the climate mitigation impact of biofuel policies due to its impact on global land use change causing GHG emissions (e.g. Searchinger et al. 2008, Fargione et al. 2008, Melillo et al. 2009).

The mechanisms through which biofuels potentially cause emissions can be distinguished into direct land use change (dLUC) and indirect land use change (iLUC). dLUC occurs when land previously not used for crop production is converted to produce bioenergy crops (Plevin et al. 2010). iLUC also describes the conversion of land previously not used for crop production but for the production of food and feed. This conversion for food and feed production is caused by increasing prices for agricultural commodities following an increasing demand for agricultural feedstocks caused by biofuel policies (Gawel and Ludwig 2011, Plevin et al 2010).

As a consequence to this critique, in January 2008, the EC presented a review of the 2003 biofuel directive, which was endorsed in December 2008 with the ‘‘Directive of the European Parliament and of the Council on the promotion of the use of energy from renewable sources’’ 2008/ 0016 (COD) (referred to as EU-RED in the following). It includes a range of sustainability requirements to prevent the promotion of environmentally harmful biofuels with a particular focus on land use change. Together with the so called ‘‘climate and energy package’’ it sets a minimum GHG reduction target of 20% (relative to 1990) and a share of 20% of renewable energy in the Community’s total energy consumption by 2020.

The first paper “The GHG balance of biofuels taking into account land use change” (Lange 2011) analyzes the sustainability regulations set by the EU-RED to account for land use change in bioenergy production in detail. The investigation focusses on how regulation effects land use decisions for the production of different biofuel feedstocks in different regions of the world. This is done with the intention of evaluating whether the sustainability criteria can effectively prevent emissions from land use change and the destruction of natural habits used for bioenergy feedstock production.

Previous studies already tried to quantify the overall land use impact and related emissions of various biofuel expansion scenarios, such as Searchinger etal. (2008), Fargione et al.(2008), Melillo etal.(2009) and Valin et al.(2009). However, they did not account for the sustainability regulations set up in Europe or other world regions. Therefore they somehow modeled an ‘‘uncontrolled’’ expansion of the biofuel feedstock production which is precisely what the sustainability regulations aim to avoid. The first paper fills this gap by investigating how the inclusion of the carbon effect of land use change into the carbon accounting framework, as intended by the EU-RED, impacts on land use choices for an expanding biofuel feedstock production.

In order to do so, the first paper illustrates the change in carbon balances of various biofuels, using methodology and data from the IPCC Guidelines for National Greenhouse Gas Inventories. The results suggest that the EU-RED promotes biofuels with higher energy yields per hectare. Thus, it fosters a reduction in the land use impact of the mandate. However, it turns out that dLUC, meaning the direct conversion of natural land for biofuel production, mostly violates the EU-RED sustainability requirements. By practically prohibiting dLUC for biofuel production, the current accounting method mainly promotes biofuel feedstock production on existing cropland and thus displacement of food and feed production. This displacement increases the competition between food and fuel production on the currently available cropland area and increases the risk of iLUC. It follows that the current regulation minimizes dLUC at the expenses of increasing iLUC.

The second paper "Indirect land use change (iLUC) revisited: An evaluation of approaches for quantifying iLUC and related policy proposals" (Delzeit, Klepper and Söder 2014) focusses on how to deal with iLUC, an issue still unresolved. A major problem is the quantification of iLUC and its attribution to the increase in biofuel production. This is due to the fact that the expansion of biofuels goes hand-in-hand with an increasing demand for food products and is often an activity characterized by joint production (such as animal feed and oil production of soy). We conclude that the identification of an unidirectional causal relationship between increased biofuel production and iLUC is essentially impossible. However, iLUC-emissions are often considered to be large compared to dLUC-emissions (Plevin et al 2010) and thus might offset any contributions of biofuels to climate mitigation (Searchinger et al. 2008).

Thus, despite the problems with defining a unidirectional causal relationship between biofuel production and iLUC, there is a need for quantified estimates of alleged iLUC-emissions. However, such estimations require a comprehensive analysis of the complex agricultural production systems. Several different conceptual approaches have been used to quantify emissions from iLUC and to deduct from the iLUC-emissions the additional GHG emissions that could be attributed to biofuels. In paper 2 we review these approaches regarding their ability to quantify iLUC based on a theoretical analysis of the necessary analytical steps. We conclude that econometric and ad-hoc approaches have greater drawbacks compared to the quantification of iLUC by simulation models.

However, we argue, consistent with Dumortier et al. (2011), that for policy inferences based on the simulation models, policymakers must be aware of the effect of key assumptions driving the results of iLUC-emission estimates. Paper 2 therefore additionally reviews key assumptions identified in the literature (as done also by others e.g. Teharipour et al. 2011, Edwards et al. 2010)).

Paper 2 is unique in the sense that we align the resulting uncertainties of model results with the current EU policy proposal on how to deal with iLUC. We evaluate available model results regarding their suitability to support binding iLUC regulations. For that purpose we use results on LUC emissions (dLUC plus iLUC) resulting from the current EU biofuel mandate calculated by Laborde 2011 by using the CGE model MIRAGE. We calculate the range of total emission balances of different biofuel options by combining the resulting emissions on LUC with emissions from production processes. We then discuss the EU policy proposal in the light of the range of total emission balances. Our discussion of the current EU policy proposal suggests that a combination of an increase in the required minimum emission savings of biofuels and a limitation of biofuel production is a safe way to ensure that the production of biofuels does not cause higher GHG emissions compared to the fossil alternatives. However, welfare losses might result by ruling out biofuel options or by reducing the consumption of biofuels that could reduce GHG emissions.

The analysis in paper 2 clearly shows that in order to control for iLUC-emissions, it comes down to controlling the price effect of biofuel policies. Consequently, an important mechanism not captured by the EC policy options discussed in paper 2 is the possibility to reduce the price effect by producing feedstock for biofuels more productively than the former production for the food and feed sector. Thus, paper 2 points out that increases in productivity to reduce the price effect of biofuel policies should be a key element of EC´s iLUC regulations.

Paper3, “Policy instruments for reducing emissions from land use change: A case study for Sumatra and Kalimantan.” (Söder 2014a) provides a synthesis of the discussion on dLUC and iLUC in a case study on biofuel production in Indonesia. We show how to calculate a carbon map according to the sustainability requirements for biofuel production adopted by the EU-RED for Kalimantan and Sumatra in Indonesia. Based on the carbon map, we derive maps showing the possible emission savings that could be generated by biofuels based on palm. We evaluate these maps according to the criterion contained in the EU-RED of 35% minimum emission savings for each biofuel option compared to its fossil alternative. Paper 3 thus shows how to use available remote sensing data to illustrate the impact of sustainability regulation policies on local land use.

The analysis shows that very few areas meet the criterion in the EU-RED. Consequently, very few areas are available for dLUC that could supply biofuels for the European market. Thus, results confirm in practice the abstract analysis in paper one that the strict criterion of the EU-RED increases the risk of iLUC. However, the practical example of Indonesia clearly indicates that the real problem of avoiding iLUC is rooted in the unique regulation of the biofuel sector. All production not dedicated to the European biofuel market, which is the lion´s share of Indonesia´s production, is allowed to freely expand into forested areas. Paper 3 argues that this can only be overcome if all agricultural production is subject to a carbon regulation. In this effort, we exemplarily discuss, based on the carbon maps, different regulatory measurements and the possible impact of a carbon market on agricultural production. The results highlight that current carbon prices are too low to effectively protect tropical forest areas from being converted into palm plantations. Thus, in practice, a combination of carbon markets and sustainability certification or sustainable land use planning might be necessary to effectively protect valuable natural areas.

The conclusion that all agricultural production should to be subject to a sustainability regulation in order to obtain sustainable biofuels as proposed in paper 3 and that productivity increases are a major factor for reducing pressure on unused areas in paper 2, can be aligned to the big picture of land change research. This is because the interactions between productivity increases and land use impacts do not apply only to the biofuel sector but to all developments that increase the demand for agricultural products. This includes the increase in the global population, the increase in the demand for meat and milk products and the increase in the use of biomass in industry. Increasing production on the currently used areas for all agricultural products reduces the pressure on, so far, unused areas. This can be further triggered by a land use regulation binding for all agricultural production.

However, restricting land use change and protecting natural land is controversial since demand increases are certain and may threaten food security objectives. In addition, for some countries, agriculture represents a substantial part of the national development strategy. This conflict between economic growth and nature protection is analyzed in the second part of this dissertation with a special focus on Brazil. Brazil is the most biodiverse country on the planet and has tremendous natural carbon sinks in its six major biomes (UNEP_WCMC 2010). However, It is also the second largest agricultural producer worldwide and has the largest forecasted increases in production till 2050 (FAO 2006). However, a recent study of Strassburg et al. (2014) claims that intensification could be a suitable strategy to solve the dilemma of economic growth and nature protection. They state that it is possible to meet the increases in demand for agricultural production from Brazil by using only the already existing agricultural areas.

In Paper 4 “From the Pampas till the Amazon: Heterogeneous agricultural development” (Söder 2014b) we claim that such intensification requires substantial changes in the agricultural structure. The past intensification of land use has already resulted in substantial changes in the agricultural production structure and technology. Such changes were in particular the replacement of labor intensive crop production by mechanized sugar, soy and corn production in the Southeast and South and the replacement of extensive cattle production by highly intensive soy production in the Central-West (Martha et al. 2014, Cohn et al. 2014). Other Brazilian regions like the Northeast lack behind and have not intensified production substantially in the last decades. Thus, the agricultural sector adapted heterogeneously to several changes in the economic and political context. Differences between regions can be identified in the intensity of crop production, in the production portfolio and in the degree of mechanization in crop production.

In order to understand potential further development path of agricultural intensification, in paper 4 we study Brazil’s agricultural development between 1970 and 2006. This is done by estimating the agricultural production function and unobservable additional factors influencing output based on 6 agricultural censuses.

Given the regionally heterogeneous development in Brazil, the paper builds upon recent developments in the literature on cross-country production function estimation that allow for heterogeneity in regional production functions (e.g. Eberhardt and Teal. 2013, 2014, Bond and Eberhardt 2013). This literature shows that a severe distortion in estimates of standard panel estimators may occur when ignoring the possible presence of technology heterogeneity, variable non-stationarity and cross-section dependence between regions (Bond and Eberhardt 2013). To the best of our knowledge, this is the first time that data for the Brazilian agricultural sector is subject to this approach. The analysis further adds to the discussion on appropriate estimation of heterogeneous production functions by applying the flexible translog functional form rather than the commonly applied Cobb-Douglas functional form. We estimate a complete production function including unobservable factors driving input and output by accommodating heterogeneous regional agricultural structures.

The results show that in the South and the Southeast intensification of production is largely the result of a replacement of labor intensive crops with capital intensive crops. This happens parallel to the intensification in cattle production which has been replacing grazing with grain fed production. The results further indicate that the potential for intensifying agricultural production depends on several regional and local factors. Those are for example road infrastructure, education of the population, closeness to markets and soil fertility. The lack of these factors results in low productive agriculture and thus an extensive use of land in many regions of Brazil, e.g. in several municipalities of the Northeast. The results also confirm the importance of research on crop varieties on the potential for land use intensification. For example, the development of new soy varieties in the 80ties made possible the expansion of mechanized agriculture in the Central West.

Overall, the detected regional heterogeneous development paths highlight the need for regional or even local agricultural policies since local and regional factors favoring or hindering intensification determine the potential for economic development. This is an important result since it points out that global “one fits all” policies do not automatically trigger development. On the contrary, results pinpoint that research and policies should focus on how to eliminate local inefficiencies in the use of land.

In addition to results on land use intensification, paper 4 adds to the methodological discussion on how to estimate production functions and unobservable factors driving output in agriculture. The importance of flexible functional forms is highlighted for production function estimation in agriculture.

In addition, our approach is supported by Eberhardt and Teal (2013) who reject a homogenous production function for cross-country analysis. Paper 4 shows that the concept of regional heterogeneity in agricultural production functions holds also for within country analysis, at least for countries as large and diverse as Brazil. The use of a translog specification instead of the Cobb Douglas specification even demonstrate that heterogeneity is also contained in the elasticities of substitution between inputs and evolution of factor shares. This further enhances the idea that heterogeneity in production functions are the result of regional and local circumstances driving e.g. the applicability of available technologies.

An additional contribution to methodologies is provided in paper 5 „Night Lights and Regional GDP“ (Bickenbach, Bode, Nunnenkamp and Söder 2014). The increased availability of remote sensing data raises the question of their usability for analyzing economic questions. In particular, remote sensing data raise hopes for spatially explicit information on economic indicators not obtainable in this spatial detail from statistical accounts. Paper 3 shows how remote sensing data can support analyzing the local impact of policy instruments. However, the most prominent example for using of remote sensing data for economic questions goes one step further and uses the remote sensing data itself as a proxy for an economic indicator. Henderson et al. (2012) (and in a similar fashion Chen and Nordhaus 2011) suggest using night lights intensities as a useful proxy for the growth rate of gross domestic product (GDP). Night lights intensities may substitute for true GDP growth when GDP data is unavailable, or may help correct observed GDP data measured with error. While Henderson et al. establish this stable GDP-lights growth nexus at the country level they suggest that lights growth may proxy for GDP growth at any spatial resolution. This suggestion paves the way for addressing another set of important questions for less developed countries, namely those related to recent local or regional economic dynamics in these countries.

Chapter 5 complements the Henderson et al. study by investigating the GDP-lights growth nexus at the subnational level where it is arguably most valuable for economic research. Adopting Henderson et al.'s empirical approach, we exemplify for two large emerging economies, India and Brazil, that the relationship between the growth of lights and that of observed GDP is unstable across regions. The relationship remains unstable even if we control, as far as possible, for potential biases from measurement errors of GDP. In addition to this, we show that the relationship is similarly unstable across regions within some of the most advanced economies, the United States and Western Europe, even though GDP data is arguably of highest quality in these countries and measurement errors of GDP are therefore particularly small. Taken together, we slow down the euphoria about the direct use of remote sensing data as proxies for economic indicators. Evidence suggests that the relationship between the growth of lights and of true GDP observed at the country level does not carry over to subnational levels as easily as suggested by Henderson et al. Results, therefore, demand a careful analysis of the relationship between remote sensing data and indicators of economic development.

Overall, this dissertation contributes both to the methodological development in land change research and to the research challenges on global land use change. It contributes to the methodological development by translating the uncertainties contained in land use change modeling for the related policy debate. In addition, it contributes to the discussion on unbiased estimation of production functions in agriculture. Finally, it demonstrates two examples of the use of available remote sensing data for economic analysis. They turned out to be useful to show local land use effects of policy instruments but (so far) less reliable as proxies for growth.

It contributes to the research challenges on global land use change by discussing the theoretical requirements and the resulting methodological problems that arise when one wants to quantify the land use effect of a demand shift. It further evaluates potential policy instruments to regulate global land use by using the example of biofuels. Overall, results highlight that the unique regulation of one sector has little to no impact on global land use. Results pinpoint the need for regulation binding for all kind of land use in order to avoid leakage effects on the one hand. In the wake of increasing demand for agricultural products, intensification of production on the currently used agricultural areas is crucial on the other hand. Results further demonstrate the role of favorable local and regional conditions in promoting intensification of production. Thus, we highlight the need of future research on local obstacles impeding intensification of production. As a consequence, individual, local and regional policies to overcome these obstacles are mandatory.

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Paper 1:

THE GHG BALANCE OF BIOFUELS TAKING INTO ACCOUNT LAND USE CHANGE[1]

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Abstract:

The contribution of biofuels to the saving of greenhouse gas (GHG) emissions has recently been questioned because of emissions resulting from land use change (LUC) for bioenergy feedstock production. We investigate how the inclusion of the carbon effect of LUC into the carbon accounting framework, as scheduled by the European Commission, impacts on land use choices for an expanding biofuel feedstock production. We first illustrate the change in the carbon balances of various biofuels, using methodology and data from the IPCC Guidelines for National Greenhouse Gas Inventories. It becomes apparent that the conversion of natural land, apart from grassy savannahs, impedes meeting the EU's 35% minimum emissions reduction target for biofuels. We show that the current accounting method mainly promotes biofuel feedstock production on former cropland, thus increasing the competition between food and fuel production on the currently available cropland area. We further discuss whether it is profitable to use degraded land for commercial bioenergy production as requested by the European Commission to avoid undesirable LUC and conclude that the current regulation provides little incentive to use such land. The exclusive consideration of LUC for bioenergy production minimizes direct LUC at the expense of increasing indirect LUC.

Keywords: land use change emissions, bioenergy, European policy

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1. Introduction

The expansion of biomass production for energy uses is seen as one of the strategies to replace fossil energy sources with non-fossil renewable sources. The European Union for example seeks to achieve a minimum target of 10% renewables in the transport sector by 2020. The contribution of bioenergy to the saving of greenhouse gas (GHG) emissions has recently been criticized because – according to previous practice –land use change (LUC) emissions so far have not been included in the GHG balances of bioenergy production. This approach has ignored the fact that, in the process of production, not only does the flow of GHGs in the production process need to be accounted for, but also the change in the stock of carbon contained in the land converted for feedstock production. This is of particular importance if land that has not been used before or has been subject to other uses such as forestry or as pasture comes into use for bioenergy production.

This practice often leads to an overestimation of the carbon mitigation potential of bioenergy considering that today, deforestation and forest degradation for agricultural expansion, conversion to pastureland, infrastructure development, destructive logging and fires cause nearly 20% of global GHG emissions (UN-REDD 2009). This figure is greater than that of the entire global transportation sector and second only to that of the energy sector. In particular, Brazil and Indonesia show a correlation of large emissions from LUC - accounting for 61% of world CO_2 emissions from LUC (Le Quéré et al. 2009) - and of having the largest increase in the production of feedstocks for biofuels which is second only to the USA. It is widely agreed that in order to keep climate change impacts within limits with which societies will be able to cope, greenhouse gas emissions need to decrease substantially. This cannot be achieved without reducing emissions from the land use sector (UN-REDD 2009).

With the Renewable Energy Directive 2003 (RES-D), the European Comission (EC) put forward sustainability regulations in order to avoid undesirable LUC for the expansion of the bioenergy feedstock production area. The implications of this regulation framework for the dynamics of agricultural expansion, and therefore for the emissions caused by LUC, have so far not been analysed. Several studies have been conducted, aiming to quantify the overall LUC impact and related emissions of various biofuel expansion scenarios, such as Searchinger et al. (2008), Fargione et al.

(2008), Melillo et al. (2009), Valin et al. (2009) e.g., but they do not account for the sustainability regulations set up in Europe or other world regions. Therefore they somehow model an “uncontrolled” expansion of the biofuel feedstock production which is precisely what the sustainability regulations aim to avoid. Other studies such as Hennenberg et al. (2009) or Fritsche and Wiegmann (2008) directly address the sustainability criteria in the RES-D, but mainly focus on public consulting for a better implementation of the RES-D into national law and into practice. Due to the fact that the EC’s “Guidelines for the Calculation of Land Carbon Stocks” (EC Guidelines), a communication related to the sustainability critiria implemented by the RES-D, were only published recently, to our knowledge no other study exists that considers these additional regulations.

In this study we analyse the sustainability regulations set by the EC to account for LUC in the bioenergy production in detail. Our investigation focusses on how the regulation will effect land use decisions for the production of different biofuel feedstocks in different regions of the world. This is done with the intention of evaluating whether the sustainability criteria can effectively prevent emissions from LUC and the destruction of natural habits used for bioenergy feedstock production.

The paper is structured as follows. In section 2 we first discuss the current political framework, in particular, we analyse the Renewable Energy Directive of the EC. In section 3 we present the LUC emission calculation method on the basis of the IPCC Guidelines for National Greenhouse Gas Inventories (IPCC Guidelines) and EC Guideline and draw first conclusions on how this method impacts on LUC choices for an expanding biofuel feedstock production. In a next step in section 4.1 and 4.2, we calculate concrete examples for LUC emissions and derive the consequences for the European biofuel policy and the various biofuel options. To evaluate the examples in terms of efficiency we compare the examples by their abatement cost in section 4.3. Furthermore, in section 4.4, we discuss the particular case of the conversion of degraded land for biofuel feedstock production in order to appraise the effect of the RES-D regulations upon the competition between food and fuel. Section 5 concludes and gives further recommendations for action.

2. European bioenergy policy and LUC regulations

2.1. Towards the Renewable Energy Directive

Since the beginning of the century, the European Union extended its efforts to increase the use of bioenergy within the Community, mainly with the goal of lowering its dependency on imported oil and reducing GHG emissions in order to tackle global warming. Biofuels receive particular attention within the European bioenergy policy due to the fact that, overall, one third of the European emissions are produced by traffic. Furthermore, in the transportation sector fossil fuels mainly need to be imported from outside the EU, whereas alternative energy sources such as wind or solar energy in the electricity sector were not commercially feasible for use in the transport sector. With the "Directive on the Promotion of the Use of Biofuels or Other Renewable Fuels in Transport" (Directive 2003/39 EC), the EC sets targets of a minimum proportion of 2% biofuels in 2005 and 5,75% in 2010, relative to the total final energy use in the transport sector.

In the meantime a discussion arose about the sustainability of global biofuel production. Particularly reports about high deforestation rates in the Amazon and in Southeast Asia, two regions with a large expansion of bioenergy production, aggravated concerns about the risks of biodiversity loss and food and water shortages arising from increasing biofuel production (Goldemberg and Guardabassi 2010; Rathmann et al. 2010). In the same way the overall GHG reduction potential of biofuels was questioned when LUC emissions for biofuel production were taken into account (Fargione et al. 2008; Searchinger et.al 2008).

In January 2008 the EC presented a review of the 2003 biofuel directive which was endorsed in December 2008 with the "Directive of the European Parliament and of the Council on the promotion of the use of energy from renewable sources" 2008/0016 (COD) (referred to as RES-D in the following). It includes a range of sustainability requirements to prevent the promotion of environmentally harmful biofuels. Together with the so called "climate and energy package" it sets a minimum GHG reduction target of 20% (relative to 1990) and a share of 20% of renewable energy in the Community´s total energy consumption by 2020.

2.2. Sustainability requirements in the RES-D

The RES-D contains sustainability requirements that mainly tackle the problem of increased bioenergy production potentially causing so called “undesirable” LUC. According to the RES-D “undesirable” LUC can be categorized as LUC for bioenergy crop production from:

- high-biodiverse land and
- land with a high carbon stock.

The latter is necessary to guarantee that the European biofuel policy actually contributes to the European climate change mitigation strategy. However, since the carbon stock of different land types depends on various factors, the RES-D trys to avoid emissions from LUC for the bioenergy feedstock production through two channels:

- via a general exclusion of some land types from the suitable land type options for bioenergy production and
- via a minimum emissions reduction target.

Concerning the first channel, it is widely agreed that some land types are always carbon rich, such as wetlands, peatlands and continuously forested areas with a canopy cover higher than 30% and therefore, in the same way as high-biodiverse land, are generally excluded from the suitable land type options for the bioenergy feedstock production.(RES-D Art.17(4)). This also applies to forests with a canopy cover of 10%-30%, unless evidence is provided that their carbon stock is low enough to justify their conversion in accordance with the rules laid down in the RES-D (RES-D Art.17(4)). These rules form part of the second channel:

For the feedstock production on every field, the emissions savings of the final biofuel or other bioliquid need to be at least 35%, considering the emissions caused in the whole value chain including LUC emissions (RES-D Art 17(2))[2]. This implies that biofuel crops produced on land with a high carbon content before the conversion are less likely to achieve this target.

[2] This threshold shall rise to 50% in 2017 and to 60% in 2018 for installations whose production will start from 2017 onwards (RES-D Art 17(2)).

According to the RES-D, the method and data used for the calculation of emissions from LUC should be based on the IPCC Guidelines and should be easy to use in practice (RES-D Annex V C(10)). With the EC Guidelines the European Comission recently published a draft on guidelines for the calculation of land carbon stocks for the purpose of Annex V of the RES-D. We will discuss this method further in section 3.

In general, the EC intents to promote the cultivation of crops on degraded land for bioenergy crop production. In other words, the conversion of degraded land into cropland is explicitly defined as a “desirable” LUC. The RES-D attributes a bonus of 29 gCO_2eq/MJ (gram carbon dioxide equivilants per megajoule) in the computation of the carbon balance, if evidence is provided that the land is significantly salinated or eroded with a low organic matter content or heavily contaminated and thus unsuitable for the cultivation of food and feed production(RES-D Annex V C(9)).

The required sustainability criteria need to be met by both imported bioliquids and bioliquids produced within the Community in order to count towards the national targets of renewable energy, and thus to be eligible for financial support for the consumption of biofuels and other bioliquids (RES-D Art. 17 (1)). Consequently, compliance with the sustainability criteria should be verified for each biofuel producer (RES-D (76)). In the next section we present and analyse the sustainability requirements for LUC emissions in detail.

3. LUC emissions calculation

The contribution of biofuels to climate change mitigation can only be assessed if an exact calculation of the GHG emission balance and hence of the LUC emissions from feedstock production, is done. In this section we show how LUC emissions should be calculated from a theoretical point of view. However, as the theoretical approach is difficult to implement in practice we proceed by assessing the calculation requirements for LUC emissions in the RES-D and show how LUC emissions can be calculated in detail based on the EC Guidelines.

3.1. Calculating LUC emissions exactly: the theoretical approach

For an exact analysis of the carbon loss or gain of an area due to its conversion for a bioenergy feedstock production, several parameters need to be quantified:

- the volume of biomass above and below ground before the conversion;
- the volume of biomass above and below ground remaining after the conversion;
- the respective carbon content in these biomass volumes;
- the carbon content stored in the soil before the conversion;
- the time path of the change in the soil carbon content after the conversion until a new equilibrium is reached;
- The effect of different management techniques and different types of crops upon the soil carbon content, especially when perennial crops are used;
- The influence of local circumstances upon all these parameters, such as climate, temperature, rainfall, soil quality, etc.

On closer examination, it becomes evident that these parameters vary substantially across regions or even from field to field. In other words, for a precise calculation of the carbon gain or loss due to LUC, an analysis of the entire individual carbon dynamics of the respective area needs to be performed in a sophisticated biological model.

However, it is neither feasible nor economical to invest such effort in each LUC that occurs for an expansion of bioenergy production, as its costs would exceed all possible gains. In the following we present the approach of the EC to standardize the LUC calculation process.

3.2. Calculation requirement for LUC emissions in the RES-D

The Commission requires the LUC emissions to be calculated and summed up for a timeframe of 20 years after the conversion. The actual land use in January 2008 serves as the benchmark (RES-D Art. 17). This is due to the fact that some emissions occur during the conversion process itself and others over a long period of time after the conversion. To simplify the calculation, the LUC emissions are to be summed up and allocated in twenty equal parts to each year (RES-D Annex V C(7)). This approach is in line with the method proposed by the IPCC Guidelines, upon which the EC Guideline’s method and data are mainly based. In both documents, the basic concept for the emissions calculation from LUC is to quantify the carbon content of a certain area before the conversion and 20 years after the conversion process. The difference of both values then defines the emissions caused by the LUC.

In the following section we will outline the calculation method and provided data for LUC emissions in the EC Guidelines by, firstly, analyzing the database and, secondly, by presenting the various calculation steps necessary for deriving the complete LUC carbon balance of biofuels. This detailed exposition is important because we can already draw conclusions from the calculation method itself on the land use incentives provided by the regulatory framework.[3]

3.3. The calculation method and data for LUC emissions in the EC Guidelines

The calculation procedure set out in the IPCC Guidelines was, to a certain extent, modified by the EC. Additionally, some, but not all gaps in the data were filled, as clarified in the following section.

3.3.1. The database

The IPCC Guidelines contain inventory lists for the carbon content of several biomass categories, soil types and soil management systems. Some of these categories differentiate between climate zones and/or regions.[4]

The EC Guidelines primarily use the categorization of default values in the IPCC Guidelines. The EC, however, did add the following values: forest with a canopy cover between 10%-30%, scrubland, shifting cultivation and perennial crops. These additions were necessary in order to account for all possible cases of LUC. However, one problem still remains: it is difficult to make a clear distinction between different natural grassland and forest categories. This distinction is vital for transitions areas ranging from grassland to forest, such as the Brazilian cerrado in the Amazon region. In the case where the IPCC Guidelines contained data ranges, the EC Guidelines

[3] We concentrate our analysis on the data presented as default values in the EC Guidelines as this is the channel used to calculate LUC emissions without an individual carbon cycle assessment. The RES-D provides the option of relying totally or partly on individual calculations instead of using default values. However, we think that this will not be a common scenario due to the cost resulting from such an assessment.

[4] Depending on the available research results at the time of writing of the IPCC Guidelines, some inventory lists are quite detailed and specific, others are relatively general. The categorization in the inventory tables mainly follows the categorization used in the studies that the IPCC Guidelines are based on. This gives rise to different categorizations among the different vegetation types causing problems in the comparison of different land use types. A consistent categorization would be desirable and probably preferable to create consistent default values. Nevertheless, the IPCC Guidelines are the most extensive source available for this purpose.

chose single values. In the following we will simply refer to the EC Guidelines as the source for the calculation procedure and data, bearing in mind, though, that it is based on the IPCC Guidelines.

3.3.2. The calculation procedure

The calculation of the carbon content of an area that is to be cleared for bioenergy crop production consists mainly of two parts, according to the EC Guidelines:

- The carbon content in the living and dead biomass and
- the carbon content in the soil carbon (IPCC 2006 chapter 2.2.1. and 5.3.).

As the calculation processes of these two parameters differ, both methods will be explained in depth in the following sections. All parameters required for the calculation process can be taken from the inventory tables in the EC Guidelines.

Biomass and dead organic matter (DOM) (Eq. 1)

For biomass and DOM, the IPCC approach implicitly assumes that the entire biomass and dead organic matter are destroyed when converting the land to cropland. Therefore, carbon stocks in biomass after conversion are assumed to be zero (IPCC 2006 chapter 5.26). Consequently, the total carbon content in biomass (B_{before}) and dead organic matter (C_{DOM}) before LUC represents the first fraction of emissions caused by LUC ($C_{Biomass+DOM}$). Therefore, it is logical to say that the emissions from LUC rise with the density and the extent of the vegetation.

Eq. 1 Change in biomass carbon content

$$C_{Biomass+DOM}\left[\frac{tC}{ha}\right] = B_{before}\left[\frac{tC}{ha}\right] + C_{DOM}\left[\frac{tC}{ha}\right]$$ For annual crops

$$C_{Biomass+DOM}\left[\frac{tC}{ha}\right] = B_{before}\left[\frac{tC}{ha}\right] - B_{20years}\left[\frac{tC}{ha}\right] + C_{DOM}\left[\frac{tC}{ha}\right]$$

The EC excludes all perennial crops from the emission calculation rule for biomass carbon that the entire living and dead biomass carbon stock is destroyed in the conversion process. In the case of biofuels, this mainly refers to sugarcane and palm oil. The EC assumes that due to the perennial growth of these plants, carbon is accumulated in the sugarcane plant or palm oil tree. Thus, the carbon stock in the biomass after the conversion ($B_{20years}$) is not zero but positive, the amount depending on the crop. However, this assumptions might lead to an underestimation of the LUC emissions for perrennial crop plantations when considering that the LUC emission values represent averages over 20 years. As sugarcane plants are harvested in their entirety after a few years the carbon stored in the biomass is released into the atmosphere. The same is true for palm oil plants when they are replaced exactly after 20 years.

To choose the right value, the respective area needs to be classified according to existing land categories. The classification is crucial for the emissions from LUC allocated to this area, hence it should be done carefully. The components defining the various categories are outlined next.[5]

The first component of land categories is the climate zone.[6] The next component - the categorization of the different biomass types - is much more sophisticated. The biomass types listed in the EC Guidelines are cropland, grassland and forest. ‘Cropland’ is divided into annual cropland and perennial cropland, listing specific values for sugarcane and oil palm trees. ‘Forest’ is divided into natural forest - separated into forest with a canopy cover between 10%-30% and over 30% - and forest plantations.[7]

Natural savannah-like vegetation still seems to be a difficult component to define, despite the EC augmenting the relevant data bases. There is a special value provided for miscanthus grassland which primarily applies to subtropical grassland regions in Europe and North America. Furthermore, there is a value for ‘scrubland’, which is defined as a vegetation composed largely of wood plants less than five meter high that do not have the clear physiognomic features of trees. These values are close to those of the subcategory ‘subtropical steppe’ in the forest category of canopy cover over 30%. In the forest category for a canopy cover between 10%-30% there is also a subcategory ‘subtropical steppe’, with much smaller carbon stock values. The augmentation of the default values for biomass types in the transition areas between

[5] There are no default values for DOM (C^{DOM}) in the EC Guidelines. As it is usually of low significance for the whole carbon loss from LUC, it only has to be accounted for in continuously forested areas (EC Guidelines).

[6] The IPCC Guidelines contain a world climate map (IPCC 2006 Annex 3A.5) from which the climate zone in question can be derived.

[7] Information on typical natural forest biomass types in different world regions can be taken from a FAO world biomass map in the IPCC Guidelines (IPCC 2006 map 4.1). However, the categories used for the map are not fully consistent with the inventory table categories and, hence, can only serve as a general orientation.

pure grassland and forest was necessary in order to better account for gradual differences in biomass densities. However, in practice, a clearer definition of and differentiation between the different subcategories and geographic ranges of the typical natural grassland types existing throughout the world would make it easier to choose an appropiate value.

Soil

Changes in soil carbon content are calculated differently because the carbon in the soil can not be fully distroyed like in biomass, since it is subject to other carbon dynamics (IPCC 2006 Eq. 2.25). The procedure we present, as well as all our exemplary calculations in section 4, refers to mineral soils only. This is due to the fact that organic soils predominantly exist in wetlands and peatlands and hence are not considered suitable for bioenergy crop production by the RES-D.

The EC Guidelines, based on FAO soil classifications, contain default values of the original or natural carbon content of different global soil categories. Natural soil carbon content (C_{native}) increases or decreases depending upon different land uses (F_{LU}), management techniques (F_{MG}) or nutrition input (F_I). To what extent these factors impact upon the soil carbon content ($C_{soilbefore/soilcrop}$) differs from climate zone to climate zone. A reduction in tillage and use of degraded land increases the natural carbon content of the soil, the plantation of perennial crops stabilizes it. Annual crop cultivation with full tillage lowers the soil´s carbon content.

Eq. 2. Soil Carbon Content

$$C_{soilbefore\ /\ soilcrop}\left[\frac{tC}{ha}\right] = C_{native}\left[\frac{tC}{ha}\right] * F_{LU} * F_{MG} * F_I$$

Eq. 3. Change in Soil Carbon Content

$$C_{soilemission}\left[\frac{tC}{ha}\right] = C_{soilbefore}\left[\frac{tC}{ha}\right] - C_{soilcrop}\left[\frac{tC}{ha}\right]$$

By accounting for these factors, soil carbon content is calculated twofold (Eq. 2): once for former land use ($C_{soilbefore}$), and once for bioenergy crop production ($C_{soilcrop}$). The difference between the two values (Eq. 3) provides the soil emissions from LUC ($C_{soilemission}$).The EC added two additional values for shifting cultivation that were not included in the IPCC Guidelines. The first value accounts for mature fallow, where the vegetation has recovered and reached a mature or near mature state. The second value accounts for shortened fallow, where the forest vegetation recovery is not attained prior to re-clearing (EC-Guidelines). The presence of shifting cultivation reduces the soil's natural carbon content. There is no specific value for the biomass of shifting cultivation. Thus, it must be classified in the forest category according to existing canopy cover.

The implementation of such values for the soil carbon of shifting cultivation areas is a useful addition to certifiers, as this kind of agriculture is quite common in transition areas of tropical rain forests. Shifting cultivation areas are often declared as degraded land, and their influence on soil carbon content is similar to the influence of degradation. However, according to the RES-D definition, they are not degraded areas and hence will not gain an additional emission saving bonus.[8]

The total LUC carbon balance

After quantifying the LUC emission values of biomass and soil, the total LUC carbon balance of the produced biofuel can be computed (Eq. 4). To further develop the calculation, the emission values of biomass ($C_{biomass+DOM}$) and soil emission $C_{soilemissions}$) are added together and allocated in equal parts over 20 years. By multiplying these emissions per hectare with the energy productivity per hectare of the bioenergy crop (P), the LUC emissions per mega joule biofuel (C_{LUC}) are computed (RES-D Annex V C(7)).

Eq. 4. Total LUC emission per MJ biofuel

$$C_{LUC}\left[\frac{gCO_2}{MJ}\right] = \left(\frac{\left(C_{biomass+DOM} + C_{soilemissions}\right)}{20}\left[\frac{tC}{ha}\right] * 3{,}664\right) * \frac{1.000.000}{P\left[\frac{MJ}{ha}\right]}$$

Consequently, a biofuel crop with a higher energy productivity will have less LUC emissions per mega joule than a less productive biofuel option from the same field. In turn, it is perfectly possible that a more productive biofuel option combined with

[8] The EC excluded the "conversion" from cropland to cropland for annual crops from the LUC definition. This is reasonable with respect to the administrative burden of certification requirements but it will not account for the various impacts of tillage levels and manure inputs which can substantially change soil carbon contents. The EC provides the possibility of accounting for these effects if the producer can prove that there was an substantial impact on the soil carbon content due to a change in the above mentioned factors. This will obviously only be used for improvements in the carbon balance. Thus, in some cases the emission saving potential of the produced biofuel will be overestimated. An example of this is the change from a low tillage level to a high tillage level with a reduction of the manure input.

favourable management techniques lies within the required 35% emission savings, but a less productive one might not, despite being cultivated in the same field.

To complete the calculation of the LUC emissions, the EC allows for an allocation of the resulting LUC emission to each biofuel or its intermediate products and possible by-products (Eq. 5). The allocation factor (A) should be calculated on the basis of the energy content, that is the lower heating value. Furthermore, in the case of degraded grassland being converted for the biofuel feedstock production, the granted additional emission saving bonus (D_{Bonus}) needs to be subtracted from the LUC emissions.

In summary, the calculation method proposed by the EC Guidelines gives rise to the

Eq. 5. Total allocated LUC emissions per MJ biofuel

$$C_{LUCallocated}\left[\frac{gCO_2}{MJ}\right] = C_{LUC}\left[\frac{gCO_2}{MJ}\right] * A - D_{Bonus}\left[\frac{gCO_2}{MJ}\right]$$

following outcomes:

- the carbon content of an area rises with the density of the vegetation;
- different crops and management systems give rise to different LUC emissions;
- factors decreasing the carbon content are: intensive use of tillage and the cultivation of annual crops;
- factors increasing or stabilizing the carbon content are: the use of perennial crops and a reduction of tillage;
- the conversion of degraded grassland or shifting cultivation forest to cropland increases the soil carbon content;
- the higher the energy productivity of a biofuel feedstock, the lower the LUC emissions allocated to each biofuel unit.

It is important to further analyse the likely consequences of an accounting of LUC emission in the sustainability regulations for biofuels. For this reason, in the next section, we present a range of examples representing the main crops and the most important growing regions for biofuel feedstocks using the above mentioned calculation method and database.

4. Including LUC emissions in the carbon balance of biofuels

To avoid the promotion of environmentally harmful biofuels, the EC integrated the LUC regulation into the current Directive. In this section, we will demonstrate the likely results and consequences of this inclusion of LUC into the carbon accounting framework. We use the current rules set by the EC to show how the carbon balance of different biofuel options changes when LUC emissions are computed according to the scientific results set out in the IPCC Guidelines. The main questions driving such an assessment forward are: Which land categories in which world regions are feasible for biofuel production in accordance with the EC's sustainability criteria? Does the accounting for LUC emissions in the carbon balance become a knock-out criterion for the feasability of some bioenergy crops?

4.1. GHG calculations for the main biofuel crops

A range of examples representing the main crops and the most important growing regions for biofuel feedstocks help illustrating how the current EC rules effect their carbon balances. The method presented above can be applied to all types of LUC, as done for the examples presented here. Annex I contains the precise definition and categorization of the examples. To start with, we calculate the pure LUC emission for different previous land uses and biofuel crops. In a second part we combine the LUC emissions with the total production emission assessment of the RES-D and analyze the results with respect to the minimum emission saving target of 35% compared to fossil fuels.

Land use change emissions

The two graphs show the emissions caused by LUC for the cultivation of bioethanol (figure 1) and biodiesel feedstocks (figure 2). According to the calculation method above, we included an allocation factor for the main co-products according to their heating value based on EU-JRC Data (IES 2008) and divided them into twenty equal parts, accounting for the time path of LUC emissions. Positive values always indicate a net carbon loss from LUC, negative values stand for an additional carbon accumulation in the soil. The amount of 83.8 gCO_2/MJ emissions from fossil fuels can serve as a general orientation here.

As expected, the emissions caused by clearing forest for crop production are very high. In tropical rainforests in Brazil (248gCO_2/MJ for sugarcane and 616gCO_2/MJ for soy) and Malaysia/Indonesia (182gCO_2/MJ) in particular, emissions are extremely high because of the amount of biomass that is destroyed. The same is true for deciduous forests and scrubland with predominantly woody vegetation.

Figure 1. Land Use Change Emissions per year for various bioethanol options and former land uses

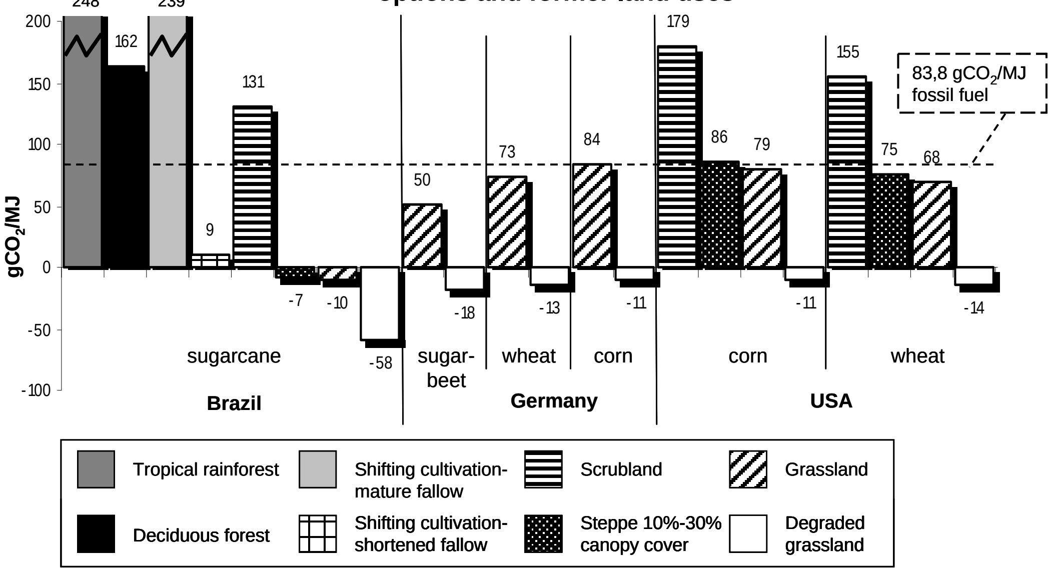
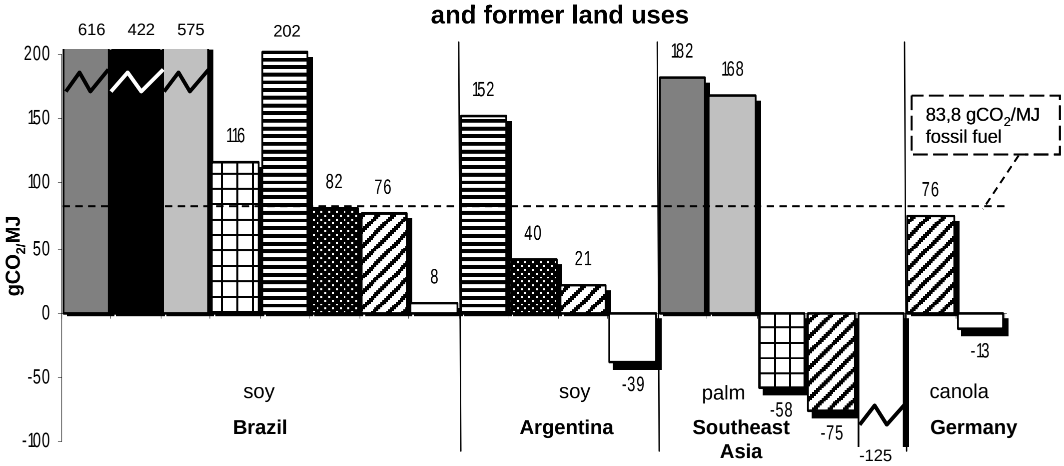


Figure 2. Land Use Change Emissions per year for various biodiesel options and former land uses



The soil carbon stock and energy productivity is more important for those land use types that contain little aboveground biomass such as steppe with a canopy cover <30% or normal grassland[9]. This can be seen for example in Brazil, where the conversion of steppe with a canopy cover of 10%-30%, that is grassy cerrado, with the subsequent cultivation of sugarcane causes a small amount of carbon accumulation (-7 gCO_2/MJ) due to the perennial growth of sugarcane, and a high energy productivity per hectare. In contrast, the conversion of the same area for the

[9] normal grassland includes natural grassland with no trees and managed pasture land

cultivation of soy for biodiesel production already causes nearly prohibitively high emissions of 82.1 gCO_2/MJ (in comparison to 83.8 gCO_2/MJ for fossil fuels). This is due to soy's lower energy productivity per hectare and the annual replantation of the crop which results in a lower carbon content in the soil and no carbon accumulation in the crop biomass. The same is true for US corn and wheat production which show similar values as soy production in Brazil for the conversion of different grassland types.

Values for shifting cultivation differ substantially for shortened or mature fallow areas converted for sugarcane production in Brazil and palmoil production in Southeast Asia. This is mainly driven by the assumption of differences in biomass density for the regrowing forest. As the LUC emission values for shortened fallow shifting cultivation, unlike those for mature fallow, still do not surpass the emission of fossil fuels, there will be an incentive for farmers to allocate their shifting cultivation areas to this category. As the transition between the two categories will be gradual in practice, the European definition should be more precise. Also, potential certifiers need to be trained in practice to be able to distinguish between the two categories.

It is important to notice the vast difference between normal grassland and degraded grassland. Apart from the conversion of grassland to sugarcane or palm oil cultivation, the conversion of normal grassland, including grassy savannahs, leads to relatively high emissions. In contrast, the emissions resulting from the conversion of degraded grassland are much smaller, often even negative. This can be seen even clearer from all German and American biofuel options where the conversion of degraded land always leads to an accumulation of carbon in the soil whereas the conversion of normal grassland already causes relatively high emissions (e.g. 76gCO_2/MJ for canola). The differences between these two, at first sight closely related, categories clearly show that a more precise and differentiated definition of various grassland categories and their geographically explicit identification on a global scale is urgently needed.

The full carbon balance

To derive the full carbon balance (C_{Total}), we now combine the LUC emissions ($C_{LUCallocated}$) with the calculation of the total process emissions caused by the production of the biofuel based on the calculation procedure in the RES-D (Eq.6). In order to do so, we add the LUC emissions to the typical total production pathway emission values that can be directly taken from the RES-D (C_{WtW}) (RES-D Annex V C (1) and (7)).

The resulting emission values need to be evaluated with respect to the minimal emission saving target of 35% in comparison with fossil fuels. By doing this, the

Eq. 6. Total allocated emissions per MJ biofuel

$$C_{Total}\left[\frac{gCO_2}{MJ}\right] = C_{LUCallocated}\left[\frac{gCO_2}{MJ}\right] + C_{WtW}\left[\frac{gCO_2}{MJ}\right]$$

main result of this assessment are illustrated in figure 3 for bioethanol and 4 for biodiesel becomes immediately apparent:

- The conversion of natural land for bioenergy production almost never meets the 35% target and in most cases even leads to much higher emissions than the use of fossil fuels.
- The only exceptions are Brazil, with 80% emission savings when grassy steppe or 60% when shortened fallow forest is converted for the sugarcane bioethanol production and Southeast Asia with 131% emission savings[10] when shortened fallow forest is converted for palm biodiesel production[11].
- Except for soy biodiesel production in Brazil, the conversion of degraded grassland for bioenergy crop production leads to high emission savings, which meet the 35% reduction target.[12] Moreover, for all German, American and Argentinean biofuel

[10] As mentioned before, this very high emission saving results, to some extent, from the assumption that palm oil cultivation accumulates carbon in the palm biomass.

[11] The distinction between „not specified" and „methane capture" for the palm oil production in Figure 4 as well as the distinction between „not specified" and „straw CHP plant" in Figure 3 result from different values used for the production process emissions. This differentiation is equivalent to the default value categories for production process emissions in the RES-D.

[12] All calculations for degraded land were done assuming the same productivity as for non degraded land. In practice this is not neccessarily the case. The energy productivity per hectare might be much lower on degraded land because of less fertile soils. Hence, the actual emission savings of biofuel

options considered in these examples, degraded grasslands provide the only option of expansion into non-agricultural land in order to meet the sustainability requirements of the EC.

Figure 3. Total emission savings (%) per year of various bioethanol options and former land uses

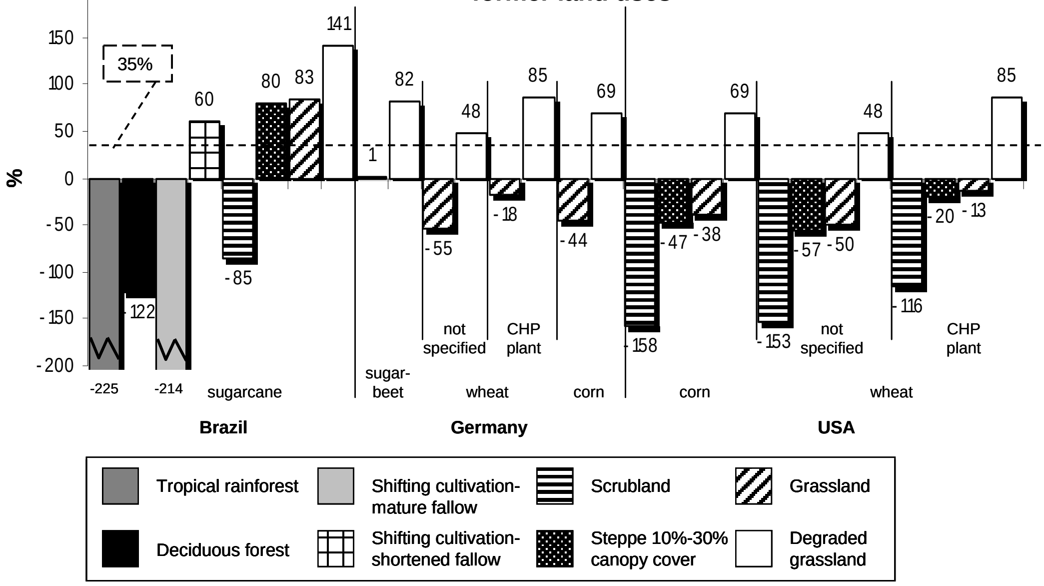
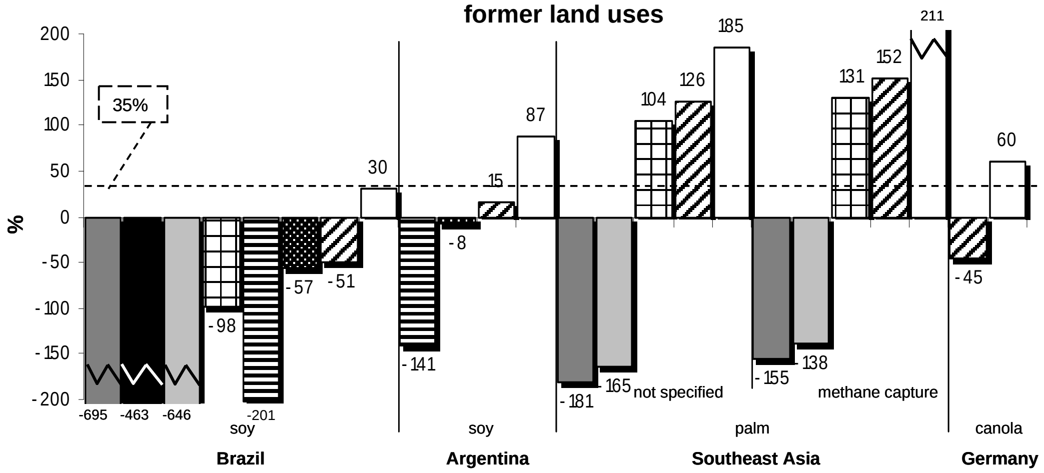


Figure 4. Total emission savings (%) per year of various biodiesel options and former land uses



4.2. Consequences for the regulatory framework and for the choice of a particular LUC

Based on the examples presented in the previous section we draw a number of conclusions from the current regulatory framework. We also suggest adjustments to the regulations, in order to make the carbon accounting more target-oriented and to

options produced on former degraded land could be much lower in reality. For further discussion see section 4.4.

improve the incentives for climate friendly production of biofuels. We draw the following conclusions:

- The accounting method for LUC emissions as prescribed by the EC Guidelines creates incentives to use areas with little or no vegetation cover, such as cropland and grassland, as well as using crops with a high energy productivity per hectare and improved management techniques.
- The variation in the carbon balances emphasize the need for assessing LUC emissions individually for each field and farm. Overall default values, for example for a region or country, would not identify the highly differing LUC emissions from different land uses and crop types. Brazil is a key example of a country where one single biofuel option has a vast range of carbon balances due to the variety of previous land uses of the crop area.
- The classification of high conservation value areas as so called "no-go areas" for bioenergy crop production is not necessary in all cases, since practically all potential high conservation value areas do not meet the emission saving target. It could ease the work of certifiers if natural land in general was excluded from the areas considered suitable for the production of bioenergy crops.
- An exception in this context is the positive emission saving of 80% for sugarcane production on former steppe with a canopy cover <30% in Brazil. There are vital strong commercial interests in Brazil to convert the *cerrado,* which, to a large extent, is already used for extensive cattle grazing. This is due to the fact that this vegetation type is dominant throughout Central Brazil and represents the main agricultural expansion area. Thus, especially for natural grasslands and savannah-like vegetation in Central Brazil, the differentiation between steppe and scrubland needs to be specified and enhanced by specific default values which consider the different vegetation types specific to Central Brazil. Furthermore, for this region, the identification of bio-diverse hotspots and high conservation value areas is extremly important.
- The results support the hypothesis that crop production for bioenergy which meets the RES-D targets is likely to take place on land already in crop production. In many regions of the world the main potential expansion area for crop production is degraded grassland. The current vague classification of various grasslands

creates the potential risk of not being certified when converting grassland to cropland. This might result in a tendency to not use the expansion areas for biofuel crop production. Hence, the current certification requirements would increase the competition between food and biofuel production. In other words, the RES-D avoids direct LUC for bioenergy production at the cost of promoting indirect LUC.

One can argue that the results based on the IPCC data are questionable due to data augmentation requirements and the employment of a standardized calculation method that does not account for every individual characteristic of an area. We already identified the need to augment existing data sets and to define different land use types more precisely. However, the results, particularly for areas with a dense vegetation cover, are clear and it is unlikely that more precise assessments will change the overall results.

4.3. Abatement Costs

It is common practice, when comparing different options of renewable energy, to evaluate them according to their abatement cost. In the case of renewable energies, this refers to the marginal cost of the energy option to abate one unit of GHG emissions. This concept captures not only the emission mitigation potential of a renewable energy option, but also its economic performance. The aim of using the marginal abatement cost as a criterion to evaluate different renewable energy sources is to assess the efficiency of a climate policy. Emissions should be reduced at the lowest cost possible. This concept can also be applied to biofuels. By only choosing biofuel options with the lowest abatement cost, the mitigation goal of the European Commission could be achieved efficiently: that is, at lowest cost.

Figure 5. Abatement cost of various biofuel options when accounting for LUC emissions

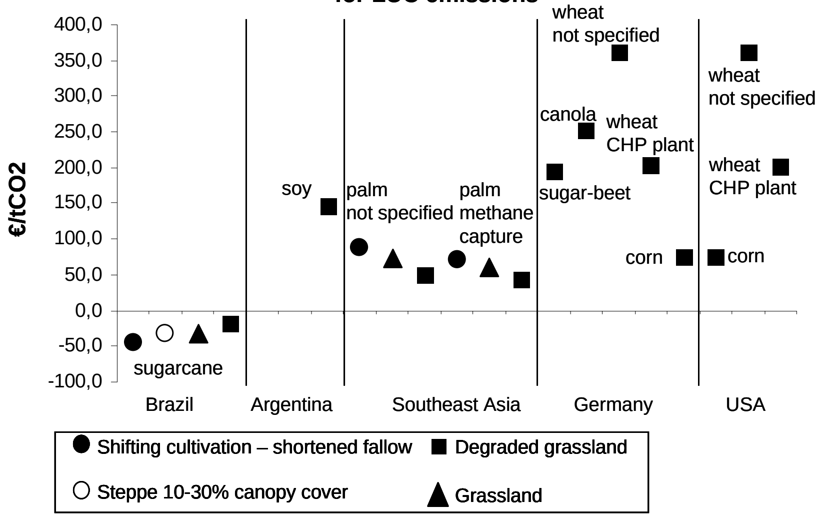


Figure 5 shows the abatement cost for the LUC emission examples used in Figures 1.-4. by dividing the production cost difference of the respective fossil fuel and biofuel by the emission savings of the biofuel. The cost for production and fossil fuels are based on FNR[13] 2007 data. Fuel costs were converted from US Dollars into Euros at the average US Dollar exchange rate of 2007. Naturally, we only used the examples that realize emission savings and skipped those with higher total emission than the respective fossil fuel.

The examples in figure 5 clearly show that biofuel options that are already highly productive in terms of a higher energy yield per hectare and, consequently, lower emissions per energy unit, also have advantages when it comes to cost per energy unit. This can be seen for example from negative abatement cost for sugarcane. Nevertheless, for some feedstocks, the differences in performance were lessened due to differences in production cost. Corn ethanol from degraded grassland, for example, costing 75€/tCO_2, comes close to the abatement cost of palm oil biodiesel from degraded grassland with 49€/tCO_2, despite this palm oil biodiesel option having with 0,155 tCO_2/GJ 3 times the emission saving of corn with 0,058 tCO_2/GJ (see figure 4). This is due to a difference in the underlying 2007 production cost of 19€/GJ for palm oil biodiesel and 16€/GJ for corn ethanol.

The only crop that achieves negative abatement cost is sugarcane because its production costs are lower than those of fossil gasoline. The problem with the

[13] Fachagentur für Nachhaltige Rohstoffe: Agency for Renewable Resources of the German Federal Ministry of Food, Agriculture and Consumer Protection

concept of abatement cost is the fact that it results in a scaling problem when it comes to negative values. The negative values need to be interpreted as cost savings by using the biofuel instead of the fossil fuel with respect to the total emission savings. Thus, with rising emission savings, the cost savings per unit of emissions saved decreases. This scaling problem was not touched upon by other studies (e.g. Kopmann et al. 2009), as they only considered one negative value for sugarcane. When differentiating between them by different LUCs, an option with lower emission savings will have more negative abatement costs than an option with higher emission savings. This mathematical problem cannot be solved without losing the entire meaning of the calculation of abatement cost. Therefore, we maintained the resulting negative values for sugarcane but did this keeping in mind that the scaling should be the other way around. Nevertheless, it becomes clear that sugarcane ethanol is by far the lowest cost biofuel option in terms of greenhouse gas savings and degraded grassland is the efficient option amongst the range of LUCs.

Amongst biodiesel, palm oil is the efficient option. However, when assuming a carbon price of 15-20 € per tonne CO_2 in the ETS, even the cheapest biodiesel option is still not competitive enough in comparison with other emission mitigation options. In the future, though, this may change if production costs decline.

Consequently, to realize an efficient climate policy, ethanol from sugarcane from converted grassland or degraded grassland should be the first option from amongst the biofuels available. The fact that the abatement cost of all other biofuel options by far supass the current ETS prices indicates that there are much cheaper options for abating carbon dioxide emissions than biofuels. Therefore, regarding an efficient greenhouse gas mitigation strategy, policies should concentrate on alternative mitigation options, unless the productivity rates of biofuel feedstocks increase substantionally. [14]

4.4. The particular case of degraded land

Considering that degraded grassland is the only option for Argentinean soy, German wheat and canola, and US wheat - if they were to achieve the minimum reduction target of the RES-D, there is a need to define these degraded grassland areas more precisely and then identify these areas on a global scale.

[14] This might be the case if second generation biofuel that are more productive and less land intensive would become commercially available.

Studies that try to compute the global potential for bioenergy production often refer to the degraded land areas that could be brought back into productive use. Such assessments indeed provide a figure – albeit currently still with a high margin of uncertainty – for the overall bioenergy potential. Estimates by Houghton (1993) (cited in Field et al. 2007) are based on areas of tropical land formerly forested but not currently used for agriculture, settlements or other purposes. He calculates a global area of 500 Mha of degraded land. Field et al. (2007) estimate that abandoned agricultural land accounts for 385-472 Mha based on an analysis of historical land use data.

When degraded land is recultivated for biofuel production, the favourable carbon balance of degraded land and the avoidance of competition with food production offer the opportunity of producing bioenergy without significant side effects. As the granted bonus for the use of degraded land is indeed the only instrument in the European biofuel policy to reduce such competition, the question is whether it sets effective incentives to use degraded areas. In this section we investigate whether the regulatory framework of the RES-D[15] indeed fosters the expansion of bioenergy, predominantly into degraded land.

The extent to which degraded land will actually be used for such activities depends on the incentives given to farmers in their decision about allocating their land to either food or biofuel feedstock production. This decision is primarily determined by the market prices of the different crops available to the farmer. The conflict between food and energy crops remains as long as the price signals do not favour decisions to bring degraded land into production. In other words, the political incentives need to be set in such a way that the bioenergy crop production on degraded land is more profitable than on cropland.

Important determinants that influence the profitability of bringing degraded land into use are production cost differences and political incentives:

[15] The RES-D provides a relatively precise definition of degraded lands as it offers the emission bonus for the use of degraded land for bioenergy production. It is important to notice that this definition does not distinguish between grassland and cropland and seems more restrictive than the IPCC Guidelines definition as degraded land needs to be *severely degraded* or *heavily contaminated*. For the practical implementation it would be necessary to verify whether the data and studies used in the IPCC Guidelines actually match the requirements for degraded land as set out in the RES-D and can thus be applied when calculating LUC for degraded land according to the RES-D.

Production cost differences depend on:

- investment cost for the restoration of degraded land for agricultural production
- differences in yields per hectare on degraded cropland relative to non-degraded land.

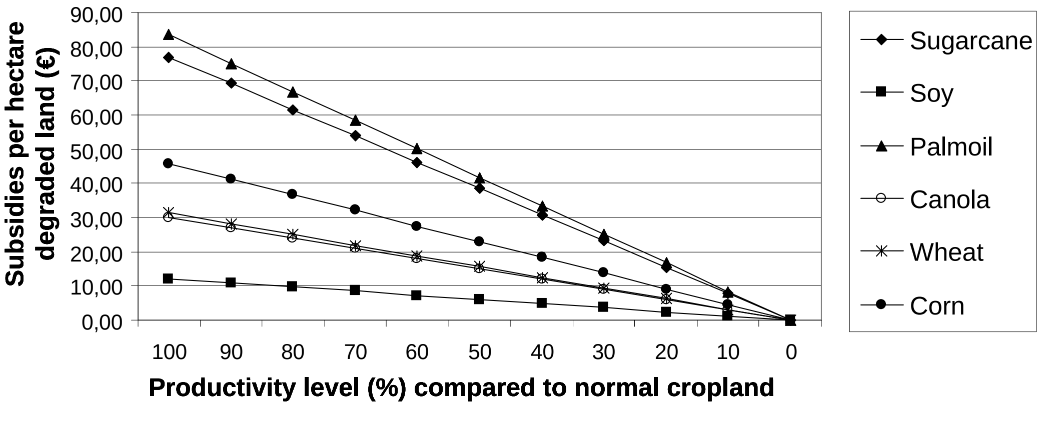
Political incentives depend on:

the incentives given by the emission bonus for LUC on degraded land that is granted by the RES-D. This procedure leads to computed (but not actual) emission savings for the final biofuel, which, in most cases, are higher than those on cropland. With this policy, Member States can achieve their emission reduction targets with a smaller amount of emission savings from biofuels than the true carbon balance. Therefore, these biofuels from degraded land can gain a premium in the market depending on the amount of emission savings.

Currently the bonus of 29gCO_2/MJ acts as an indirect subsidy for production on degraded land. We made an exploratory calculation of the incentives this bonus system creates. For these calculations we assumed that the CO_2-prices of the ETS represent the premium for emission savings.

In Figure 6 we assumed a constant carbon price of 20€/tCO_2 and computed the subsidies per hectare of degraded land for different biofuel crops at various productivity levels. Since the bonus is granted per mega joule fuel, more productive biofuel crops such as sugarcane and palmoil, receive a higher subsidy per hectare. The subsidies vary strongly for the different crops cultivated.

Figure 6. Subsidies per hectare degraded land for different productivity levels under a constant carbon price of 20€



This setting of the degraded land bonus further implies that a strongly degraded land – i.e. land with low productivity compared to the productivity on normal cropland – receives a lower subsidy per hectare than less degraded land. This does not seem to be a suitable framework for fostering the use of degraded land. On the contrary, the higher the level of degradation, the higher are investment costs for restoring the area and the lower is the expected productivity.

Lets consider the example of canola biodiesel to get an idea of the monetary impact of the subsidy. We assume that the producer realizes a price at the market for the canola biodiesel that is equal to the production cost on normal cropland. Based on 2007 FNR data, for canola biodiesel this means a price of 24 €/GJ or 1248 €/ha with an underlying productivity of 52 GJ/ha. We ignore possible investment cost and keep the assumption of a carbon price of 20 €/tCO_2. It turns out that already with a productivity level of 97% of the degraded land, the subsidy of 29.56 €/ha for this productivity level is not sufficiently high anymore to compensate for the decrease in rent compared to normally productive cropland which declines to 1210.56 €/ha under these assumptions. Doing the same for Braszilien sugarcane, this productivity threshold is achieved at a productivity level of 93% compared to normally productive cropland.

Thus, under the current regulatory structure it is more likely that the subsidy creates incentives for using areas with very little degradation and highly productive crops, particularly sugarcane and palm. Otherwise the bonus is not high enough to exceed the loss from investment costs and lower productivity. However, it is highly questionable whether a degree of degradation, of say 2-7%, fits into the definition of "highly salinated" and "highly contaminated" of the RES-D. Consequently, the RES-D definition is likely to create only limited incentives for using such land since the bonus becomes very small for higher levels of degradation. A better alternative for the calculation of the granted bonus would be to increase subsidies with the level of degradation of an area and to distribute it directly per hectare.

5. Conclusions

We analyzed the EC´s current sustainability regulations for biofuels with respect to LUC. The RES-D aims to control direct LUC by entirely excluding peatland, natural forest and other high bio-diverse land from the conversion to bioenergy crop production. Furthermore, to monitor the emission saving target of 35% when compared to fossil fuels, the emissions from direct LUC for bioenergy crop cultivation need to be added to the process emissions of the biofuel option. For the calculation of emissions from LUC, the EC recently published a Communication with guidelines for a standardized calculation method based on method and data of the IPCC Guidelines for National Greenhouse Gas Inventories as a detailed individual accounting of the carbon cycle for each production area is not practical.

We illustrated the proposed procedures and highlighted the consequences of including LUC into the carbon accounting framework. We found that the conversion of natural land for bioenergy production almost never meets the minimum emissions reduction target of 35% and in most cases even leads to much higher emissions than the use of fossil fuels. Consequently, concerns about the protection of high conservation value areas would automatically be resolved since the integration of LUC emissions would already prohibit the use of such areas. The identification of high biodiversity hotspots is necessary only for grassy savannahs, especially in Brazil as it is classified as natural land with a small vegetation cover but often a high level of biodiversity. The precise identification and distinction between different types of natural savannah-like vegetation is of particular interest to the Brazilian sugarcane production, as the high energy productivity of sugarcane results in emission savings when converting grassy savannah.

In addition, we found that the current arrangement of the RES-D predominantly promotes crop production for bioenergy on land already in crop production. Hence, the current certification requirements would increase the competition between food and biofuel production. To avoid such a competition effect between food and fuel production, the EC aims at promoting the expansion of bioenergy production on degraded land by granting an emission bonus for biofuel crops planted on such land. Our results support such a policy. Our examples showed that - apart from growing biofuel feedstocks on normal and designated croplands - degraded grassland is the only option for Argentinean soy, German wheat and canola, and US wheat in order to achieve the minimum reduction target of the RES-D. Nevertheless, we critically examined whether it is profitable, even with the degraded land bonus, to use such degraded land for commercial bioenergy use since degraded land is most likely to be less productive than normal cropland and requires investment costs for the restoration of the area.

By assuming that a market premium is paid for a biofuel option with higher emission savings the degraded land bonus serves as an indirect subsidy. We showed how under the current arrangement the subsidy per hectare of degraded land falls with the level of degradation. Therefore, it is likely that only limited incentives for using such land are created, since the bonus becomes very small for higher levels of degradation. The current arrangement should be changed into an incentive system that increases with the level of degradation and is high enough to make the use of degraded land more profitable than the use of cropland for bioenergy crop production.

Our results illustrate that the accounting for LUC in sustainability requirements for bioenergy production creates incentives to use cropland for bioenergy production and – as a consequence - to convert natural land or pasture for other agricultural uses such as food production. In other words, the current regulatory system taking LUCs into account minimizes direct LUC at the cost of increasing indirect LUC. At the same time, we have so far not come across a convincing proposal to implement indirect LUC into the LUC assessment of biofuels because of the underlying complex global land use dynamics. Instead, we propose subjecting all agricultural activities to a carbon accounting system. Hence, the burden of LUC would always be imposed upon the activity replacing the previous type of land use. Thus, all LUC would, by definition, be direct LUC. Unfortunately, the implementation of a global system of GHG accounting for all agricultural products still seems a long way off. However, in the meantime, the risk of ILUC through biofuels can be reduced by promoting high energy productive crops and biofuel feedstock production on degraded land.

Finally, it needs to be pointed out that the LUC as well as the ILUC problems of biofuel production need to be considered in the context of an increasing scarcity of the globally available land area with several competing uses. Especially the rising world population with an increasingly milk and meat intensive - and thus land intensive - diet will likely require an expansion of agricultural areas at the expense of other land uses. Erb et al. (2009) show that the bioenergy potential, the development of agricultural production technologies and the shift to a more vegetarian diet are closely interrelated with respect to their demand for fertile land. Thus, the land use change following an increasing biofuel feedstock production would be smaller the less area were needed for food and feed production which in turn depend on diets and the advance in agricultural productivity. Consequently the degree by which the European regulations aggravate the competition between food and fuel by promoting biofuels mainly from agricultural areas depends in the long term strongly on the development of global diets and investments in agricultural technologies.

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Appendix A

The following tables represent the assumptions underlying the examples in figure 1-4. They are based on the categorization in the EC Guidelines for land use categories and the RES-D for the production pathway emissions. For the categorization of the climate region and the soil type, the IPCC climate map and the FAO world soil map were used respectively. The examples were chosen so that they represent a typical production area in the regions. We deliver these tables in order to make clear that results might differ when other assumptions are made in categorizing a land area. This mainly refers to the assumptions made for the soil carbon factors concerning tillage practice and manure input.

Bioethanol options: Assumptions for Examples in Figure 1. and 3.

country	crop	vegetation category	climate	soil	Biomass: land use before	Biomass: cropland	Soil:land use before	Soil: cropland	Bonus
Brazil	sugarcane	rainforest	tropical wet	LAC	tropical rainforest >30%	sugarcane	no management	perrennial crop/ no tillage	no
		shifting cultivation mature fallow			tropical rainforest >30%		shifting cultivation / mature fallow		no
		shifting cultivation shortened fallow			tropical rainforest 10-30%		shifting cultivation / shortened fallow		no
		deciduous forest	tropical moist		tropical moist forest		no management		no
		steppe			subtropcial steppe 10-30%		no management		no
		scrubland			tropical scrubland		no management		no
		grassland normal			grassland		normal managed/natural land		no
		grassland degraded			grassland		severely degraded		yes
Germany	sugarbeet	grassland normal	cool tempered moist	HAC	grassland	zero	normal managed/natural land	annual crop / full tillage	no
		grassland degraded			grassland		severely degraded		yes
	wheat not specified	grassland normal			grassland		normal managed/natural land	annual crop / full tillage	no
		grassland degraded			grassland		severely degraded		yes
	wheat straw CHP plant	grassland normal			grassland		normal managed/natural land	annual crop / full tillage	no
		grassland degraded			grassland		severely degraded		yes
	corn	grassland normal			grassland		normal managed/natural land	annual crop / full tillage	no
		grassland degraded			grassland		severely degraded		yes
US	corn	scrubland	subtropical	HAC	subtropical scrubland	zero	no management	annual crop / full tillage	no
		steppe			subtropical steppe 10-30%		no management		no
		grassland normal	warm tempered moist		grassland		normal managed/natural land		no
		grassland degraded			grassland		severely degraded		yes
	wheat not specified	scrubland	subtropical		subtropical scrubland	zero	no management	annual crop / full tillage	no
		steppe			subtropical steppe 10-30%		no management		no
		grassland normal	warm tempered moist		grassland		normal managed/natural land		no
		grassland degraded			grassland		severely degraded		yes
	wheat straw CHP plant	scrubland	subtropical		subtropical scrubland	zero	no management	annual crop/ full tillage	no
		steppe			subtropical steppe 10-30%		no management		no
		grassland normal	warm tempered moist		grassland		normal managed/natural land		no
		grassland degraded			grassland		severely degraded		yes

Biodiesel options: Assumptions for Examples in Figure 2. and 4.

country	crop	vegetation category	climate	soil	Biomass: land use before	Biomass: cropland	Soil:land use before	Soil: cropland	Bonus
Brazil	soy	rainforest	tropical wet	LAC	tropical rainforest >30%	zero	no management	annual crop/ no tillage	no
		shifting cultivation mature fallow			tropical rainforest >30%		shifting cultivation / mature fallow		no
		shifting cultivation shortened fallow			tropical rainforest 10-30%		shifting cultivation / shortened fallow		no
		deciduous forest	tropical moist		tropical moist forest		no management		no
		steppe			subtropcial steppe 10-30%		no management		no
		scrubland			tropical scrubland		no management		no
		grassland normal			grassland		normal managed/natural land		no
		grassland degraded			grassland		severely degraded		yes
Argentina	soy	scrubland	warm tempered try	HAC	subtropical scrubland	zero	no management	annual crop/ no tillage	no
		steppe			subtropical steppe 10-30%		no management		no
		grassland normal			grassland		normal managed/natural land		no
		grassland degraded			grassland		severely degraded		yes
Southeast Asia	palm not specified	rainforest	tropical wet	LAC	tropical rainforest >30%	palm plantation	no managment	perrennial crop/ no tillage	no
		shifting cultivation mature fallow			tropical rainforest >30%		no managment		no
		shifting cultivation shortened fallow			tropical rainforest 10-30%		no managment		no
		grassland normal			grassland		normal managed/natural land		no
		grassland degraded			grassland		severely degraded		yes
	palm methane capture	rainforest			tropical rainforest >30%	palm plantation	no managment	perrennial crop/ no tillage	no
		shifting cultivation mature fallow			tropical rainforest >30%		no managment		no
		shifting cultivation shortened fallow			tropical rainforest 10-30%		no managment		no
		grassland normal			grassland		normal managed/natural land		no
		grassland degraded			grassland		severely degraded		yes
Germany	canola	grassland normal	cool tempered moist	HAC	grassland	zero	normal managed/natural land	annual crop / full tillage	no
		grassland degraded			grassland		severely degraded		yes

Paper 2:

INDIRECT LAND USE CHANGE (iLUC) REVISITED: An evaluation of approaches for quantifying iLUC and related policy proposals[16]

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Abstract:

Biofuel policies in the transport sector that aim to contribute to climate policy targets have been criticised over the last several years. Among other concerns, their contribution to save greenhouse gas emissions has been challenged. A still unresolved question in this regard is how to address emissions from indirect land use change (iLUC). This paper reviews approaches to quantify iLUC emissions and is the first to evaluate these emissions with respect to their ability to correctly quantify iLUC and their implications for regulating iLUC caused by biofuel production. We conclude that econometric and ad-hoc approaches have greater drawbacks compared to the quantification of iLUC by economic simulation models. By examining economic simulation models, we find that such models still contain a high level of uncertainty with respect to key model parameters. Further, we conclude that it is inappropriate to calculate crop-specific emissions from iLUC. We argue that modelling results, particularly crop-specific ones, should not be used for policy decisions. Our discussion of the current EU policy proposal suggests that a combination of an increase in the minimum emissions savings threshold and limits to biofuel production is a safe way to ensure that the production of biofuels does not cause higher greenhouse gas emissions when compared to the fossil alternative.

Keywords: biofuels, indirect land use change, EU biofuel policies, economic simulation models

[16] Unpublished manuscript

1. Introduction

The production of biofuels in the transport sector of the European Union (EU) has been promoted for over a decade, but the question on how to address the so-called indirect land use change (iLUC) effects remains unresolved. This situation is the result of massive problems in the scientific community related to its inability to deliver reliable numbers regarding the exact amount of emissions from iLUC (ILUC emissions). This paper is the first to offer insights into the sources of uncertainty regarding the scientific results on the quantity of iLUC emissions and to discuss the implications of these uncertainties for regulating iLUC caused by biofuel production. Furthermore, in this paper, we disentangle various quantifications of iLUC emissions by reviewing the pros and cons of various approaches. Differences in assumptions and technical details are explained wherever they significantly influence the result of the iLUC emission assessments. This paper adds important insights to the debate on how to address the indirect land use change (iLUC) compared to existing reviews on LUC modelling (e.g., Galub and Hertel (2012) and Dumortier et al. (2011)). We explain opportunities and challenges when using scientific results for formulating effective policy measures for iLUC. In particular, we comment on the current proposal of the European Commission (EC) to include iLUC into the EU-RED regulation.

In 2003, the EU passed a directive aimed at reaching a 5.75% share of renewable energy in the transport sector by 2010 (EU 2003). This goal was extended in 2009 to a share of 10% by 2020 (EU-RED 2009). In addition to increasing energy security and promoting the agricultural sector, the expected reduction in greenhouse gas (GHG) emissions is the main reason for subsidising biofuel production. The EU-RED, recognising the need for an exact calculation of GHG emissions, requires the accounting of emissions from land use change (LUC) in the GHG balance as part of the certification of biofuels (EU-RED 2009). The debate regarding the climate impact of biofuels was particularly triggered by a publication by Searchinger et al. (2008) in which the view that biofuels provide GHG savings was challenged. They argue that GHG emissions from LUC caused by feedstock production for biofuels and from other production somewhere else caused by the increasing demand for crops outweigh the savings from the use of biofuels rather than fossil fuels. Currently, the EU-RED directive obliges biofuel producers to provide certification that their biofuels meet certain sustainability criteria. Only then can the biofuel be counted in biofuel quotas and receive a premium (EU-RED 2009). The EU-RED only requires computing GHG emissions from the production process, transport and direct land use change (dLUC). By definition, dLUC "occurs when a previous land use is converted to bioenergy crop production" (Plevin et al. 2010, p. 8015). These direct emissions are part of standard life cycle assessments (LCA), which are used to calculate emissions for biofuels (as in the EU-RED 2009, the US Energy Independence and Security Act (EISA) of 2007, and California's Low Carbon Fuel Standard (LCFS)).

The controversial issue with LUC concerns the indirect land use change (iLUC). Plevin et al. (2010, p. 8015) state that emissions from indirect land use change (iLUC) "occur when grassland and forest are converted to cropland somewhere on the globe to meet the demand for commodities displaced by the production of biofuel feedstocks". Gawel and Ludwig (2011, p. 846) contend, "(I)ndirect land use change occurs when land that was formerly used for the cultivation of food, feed or fiber is now used for biomass production shifting the original land use to an alternative area that might have a high carbon stock".

To differentiate iLUC from dLUC, it is crucial to correctly identify the cause of the land use change. Accordingly, we use the following definition of the origin of iLUC: iLUC describes the conversion of land that, to date, has not been used for agriculture. iLUC then is caused by increasing prices for agricultural commodities thus making land expansion profitable. In the debate about biofuels, these price increases are presumed to come exclusively from the increase in demand for feedstocks for biofuel production, mainly grains and oilseeds. If this were the only cause of demand changes, iLUC indeed could be completely attributed to the promotion of biofuels.

In summary, iLUC is a global phenomenon that is transmitted through global markets for agricultural commodities. As a consequence, iLUC induced by national biofuel support policies may occur anywhere in the world and not necessarily in the country that implemented the policy.

The identification of iLUC and its attribution to the increase in biofuel production is made difficult, if not impossible, by two effects. The expansion of biofuel production goes hand-in-hand with an increasing demand for food products, particularly meat. In addition, the production of feedstocks for biofuels is, in most cases – sugar cane and palm may be exceptions, an activity characterised by joint production. Oilseed production, such as soy or rape, yields both meals that are used as animal feed and oils that could be used for biodiesel production as well as for human consumption. Corn, as well as other grains, provides dried distiller grains with solubles (DDGS) as an important by-product. In the case of soy, only 20 percent of the harvest is oils whereas the rest is soy-meal produced as animal feed. Thus, it is concluded that a unidirectional causal relationship between increased biofuel production and iLUC is essentially impossible.

Because emissions from iLUC are often considerably large compared to dLUC emissions when calculated along the process chain in life cycle assessments (LCAs) (Penin et al. 2010), it is important to take both, dLUC and iLUC, into account when evaluating GHG savings associated with biofuels. Thus, despite the problem with defining an unidirectional causal relationship between biofuel production and iLUC, there is a need for quantified estimates of alleged iLUC-emissions. However, such estimations require a comprehensive analysis of the complex agricultural production systems. Several different conceptual approaches have been used to quantify emissions from iLUC and to deduct from the iLUC-emissions the additional GHG emissions that could be attributed to biofuels. These different approaches result in quite different contributions to the identification and quantification of ilUC and to the determination of a causal relationship between iLUC and the expansion of biofuel production.

All approaches and studies are faced with massive conceptual as well as observational and statistical problems. In addition to the conceptual differences, the persuasiveness of the approaches in policy circles varies. Modelling frameworks using computable general equilibrium models that attempt to reflect the complex market interactions globally as accurately as possible are often perceived as being too complicated to understand. The complexity of the models often leads to a lack of acceptance of their results among stakeholders and has made alternative deterministic approaches to quantify iLUC emissions more attractive. While these alternative approaches are much easier to understand, they are deemed unscientific and, thus, are usually not accepted in the academic community.

The different conceptual approaches for assessing iLUC emissions result in diverse conclusions. To appraise the quality of the various results, it is important to understand how the conceptual differences and main assumptions of the various approaches influence the estimates of the iLUC emissions.

The paper is organised as follows. In section 2, we provide an overview of the current discussion about LUC regulations in the European Union. In section 3, we discuss and assess the various methods that have been used to quantify emissions from iLUC. In section 4, we present modelling results that quantify the price and LUC effect of biofuel promotion and discuss possible limitations of the models. Based on the modelling results, in section 5, we assess current policy proposals to control for iLUC. In particular, we comment on their potential success in controlling for iLUC emissions. Finally, we summarise our findings and conclude the paper.

2. Emissions from LUC in the EU-RED

To understand the request of the European Commission for a quantification of iLUC emissions, we briefly review the existing biofuel regulation and proposals for iLUC regulation. The EU-RED recognises the need for an exact calculation of GHG emissions and requires accounting for emissions of LUC in the GHG balance as part of the certification of biofuels (EU-RED 2009). The main discussion among scientists, policy makers and stakeholders is whether the current regulation in the EU-RED is strict enough to indirectly account for iLUC or whether it needs to be revised.

The current regulation of GHG emissions in the EU-RED has two major components:

- High carbon stocks are presumed to exist in continuously forested areas or peat land (EU-RED 2009). EU-RED prohibits using land with high carbon stocks or high biodiversity for producing feedstocks for biofuel production.
- For production in all other areas, the certification procedure must include an assessment of GHG emissions throughout the value chain. This can be conducted using the default values of the EU-RED, the individual GHG emissions values of a particular value chain, or using normalised (standardised) regional GHG values. The assessment of GHG emissions must

include emissions from transport and production as well as emissions from dLUC. The resulting GHG emission balance is then evaluated and compared with the comparable emissions from fossil fuels (diesel or gasoline)[17]. Currently, each biofuel must achieve a minimum emission saving threshold (MEST) of 35%.

Only biofuels that meet these requirements are eligible for inclusion in the national quotas. Hence, only biofuels that meet these requirements are given a price premium on the market.[18]

The 35% MEST can be interpreted as a precautionary measure to ensure that biofuels do indeed lead to GHG emissions savings in light of the uncertainties involved in assessing a particular biofuel produced in a particular location that enforces more or less global criteria. A similar precautionary approach involves determining the standardised default values for emissions from the whole production process and the dLUC, which represents a conservative estimate of the actual values. [19] Consequently, the required 35% MEST, combined with the default values, could be understood as a "risk premium" that prevents biofuels from potentially violating the objective of climate change mitigation. Because the "risk premium" for emissions from the production process and the dLUC do not explicitly account for emissions from iLUC, the question is whether the 35% MEST is high enough to cover potential emissions from iLUC.

The mechanism through which the level of the MEST influences iLUC is straightforward. Whether a biofuel option can be counted towards the EU biofuel target under the implemented MEST is determined purely by the emission balance of the entire production process in the event of no dLUC[20]. Thus, the default values for the production process expressed by gCO_{2eq}/MJ of the EU-RED are the assumed values if no individual emission assessment for a specific biofuel production is performed during the certification process. This means that a biofuel is not allowed to exceed ~54.5 gCO_{2eq}/MJ emissions from fossil sources throughout the production process under the current required 35% MEST level. Increasing the MEST implies

[17] The biofuel is compared only to the carbon content of the fossil fuel and not to a carbon balance as the result of a life cycle assessment.
[18] For a detailed discussion of these EC guidelines, see Lange (2011).
[19] A company can replace the default values by a process based detailed proof of the actual carbon balance.
[20] We presume that if a production causes dLUC, no iLUC effect occurs.

that the allowed emissions during the production process are reduced, and a reduction in the allowed emissions results in a reduction in the currently available biofuel options.[21] Accordingly, an increase in the MEST reduces the portfolio of biofuel feedstocks eligible for fulfilling the EU biofuel target. The biofuels remaining in the market are those with high energy yields per hectare as this is a major factor influencing the emission balance of a biofuel (Lange 2011). Thus, the remaining portfolio consists of biofuels that, on average, produce more energy per hectare than the portfolio under the lower MEST, which reduces the price effect of the whole biofuel mandate as less area is required to fulfil the directive. Furthermore, emissions from iLUC would also be reduced.

Several scientists posit that iLUC emissions are not sufficiently covered by the current 35% MEST and that "*current scientific understanding is sufficient to warrant immediate action*", and they urge the EC "*to align the EU biofuels policy with the best scientific knowledge and take into account emissions from ILUC*" (USC 2011). Lange (2011) finds that the sustainability criteria of the EU-RED concerning GHG emissions from dLUC generate an incentive, particularly for the biofuel options from temperate regions, to produce biofuel feedstocks only on land already used to produce crops. While this effectively avoids dLUC, it increases the likelihood that iLUC takes place because it means that the EU biofuel target must be fulfilled by using feedstock produced on current cropland (Lange 2011).

The EC also states in its "Report from the Commission on ILUC related to biofuels and bioliquids" (EC 2010), *"in the absence of intervention - there can be an effect of ILUC on the GHG balance of biofuels with the potential to substantially reduce their impact on climate change mitigation*" (EC 2010 p. 14). In this first report on ILUC, to realise possible intervention, the EC proposes five policy options (see annex for details). Option A: Take no action for the time being, but continue to monitor;

Option B: Increase the MEST for biofuels;

Option C: Introduce additional sustainability requirements on certain categories of biofuels;

[21]This holds in the case that default values are used to calculate the emission balance. A biofuel producer could not use the default values and prove in an individual assessment that it achieves the higher MEST.

Option D: Attribute a quantity of greenhouse gas emissions to biofuels that reflects the estimated indirect land use change impact.

Option E: Limit the contribution from conventional biofuels to the EU-RED targets.

The EC concludes "that a balanced approach on option E, accompanied by complementary elements of options B and D and additional incentives for advanced biofuels would be the best way to minimise estimated indirect land-use change emissions" (EC 2012). In June 2014, the Energy Council of the EU finally reached a political agreement on a draft directive on ILUC that amends the fuel quality (98/70/EC) and renewable energy (2009/28/EC) directives. The EC proposes to

- limit the consumption of conventional biofuels from the current production level of 10% to 7% by 2020;
- to increase the amount of advanced biofuels to achieve the 10% target by 2020 by double-counting them;
- to report on ILUC and its influence on GHG emissions savings based on estimated ILUC factors; and
- to retain the option to introduce adjusted estimated ILUC factors into the sustainability criteria.

This suggests an underlying assumption that the current legislation's required MEST is not sufficiently high enough to ensure a net reduction of GHG emissions of biofuels. The proposal further implies that the EC does not see the need to immediately increase the MEST, but rather, it aims to directly reduce the market share of conventional biofuels. Additionally, it preserves the option to introduce additional iLUC regulations in the future. Therefore, it is deemed important to assess and discuss possibilities to quantify emissions from iLUC as well as the factors driving iLUC based on scientific assessments. Accordingly, we review and assess various approaches for calculating iLUC emissions.

3. Calculating GHG emissions from ILUC: A review

3.1. Requirements

A disaggregated and causally correct determination of GHG emissions from iLUC requires a series of analytical steps: first, a site-specific identification of replacements of food and feed production by biofuel feedstocks; second, an economic analysis of the global market responses to this replacement; and third, a site-specific identification of the formerly unused land that is converted to cropland to produce a particular food or feed as a result of the market response.

Thus, it is first necessary to identify where feedstock production for biofuels is occurring. This is accomplished using the certification systems approved by the EU in accordance with the EU-RED. Then the response of increasing feedstock production for biofuels in the market for agricultural commodities must be assessed. One of the most direct indicators is the response of market prices for agricultural commodities. The economic drivers for the magnitude of the price effect, and thus LUC, are the demand and supply conditions for food and feed products. These are not confined to changes in the demand for biofuel feedstocks alone, however, as there are numerous other changes in demand and supply that are important. Because the feedstocks for biofuels often carry joint products, such as rapeseed oil, rape meal or corn and DDGS, these parallel developments must be taken into account as well. These changes are not confined to local market responses because today, most local markets are integrated into the global demand and supply conditions of agricultural products. The global market conditions, in turn, are the simultaneous result of many factors that have sectorial, geographic and temporal dimensions.

There are several inter-connections among the agricultural sector, the energy sector and the land markets. One example is the relation between the biofuel and the animal feed sector as several biofuel production pathways produce animal feed as a by-product. However, this relationship varies according to the crops used as a biofuel feedstock. Thus, it is important to differentiate between different biofuel feedstocks that replace food and feed production because their impact on the need to expand the agricultural area can differ substantially. In general, the direct as well as the indirect responses to increased biofuel demand in the different agricultural markets depends on local as well as global factors, both of which are likely to change over time. Quantifying these market responses requires an elaborate modelling framework not only for the agricultural market but also for the energy market.

In the next step, it is necessary to assess how the price effect of an increased biofuel demand on agricultural product markets influences the demand for agricultural land. The final challenge, and probably the most difficult, for quantifying iLUC emissions is to quantify how much area is actually converted as a response to the increased demand for land. This land use change is local by nature and thus strongly determined by local conditions, such as land use regulations, the rule of law, land ownership structures, alternative land use options, land prices, among others. The amount of land use change additionally depends on the geographic and temporal possibility to intensify agricultural production on the existing cropland compared to the potential to convert new land to produce crops. This is influenced by the geophysical suitability of the land for agricultural production. In addition, regional support policies in the agricultural sector, local infrastructure conditions, and local markets for land as well as relevant regulations play a major role.

Furthermore, the direct and indirect LUCs must be disentangled as dLUC emissions are already regulated by the EU-RED. Thus, approaches and studies that reflect land markets, agricultural technology and geophysical production conditions at a highly disaggregated level more accurately identify the location of LUC.

Finally, if the amount of iLUC caused by biofuel production is known, it is necessary to determine in which geographical location this additional demand will, in fact, lead to land expansion. Only with this information is it possible to determine the exact amount of GHG emissions caused by the land use change. Thus, it is important that not only the location of iLUC but also the detailed information about GHG emission factors for land conversion (e.g., gCO_{2eq}/ha of land type) for each geographic location be known.

In addition to the complex theoretical requirements to quantify GHG emissions from iLUC caused by biofuel production, several alternative methods have been proposed. They can be classified as a) ad-hoc/deterministic approaches, b) econometric analyses and c) numerical simulation models. These various approaches have been applied in several studies, and the most important of these approaches with respect to their ability to accurately reflect the described mechanism of iLUC are reviewed herein.

3.2. Ad-hoc deterministic approaches

The current iLUC debate advances several ad-hoc deterministic approaches to quantify GHG emissions from iLUC. Ad-hoc deterministic approaches are not based on economic models (econometric or simulation), but rather, assumptions are made on correlations from past trends observed in the data. For policymakers and stakeholders not familiar with economic models, the models sometimes appear as black boxes, which causes doubts regarding the reliability of results. Furthermore, uncertainties in model results are not easily communicated, and the assumptions made are often criticised. Deterministic approaches appear easier to understand and more straight forward.

One ad-hoc deterministic approach that is discussed by stakeholders and policymakers is the iLUC – Factor of Fritsche et al. (2010). They first derive the amount of land used to produce agricultural commodities for export in each country. The sum of this land represents the global mix of land used to produce the globally traded agricultural commodities. Second, they derive the CO_2 emissions released in the past for converting this land into agricultural production areas. The amount of CO_2 emissions are determined by using information about the share of different land use types in the total area previously converted to agricultural production, e.g., the share of previous peat land forest in the total agricultural production area of Malaysia. As the associated CO_2 emissions are computed using IPCC 2006 data, the global amount of past LUC resulting from the land area used to produce the current globally traded agricultural commodities is determined. On average, this is 270 t CO_2/ha or, for a 20-year period, 13.5 t CO_2/ha/year. Furthermore, they assume that future land use change caused by iLUC will cause, on average, this same amount of CO_2 emissions per hectare per year. Accordingly, Fritsche et al. (2010) assume that one hectare for producing biofuel feedstock on land formerly used for other production does not cause one hectare of iLUC but, due to increases in yields 0.25 to 0.5 ha of iLUC . This means that emissions of 3.4 to 6.8 t CO_2/ha/year are caused by the displacement, which Fritsche et al. (2010) call the iLUC-factor. Thus, the amount of iLUC-emissions is determined by using simple interpolations of past experiences rather than by modelling the market interactions.

In a similar way, Cornelissen and Dehue (2009) promote the notion of identifying biofuels that have a higher risk of causing iLUC emissions rather than trying to quantify emissions. Low risk iLUC production is defined as that which expands into land without provisioning services (e.g., areas without food or feed supply or any other crucial ecosystem service) or production that results in increased productivity.

We identify four important drawbacks of the deterministic approaches. a) The interrelation of sectorial, temporal and geographical factors influencing the quantity of iLUC emissions described herein are not reflected in the approaches. b) Future impacts of biofuel policies do not necessarily follow trends of the past (EC 2012). In fact, as iLUC estimates are nonlinear and specific to particular scenarios, the iLUC factor does not remain constant (Khanna et al. 2012). c) Given strong assumptions compared to economic models, the range of results and uncertainties cannot be addressed. d) Because the iLUC-factor is determined at a country-wide level, it might be perceived as a trade barrier (Klepper 2008).

3.3. Econometric approaches

In contrast to deterministic approaches, econometric approaches do not attempt to approximate the mechanism of iLUC. Instead they aim at finding evidence for iLUC by examining historical data to find statistical evidence for the amount of land expansion caused by biofuel policies. Kim and Dale (2011) correlate US biofuel production with deforestation in other regions of the world and find no evidence for iLUC induced by US biofuel production. However, their approach is criticised by O'Hare et al. (2011) for correlating two variables in a system with many interacting factors.

Other econometric studies do not focus specifically on biofuel policies but attempt to find a significant relationship between the expansion of an agricultural production process in a certain location and an LUC elsewhere. Thus, these studies presume that they know the location where the market response caused by a production results in a LUC, and they search for statistical evidence to support the hypothesis without modelling the market response itself. In a spatial temporal regression model, Arima et al. (2011) link the expansion of mechanised agriculture in existing agricultural areas in Brazil to pasture conversion for soy production on distant, forest frontiers in the Amazon. Changes in demand for agricultural products other than pasture conversion for soy production, however, are not considered. In a similar way, Andrade de Sá et al. (2012) analyse the spatial-temporal relationship between sugarcane expansions in the south of Brazil and cattle ranching in the Amazon, thus suggesting that the former is displacing the later in the forest frontier. The econometric analysis includes as explanatory variables the number of cattle in the Amazon region and the amount of sugarcane in the São Paulo region as well as their interactions and temporal lags. Though other commodities are not included, explanatory variables regarding the structure of the agricultural sector are.

The general drawback of the results regarding iLUC caused by biofuels is that the discussions ignore demand and price developments in global agricultural markets into which Brazil is highly integrated. As suggested by Arima et al. (2011) and Andrade de Sá et al. (2012), a price effect due to the expansion of agricultural production in one region may have regional impacts on land use change decisions in another region. However, by not including the development of prices in the analysis, these studies might only detect parallel developments without finding evidence for causality.

The general problem with the econometric approaches is that the impacts of biofuel policies must be projected into the future while they do not necessarily follow trends of the past. In addition, current available studies focus on the expansion effect of a single commodity while ignoring changes in the demand for other commodities

3.4. Quantitative numerical models

There is a growing literature that attempts to directly simulate the impact of certain policies on land use by using numerical models that reflect, as accurately as possible, real market interactions. Two model types that are used in studies of biofuel policies on a global and a regional scale are identified - partial equilibrium (PE) models and computable general equilibrium (CGE) models. Both model types equilibrate supply and demand for goods and services given the existing technologies, resource endowments, and policies. These models usually create a baseline scenario that simulates current trends on the markets up to a certain target year in the future. This baseline scenario is then used to compare the impact of alternative scenarios that may contain additional policy measures, such as biofuel targets. The comparison of the baseline scenario with the policy scenario provides the information necessary for the assessment of the policy measure. Price effects, land use change, and welfare impacts can be derived from such simulation models.

Regarding their suitability for quantifying the LUC effect of biofuel policies, it is necessary to distinguish between PE and CGE models. PE models have the advantage of capturing the agricultural sector in greater detail than CGE models, but because they treat changes in other sectors exogenously, they are unable to incorporate feedback effects between different sectors, e.g., those between bioenergy in the agricultural sector and fossil energy markets. CGE models treat changes in other sectors endogenously, as they both address the world agricultural market as well as the repercussions on other markets, especially the energy markets. Hence, CGE models are able to quantify the LUC of (future) biofuel policies on a global and a multisectoral scale, but there are some drawbacks in the availability of data with respect to CGE models.

Most numerical models seek to quantify the emissions from iLUC that are caused by the EU target or by other biofuel targets (OECD 2008; Dumortier et al. 2009; Dumortier et al. 2011; Rosegrant et al. 2008; Prins et al. 2011; Hertel et al. 2010; McDougall and Golub 2009, Lapola et al. 2010).

A controversial discussion regarding the ability of economic models to quantify iLUC in the EU arose from a modelling exercise introduced by Laborde (2011) and commissioned by the EC. Its objective is to assess the GHG emissions caused by iLUC under the EU biofuel target. Laborde (2011) uses the CGE model MIRAGE and tests the sensitivity of his results to some of the key model parameters. In addition, Galub and Hertel (2012) review the key assumptions that influence results on land use change caused by biofuels based on the GTAP-BIO model. They discuss these key assumptions and conclude that there is lack of empirical evidence for several sensitive parameters, such as the endogenous change in yields caused by price changes and the possibility to expand or change cropland into other land use types. The sensitivity of the modelling results on emissions caused by iLUC is also discussed by Dumortier et al. (2011) using the CARD model, the model applied by Searchinger et al. (2008). They find massive differences in emissions depending on the assumptions set and conclude that policymakers should be aware of these differences.

Given that error margins can be displayed by sensitivity analysis in numerical models and that the models have the ability to conceptually incorporate market interactions on a disaggregated level, we conclude that among the described approaches to quantify GHG emissions from iLUC, numerical models are best suited for studying the iLUC effect of biofuels. Furthermore, they can model future biofuel policies, and take market interactions into account.

However, we argue, consistent with Dumortier et al. (2011), that for policy inferences based on the model results, policymakers must be aware of the effect of key assumptions driving the results of iLUC emissions estimates. In the following section we shortly present these key assumptions identified in the literature in order to evaluate model results regarding their suitability to support binding regulations.

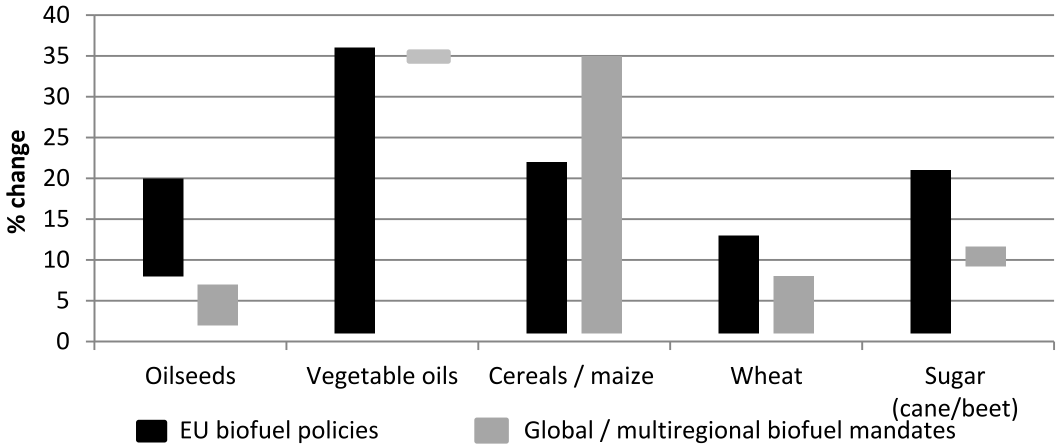
4. Quantifying GHG emissions from iLUC using numerical models

In the introduction, we explain the mechanism that drives iLUC. We now discuss the model structures, assumptions and different steps along this mechanism that drive differences in the model results with respect to the GHG emissions caused by iLUC to evaluate the uncertainty involved with currently available model results of iLUC GHG-emissions. To do so, according to the iLUC definition presented herein, we distinguish between the price effect of biofuel policies, the modelling of land use change caused by biofuel policies and the GHG emissions from this land use change.

4.1. Price-effect biofuel policies

Price changes for agricultural goods caused by biofuel production create incentives for possible LUC and are therefore one of the key indicators when assessing the effect of biofuel policies. An overview on different price effects as well as on underlying assumptions of modelling of biofuel policies is provided in Kretschmer et al. (2012). Figure 1 illustrates the results compiled by Kretschmer et al. (2012) and illustrated as in Calzadilla et al. (2014). The bars indicate large ranges of price effects in 2020 by comparing reference scenarios without biofuel policies with scenarios implementing biofuel mandates. The black bars indicate the range of price effects found by studies on EU biofuel policies, and the grey bars represent the range of effects reported by studies on either global or, at the least, multiregional biofuel mandates.

Figure 1: Overview on price effects of different studies



Source: Compiled from Kretschmer et al. 2012 in Calzadilla et al. 2014. Note: there is only one study on price effects of global mandates on vegetable oils and sugar (cane/beet).

Results of a current study on global biofuel mandates by Timilsina et al. (2012) are located at the lower bound of these price ranges (oil seeds 2.9%, wheat 2.3%, maize 3.6%). Clearly, the range of all estimates is significantly large thereby making it difficult to determine the "real" level of price effects induced by biofuel policies. Therefore, based on these results, it is difficult to draw conclusions regarding the price effects on the resulting emissions caused by iLUC. In fact, Kretschmer et al. (2012) note that such wide results arise from the varied contexts, scopes and methodologies of the models.

Several important assumptions driving the range of results have been identified by Calzadilla et al. (2014) using the DART-BIO model and by Taheripour et al. (2011) and Golub and Hertel (2012) using the GTAP model. In a similar effort, Khanna et al. (2012) review the various models, and Edwards et al. (2010) compare the different models.

First, the interrelation of the livestock sector with bioenergy production is of particular importance as by-products from many biofuels (e.g., soy cake from soy biodiesel) can be used as animal feed (Calzadilla et al. 2014, Taheripour et al. 2011). Thus, an increased production of biofuel can substitute for part of the traditional demand for animal feed. When this interrelation is included in the model, it reduces the demand from the livestock sector for land for animal feed production (Golub and Hertel 2012, Taheripour et al. 2011) and, via a price effect, it can lead to considerable variation in the iLUC estimate (Khanna et al. 2012, Edwards et al. 2010). By ignoring this relationship, Taheripour et al. (2010) find that cropland conversion due to the US and EU biofuel mandates can be overestimated by approximately 27%. Second, differences in the change of food demand following a change in crop prices is a key parameter for differences in model results (Khanna et al. 2012, and Golup and Hertel 2012). Third, the assumptions regarding changes in productivity resulting from price changes is of great importance as it directly influences the production potential of the existing cropland and, in turn, the capacity to absorb increases in demand (Calzadilla et al. 2014, Edwards et al. 2010). Fourth, the effect of feedstock substitution on the demand for cropland (elasticity of substitution) is determined to be crucial for the resulting price effect (Edwards et al. 2010). Finally, Calzadilla et al. (2014) show that the price effect is, inter alia, driven by the approach of how land use change is modelled. In the following section, the modelling of the effect of price changes on land use change is discussed.

4.2. Modelling land use changed caused by biofuel policies

After determining the price effect of biofuel policies, the next step is to determine the resulting LUC effect on the existing managed land (substitution effect) and on land that formerly has not been used for production (land expansion).

To make existing modelling approaches comparable, Edwards et al. (2010) standardise the results of modelling LUC, that is, dLUC plus iLUC. Standardised results of land use change caused by the biodiesel scenario vary from 242 kHa (thousand hectars)/Mtoe (million tons) to 1928 kHa/Mtoe. The range for EU ethanol scenarios is smaller, as land use change varies from 223 to743 kHa/Mtoe. Thus, consistent with the already high range of results in price effects from different model exercises, results on land expansion also show a wide range of results.

Regarding the substitution effect, in many CGE models, the constant elasticity of transformation (CET) approach is applied as it allows land to be transformed to different uses while the ease of transformation between different uses is characterised by elasticities of transformation. Managed land includes cropland, pasture land, and managed forest. These elasticities are crucial when analysing land use change effects as they determine the magnitude of a price effect on the land use change of different types of land use[22].

Land expansion into unused areas can either be modelled endogenously by presuming, e.g., a land supply curve or by adding additional land endowment in a scenario analysis. In the case of the latter, the expansion into unused land (e.g., unmanaged forest) is assumed to be exogenous and based on, e.g., historic trends of land expansion in a scenario. When using land supply curves, assumptions regarding the productivity of the thus far unused land must be made as these assumptions are an important factor in determining the profitability of land use expansion.

4.3. GHG emissions from land use change

After determining the price effect of biofuel policies and the resulting LUC, the GHG emissions caused by LUC must be calculated.

For determining GHG emissions from the modelled land use change, several assumptions must be made. Edwards et al. (2010) find that the standardised results indicate a considerably large range of emissions for all biofuel options: biodiesel emissions range between approximately 40 gCO_2/MJ (AGLINK biodiesel EU) and 350 gCO_2/MJ (LEITAP biodiesel EU-DEU) annually, bioethanol emissions range between approximately 25 gCO_2/MJ (IMPACT coarse grains EU) and approximately 140 gCO_2/MJ (LEITAP bioethanol wheat EU-Fr) annually (see Edwards et al. (2010), Fig. 22). Hertel et al. (2010) calculate a range of emissions between 15 and 90 gCO_2/MJ per year from US-bioethanol derived from corn, depending on the inclusion of by-products, price responses in the food sector, and price responses in yields. Thus, again, model results differ substantially. Keeping in mind that under the 35% MEST a biofuel is allowed to cause not more than 54.5 gCO_{2eq}/MJ, the results thus far do not clearly prove whether biofuels have a climate change mitigation or acceleration effect.

Results indicate that the assumption on where additional managed land expands into former unused land is particularly sensitive in the case of tropical forests and/or peat land as these areas represent large carbon sources. Differences in the assumption

[22] Land types in the databases used by CGE models usually include cropland, pasture, and managed forest.

about the portion of land use expanding into these rich carbon sinks result in huge differences in the calculated GHG emissions from LUC.

4.4. Model results on GHG emission from the EU biofuel mandate

After identifying parameters that drive model results in general, there are additional factors that drive the range of results of existing models. Given that our objective is to evaluate EU policies on emissions from iLUC, we examine an already mentioned study by the International Food Policy Research Institute (IFPRI) that was commissioned by the EC to study the iLUC GHG emissions from the EU biofuel target. The study was performed by Laborde (2011), who uses the CGE model MIRAGE, which is currently the most sophisticated model available for the quantification of the LUC effect of biofuel policies, in general, and the only model available to quantify the effect of the EU biofuel mandate, in particular. It addresses the range of model results driven by the uncertainty contained in key model parameters and thus addresses, at least to some extent, the uncertainty of model results caused by the sensitive parameters discussed thus far.

A first version of this modelling exercise (Al-Raffai et al. 2010) is launched by the EC, and after a public consultation, several model assumptions are changed. A peer-reviewed version is then published by Valin and Laborde (2012). Laborde (2011) simulates the LUC effect of the EU biofuel target for 2020 and its related emissions using the biofuel production plan from the national renewable energy action plans in the EU member states (EC 2011).

The model used in the modelling exercise of Laborde (2011) includes a detailed representation of important biofuel feedstock and biofuel options. LUC is driven by price changes that affect the production activity of a particular type of land. LUC is addressed both in the form of substitution within cropland between different agricultural products on these croplands and the expansion of croplands on new land. The conversion of cropland used to produce food and feed into cropland used to produce biofuel feedstock represents a pure substitution effect. The conversion of new land into cropland used to produce food, feed or biofuel feedstock represents either dLUC or iLUC.

Emissions associated with the conversion of new land are computed by using the standard values associated to the EU-RED, which draw on the results of the IPCC

(2006). Laborde (2011) presents his results regarding the LUC effect of the EU biofuel target for 2020 in the form of specific marginal, biofuel feedstock specific emissions from LUC [23] and aggregated global emissions from LUC. His results with respect to the LUC effect are the sum of dLUC and iLUC as the model is not able to differentiate between the two types of LUC. The results are presented for two policy scenarios - one simulating the EU biofuel target for 2020 with free trade and one without free trade.

Laborde (2011) performs a Monte Carlo simulation to assess the sensitivity of the results regarding the LUC effect to the uncertainty range of several key model parameters. We present the characteristics of the Monte Carlo simulation because we use its results as confidence intervals of the LUC effect when discussing the policy proposals put forward by the EC to control iLUC. The following key model parameters are addressed in the Monte Carlo simulation:

- A shift in the share of land expansions into primary forest, which modifies the emissions released by unit of exploited land expansion;
- A shift in intermediate demand price elasticity of agricultural inputs, indicating how easily the processing sector releases inputs after a biofuel demand shock;
- The ratio between the yield on new cropland and the average yield, which determines the productivity of the newly converted land compared to the already used land;
- The elasticity of substitution between land and other factors (factor intensification);
- The elasticity of substitution between key inputs (feedstuff and fertiliser) and land (input intensification);
- The elasticity of transformation of land and extension elasticity.

Furthermore, Laborde (2011) assumes that a share of 33% of the new palm plantations expands into peat land in Indonesia and Malaysia, which is of particular importance with respect to emissions following a land expansion for palm production. This assumption is not further addressed even though in the earlier version, Al-Raffai et al. (2010) assume that a share of 10% of the new palm plantations expand into peat land in Malaysia and a share of 27% do so in Indonesia.

23For a description of the calculation of feedstock specific ILUC-emission factors see Laborde (2011) p. 23.-28.

This in addition to other changes in assumptions (e.g., share of different biofuel mandates) that result in an increase in the average LUC factor from 17gCO2eq/MJ in the study by Al-Raffai et al. (2010) to 38.4 gCO2eq/MJ in the study by Laborde (2011).

With respect to model sensitivity, there are certain generic limitations in the CGE models that should be kept in mind when drawing policy conclusions.

4.5. Limitations of models for determining iLUC

With regard to generic limitations, it must be emphasised that, in general, CGE models are a suitable tool to use to better understand certain effects, such as the influence of biofuel policies on the direction of changes in feedstock, energy prices and output quantities. However, to draft an iLUC regulation based on model results, the following limitations should be considered:

- The effect of cropland expansion is modelled in a simplified way and is only driven by market effects. Other important factors that similarly play a major role in local land use decisions, such as land market regulations, environmental protection laws and their level of enforcement, tenure rights and other local institutional factors, are considered only indirectly, if at all.
- The LUC emission factors applied represent average values for a particular land use category due to a limited differentiation within one land category. Only a further differentiation of different land categories in the model would result in more precise LUC emission factors. This would require a much more elaborate database of the spatial distribution of global land categories.
- It is not possible to split the modelled LUC into iLUC and dLUC (see also Valin and Laborde (2012)). Because all markets are cleared simultaneously in the CGE models, only the net LUC can be computed. Thus, GHG emissions from LUC calculated on the basis of a CGE model will always include dLUC and iLUC.
- A distinction between the effect of the EU biofuel target for a specific biofuel feedstock or for a biofuel production option is not possible, which is also due to simultaneous market clearing. The assumption that the marginal effect of a particular biofuel feedstock is the same as the effect of that biofuel feedstock when the model clears all markets and feedstocks simultaneously is, at best, doubtful as it assumes perfect linearity of effects.

Comparing these generic limitations and the data shortcomings for key model parameters with the requirements previously defined herein, it is clear that a conceptually correct identification of iLUC emissions is, at this time, impossible. Therefore, the decision as to the correct iLUC policy remains uncertain. In the next section we show how the modelling results of Laborde (2011) can be nevertheless helpful to better understand the uncertainty involved.

5. Calculating GHG emissions of biofuels along the process chain

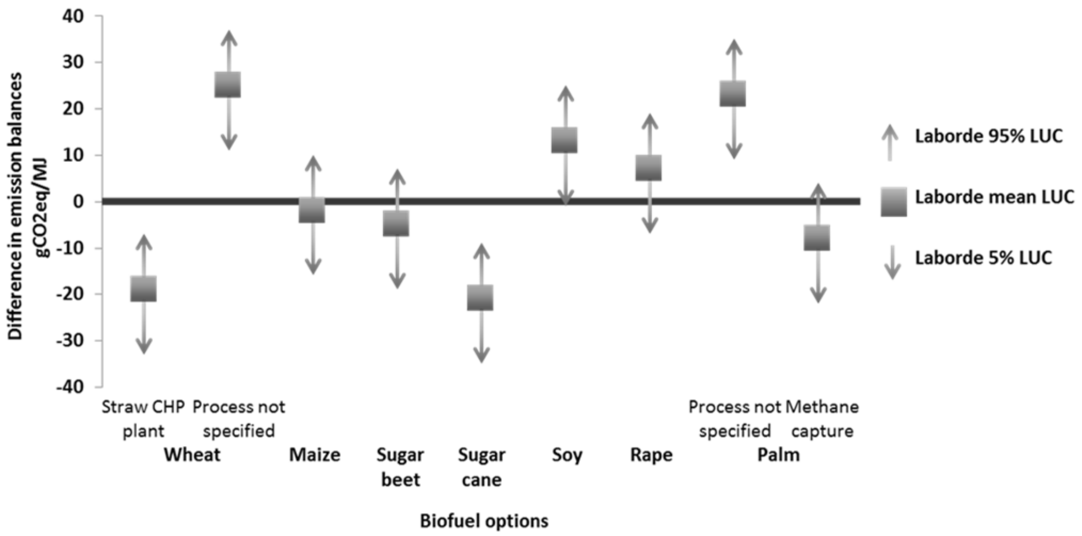
The Monte Carlo study of Laborde (2011) allows us to define the probability distribution of the range of emissions from LUC caused by the EC biofuel mandate. By including this range of emissions from LUC into the GHG emission balance of biofuels, it is possible to address the uncertainty regarding the climate mitigation effect of the different biofuel options.

For the resulting LUC emission values, Laborde (2011) displays the 5 and 95 percentile levels of the confidence interval. This means that 90% of all of the resulting values for LUC emissions in the Monte Carlo simulation lie within this confidence interval. In other words, the probability that the values for LUC emissions lie outside this confidence interval is considerably small.

We combine these results with the EU-RED default values for emissions from the production process (well-to-wheel emissions = WTW emissions) to assess the probability distribution of the total emission balances of the different biofuel options. We assume that the emissions from LUC represent the iLUC effect of the EU biofuel target, thus representing a worst case scenario for emissions from iLUC presuming there are no emissions from dLUC. This assumption is realistic because of the sustainability requirements concerning dLUC (Lange 2011).

To calculate the emission balance, we use the average (not the specific biofuel feedstock) value for emissions from LUC computed by Laborde (2011). Because the emissions from LUC are the same for every biofuel option, it is only the default value for the WTW emissions that causes the differences in the emission balances of the various biofuel options. The calculated LUC emissions have a mean of 38.8 gCO2/MJ and a confidence interval of 24.4-50.4 gCO2/MJ for the 5% and 95% intervals. Figure 1 presents these results.

Figure 2: Difference between emission balances of biofuel options and emissions balances of fossil fuel alternative



Source: Own presentation based on Laborde 2011 and EU-RED

In Figure 2, the vertical axis expresses the difference between emission balances of biofuel options and emission balances of fossil fuel alternatives. At the zero line, a biofuel option causes exactly the same amount of emissions as the fossil fuel alternatives. Thus, the zero line can be interpreted as the zero emissions savings line. Negative values indicate that a certain biofuel option causes fewer emissions in the total production process and therefore saves emissions compared to the fossil fuel alternatives. Positive values indicate that a certain biofuel option causes more emissions, and consequently, it does not contribute to climate mitigation.

The upper arrows point to the 95 percentile limit of the Monte Carlo simulation, thus denoting that 95% of all simulated LUC values are below this emission value. The lower arrows point to the 5 percentile limit, thus denoting that only 5% of all simulated LUC values are below this emission value. Accordingly, the arrows represent the probability distribution of the model results within the 95% and 5% confidence intervals caused by the uncertainty range of the key model parameters. Large arrows, which represent large confidence intervals of the total emission balances of the various biofuel options, occur due to the strong sensitivity of model results to several key model parameters.

The particular biofuel option only contributes to climate change mitigation with a high degree of certainty if upward arrows are below the zero emissions savings line.

Accordingly, only bioethanol derived from sugarcane or from wheat processed by efficient straw-fired combined heat and power (CHP) plants contributes to climate change mitigation with a high degree of certainty. In contrast, biodiesel derived from palm processing without methane capture and ethanol derived from wheat processed by inefficient plants most likely do not contribute to climate change mitigation as the arrows are above the zero emissions savings line.

Due to large confidence intervals for all other biofuels, it is uncertain whether these biofuels contribute to climate change mitigation. However, there is a good chance that biofuels derived from maize, sugar beet and palm with methane capture contribute to climate change mitigation. The size of the confidence intervals for the emission balances may become somewhat smaller with more sophisticated modelling and improved data. Nonetheless, a range of uncertainty will remain.

To assure that biofuels contribute to climate mitigation, the following question arises. How should iLUC be regulated so that only those biofuel options that have a positive emissions balance with a sufficient degree of confidence are chosen? The next section evaluates the policy proposals of the EU-RED based on the presented knowledge on the quantity of iLUC.

6. Evaluating policy proposals to capture iLUC

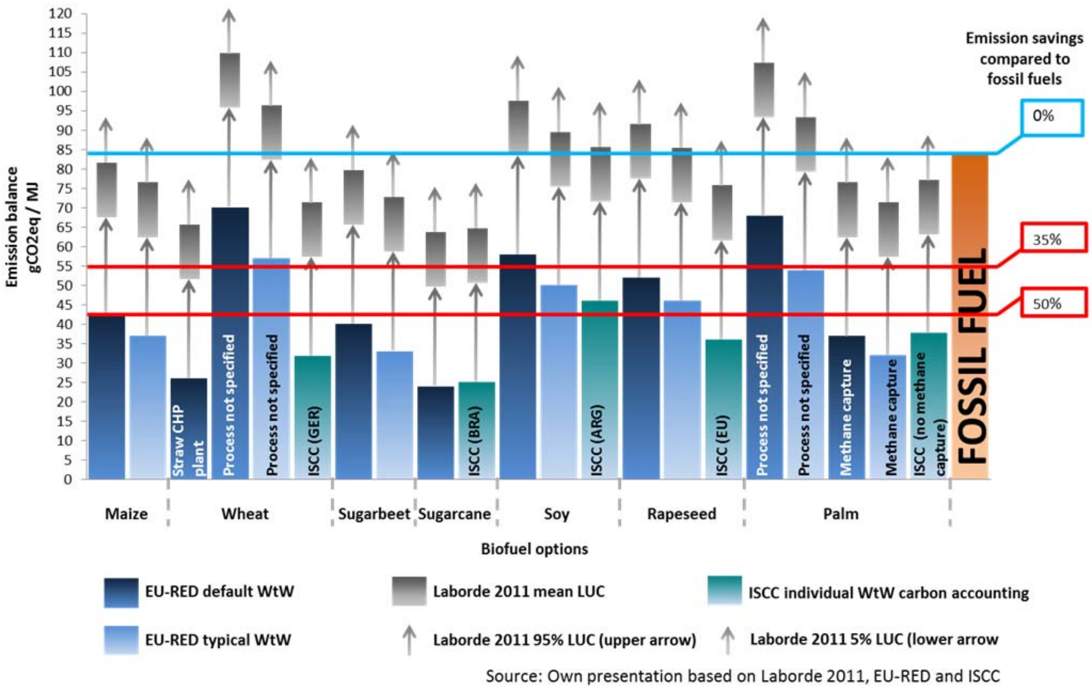
To examine the EC's proposal based on the uncertainty regarding iLUC quantification discussed herein, we do not consider approaches dealing with good governance of local land use or other sustainability policies because, one, they are discussed in Miyake et al. (2012), Purkus et al. (2012) and Gawel and Ludwig (2011, p.852), and two, these studies conclude that "certification is not in a position to effectively compensate for shortcomings of public action".

Based on the classification of decision making under uncertainty as discussed by Lucia et al. (2012), the new proposal by the EC (EC 2012) includes a policy mix of preventive (support of non-land using biofuel option) and precautionary (limit production levels) policies.

In general, a high MEST creates incentives to implement modern energy efficient production processes. Calculations from the certification scheme ISCC show that in the field, WTW emissions can be significantly lower than the standard values in the

EU-RED (European Union 2009, Directive 2009/28/EC). The decision not to increase the MEST early must be evaluated in the context of the uncertainty about the correct level of the MEST. Figure *3* illustrates emission balances of different biofuel options. The blue bars indicate the WTW emissions, and the grey arrows denote the iLUC emissions based on Laborde's results of emissions from LUC. The figure compares the emission balances of different biofuel options with the emission balances of the fossil fuel alternatives as indicated by the orange bar. Vertical lines indicate zero, 35% and 50%[24] emissions savings.

Figure 3: Full Emission Balances of Various Biofuel Options



Note: The dark blue bars represent the default values for the WTW emissions from the EU-RED. As the default values are intentionally set at a high level to capture less efficient production processes, we also include the typical values for the WTW emissions from the EU-RED.[25] Furthermore, where available, we consider values for WTW emissions calculated in practice by the biomass certification system ISCC (International Sustainability and Carbon Certification), which has been recognised by the EC for performing individual emission accounting to verify compliance with the sustainability criteria of the EU-RED. Data from ISCC are unpublished and based on personal correspondence. Grey rectangles with arrows represent the confidence interval of the values for emissions from ILUC in the Laborde Monte Carlo study.

The results imply that if the MEST remained at the 35% level, based on figure 2, it would not rule out all biofuel options that cause more emissions than the fossil fuel

[24] We choos 50% because the minimum emission saving threshold will be increased to 50% in 2017.

[25]EU-RED provides the default and the typical values. The default values represent conservative estimates to capture less efficient production. They must be used when no individual carbon accounting is realised in the certification process. The provided typical values serve only as an orientation about the potential result of individually calculated values.

alternatives when possible emissions from ILUC are considered (for details on this figure, see the Annex). Gawel and Ludwig (2012) refer to this as a type I error. Only biofuels derived from sugar beet, sugarcane, and maize would cause lower emissions than the fossil fuel alternatives based on the sum of the biofuel emissions from the average iLUC and WTW. According to this emission balance, while biofuel derived from rapeseed would cause more emissions than the fossil fuel alternative, the 35% MEST would not rule out this option. Furthermore, if, to compute the sum of the biofuel emission balance, one were to use the typical values for the WTW emissions of the EU-RED rather than the default values, the biofuels derived from palm processed without methane capture and from rapeseed, soy and wheat would meet the requirements pertaining to the 35% threshold despite causing more emissions than the fossil fuel alternatives due to LUC.

Increasing the MEST to, e.g., 50% may rule out some biofuel options even though they may not cause more emissions than the fossil fuel alternatives. Thus, Gawel and Ludwig (2012) call the resulting risk of welfare losses due to no or to too little biofuel production a type II error, and they conclude that this requires the further use of biofuels in a moderate way, as approaches to calculate iLUC are either non-existent or not sufficiently accurate. The error is caused by the large ranges in the confidence intervals of emissions from LUC as computed by Laborde (2011). These large ranges are the result of a high variance in the assumed distribution of the analysed key model parameters.

Of course, these results depend heavily on the modelling results for the net effect of emissions from LUC induced by the expansion of biofuel feedstock production. As these results are generated by only one model and depend on a number of assumptions that must still be verified by empirical observations and by additional modelling exercises, there still exists considerable uncertainty regarding the robustness of the conclusions that can be drawn.

The EU proposal further suggests lowering the pressure on land by reducing the contribution of conventional biofuels to 7% by 2020. This implies that while no new installations can be constructed, already existing plants can produce such biofuels at a 35% MEST until 2017. As the EC states, this is a clear indication that capacities already in place can run for the lifetime for which they were initially constructed for, but new investments are deemed not profitable and not politically desired.

The current EU proposal also includes the double counting of second-generation biofuels at the 10% biofuel target of 2020. This means that the actual amount of biofuels in the market could be substantially lower than the counted amount of biofuels. It is questionable whether incentives set by the proposal are target-oriented (i.e., meeting the 10% target in 2020) as several biofuel options that would be double-counted have not achieved marketability. Although these second-generation biofuels are expected to have less land use impact and to not cause LUC emissions, the double counting towards the target reduces the produced amount of biofuels. As biofuels are currently the major option for reducing emissions in the transport sector, double counting also lowers the potential GHG reduction in the sector under the 10% target by 2020. Moreover, the MEST should already set incentives for second-generation biofuels if they indeed exhibit a lower emission balance than traditional biofuels.

Finally, the EC proposal contains the provision of reporting iLUC emissions based on estimated iLUC factors. These calculated iLUC factors, which are reported as crop specific factors, suffer from considerable drawbacks. a) Current approaches that calculate crop-specific LUC emission factors suffer from ambiguity and arbitrariness. b) Economic models are not able to differentiate between iLUC and dLUC. c) A general LUC emission factor that includes dLUC and iLUC eliminates the individual incentive for producers to reduce dLUC. Factors included in the proposal represent marginal LUC emissions of different crops rather than the iLUC emissions of a certain crop when markets clear simultaneously. The EC recognises and takes these problems into account by only requiring reporting. The option to introduce iLUC factors into sustainability criteria is left open in the event that adjusted estimated iLUC factors are available.

7. Summary and Conclusions

In this paper, we shed light on different approaches to quantify emissions from iLUC and discuss the current EU policy proposal to reduce the iLUC impact of the EU biofuel target. LUC can be quantified using economic simulation models, while a distinction in emissions from iLUC and dLUC is not possible. The currently available models still contain a high level of uncertainty with respect to key model parameters which determine the price, LUC and resulting GHG emissions of biofuel policies. Consequently, the transfer of the results of the current models into iLUC factors as part of the sustainability criteria is not possible.

In addition, we argue that it is inappropriate to calculate crop-specific emissions from iLUC. This is because calculating LUC emissions for different crops suffers from methodological drawbacks, as price effects on demand and substitution of feedstuff are an aggregated effect. Accordingly, LUC emissions cannot be attributed to single crops. Furthermore, it is determined that econometric and ad-hoc approaches have greater drawbacks than do economic simulation models, and therefore, the econometric and ad-hoc approaches should not be used for policy advice.

The uncertainty in quantifying iLUC emissions also guides the evaluation of the policy proposals. Our discussion of the current EU policy proposal suggests that a combination of an increase in the MEST and a limitation of biofuel production is a safe way to ensure that the production of biofuels does not cause higher GHG emissions compared to the fossil alternatives. However, welfare losses might result by ruling out biofuel options or by reducing the consumption of biofuels that could reduce GHG emissions. Thus, the exact level of the MEST is a question of readiness to assume the risk of ruling out certain biofuel options even though they would cause lower emissions than the fossil fuel alternatives and the risk of including some biofuel options even though they would cause more emissions than the fossil fuel alternatives.

The EU proposal currently focuses on reducing biofuel production from the first generation, in general, by double counting second-generation biofuels and by limiting first-generation biofuels. We agree that a reduction in the overall amount of conventional biofuels reduces LUC and related GHG emissions. However, double counting second-generation biofuels may not be target-oriented and may result in fewer reductions of the actual (not counted) GHG emissions savings in the transport sector.

We show that to control for iLUC-emissions, it comes down to controlling the price effect of biofuel policies. Model results based on the DART model by Calzadilla et al. (2014) show that price effects may not be as high as expected once models consider a certain degree of detail, especially in the by-product sector.

Consequently, an important mechanism not captured by the EC policy options discussed in this paper is the possibility to reduce the price effect by producing feedstock for biofuels more productively than the former production for the food and feed sector. This means, in practice, that iLUC is reduced or even eliminated if production of biofuel feedstock has a higher productivity than the former food or feed production process. First experiences from the certification scheme ISCC show that an increase in productivity is possible when the establishment of rules on good agricultural practices based on the requirements for achieving an EU-RED certificate serves as extension services.

Increases in productivity to reduce the price effect of biofuel policies should be a key element of the EU-RED iLUC regulations. A possible way of implementing this into the current iLUC proposal is to apply an iLUC factor as a risk premium on all production on already existing cropland and to reduce or eliminate this factor when producers prove a certain degree of productivity increase in their production area.

Finally, the lessons learned regarding the interactions between productivity increases and land use impacts do not only apply to only the biofuel sector but to all developments that increase the demand for agricultural products. This includes the increase in the global population, the increase in the demand for meat and milk products and the increase in the use of biomass in the industry. Increasing production on the currently used areas reduces the impact of these developments on prices for agricultural goods and, therefore, reduces the incentive to convert new areas for agricultural production. This, in turn, reduces LUC emissions. Therefore, increasing productivity on already used areas should be a key component of all agricultural policies to reduce emissions from LUC.

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Annex

In this annex, we explain and evaluate the 4 policy options presented in the EC´s "Report from the Commission on ILUC related to biofuels and bioliquids".

Option A: Take no action for the time being but continue to monitor

To evaluate Option A and B it is necessary to compare various levels of the MEST. For this purpose we rely on the results of Figure 2.

Option A implies that the MEST will remain at the 35% level until 2017 and will then be increased to 50%. Based on figure 2, allowing the MEST to remain at the 35% level would not rule out or eliminate all biofuel options that cause more emissions than the fossil fuel alternatives when possible emissions from ILUC are considered. Gawel and Ludwig (2012) call this a type I error. Only biofuels derived from sugar beet, sugarcane, and maize would cause lower emissions than the fossil fuel alternatives, based on the sums of the biofuel emissions from the average iLUC and the WTW. According to this emission balance, biofuel derived from rapeseed would cause more emissions than the fossil fuel alternative; however, the 35% MEST would not rule out this option. In addition, if, to compute the sum of the biofuel emission balance, the typical values for WTW emissions from the EU-RED rather than the default values were used, the biofuels derived from palm processed without methane capture and from rapeseed, soy and wheat would meet the requirements for the MEST of 35% despite causing more emissions than the fossil fuel alternatives due to LUC.

Option B: Increase the MEST for biofuels

Option B proposes that the MEST be increased to 60% for plants constructed after 2013 and to increase the MEST for plants constructed before 2014 to 50% in 2018.

Figure 2 illustrates that with the MEST at the 50%, the portfolio of eligible biofuel feedstocks is strongly reduced. Only bioethanol derived from sugar beet and sugarcane and from wheat processed by efficient straw-fired CHP plants would meet the requirements of an MEST of 50%. Biofuel from palm processed with methane capture would be the only eligible biodiesel option. According to the Laborde data, all of these options have a very low risk of causing excessive iLUC-emissions as their emission balance is below the blue zero emissions savings line.

However, an MEST of 50% may rule out some biofuel options even though they may not cause more emissions than the fossil fuel alternatives. Gawel and Ludwig (2012) call the resulting risk of welfare losses due to no or too little biofuel production a type II error. Furthermore, they conclude that this requires further moderation in the use of biofuels as the approaches to calculate iLUC are either nonexistent or not sufficiently accurate. The error is caused by large confidence interval ranges with respect to emissions from LUC computed by Laborde (2011). The large ranges result from a high variance in the assumed distribution of the analyzed key model parameters.

Suppose the 5 percentile limit of the confidence interval of emissions from LUC is closest to the real iLUC emission. Then, only biofuel derived from wheat processed by inefficient plants and palm processed without methane capture would actually cause more emissions than the fossil fuel alternatives. However, the 50% MEST would also rule out biofuels derived from soy and rapeseed.

These results illustrate the role of risk when specific levels of MEST are chosen. The 50% level essentially ensures that there is a high likelihood that biofuels that pass this threshold actually cause fewer emissions than the fossil fuel alternatives, though a type II error may occur. The 35% level, to the contrary, may lead to a type I error. Therefore, the choice between the two options comes down to a choice between two errors, that of ruling out some biofuel options even though they would cause fewer emissions than the fossil fuel alternatives and that of including some biofuel options even though they would cause more emissions than the fossil fuel alternatives.

Despite the uncertainty, the advantage of option B is that it can be implemented easily and quickly within the current EU-RED because it builds on the sustainability regulation already in place, especially on the certification schemes approved by the EC. Schemes such as the ISCC provide a means to account for WTW emissions at the individual level, which could potentially reduce the amount of WTW emissions and thus bring the overall emissions balance in line with the 50% MEST.

Option C: Introduce additional sustainability requirements on certain categories of biofuels

Option C consists of introducing more sustainability criteria than currently implemented to the existing certification process and is divided into two options, C1 and C2. Under C1, EU member states and countries exporting to the EU must comply with requirements to reduce deforestation and must introduce measures to increase the availability of feedstocks in a sustainable manner. Under C2, EU member states and countries exporting to the EU must comply with requirements to produce biofuels through practices with minimal risk of causing GHG emissions from iLUC.

The problem with implementing more sustainability criteria is that certification schemes (usually at the firm/farm level) cannot take into account issues of larger scale. In other words, they cannot control for food security or indirect effects on deforestation (Delzeit et al. 2009). This is consistent with the definition of iLUC as a market effect from an aggregate demand shock for agricultural feedstock caused by biofuel policies. Because the effect is aggregated, a direct link from individual producers cannot be established (Turner et al. 2007).

Even more restrictive sustainability criteria might increase the share of iLUC in the LUC impact of biofuel policies. This is because sustainability criteria can only be applied to a particular biofuel production process that is subject to a certification process. The sustainability criteria currently applied have already resulted in the production of biofuel feedstocks predominantly on land already used to produce crops (Lange 2011). Additional sustainability criteria might increase the leakage from the green biofuels production chain to unregulated systems (Turner et al. 2007). Furthermore, Gawel and Ludwig (2011, p.849) conclude that this instrument "completely lacks practicability and cannot guarantee the absence of iLUC".

There is only one sustainability criterion that could influence the iLUC effect of the EU biofuel target, that is, only one that would allow biofuel feedstock production only on degraded land. However, there is no consensus about the location or the definition of degraded land. Hence, such a sustainability criterion cannot be implemented at this time. Furthermore, even if a workable definition of degraded land could be established, it is doubtful whether biofuel feedstock production on such land would be profitable.

Option D: Attribute a quantity of greenhouse gas emissions to biofuels that reflect the estimated indirect land use change impact

Under Option D, estimated iLUC-emission values are incorporated in the existing GHG methodology for biofuels, with the exception of non-land using biofuel options and production that causes dLUC. The mechanism used by this proposal is similar to the increase of the MEST. However, several problems must be resolved:

- Current models are not able to differentiate between iLUC and dLUC, i.e., they can only identify the combined effect of dLUC and iLUC.
- Current approaches that calculate crop-specific LUC emission factors suffer from ambiguity and arbitrariness. Modelling approaches can only identify the LUC effect for all crops together, while econometric and ad-hoc approaches are not considered to be appropriate approaches to calculate these factors (see section 4).
- A general LUC emission factor including dLUC and iLUC destroys the individual incentive for producers to reduce dLUC. Hence, without direct control of the producer´s land use for biofuel feedstock production, the direct incentive for a good agricultural practice would vanish.

Paper 3:

POLICY INSTRUMENTS FOR REDUCING EMISSIONS FROM LAND USE CHANGE: A case study for Sumatra and Kalimantan[26]

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Abstract:

Land use change (LUC) is the second largest anthropogenic source of carbon dioxide emissions (emissions) into the atmosphere. Nonetheless, a binding regulation of LUC emissions only exists for the European biofuel sector. To implement such regulation in the feedstock-producing countries, a carbon map is a valuable tool. We show how to calculate a carbon map according to the sustainability requirements for biofuel production adopted by the European Commission (EU-RED) for Kalimantan and Sumatra in Indonesia. Based on the carbon map, we derive maps showing the possible emission savings that could be generated by biofuels based on palm. We evaluate these maps according to the criterion contained in the EU-RED of 35% minimum emission savings for each biofuel option compared to its fossil alternative. Very few unused areas meet this criterion. This increases the risk of indirect LUC that might offset any contribution of biofuels to the reduction of emissions. We argue that this can only be overcome if all agricultural production is subject to a carbon regulation. In this effort, we exemplarily discuss, based on the carbon maps, different regulatory measurements and the possible impact of a carbon market on agricultural production in Indonesia. The results show that current carbon prices are too low to effectively protect tropical forest areas from being converted into palm plantations. Thus, in practice, a combination of carbon markets and sustainability certification or sustainable land use planning might be necessary to effectively protect valuable natural areas.

Keywords: policy instruments, carbon mapping, biofuel policies

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[26] Unpublished manuscript

1. Introduction

Deforestation is the second largest anthropogenic source of carbon dioxide in the atmosphere after fossil fuel combustion (Van der Werf et al. 2009). It is clear that it is practically impossible to constrain the impacts of climate change within the reasonably tolerable limits of society without reducing emissions from land use and land cover change (LUC)[27] (UN-REDD Programme2014). In this paper, we use the biofuel sector in Indonesia to show how LUC can be quantified and regulated using carbon maps. Based on these findings, we discuss alternative means for reducing emissions from LUC from all forms of agricultural production.

The only global method for reducing emissions from LUC currently in practice is the United Nation’s Program for Reducing Emissions from Deforestation and Forest Degradation (UN- REDD+). It aims to put a monetary value on carbon stored in tropical forests and thus decrease any incentives for deforestation. However, the voluntary carbon markets for trading project level UN-REDD+ emission reductions so far suffer from heterogeneity of demand, high price variability amidst overall low prices, and a lack of transparency (World Bank 2014). At the same time, global change continuously increases incentives to convert all fertile natural land, thus offsetting the UN-REDD+ incentives to conserve the forests. This global change is mainly driven by an increasing world population with a more meat-based, and therefore land intensive, diet, which increases the demand for agricultural goods (Krausmann et al. 2008). Despite being the major driving force behind LUC, there is so far no discussion on how to directly regulate the land use impact of the agricultural sector on a global level. The only agricultural sub-sector where a binding regulation of emissions from LUC exists is the biofuel sector, most notably in the European Union (EU) and the United States (US). The remainder of this paper focuses on the European biofuel sector.

Through its biofuel sustainability regulation (EU-RED), the European Commission seeks to achieve a minimum target of 10% renewables in the transport sector by 2020 (EU-RED 2009) to which biofuels will contribute over 90% (EC 2011). To ensure that biofuels contribute to a reduction in emissions and that biofuels are sustainably

[27] LUC in this context includes all changes in the use of an area. This could be a land cover change when a forest is converted into a soy field. It could also only be a land use change without a land cover change when a soy field is converted into a sugar-cane field. In the context of this paper, all land cover changes also represent land use changes but not vice versa. I therefore use the simplifying abbreviation LUC, which is the commonly used term in the EU-RED discussion.

produced, the EU-RED contains a sustainability regulation to avoid the high emissions from LUCs caused by expanding biofuel feedstock production.

A LUC impact from expanding biofuel feedstock production is expected because an increase in the demand for biofuel feedstock correspondingly increases their prices, generating incentives for farmers to produce them. Farmers decide to produce the biofuel feedstock on their existing cropland or to expand into unused, natural areas depending on the expected return of each option. If unused, the natural area is converted to produce the biofuel feedstock, a process called the direct land use change (dLUC) of biofuel production. As this dLUC with its related emissions is directly related to the biofuel production, it can be causally linked to it and retraced in a certification process. The EU-RED requires a certification of each biofuel imported or produced within the European Union verifying that dLUC emissions have not been prohibitively high.

The amount of dLUC emissions caused by an expansion into unused, natural land can be determined with a carbon map. A complete carbon map shows the carbon stored in all of the biomass and soil within each spatial unit. The use of maps to determine forest biomass carbon has already become a common tool for countries preparing for UN-REDD+ (e.g., Gibbs et al. 2007). In the UN-REDD+ context, carbon maps can be used to determine a baseline for the payments for forest preservation and to monitor deforestation over time. Two examples of global carbon maps for tropical forest biomass can be found in the works of Saatchi et al. (2011) and Baccini et al. (2012). Due to their contrasting purposes, maps produced for UN-REDD+ cannot be used in the EU-RED context because they focus only on determining carbon in tropical forest biomass and do not include emissions due to LUC for biofuel production. Ruesch and Gibbs (2008) calculated a global map of biomass carbon stored in above- and below-ground living vegetation using the International Panel on Climate Change Good Practice Guidance for reporting national greenhouse gas inventories (IPCC- Guidelines) with a resolution of 1 km for the year 2000. The EU-RED LUC regulations also build upon the IPCC Guidelines but stipulate a resolution of 30 meters for the benchmark year 2008 and an additional calculation of the amount of non-biomass carbon stored in the soil.

The first aim of this paper is to calculate a carbon map for the Kalimantan and Sumatra regions of study in Indonesia that is in line with the EU-RED requirements and to show how it can be used to facilitate compliance with the EU-RED criteria.

After this analysis, we then consider the potential choice of farmers not to expand into natural areas but instead to produce the biofuel feedstock on the already-existing cropland. This does not cause dLUC emissions[28]. However, the demand for biofuel feedstock adds to the demand for all feedstock, mainly in the food and feed sector, therefore increasing demand overall. This can increase prices for feedstock and consequently generate incentives for expanding into unused, natural areas to meet demand. This expansion in the production of agricultural products for the food and feed sector likewise causes LUC emissions and is termed the indirect land use change (iLUC) of biofuel production. The emissions from iLUC are caused by the overall price effect on agricultural markets induced by the increasing demand for biofuel feedstock production (Delzeit et al. 2014). Being an overall market effect, it cannot be linked to an individual biofuel feedstock production, and thus, cannot be included within a certification process. However, the iLUC effect is the major reason for blaming biofuel policies for being harmful to the climate rather than useful for climate mitigation (e.g., Searchinger et al. 2008).

On a regional level, a major influence on the potential extension of the iLUC effect is the availability of unused, natural areas that when directly converted into biofuel production areas still meet the requirements of the EU-RED. In other words, for the representative farmer, the decision on whether to cause dLUC by converting natural, unused land to produce biofuel feedstock or to produce on existing cropland and potentially cause iLUC is influenced by the availability of natural, unused land that would meet the EU-RED sustainability criteria.[29]

Thus, the second aim of this paper is to determine the availability of any unused area that if converted for biofuel feedstock production would still meet the requirements of the EU-RED. This analysis concludes that for the Kalimantan and Sumatra study regions, this area is rather small and might require a high level of investment due to its level of degradation. Consequently, the potential to meet the demand for biofuel

[28] This is a simplifying assumption, as a change between crops can cause emissions from dLUC, such as the change from an annually harvested crop to a plantation crop.
[29] This is based on the assumption that profit-maximizing farmers first convert the most profitable areas due to the fertility of the soil or the accessibility of the area.

feedstock from the European markets by dLUC is rather small, thereby increasing the potential of iLUC.

However, the main reason why an iLUC effect is possible is rooted in the fact that while the biofuel sector is the only agricultural product subject to an emission regulation, production for the food and feed sector can expand into unused, natural areas without any internalization of LUC emissions. Moreover, all increases in the demand for agricultural products, like increases in world population or meat consumption, will create incentives to expand into unused, natural areas by means of increasing prices in the agricultural markets. Thus, iLUC is not an effect limited to the biofuel market. It is the result of an incomplete accounting of carbon in the agricultural market. To decrease overall emissions from LUC, policies must be implemented that would internalize emissions from LUC into the production decisions involving all agricultural production, independent of the final use of the produced feedstock. The use of calculated carbon maps can illustrate the functioning of such policy means. Thus, the third aim of this paper is to use the calculated carbon maps to show the implications of a carbon pricing binding for all agricultural production in the study regions.

The Kalimantan and Sumatra regions of Indonesia were chosen for this study because Indonesia is the largest producer of palm oil in the world. This fact drives to a large extent the discussion about sustainable biofuels as Indonesia has experienced tremendous forest losses in the last decade causing accelerated biodiversity loss and very high LUC emissions from converted forest and peatland areas (Edwards et al. 2010). Due to the low price of palm oil on the world market, it is not only used to produce biodiesel for the EU biofuel target but also represents the main cooking oil in Asia. Additionally, it is contained in many food and cosmetic products worldwide. Thus, the need to reduce emissions from LUC not only in the EU biofuel context is particularly urgent for Indonesia.

The rest of the paper is structured as follows: In section 2, we briefly introduce the EU-RED sustainability requirements. Section 3 presents the method and data used to calculate the carbon maps for Sumatra and Kalimantan. In section 4, we show how the resulting carbon maps can be used to evaluate potential biofuel production with the EU-RED sustainability requirements. In section 5, we present the results for different palm biodiesel production pathways and discuss the implication of results concerning dLUC and iLUC in section 6. Based on these results, section 7 shows how the carbon maps can be used to implement a carbon pricing scheme. In section 8, we briefly summarize the results and draw conclusions.

2. EU-RED sustainability requirements

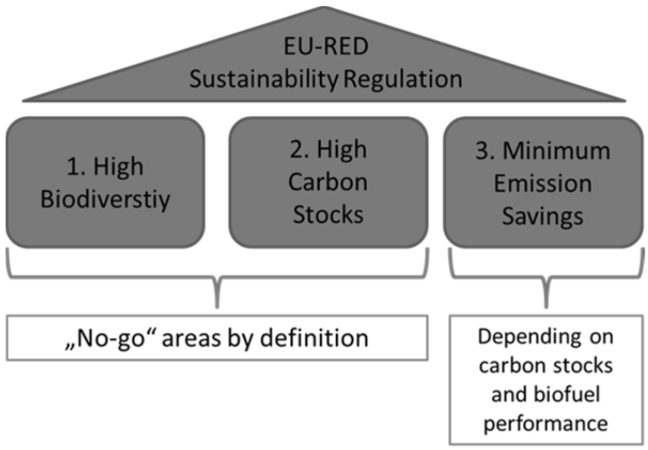
To illustrate which criteria a carbon map for the EU-RED must meet, in this section, we briefly discuss the sustainability requirements of the EU-RED. These sustainability requirements mainly tackle the problem of possible dLUC as a result of biofuel feedstock production. Under the EU-RED framework shown systematically in figure 1, biofuels and bioloquids shall not be made from raw material obtained from land with a high biodiversity value or lands with high carbon stocks.[30] Thus, these areas are generally a "no-go" with respect to feedstock production.

For all other areas, it must be proved that the resulting biofuel provides emission savings of at least 35% compared to the fossil fuel alternatives by accounting for possible emissions from dLUC as well as production and transportation emissions (EU-RED Art 17(2)). This implies that biofuel crops produced on land with previously high carbon content are less likely to achieve this target. This minimum emission saving threshold (EST) will be increased to 50% in 2017 and 60% in 2018 for new installations for biofuel production (EU-RED 2009).

These sustainability requirements must be met by both imported bioliquids and those produced within the European Union to count toward the national targets of renewable energy.

[30] These are wetlands, continuously forested areas with a canopy cover higher than 30%[30], and land spanning more than one hectare with trees higher than five meters and canopy cover of between 10% and 30%, unless evidence is provided that the carbon stock before and after conversion apply to saving greenhouse gas emissions at least at 35% (EU-RED Art.17(3,4).

Figure 1. Framework of the EU-RED sustainability regulation



This paper focuses on the third column of the sustainability criteria (see figure 1), which includes all areas not already excluded by definition from being suitable for biofuel production. However, as far as possible, areas falling under columns 1 and 2 in figure 1 are included in the analysis. A basic requirement for testing compliance with column 3 is the information on potential dLUC emissions that would occur if an area were to be converted for biofuel feedstock production. Such information can be provided by carbon maps, which are introduced in the next section.

3. Carbon Mapping according to the EU-RED for Sumatra and Kalimantan

The method used for calculating carbon maps in this section builds upon the EU-RED framework for calculating carbon emissions from dLUC as presented in Carré et al. (2010). A more detailed description of the calculation steps can be found in Annex 1 of this paper or in Lange and Suarez (2013) who calculated an EU-RED carbon map for the Llanos Orientales and Söder (2014) who calculated an EU-RED carbon map for the Brazilian Cerrado.

To determine the carbon stock (CS_{il}) per unit area *i* associated with a particular land use *l,* one must summarize the carbon stock stored in the soil ($SOCact_{il}$) and biomass ($Cbio_{il}$) and then multiply the result by the hectares per unit area (A_i) (see equation 1). [31]

$$CS_{il} = (SOCact_{il} + Cbio_{il}) \times A_i \qquad (1)$$

[31] Normally, one uses one hectare as the unit area. However, it could be every other area like the area of a pixel if the analysis is made on the basis of a raster data set.

The following two sections present the method and data separately for each carbon stock.

3.1. Carbon in Biomass

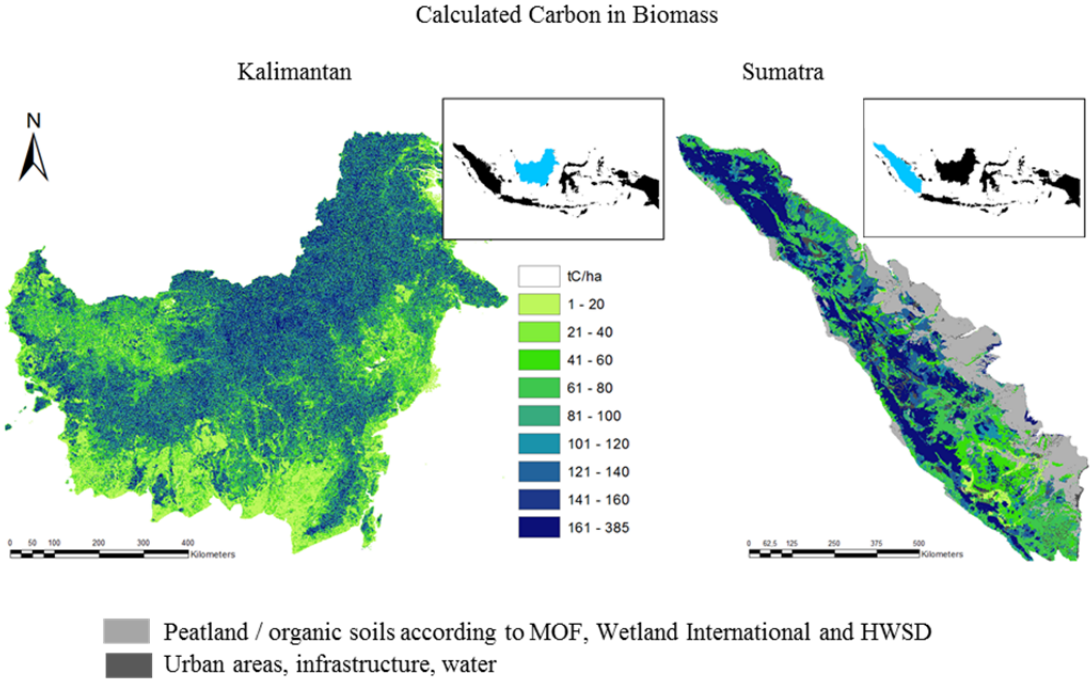
A comparison of different methods for determining biomass carbon stock can be found in Goetz et al. (2009) or Wertz-Kanounnikoff (2008). Annex 1 of this paper summarizes the most important ones. For the study regions, we use two different methods due to the different availability of data. For Sumatra, we use the official land cover map of the Ministry of Forestry of Indonesia (MoF 2009) and combine it with the average carbon values for each land cover class from the literature. For Kalimantan, we use a map based on ALOS PALSAR radar satellite imagery and ICESat-GLAS spaceborne LIDAR height measurements (Sarvision 2011). The main difference between the two maps is that the map based on the land cover map contains only one carbon value per land cover class, whereas the vegetation structural type map directly measures the carbon value per unit area. Thus, the local carbon value of a unit area is explicitly determined, and therefore, one land cover class can generate a whole range of local carbon contents.[32]

To convert the Sumatra land cover map into a map that displays the carbon stock stored in both above and below-ground biomass, the values for carbon stocks associated with different land cover classes were taken from several sources. The exact values used in the calculation and their respective sources are listed in the data tables of Annex 2. To choose some of the carbon values from Carré et al. (2010) or the IPCC (2006), the climate zone of the area must be known. For this purpose, we use the climate zone map provided by the Joint Research Centre (EC-JRC 2010).

The resulting map on carbon stocks stored in total biomass in Sumatra, 2008, is shown in figure 2. One can clearly identify the difference between the large carbon stocks in the remaining natural forest and the very low carbon stocks in the already cleared and used areas.

[32] Even though locally less specific, the use of a land cover map like the MOF map for Sumatra is appropriate for EU-RED carbon mapping. The motivation behind Lidar and Radar applications is mostly because UN-REDD projects require an explicit determination of the carbon stored in the biomass of forests to determine a baseline for the payments for the ecosystem service mechanism. However, this is less relevant for the EU-RED as forests and wetlands are generally excluded from being suitable areas for feedstock to produce biofuels in the EU-RED. In addition, there is also a cost benefit in the choice of the method as Landsat and others optical sensors are cheaper than LIDAR or SAR technology. Last but not least, the impact of a derived carbon map strongly depends on the acceptance of policy makers and producers in the country. The MOF map is officially recognized by the Indonesian authorities.

Figure 2



For Kalimantan, a map based on active[33] data is available which was generated by Sarvision[34] within the Global Land Use Change Project of WWF Germany. A detailed description of the data-generating process can be found in Sarvision (2011), and Annex 1 contains a short summary. To derive an above-ground biomass density map[35], Sarvision (2011) used a combination of a vegetation structural type map derived from recent ALOS PALSAR radar satellite imagery, ICESat-GLAS spaceborne LIDAR height measurements that can be related to above ground biomass, and a field survey.

We convert the unit of the map of biomass densities into carbon by multiplying the all values by 0.47[36]. In addition, carbon in the below-ground biomass is added by applying a constant ratio factor R. Figure 2 shows the resulting map, displaying the carbon stored in total biomass in Kalimantan in 2008.

Compared to Sumatra, in Kalimantan large forest areas still remain. However, in the southern part of the island and in parts to the east, large plantation areas and degraded forests already exist in particular. Naturally, this structure is also observed

[33] Active data are based on sensors which measure reflected energy and which have their own source of light whereas passive sensors measure reflected sunlight.
[34] Sarvision is a spin-off of Wageningen Universtiy http://www.sarvision.nl/.
[35] Sarvision also provided a land cover map which was needed to calculated the soil carbon stock
[36] 0.47 tonne of C per tonne biomass (dry weight) is the default assumption in IPCC 2006

in the biomass carbon map, where the highest carbon stocks emerge in the forests of Central Kalimantan.

Comparison of both biomass carbon maps for Sumatra and Kalimantan clearly shows the strength of Lidar and Radar analysis compared to the use of only land cover maps combined with average carbon values from the literature. The combination of both maps shows the high range of carbon values within one land cover class. In contrast, a unique value from the literature can at best show the average carbon stored in a particular land cover class. For instance, for the land cover class of “high forest with closed canopy,” the mean value for carbon in biomass is 139 tC/ha in the Kalimantan map. However, the standard deviation of 91 tC/ha highlights the high range of possible carbon values within one land cover class. The detailed carbon map for Kalimantan in figure 2 covers the whole range of carbon values, and therefore, more accurately represents the carbon stock at the local level.

3.2. Soil Carbon

After calculating the carbon stocks in above- and below-ground biomass, calculation of the carbon in the soil, which is not part of the living biomass of roots, remains necessary. The carbon stock stored in the soil changes once the land is used for agricultural production. Thus, for the calculation of the present carbon stock stored in the soil, information from the land cover map must be combined with a soil map. Here, we only consider the Tier 1 approach of the IPCC 2006 which modeled soil carbon stocks influenced by climate, soil type, land use, management practices and inputs.

The EC provides a soil map based on the FAO harmonized world soil database (HWSD) generated by IIASA (FAO/IIASA/ISRIC/ISSCAS/JRC, (2012). We use this soils map combined with soil carbon values from the IPCC 2006. The IPCC 2006 also provides the factor values needed to model the impact of the land use type, management regime and inputs. We generate these factors by defining the typical management regime and input for each land use type based on the land cover map. A detailed description of these calculation steps and the data input for the soil carbon map are contained in Annex 1 of this paper.

We generally exclude peatland areas from this mapping exercise because, due to their high carbon content, the EU-RED generally excludes them from being suitable areas for biofuel production.[37] To identify peatswamp areas, we use three different sources in order to increase the probability that all peatswamp areas were identified. These areas include all swamp areas from the MOF land cover map, and information from Wetlands International (Wetlands International 2008) on organic soil content as well as information on organic soils taken from the soil map based on the FAO harmonized world soil database generated by IIASA (FAO/IIASA/ISRIC/ISSCAS/JRC (2012).

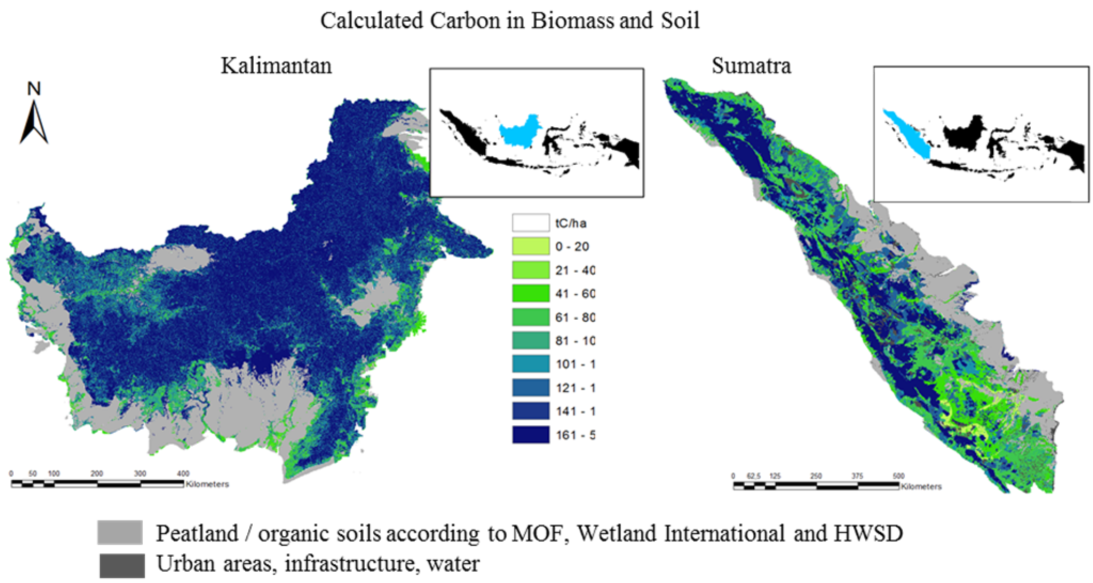
3.3. The Total Carbon Map

The final carbon map is calculated by overlaying and summarizing the map of carbon stocks stored in total biomass and the map of actual carbon stocks stored in the soil. The result is a carbon map that indicates the high and low carbon stock areas.

Figure 3 shows these maps for Sumatra and Kalimantan. The results mainly mirror the results of the carbon maps of biomass but at a higher level of overall carbon content. This is because we exclude the very large carbon pools in peatland soils. Consequently, the maps in figure 3 show very high carbon stocks in the forest areas and low carbon stocks in the areas already used for agricultural production. Again, the Kalimantan map shows in much greater detail the possibility that the local carbon stocks can generate variable carbon values within one land cover class. The areas with medium biomass cover in the transition areas to the forest and the areas at the deforestation frontier are represented with a higher degree of detail in particular. These areas will be the first deforested for new plantations as they are closest to already existing production areas. Thus, these areas are important to certifiers, and the higher accuracy of local carbon values can guide a more realistic result of carbon balances in the certification process.

[37]Several difficulties arise when calculating emissions from peatland based on the method presented here. According to EU-RED, the carbon content is to be calculated for the first 30 centimeters of the soil as this is the layer where most of the carbon is stored in mineral soils. This does not apply for peatswamp areas which can have a thickness of several meters. In addition, the EU-RED method based on the IPCC 2006 assumes that the carbon content of a soil after a LUC stabilizes again after 20 years of agricultural production (excluding emissions from tillage and inputs). This is an arbitrary assumption for calculation purposes but not totally unrealistic for mineral soils. However, peatland soils converted to agriculture can keep on causing emissions for hundreds of years and certainly do not fully stabilize after 20 years. For a discussion of annual emission factors for different land uses in Southeast Asian peatlands, see Hergoulc'h and Verchot (2013).

Figure 3



4. Sustainable production areas under the EU-RED emission saving requirements

The determined total carbon stocks can indicate high and low carbon stock areas but do not yet indicate whether biofuel production in these areas contribute to climate mitigation or not. This section evaluates the carbon maps with respect to the EU-RED sustainability regulation for the example of palm based biofuel production. To prove compliance with the 35% EST, the potential emission savings for each spatial unit must be calculated. These potential emission savings emerge if this spatial unit is converted into a palm plantation to produce feedstock for biofuel production. Emission savings represent average annual savings for a production period of 20 years. For this purpose, a few more steps of calculation are necessary:

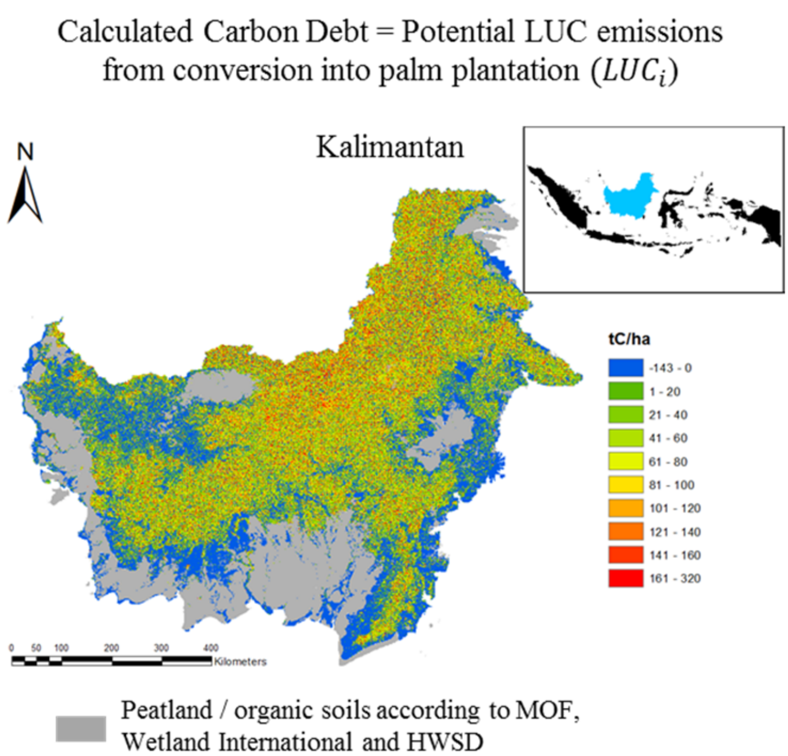
First, the emissions caused by the land use change (LUC_i) must be identified by simply taking the difference between the carbon stocks stored in the land use at t0 (CS_{i_before}) (which is 2008 for the current regulation) and the carbon stocks stored in the land use at t1 (which is the time after the LUC). Here, t1 represents the carbon stock stored in a palm plantation ($CS_{i\_biofuel\_feedstock}$) (see equation 2).

$$LUC_i = CS_{i\_before} - CS_{i\_biofuel\_feedstock} \qquad (2)$$

We then derive $CS_{i\_biofuel\_feedstock}$ by repeating all calculation steps performed so far under the assumption that each area lies within a palm plantation.

Figure 4 shows the result of equation 2 pertaining to Kalimantan. Areas colored in blue would generate a gain in carbon storage when converted into a palm plantation. All other areas result in carbon emissions. Thus, the conversion of these areas into palm plantations would generate a carbon debt. Figure 4 shows that this mainly applies to all forest areas.

Figure 4:



Second, we convert the total emissions caused by the land use change (LUC_i) into emissions per year on the basis of a 20-year period and then convert carbon stocks into carbon dioxide stocks by multiplying the former by the conversion factor 3.664 (IPCC 2006). Third, we convert the LUC emissions per hectare into LUC emissions of the final biofuel unit (LUC_{mji}). For this purpose, we divide the LUC emissions per hectare by the energy yield per hectare of the biofuel feedstock (P_i). Consequently, the resulting LUC emissions per MJ biofuel (LUC_{mji}) are specific to each biofuel due to the specific energy yield per hectare. Higher energy yields result in fewer emissions per MJ biofuel.[38]

Fourth, the EC allows the allocation of the resulting LUC emission to each biofuel or its intermediate products and possible by-products. The allocation factor (AL) should be calculated on the basis of the energy content, that is, the lower heating value. This means, for example, that from the palm fruit, only the oil is used for biodiesel production. The remaining palm cake is mainly used as animal feed. We evaluate both the palm cake and the palm oil with their lower heating values. Then, we allocate the land use and production pathway emissions to the emission balance of palm biodiesel in the same proportion as the share of palm oil on the total lower heating value of the harvested palm fruit. Equation 3 summarizes these calculation steps.

$$LUC_{mj_i} \frac{CO_2}{MJ} = LUC_i \frac{C}{ha} * 3.664 * \frac{1}{20} * \frac{1000000}{P_i \frac{MJ}{ha}} * AL_i \qquad (3)$$

To evaluate the calculations of LUC emissions per energy unit of palm based biodiesel, it remains necessary to compare the emission balance of the biodiesel to that of the fossil fuel alternative. Thus, as a last step, we calculate emission savings (ES_i). Emission savings refers to the savings generated due to the use of biofuel feedstock compared to the alternative use of fossil fuels. The term "emission savings" introduced by the EU-RED is slightly misleading, as it does not indicate that every biofuel saves emissions. Emission savings could also be a negative outcome if the production and use of the biofuel causes higher emissions than the fossil fuel alternative. With respect to LUC emissions, one can generally say that high LUC emissions due to high carbon stocks before the LUC result in low or negative emission savings. To calculate the emissions savings, one has to add to the LUC emissions (LUC_{mj_i}), the emissions resulting from the production process (WTW_i). These emissions include all emissions from well-to-wheel (WTW), meaning all emissions from the production of the feedstock until the transportation of the biofuel to the gas station. The resulting total emissions are then compared to the 83.8 gCO2/MJ emissions contained in the fossil fuel alternative, and resulting

[38] I assume no production on degraded land, and thus, ignore a possible emission bonus granted by the EU-RED for emission savings.

emission savings are derived in percentages. These calculation steps are summarized in equation 4.

$$ES_i\% = \frac{100}{83.8} * \left[83.8 - \left(LUC_{mj_i} + WTW_i\right)\right] \quad (4)$$

In addition, the energy yield per hectare ($P_i \frac{MJ}{ha}$), the emissions resulting from the production process (WTW_i) and the fraction of the biomass that is allocated to the biofuel production (AL_i) are specific for each biofuel option. Thus, emission savings are also specific for each biofuel option. Table 1 contains the values used for equations 3 and 4 in the carbon maps. We use the default values for production emission (WTW_i) from the EU-RED for different biofuel production pathways and take average values for energy yields from the German Agency of Renewable Resources FNR (2012). An allocation factor (AL_i) is considered for the main co-products according to their heating value[39] calculated with EU-JRC Data (IES 2008).

Table 1. Production processes and yields

	$P_i \frac{MJ}{ha}$	Source	AL_i	Source	WTW_i	Source
Palm biodiesel with methane capture in the production process	123344.4 = 17t/ha	Pancheco (2012) and FNR (2012)	0.91	IES 2008	37	EU-RED
Palm biodiesel without methane capture in the production process	123344.4 = 17t/ha	Pancheco (2012) and FNR (2012)	0.91	IES 2008	68	EU-RED
Palm biodiesel with methane capture in the production process and higher yields	145111.1 = 20t/ha	Pancheco (2012) and FNR (2012)	0.91	IES 2008	37	EU-RED

Furthermore, we calculate the emission savings from three different palm production processes to identify the full range of development of the palm sector in Indonesia. These processes include 1) palm oil production with methane capture during the production process[40] and an average yield of 17t/ha (Pancheco 2012); 2) palm oil

[39] The lower heating value is used as an indicator of the heating energy contained in a fossil fuel or organic material. The EC decided to use this value as a unit on which to base on the allocation of emission on different co-products.

[40] Methane emissions in the production process result from the storage of the palm oil mill effluent (POME). POME is the liquid residue when fresh palm fruit bunches are processed into crude palm oil. In many mills, POME is stored in a chain of open lagoons during a certain period of time, where it is cooled and where part of its organic matter content is degraded biologically which causes emissions of biogas (Waarts and Zwart 2013). In addition to carbon dioxide, methane is a major component of this biogas. If the biogas escapes uncontrolled from the pond into the atmosphere it can strongly worsen

production without methane capture in the production process and an average yield of 17 t/ha; and 3) palm oil production with methane capture in the production process and an average yield of 20 t/ha (FNR 2012). We do this in order to check the sensitivity of the results with respect to efficiency in the production process and the productivity assumed in the calculation. While 17 t/ha is the average yield on Indonesian palm plantations (Pancheco 2012), a yield of 20 t/ha can be found on more modern and productive plantations (FNR 2012). The next section presents the resulting maps.

5. Results for different palm biodiesel production pathways

The minimum EST allows the use and conversion of land when the final biofuel option creates at least 35% emission savings. Thus, according to the EU-RED, all areas that result in 35% or more emission savings would be potentially eligible for certification with respect to carbon emissions when converted for biofuel production. However, we do not consider biodiversity or other sustainability criteria here and, consequently, do not call these areas "go-areas."[41] The minimum emission savings threshold will soon rise to 50% for new installations from 2017 on and to 60% in 2018 for installations built after 2017. These thresholds are indicated in the maps of figure 5 (see page 103), which show the emission savings for Sumatra and Kalimantan assuming the three different palm production processes. The green areas represent sustainable production areas under the minimum emission saving criterion. The different shades of green indicate the different levels of the minimum EST. Based on the total carbon map derived above, it is only logical that areas with high carbon stocks are less likely to achieve the 35% minimum EST than areas with low carbon stocks.

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the carbon balance of palm based biofuel since methane is 21 times more effective as a greenhouse gas than carbon dioxide (Waarts and Zwart 2013). In more modern palm oil mills, methane is captured and can be used for power generation.

[41] Hadian et al. 2013 "Promoting sustainable land use planning in Sumatra and Kalimantan, Indonesia" mapped several biodiversity indicators for Sumatra and Kalimantan (Forthcoming on www.globallandusechange.org).

Table 2: Area achieving the minimum EST in Sumatra (47.3 million ha total island area)

Palm oil production process	Areas excluded from analysis	Area achieving the minimum EST under different ESTs			
		0%	35%	50%	60%
No methane capture and 17t/ha yield	peatland soils / swamp areas	20.5	16.7	16.7	16.3
Methane capture and 20t/ha yield	peatland soils / swamp areas	20.5	20.5	20.5	16.7
Methane capture and 17t/ha yield	peatland soils / swamp areas	20.5	20.5	20.5	16.7
	No-go areas by land cover definition (forest and peatland areas) and without areas already used	3.4	3.4	3.4	3.4
	No-go areas by land cover definition (forest and peatland areas)	20.5	20.5	20.5	16.7

For Sumatra, the results clearly show that the assumed production process and productivity have only a minor impact. This is because the remaining forest area is under no assumption in line with the EU-RED sustainability criteria when converted into palm plantations. This area is colored in red in all emission savings maps. With respect to carbon, it is only the non-forest areas which are in line with the EU-RED. Under the current 35% EST, approximately 20.5 million hectares achieve this threshold under the assumption of methane capture in Sumatra (see Table 2 for an overview of areas achieving the minimum EST). Higher yields do not change this result. The increase in the minimum EST to 50% has no impact compared to the area available under 35% EST. An increase to 60% would only slightly reduce the available production area by approximately 4 million hectare. When no methane capture is applied in the production process, the area available under the 35% EST reduces to 16.7 million hectare. The increase in EST to 60% only marginally affects the available area.[42]

For Kalimantan, the results are similar to those in Sumatra. All forest and forest-like biomass is well beyond the 35% EST, and in most cases result in even much higher emissions than those which can be saved in 20 years of biofuel production and use. The different thresholds show differences in the available area on the local level due to the very high resolution of the Sarvision (2011) data, which also capture small openings, water bodies and degraded areas. Thus, because of the high range of

[42] Naturally, palm plantations remaining palm plantations and keeping their management practices have no LUC emissions. Here, the results in figures 7-9 are purely driven by the process and transport emissions. Under the EU-RED default WTW values, that means that a production with methane capture is in line with the 35% EST but a production without methane capture is not.

carbon values within one land cover class, it is entirely possible to find pixels both above and below the 35% EST within each class.[43]

Table 3: Area achieving the minimum EST in Kalimantan (61.5 million ha total island area)

Palm oil production process	Areas excluded from analysis	Area achieving the minimum EST			
		Neutral Emission Balance	35%	50%	60%
No methane capture and 17t/ha yield	peatland soils / swamp areas	19.3	14.1	12.4	10.4
Methane capture and 20t/ha yield	peatland soils / swamp areas	26.8	20.9	17.9	15.8
Methane capture and 17t/ha yield	peatland soils / swamp areas	25.3	19.4	17.9	15.8
	No-go areas by land cover definition (forest and peatland areas)	12.4	10.9	10.3	9.7
	No-go areas by land cover definition (forest and peatland areas) and without areas already used	8.8	7.3	6.7	6.4

For a production process with methane capture and an average yield of 17 t/ha, the possible sustainable production areas under the EST criterion range from 19.4 – 15.8 million ha for the 35% EST to the 60% EST. Thus, the increase in threshold further reduces the sustainable production area but does not substantially change the outcome (see Table 3).

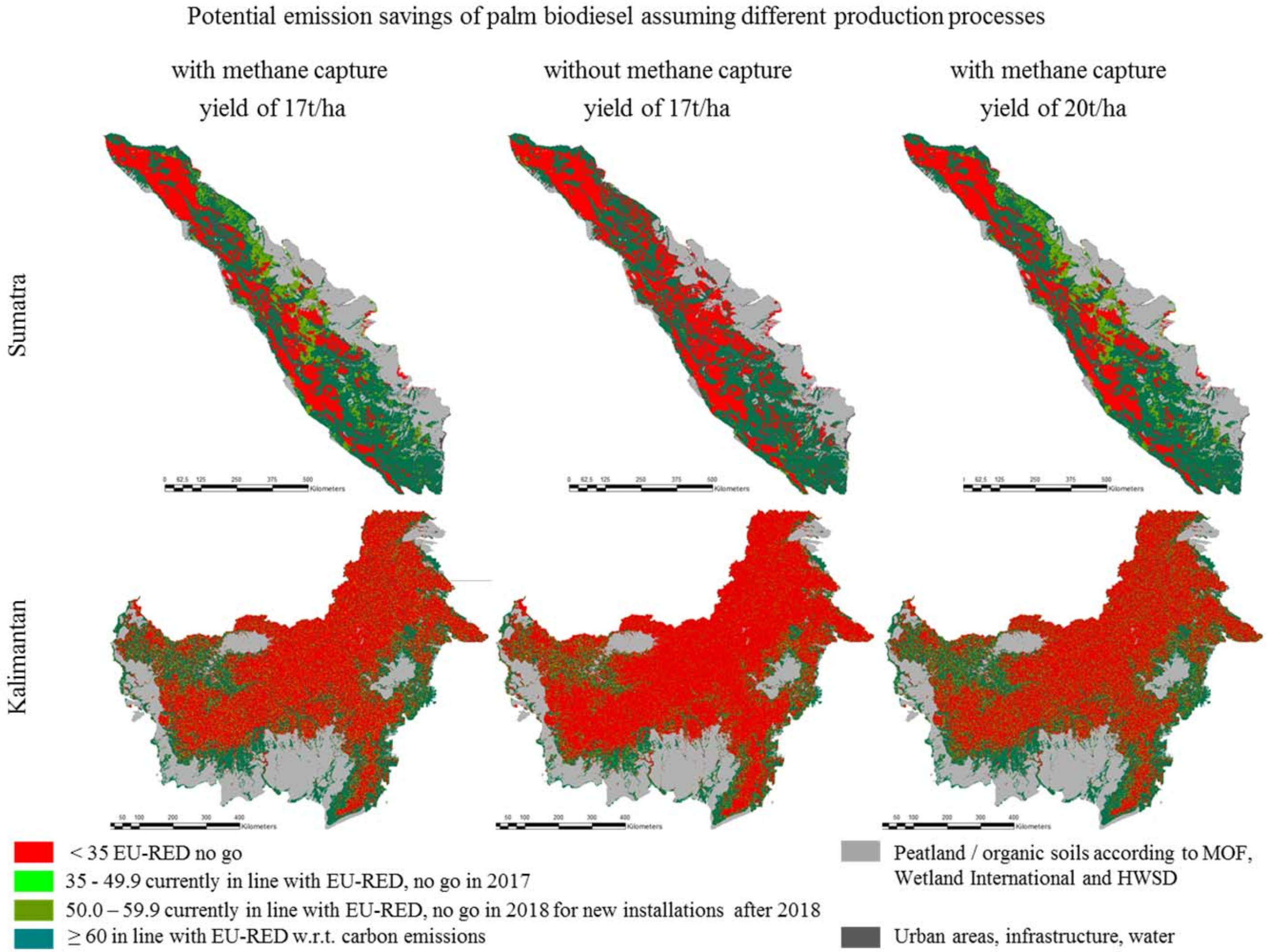
Evaluating the more detailed data from Kalimantan, the production process substantially impacts the areas achieving the minimum EST. If methane is not captured in the production process, it leads to a strong decrease in production possibilities to roughly ¼ under the 35% EST (to 14.1 million ha) and to approximately $^{1}/_{3}$ under the 60% EST (to 10.4 million ha), compared to production during which methane is captured. Therefore, the implementation of methane capture into all production processes could increase the sustainable production area available under the emission saving criterion for the European market.

[43] A comparison of two global carbon maps from Saatchi et al. 2011 (1 km resolution) and Baccini et al. 2012 (500m resolution) by Ed Mitchard from the University of Edinburgh (http://carbonmaps.ourecosystem.com/interface/ access 10.07.2013) show local differences in results by up to +/- 150 tC and much less variability in values especially in the continuous forest areas. As more maps derived on active data emerge for this region, the sensitivity of the results against methodological differences and scales should be analyzed. This variability in carbon values are not that important for our results as the land cover map from Sarvision 2011 defines these areas as continuous forest which are no-go areas by definition in the EU-RED. However, for UN-REDD assessments results should reflect the "real" carbon values as accurately as possible as payments are related to the carbon stored in the forest biomass.

The increase in yield to 20 t/ha, however, only has an effect on the available area under the 35% EST, slightly increasing it to 20.9 million ha. With an increase in the EST, the available sustainable production area is the same as that under the yield of 17 t/ha because both examples result in negative emission savings for forest areas with high biomass cover.

Summarizing the evaluation of the carbon maps against the EST, the results show that increasing yields and implementing methane capture into the production process increases the sustainable production area in regions with a medium biomass cover. However, this does not change the fact that an expansion into forest or forest-like areas will never be sustainable in terms of carbon emissions.

Figure 5


Potential emission savings of palm biodiesel assuming different production processes
with methane capture
yield of 17t/ha
without methane capture
yield of 17t/ha
with methane capture
yield of 20t/ha
Sumatra
Kalimantan
< 35 EU-RED no go
35 - 49.9 currently in line with EU-RED, no go in 2017
50.0 – 59.9 currently in line with EU-RED, no go in 2018 for new installations after 2018
≥ 60 in line with EU-RED w.r.t. carbon emissions
Peatland / organic soils according to MOF, Wetland International and HWSD
Urban areas, infrastructure, water

6. Implications for dLUC and iLUC

The analysis in the previous section shows the areas suitable for palm production with respect to the EU-RED minimum EST. However, the results do not yet indicate whether production in these areas causes emissions from dLUC or incurs the risk of causing iLUC. Therefore, in this section we first calculate how much area for expansion still remains that has not yet been used for agricultural production but still achieves the minimum EST. These are those areas where an expansion causes dLUC emissions but still produces sufficient emission savings to be eligible under the EU-RED criteria. They can be calculated by subtracting the area already used for agricultural production from the suitable area under EU-RED calculated in section 5.

Calculating the available dLUC expansion area is the basis for the analysis of iLUC-related implications of the EU-biofuel mandate from palm oil demand. Because, if palm oil for the EU biofuel mandate is produced on already-existing plantation areas or on areas previously used for other agriculture production, palm oil plantations might expand into natural areas due to increasing prices.[44] This expansion of palm plantations that may produce palm oil for markets other than the EU-biofuel market is possible because no binding sustainable criteria exist for these markets.[45] Although there is no guarantee, the possibility of avoiding the iLUC mechanism only exists if there are expansion areas in Indonesia that are in line with the EU-RED sustainability criteria and not yet used for agricultural production.

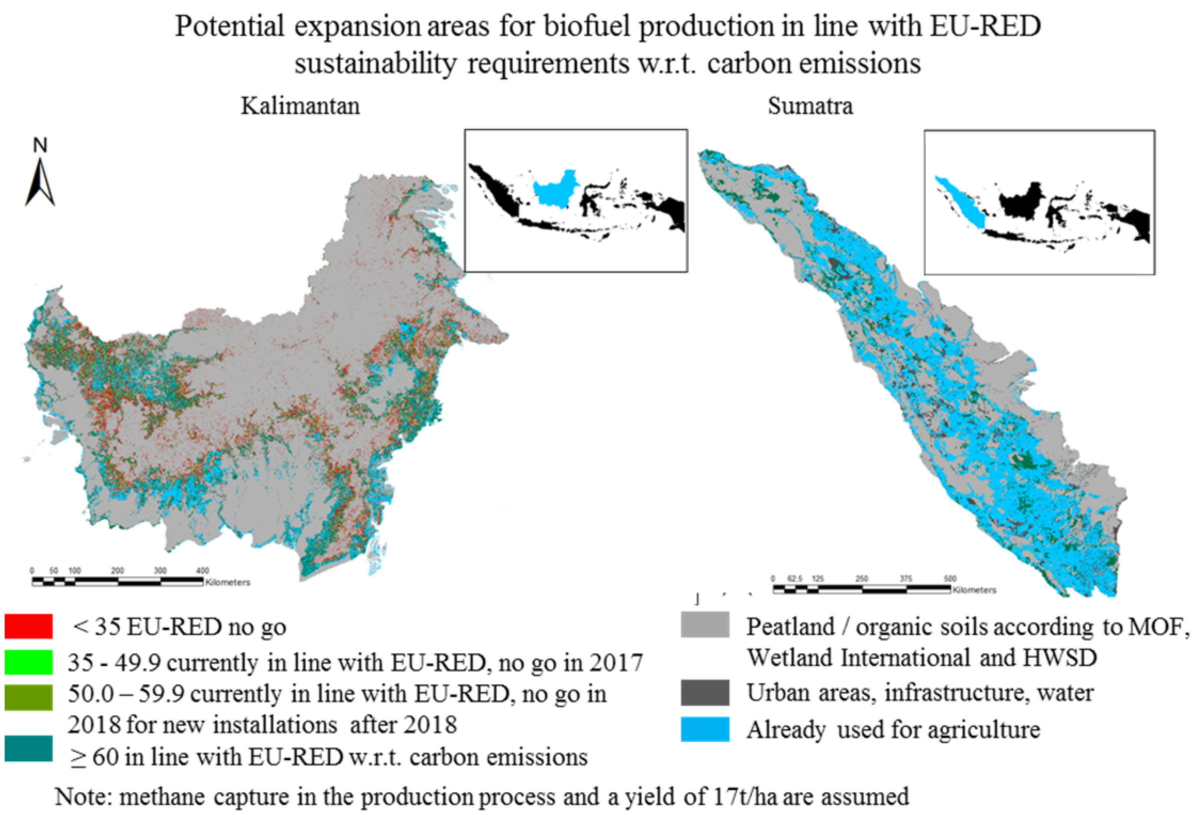
With respect to carbon, these areas are determinable. In addition to figure 5 from which wetland areas and peatswamp areas are already excluded, we also exclude all forest areas (over 30% canopy cover) because they are no-go areas by definition in the EU-RED (light gray in figure 6). This calculation step only changes the results for Kalimantan because the Sarvision approach allows different carbon values within the forest land cover class (see Tables 2 and 3). For Sumatra, the carbon value for a forest is the same for all forest areas, which is clearly beyond the 35% EST. In addition, the areas which are already used for agricultural production are now marked in light blue. The EST for the remaining areas is indicated as in the previous set of maps. The results of this exercise are shown in figure 6 for Sumatra and Kalimantan.

[44] Under the assumption that the demand for palm oil from other sectors remains stable or increases

[45] The same mechanism is in place if a vegetable oil other than palm oil is used for European biofuel production and the “missing” oil in the food market (indicated by increasing prices for vegetable oils) is replaced with palm oil from Indonesia.

It becomes evident that there are few areas left for expansion into unused areas. For Sumatra, the subtraction of the areas already used for agricultural production has the highest impact. This is because in 2008 large areas of the island had already been deforested and used for production. Expansion areas under the emission saving criterion decrease to only 3.4 million ha (see Table 2).

Figure 6



For Kalimantan, this calculation step is less substantial because less area has already been used for agricultural production. However, the general exclusion of forested areas excludes pixels which are in forest areas but have low biomass due to degradation or small openings. However, as these pixels can be in very remote areas and normally do not represent a large continuous area that would be needed for the installation of a palm plantation, they are most likely unsuitable expansion areas anyway. Thus, for Kalimantan, after this calculation step, expansion areas under a production process with methane capture and a yield of 17t/ha amount to 7.3 million ha (see Table 3). This further reduces to 6.4 million ha when the 60% EST is implemented, which is approximately 10% of the island area.

To evaluate the results, one must keep in mind that these maps do not include biodiversity factors and areas needed for other infrastructure, settlements etc.

Furthermore, they do not account for the suitability or productivity of the land for production, which can further decrease area availability. Thus, even though this conclusion is tempting, the 10% will not reflect the entire available expansion area for palm oil production in Kalimantan, keeping in mind that in addition, all production would need to achieve a yield of 17 t/ha and apply methane capture for this number to hold. Moreover, this area is only freely available if all other production remains constant.

Summarizing this section, it shows that the expansion areas for palm production causing dLUC are not very large; therefore, iLUC can become a problem because most of the palm oil for the European biofuel market will be produced on already-existing agricultural land. In the next section, we discuss options for tackling the problem of iLUC emissions.

7. ILUC and how it could be overcome

The effects of iLUC exist under two assumptions. First, the replacement of other production results in a price effect on the world market; second, other production does not underlie any sustainability requirements. In this section, we briefly discuss the price effect of iLUC as a first step. As a second step, we discuss options for implementing sustainability requirements for markets other than the European biofuel sector based on the calculated carbon maps. Upon the latter, we return to the initial claim that LUC emissions cannot be controlled for one sector alone. Therefore, we argue that the real solution to the iLUC debate is to implement a sustainability regulation that is binding for all agricultural production.

One reason for expecting a price effect from an increase in biofuel production is because the demand for vegetable oils is expected to be inelastic and to further increase in the future (Banse et al. 2008). The OECD expects an increase in global consumption of vegetable oils by 30 % by 2021 compared to 2009 (OECD Agricultural Outlook). Indonesia plans to respond to this increase in demand by increasing its production from 25m tones in 2012 to 40m tones by 2020. Environmentalists doubt that this can be achieved without further forest destruction (McClanahan 2013). Thus, demand for biofuel production will further increase demand overall, and thus, the incentives to increase production.

One way to decrease the pressure on unused areas from increasing demand is to increase productivity in the biofuel feedstock production sides relative to former production (Klepper 2013). Based on past experience of certification systems, this is indeed possible when the certification process and the implementation of all criteria on the production sides serve as an extension service. This is in line with other research showing, particularly for Indonesia, that, by far, not all areas in use are managed efficiently, but can be degraded or are prone to low productivity. Koh and Ghazoul (2010) showed that a sustainable expansion of palm plantations without further substantial forest loss is possible with a development strategy that particularly accounts for restoration of degraded areas. Given an appropriate set of incentives, according to Koh and Ghazoul (2010), oil palm producers could completely abandon expansion in areas of high biomass while retaining plenty of growth opportunities in low biomass zones. Thus, in the next section, we discuss policy options for controlling LUC emissions due to other agricultural production under the assumption that while biofuel production probably increases incentives for LUC in the future, it remains possible to increase production in existing Indonesian agricultural areas as well.

7.1. Policy options for reducing emissions from LUC for all agricultural production

Increasing prices on the world market caused by biofuels can cause LUC because other production does not underlie any sustainability regulation. A climate-friendly expansion path for any agricultural production, induced by biofuel demand or increasing demand for other markets, can only be achieved if all production is subject to a carbon-based sustainability regulation. Consequently, the emission impact of an activity would be part of every production decision. In the following section, we present options for implementing such carbon-based sustainability regulation by distinguishing between two possible regulatory measurements and a carbon pricing system.

A regulatory measurement closest to existing EU biofuel regulation would be one that implements a binding sustainability regulation for all agricultural consumer markets. In practice, this means the implementation of sustainability requirements for all agricultural products consumed in a country. As a consequence, a sustainability certification for all agriculturally based input into the food and industry sectors is required. Although voluntary sustainability certification already exists in several sectors such as coffee, chocolate, cotton or wood, implementation of a binding and consistent regulation for all sectors is far from being implemented in any of the main consumer markets.

The second possible regulatory measurement has an impact similar to that from the implementation of sustainability requirements in consumer markets but institutes a binding sustainable land use planning in feedstock producing countries. A sustainable land use planning defines areas for expansion and protection that are binding for all agricultural production in a country. Low carbon stock areas could be priority areas for agricultural expansion whereas high carbon stock areas should remain untouched for a climate-friendly expansion policy. As such, leakage effects would be avoided within the planning area. However, the implementation of such maps into the official spatial planning processes is challenging when it limits national development plans. The feasibility of such a policy in a country where weak institutions and corruption are part of the deforestation problem is at least questionable when it is not combined with serious policy reform (Lange and Bertelmann 2013). However, first initiatives for a sustainable land use planning, even though not explicitly including carbon, do exist, such as that for the Brazilian Cerrado (MMA 2013).

Carbon maps can support sustainability certification for agricultural products in consumer countries and sustainable land use planning in producer countries. However, both require a political decision about areas that are suitable and not suitable, e.g., due to high carbon stocks. Because other markets in addition to the energy sector normally do not have a fossil counterfactual, emission savings cannot be computed.

In addition to existing regulatory measurements, economic theory provides more market-based solutions to the problem of carbon leakage. Leakage exists because the externality climate change caused by LUC is not reflected in the market price of agricultural goods. The basic idea of carbon pricing is therefore to incorporate the carbon cost into the market and let producers and consumers adjust their decision-making accordingly (Bowen 2011). Two major instruments exist to correct the market price according to carbon emissions. The first option is to introduce a tax that reflects the cost of emissions. The second approach is to introduce well-defined property rights for carbon emissions with an allowance price signaling the scarcity of these rights on markets where they are traded (Edenhofer et al. 2012). While the tax fixes the price and leaves the market to decide on the actual emission reduction, the emission trading fixes the overall emission reduction and leaves the market to decide actual carbon prices (Edenhofer et al. 2012).

In particular, the idea of including the agricultural sector into an emission trading scheme has already been discussed in practice, albeit focusing only on the emissions from agricultural practices and not LUC. New Zealand had plans to implement the agricultural sector into its emission trading scheme (ETS) but has not yet done so (Kerr and Sweet 2008). Australia allows agricultural producers to generate emission reduction ‘credits’ and to sell them to scheme participants via the Carbon Farming Initiative (CFI) (Talberg and Swoboda 2013).

Emission trading in the agricultural sector is also an option discussed in the scientific literature, but it focuses only on emissions from agricultural practices. Perez Dominges et al. (2009) model the incorporation of the agricultural sector into the EU-ETS. Ancev (2011) analyze the costs and benefits of an integration of the agricultural sector into an ETS scheme, and Bakam and Matthews (2009) study the different design options for an emission trading scheme in agriculture by using agent-based modeling. Moreover, several studies analyze the implications of implementing an emission trading scheme within local agriculture. These studies include those of Breen (2008) and Donellan and Hanrahan (2006) on Irish farmers, those of Bullok (2009) and Kerr and Sweet (2008) on New Zealand farmers and those of MCCarl and Schneider (2000) on farmers in the US.

All of these policy initiatives and studies have in common a focus on emissions from the agricultural sector in developed countries. These predominantly include emissions from the use of fertilizers, pesticides and fuels in agricultural machineries. LUC is an increasingly rare phenomenon in these countries, and therefore, they are generally not included within the analysis. In addition, LUC emissions included in imports such as palm oil were not considered. Golub et al. (2013) study the effect of land based carbon policies in a global CGE model. The policy option of a carbon pricing system presented in the next section differs from the existing literature in that it would incorporate all emissions of all agricultural production, and thus also LUC emissions, into an ETS or tax system. In addition, it focusses on the local land use effects.

7.2. Carbon pricing and land use change emissions

The calculated carbon maps enable one to simulate the implementation of emissions from LUC into a carbon pricing scheme. The maps foster the evaluation of each production with its carbon balance, including emissions from dLUC, and then impose the emission cost on each production based on the carbon price. With the inclusion of the whole agricultural sector into an emission trading scheme or a carbon tax system, one would achieve a level playing field across all agricultural production. As such, all dLUC emissions would be reflected directly in the market price for the produced good, and leakage effects such as iLUC would be avoided.

In the following section, we simulate a carbon pricing scheme based on the carbon map of Kalimantan. We focus on the local impact of such carbon pricing and do not discuss the difficulties of incorporating it into an emission trading scheme. Furthermore, we only discuss the impacts of such carbon pricing on palm oil production. Although rice and rubber production are also important crops within the Indonesian agricultural sector, the expansion of palm shows that farmers prefer palm oil if they can afford the investment for clearing, palm seedlings and low yields from premature plantation stands (Feintrenie et al. 2010). This becomes even more evident when comparing the average return to the farmer of different crops with 36€ per man day for palm oil, 17€ per man day for clonal rubber, 21€ for rubber agroforestry and only 1.7€ for wet rice (Feintrenie et al. 2010). Thus, impacts from carbon pricing on palm oil will be the benchmark by which to analyze impacts on LUC.

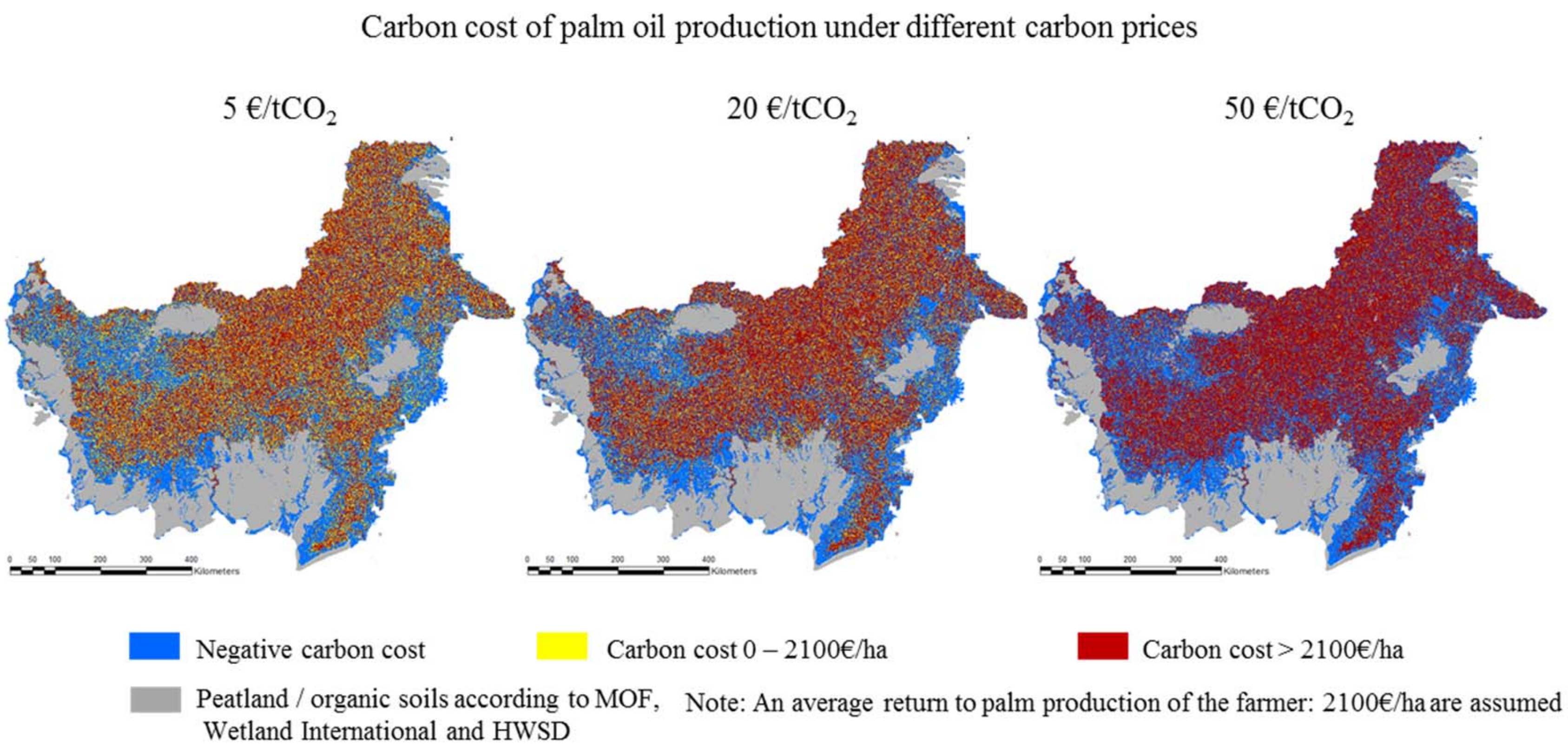
To simulate the impact of a carbon pricing scheme on decisions affecting palm oil production, we first calculate the potential carbon cost of palm production for each spatial unit by evaluating the potential LUC carbon emissions calculated for figure 4 with a carbon price of 5 €/tCO2, 20€/tCO2 and 50 €/tCO2[46]. Next, we compare the resulting carbon cost[47] to the average return to land on a full plantation cycle of 2100€/ha palm oil calculated by Feintrenie et al. (2010). [48] The estimates in the work of Feintrenie et al. 2010 include all possible investment and production costs as well as possible gains from selling valuable woods in the deforestation process.

[46] I first convert the carbon emissions into carbon dioxide emissions by multiplying the map by 3.664 (IPCC 2006)
[47] I ignore natural increase in carbon due to plant growth (net primary production NPP)
[48] Johannson et al. (2012) estimate using the CGE model DART that roughly 50$/tCO2 ($ of 2005) would be necessary to achieve the 2-degree goal.

The map in figure 7 shows the carbon cost of palm oil production at the farm gate for carbon prices of 5, 20 and 50€/tCO2. The color scheme in the maps is oriented to the average return to land of 2100€/ha for palm oil. Blue areas indicate negative carbon cost. In these areas, the farmer would gain a carbon subsidy or receive carbon credits tradable on the carbon market, all of which translates into additional income from palm production which increases incentives to use these areas. In yellow areas, farmers must buy carbon credits or pay carbon taxes. However, the carbon costs are still below the average return on palm production and, consequently, returns remain positive to the farmer. Thus, depending on alternative income possibilities, farmers might still decide to convert these areas for palm production. In the red areas, carbon costs exceed the average return on palm production, and thus, farmers would generate negative returns, leaving farmers with no incentive to convert these areas in such instances.

The map in figure 7 illustrates that below a low carbon price of 5€/tCO_2, very few areas are red and therefore are certainly excluded from the profitable production areas for palm production. For large parts of the natural areas, farmers would have to bare the carbon costs but still gain a positive return from palm oil production. This is consistent with results from

Figure 7


Carbon cost of palm oil production under different carbon prices
5 €/tCO2
20 €/tCO2
50 €/tCO2
Negative carbon cost
Carbon cost 0 – 2100€/ha
Carbon cost > 2100€/ha
Peatland / organic soils according to MOF, Wetland International and HWSD
Note: An average return to palm production of the farmer: 2100€/ha are assumed

Butler et al. (2009) who show that high returns on palm oil might undermine carbon payment schemes such as UN-REDD+ under low carbon prices.

An increase in the carbon price to 20€/tCO_2 substantially reduces the area having positive returns from palm oil. A large part of the natural forest area now generates higher carbon costs than potential gains from palm production. This further aggravates at the level of 50€/tCO_2, where only a few spots within the natural areas would gain positive returns from palm production. These are mainly small openings within the forest area, which are detected due to the high resolution of the map but do not represent areas large enough for palm plantations.

In all three maps, the blue areas are predominantly those areas that are already used for crop production or that have very low biomass cover. Here, farmers receive an additional return from carbon credits or carbon subsidies, and consequently, generate an income additional to palm production. Thus, the incentive to use these areas for palm production is very high.

In summary, the results from figure 7 show that a carbon pricing scheme is able to decrease incentives to convert forested areas. In this sense, carbon pricing is similar to the UN-REDD+ mechanism. The main difference in the setting presented here is the fact that the producer has to pay for its carbon cost whereas under UN-REDD+ a land owner, community or government receives payments for not converting forest land. The incentive under UN-REDD+ to not convert the forest is therefore the forgone income of UN-REDD+ carbon credits in the future. The advantage of imposing the carbon cost on the producer is that he is a clearly identifiable agent who would have to bare its carbon cost in order to participate in the market. One major problem of first UN-REDD+ projects is to define clear property rights for natural forests in order to address the payment (Angelsen and Brockhaus 2009). In addition, emissions from converting non-forest areas or emissions along the production process such as methane remain outside the UN-REDD+ scheme. However, for a full carbon accounting system, the carbon pricing scheme complements the system of UN-REDD+ if UN-REDD+ generates carbon credits for avoided deforestation based on the additional biomass growth in a forest. In the case of deforestation, the forgone carbon credits would add to the carbon cost of deforestation in a carbon pricing scheme.

The mapping exercise illustrates the possibility of including emissions from LUC into a carbon pricing scheme. It shows that, under current palm oil prices, carbon prices need to be high enough to protect natural forests from being converted for palm production. 5€/tCO2 are too low to destroy any incentive for converting natural forests. This might represent an efficient solution in a carbon market where carbon prices reflect the true cost of carbon in the world economy. However, natural forests obviously not only have importance to the economy as a carbon sink but for preserving biodiversity and providing other ecosystem services (Sheil 2001). A combination of different instruments might be necessary to achieve goals beyond climate mitigation such as biodiversity protection. For that purpose, a combination of a carbon pricing scheme with additional sustainability requirements for biodiversity protection is possible. In the same manner, a land use planning that defines areas that are ineligible for conversion independent of the carbon price can protect valuable areas.

A discussion of all possible combinations and pros and cons of each policy option is beyond the scope of this paper. In addition, we do not address the practical implementation of each policy option. However, it is evident that there are regulatory and market-based instruments available to impose carbon-based sustainability regulation onto all agricultural production to avoid leakage effects as a result of exclusive regulation of the biofuel sector. Carbon maps are an important source of information on which to base the implementation of such policies.

8. Conclusions

We show how to calculate a carbon map according to the sustainability requirements of the EU-RED for biofuel production using the example of Kalimantan and Sumatra in Indonesia. Based on the carbon map, we derive maps showing the emission savings for biodiesel based on palm, assuming different production processes and productivity.

The generated maps can serve as a basis for investors who want to produce biofuels for the European market. In addition, they can provide reliable information for certifiers and producers in the biofuel sector. However, the results clearly indicate that there are few areas remaining for a sustainable expansion of palm plantations producing for the European fuel market. The implementation of methane capture in the production process and an increase in yield might only have a small impact on possible expansion areas. This increases the risk of iLUC and underlines the importance of a sustainability regulation for all biomass production in Indonesia.

The impact of a regulation such as EU-RED for bioenergy is minimal if no other biomass production is subject to any sustainability regulation. Thus, the problem of iLUC regulation is a problem of an incomplete emission accounting of land use practices when only biofuel production is subject to such accounting while food, feed and bioenergy production other than biofuel production are not.

Carbon maps constitute valuable tools for implementing policy instruments that cover all agricultural production. A binding sustainability certification of all agricultural products consumed in a country is the policy instrument closest to the existing EU-RED for biofuels. However, as is true for all discussed policy instruments that focus on the production side, it is only effective if all production is integrated into the system and if the major consuming countries participate. In addition, the criterion of emission savings is only definable if there is a fossil alternative against which to compare agricultural production. Hence, if sustainability certification should cover not only the protection of e.g., high biodiverse areas or primary forests but also carbon emissions, a definition of prohibitively high carbon emissions from palm production, e.g., for the food sector, is needed.

We further discuss a carbon-based, sustainable land use planning, binding for all agricultural production in the feedstock producing countries. First, initiatives of sustainable land use planning exist, for example, in Brazil. However, for effective protection of high carbon stock areas, it requires functioning institutions to implement and control such sustainable land use planning. Additionally, similar to the sustainability certification, a definition of a carbon threshold for high carbon areas is needed.

Finally, we discuss the use of carbon maps to implement a market-based carbon pricing of possible LUC emissions in an emission trading scheme or carbon tax system. Although it is far from being implemented, the integration of carbon cost into the LUC decision of the farmer would result in a protection of natural areas if carbon cost ultimately offset possible gains from agricultural production. The LUC decision would be independent of the final use of the palm oil and purely market-based according to the prices for carbon and palm oil. By integrating the whole agricultural market into such a framework, only dLUC emissions would exist and would always be imposed as a carbon cost upon the activity directly causing them. The carbon market creates a level playing field for all final uses of biomass production, and therefore, avoids market distortion and leakage effects from regulating only the biofuel sector.

Similar to first experiences with UN-REDD+, the results show that to protect native forests in Kalimantan, carbon prices must be high enough due to the large returns from palm oil production. Current carbon prices are too low to achieve long-term protection. To avoid a loss of unreplaceable ecosystem services in times of low carbon prices, a combination of carbon pricing together with the protection of high value areas, e.g., high biodiversity areas with additional sustainability requirements in a certification process or a land use planning system, can be a solution. Such a framework would consist of the first two pillars in the current EU- RED (figure 1) on the protection of high biodiversity areas and high carbon areas such as primary forest and peatland. The third pillar on emission savings could be replaced by a carbon pricing for all areas not already protected by the first two pillars. The control of carbon emissions and the protection of high biodiverse areas have already been implemented for biofuel production with functional certification schemes. Hence, experiences made within the regulation of biofuels can be used to integrate more agricultural production into emission regulation to decreases overall emissions from LUC.

The goal of decreasing emissions from LUC does not necessarily compete against the growth potentials of agricultural supply. Studies of production potentials on the already-used palm oil area show that there are large potentials to increases productivity in these areas (Koh and Ghazoul 2010). This is in line with findings from Mauser et al. (2014) that, given an optimal allocation of crops on the currently used cropland, substantial global yield potentials are available without an increase in crop acreage and without expansion into protected areas or dense forests. A regulation of LUC emissions can trigger the necessary investments to achieve such productivity increases.

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Annex 1 Details on the calculation of the carbon maps

For the calculation of carbon stock stored in biomass $(Cbio_{il})$ it is assumed that it can be subdivided into carbon stock stored in above-ground biomass (C_{AGB}), below-ground biomass (C_{BGB}) and dead organic matter (C_{DOM})[49]. The carbon stock stored in below ground biomass is normally calculated by applying a constant ratio factor (R) to the carbon stock stored in above-ground biomass.

$$Cbio_{il} = C_{AGB} + C_{BGB} + C_{DOM} \qquad (A1)$$

$$C_{BGB} = C_{AGB} \times R \qquad (A2)$$

Different methods are available for the calculation of the carbon stock stored in biomass. The most basic method for producers is to produce ground-based inventory data on the land cover classes present on their land, combined with field surveys on the related carbon stocks (Wertz-Kanounnikoff 2008). However, this method seems like a disproportional burden, particularly for small producers. In addition, to determine LUC emissions, not the present but the land cover present in 2008 is the reference land cover. If there have been changes in between, it might be difficult to retrace the land cover in 2008.

The most commonly used method is to use land cover maps based on satellite images and to combine them with carbon values that represent the biome-average carbon value. This method corresponds to the Tier 1 method of the IPCC adopted by the EC. Data sources other than the IPCC include the scientific literature on carbon values generated on sample sites. A major drawback of this method, however, is that the biome average analyzed in the scientific literature does not necessarily adequately represent the biome or region, or overestimate the carbon stored in premature stands (Gibbs et al. 2007, Wertz-Kanounnikoff 2008, Goetz et al. 2009).

There has been a rapid development of techniques for determining above-ground biomass carbon, particularly for tropical forests via remote sensing techniques based on active signals such as Synthetic Aperture Radar technologies (SAR) and/or Light Detection and Ranging (LIDAR) (Engelhart et al. 2011). The signal of SAR penetrates through clouds and returns the ground terrain as well as the level of the top of the canopy cover which in turn gives the basis for deriving the height of the

[49] In line with the EU-Red, we use a value of 0 for C_DOM, except in the case of forest land – excluding forest plantations – having more than 30% canopy cover.

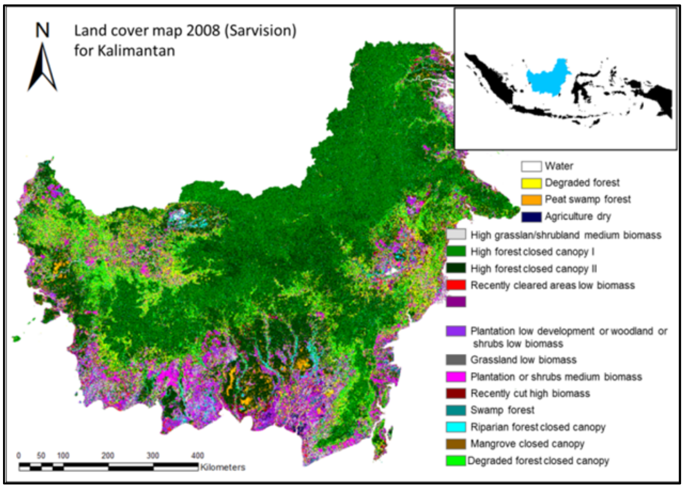
biomass cover. Thus, SAR provides a 2-dimensional image of the ground. If slightly different angles are used, this 2D image can be converted into a 3D image. The knowledge about typical biomass heights of different land covers can then be used to derive a land cover map (Mette et al 2003, Kellndorfer et al, 2004, Shimada et al 2005). Recent applications to tropical forests can be found, e.g., in the works of Gama et al. (2010), Engelhart et al. (2011), Kuplich et al. (2005), Michard et al. (2009), Pandey et al. (2010) or Santos et al. (2006).

Instead of using radar signals, the Light Detection and Ranging (LIDAR) method uses pulses of laser light and analyzes the signal return time (Engelhart et al. 2011). While this method cannot penetrate through clouds, it is possible to estimate the height and density of the biomass cover resulting in a detailed 3D image (Patenaude et al 2004). The biomass density and height is linked to biomasses, and thus, the 3D image can be converted into above-ground carbon estimates by applying allometric height–carbon relationships (Hese et al 2005). Recent application to tropical forests can be found, e.g. in the works of Saatchi et al (2011), Duncanson et al. (2010) or Zao et al. (2009).

The Kalimantan land cover map

A total of 17 different structural types of vegetation were detected in the coastal zones and the interior of Kalimantan using supervised classification techniques over the radar images (Sarvision 2011). Two different types of high forest were mapped in addition to peat swamp forest, mangrove forest, riparian forest, swamp forest and grasslands (Sarvision 2011). Detection of human affected areas was also possible including two types of degraded forest, shrublands, (oil palm) plantations and agricultural areas (Sarvision 2011). The vegetation structural type map was thoroughly validated using available field data observations in different areas of Kalimantan, georeferenced photographs and very high (0.5-1 m) resolution remote sensing imagery available in Google Earth (Sarvision 2011). Validation of the biomass map was performed using biomass data based on field measurements collected for the assignment by Utrecht University (Sarvision 2011).

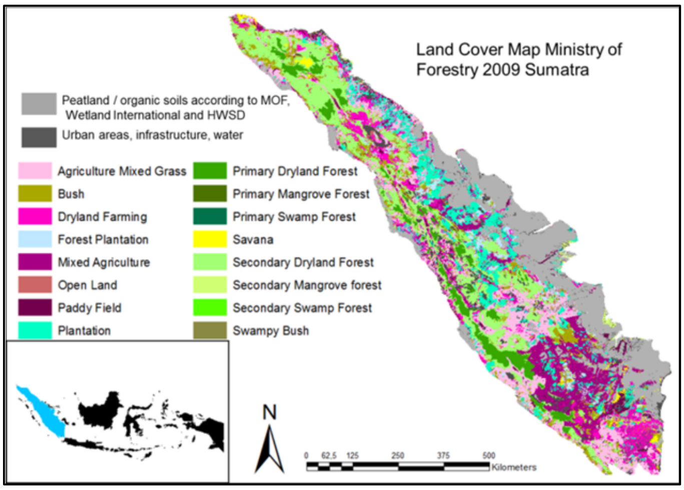
Figure A1



The Sumatra land cover map

The Sumatra land cover map is provided by the Ministry of Forestry of Indonesia via web service (http://webgis.dephut.go.id/ditplanjs/index.html). It is based on Landsat 7 ETM and has a resolution of 30 meters.

Figure A2



Soil Carbon Stocks

The method for calculating carbon stocks stored in the soil is based on the assumption that the actual carbon stock stored in the soil ($SOCact_{il}$) is the product of the carbon stock under natural land cover ($SOCref_i$) and the influence of land use (Flu_l), management (Fmg_l) and input factors (Fi_l), which can increase or decrease the carbon content under natural land cover.[50] Thus, the working steps to be performed for the calculation of a soil carbon map are to first choose a suitable soil map. Second, one must allocate the carbon values for soil under natural land cover to the soil categories in the map, and third, define and allocate the influence factors from the IPCC 2006 based on the land cover map (see equation A3).

$$SOCact_{il}\left(\frac{tC}{ha}\right) = SOCref_i\left(\frac{tC}{ha}\right) \times Flu_l \times Fmg_l \times Fi_l \qquad (A3)$$

Figure A3

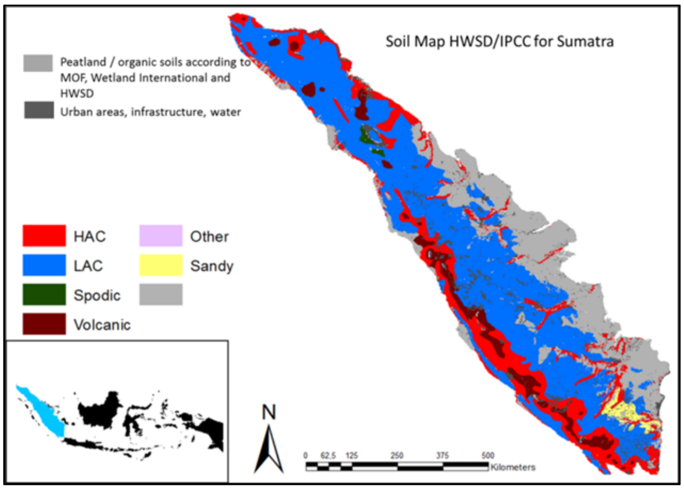
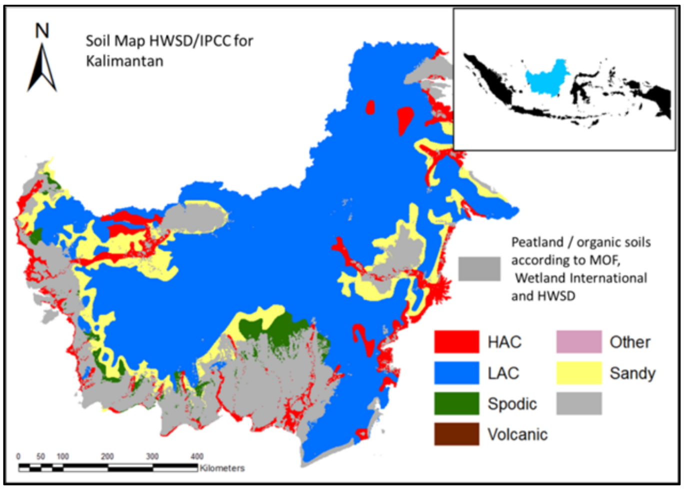


Figure A4

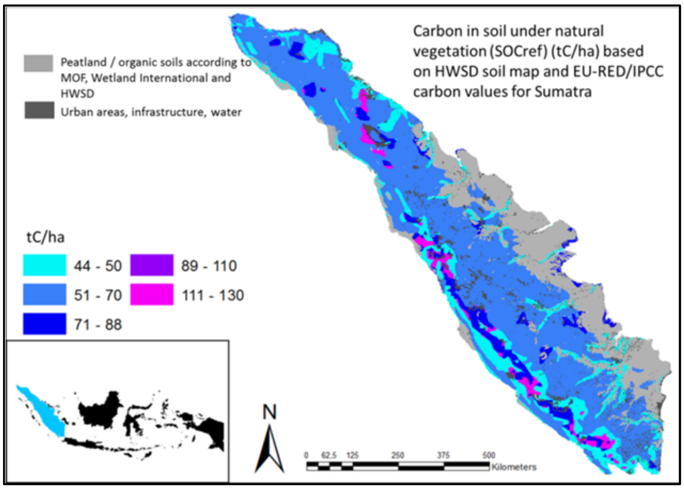


The categories used in this map correspond to the categories of the SOCref values in the IPCC 2006. These values are specific to climate regions. To determine the climate zone of a certain area, we use the climate map provided by the EC. As a first

[50] The EU Background Guide gives more details and data about land cover classes not explicitly covered by the IPCC 2006 e.g. savannahs and degraded land.

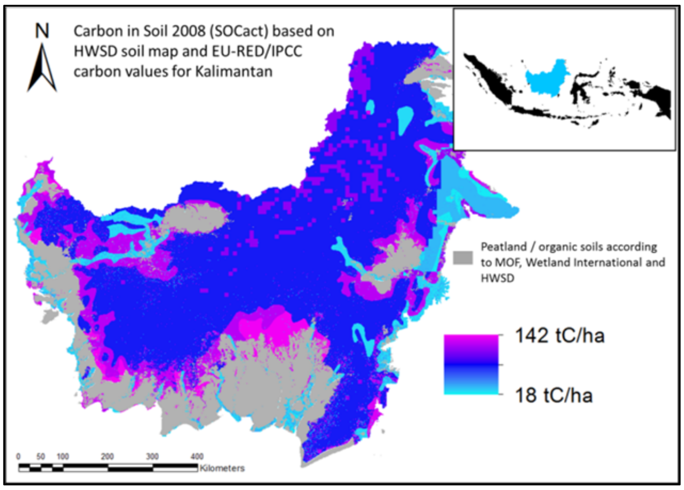
step, we generate a map of soil carbon as if the whole area were under natural land cover by combining the SOCref carbon values with the HWSD soil map. The SOCref carbon values corresponding to the soil map categories are taken from the EU Guidelines which draw on the data from IPCC 2006. Figures 20 and 21 show the HWSD maps used for Sumatra and Kalimantan. Figure A3 shows the SOCref map of Sumatra.

Figure A3



To determine the actual carbon stock stored in the soil, the carbon stock under natural land cover must be adjusted with the soil use factors that correspond to the current (2008) land use. For natural land cover, these factors are one. Thus, the soil carbon under natural vegetation remains the same after this calculation step. For all other land use with non-natural land cover, these factors indicate how much the land use type, the management practice and the inputs change the carbon stock stored in the soil compared to a natural land cover. The categories for the land use type factor include annual cropland, perennial cropland, pasture or forest plantations. The categories for the management factor mainly account for the tillage regime, while the input factor accounts for the amount of fertilizer/manure applied to the production. To determine which of these factors apply, we use the land cover map, defining for each land cover category the land use factor, the typical management regime applied for a particular land use in the region and the corresponding typical input. The corresponding values for the factors were exclusively taken from the EU/RED and the IPCC 2006. Thus, to determine the actual carbon stock stored in the soil ($SOCact_{il}$) We can multiply the SOCref calculated in the first step with these soil factors according to equation A3. Figure A4 shows the SOCact value for Kalimantan.

Figure A4



Annex 2.Source values for above ground carbon

Land Cover Class	AGC	Source
	tC/ha	
Paddy Field	3	APN 2001; Lasco et al. 1999
Plantation	60	EU-RED palm plantation
Primary Dryland Forest	277	Murdiyarso and Wasrin 1995 (Primary humid evergreen; lower montane; lowland dipterocarp); Hairiah and Sitompul (2000); Noorwijk et al.(2000)
Primary Mangrove Forest	159	Donato et al. (2011)
Savana	13	Murdiyarso and Wasrin (1996); Prasetyo et al.2000)
Secondary Dryland Forest	200	57% of Primary Forest APN (2001) average of studies on logged over forest
Secondary Mangrove forest	91	57% of Primary Forest APN (2001) average of studies on logged over forest
Agriculture mixed Grass	21	Sitompul and Hairiah (2000) (Chromolaena); Gintings (2000) (Imperate; Cassava);Noordwijk et al.(2000) (Cassava/imperata sp.; uplandrice/bush fallo rotation); Murdiyarso and Wasrin (1996) (grassland);Prasetyo et al. (2000) (grassland)
Bush	30	Lasco and Pulhin (2004)
Dryland farming	5	Murdiyarso and Wasrin (1996)
Forest Plantation	151	Sitompul and Hairiah (2000) (rubber agroforestry); IPCC (2006)(broadleaf; other)
Mixed Agriculture	5	Murdiyarso and Wasrin (1996)
Open Land	0	

* for Podzols no data are available for tropical regions from the EU-RED. We use values from Montes et al. (2011) and assume 20 cm upper organic-rich horizons with 170tC/ha and 10 cm middle sandy horizons with 31tC/ha

** we assume total soil factors for palm plantations of 1.15 and 1.09 in montane regions and 60tC/ha in biomass according to EU-RED

*** For all caluclations we assume 4.5 kg biomass per 1 l fuel and a heating value of 32.65 MJ/l biodiesel (FNR 2012)

Paper 4:

FROM THE PAMPAS TILL THE AMAZON:

Heterogeneous agricultural development[51]

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Abstract:

Brazil is the second largest agricultural producer worldwide and exhibits the largest forecasted increase in output over the next 40 years. Such an increase requires substantial intensification in production to avoid high conversion rates for Brazil´s valuable ecosystems. This paper claims that an identification and analysis of regional and local differences in agricultural productivity is essential to understand potential future development of agricultural intensification. We estimate the production function of the Brazilian agricultural sector based on census data for the period 1970-2006 by applying an approach that allows for changing factor shares over time and across regions and different elasticities of substitution between inputs across regions. In addition, it simultaneously accommodates heterogeneity in the productivity of inputs, variable time-series properties and the potential for heterogeneous but correlated impacts of unobservable factors. The results highlight the importance of flexible functional forms for production function estimation in agriculture. They further confirm the heterogeneity of regional production functions resulting from differences in the existing transportation infrastructure, fertility of soils, closeness to markets, available technologies, governmental support and education. Thus, the results emphasize the need for regional or even local agricultural policies to address heterogeneous constraints to development.

Keywords: agricultural development, Brazil, intensification, production function estimation

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[51] Unpublished manuscript

1. Introduction

Between 1970 and 2006, Brazil changed from a dictatorship to a democracy, opened its markets after decades of import substitution, was bankrupt and changed its currency five times. Within this setting, Brazil became one of the most important grain producers in the world (Rada and Buccola 2012). Today, it is the largest producer of sugar, coffee and oranges and the second largest producer of cattle meat and soybeans (FAOstat based on 2013 data), making Brazil the second largest agricultural producer worldwide. Moreover, it is the country with the largest forecasted increases in agricultural output over the next 40 years (FAO 2006). This gives Brazil a key role in meeting the globally increasing demand to feed 9 billion people with changing and more land-intensive nutritional habits (Godfray et al. 2010).

However, the projected increase in production does not come without risk because the development in the past resulted in tremendous conversion rates of Cerrado savannahs and Amazon forest. Brazil is the largest producer of greenhouse gas emissions resulting from land use change (LUC) (FAOstat based on 1990-2010 data). In addition, its six major biomes, the Amazon Forest, Cerrado, Caatinga, Atlantic Forest, Pantanal and the Pampas, make Brazil the most biodiverse country on the planet (UNEP_WCMC 2010). Consequently, further increases in production bear the risk of causing massive losses of biodiversity and naturally stored carbon.

Nonetheless, according to a recent study of Strassburg et al. (2014), it is possible to meet the increases in demand for agricultural production from Brazil by using the already existing agricultural areas. Strassburg et al. (2014) focus on the biophysical sustainable production capacity on the already used land and do not further analyze the necessary changes in the economic structure of the sector to achieve such intensification. However, Brazil itself is the best example suggesting that the intensification of production results in substantial changes in the agricultural sector. In addition to the conversion of natural areas, the strong increase in agricultural output in the recent past resulted from replacing labor intensive crop production with mechanized sugar production in the Southeast or from replacing extensive cattle production with highly intensive soy production in the Central-West (Martha et al. 2014., Cohn et al. 2014). Other regions such as the Northeast have fallen behind and have not substantially intensified production in the last decades. Thus, the agricultural sector adapted heterogeneously to the several changes in the economic and political context, some regions by changing the production portfolio, by modernizing production techniques and by increasing other inputs than land.

This paper claims that an analysis of the past agricultural development in Brazil is important to understand the potential future development of agricultural production. The projected high increases in demand on the one hand and the ecosystems at risk on the other hand require further intensification of production to achieve the feasible non-expansion scenario outlined by Strassburg et al. (2014). This paper contributes to the economic analysis of agricultural development in the past by deriving an estimate of the agricultural production function for Brazil. It uses data on the agricultural sector based on six agricultural censuses from 1970, 1975, 1980, 1985, 1995 and 2006. Such estimate is important in particular to determine differences in the productivity of land but also of other inputs. The estimation of these differences in productivity delivers an important basis to study factors influencing these differences, such as infrastructure or public policies, in future analysis.

Given the heterogeneous development in Brazil, this paper builds upon recent developments in the literature on cross-country production function estimation that allow for heterogeneity in regional production functions (e.g. Eberhardt and Teal. 2013a, 2014, Bond and Eberhardt 2013, Exenberger et al. 2014). This literature indicates that a severe distortion in estimates of standard panel estimators may occur when ignoring the possible presence of endogeneity of input choice, technology heterogeneity, variable non-stationarity and cross-section dependence between regions (Bond and Eberhardt 2013). To our best knowledge, this is the first time that the Brazilian agricultural sector or any other national agricultural sector has been subjected to this approach since Eberhardt and Teal (2013) and Exenberger et al. (2014) estimate an agricultural production function for the whole world. Most studies on the development of Brazilian agricultural sector focus on the determination of total factor productivity (TFP) and efficiency measurements by using the index method[52] or stochastic frontier analysis and are reviewed later on in this paper. We use an alternative measurement of TFP by measuring TFP as the "residual" of the estimated production function. It is consequently directly related to the estimation of the production function and includes all unobservable factors not incorporated as

[52] Such as the Törnquist index as a discrete approximation of a continuous index.

inputs in the production function. It thus can be considered a "measure of ignorance" (Abramowitz 1956), which can incorporate everything that shifts the production possibility frontier (Eberhardt and Teal 2014) beyond the productivity of the individual inputs. It thus implies an incorporation of a wide set of factors and does not necessarily mean technological progress (Baier, Dwyner and Tamura 2006).

Further, the analysis adds to the discussion on appropriate estimation of heterogeneous production functions by applying the flexible translog functional form rather than the commonly applied Cobb-Douglas functional form. This flexible setting allows estimating the production function by accommodating heterogeneous regional agricultural structures.

The rest of the paper is structured as follows. Section 2 gives an overview about the historical development and the resulting regional changes of the agricultural sector for the time period between the years 1970 and 2006. Section 3 reviews the existing literature. Section 4 introduces the empirical model. Section 4 also gives an overview about the different estimators applied, which differ in their magnitude of allowed heterogeneity between regions. This section also introduces the specification of the data. Section 5 presents the results and interpretation of the estimated production function. Finally, section 6 concludes.

2. The Brazilian agricultural sector between the years 1970 and 2006

As a first step, this section describes the historical context and the resulting development of the Brazilian agricultural sector between the years 1970 and 2006. It therefore delivers the setup that the economic model and estimation strategy need to accommodate.

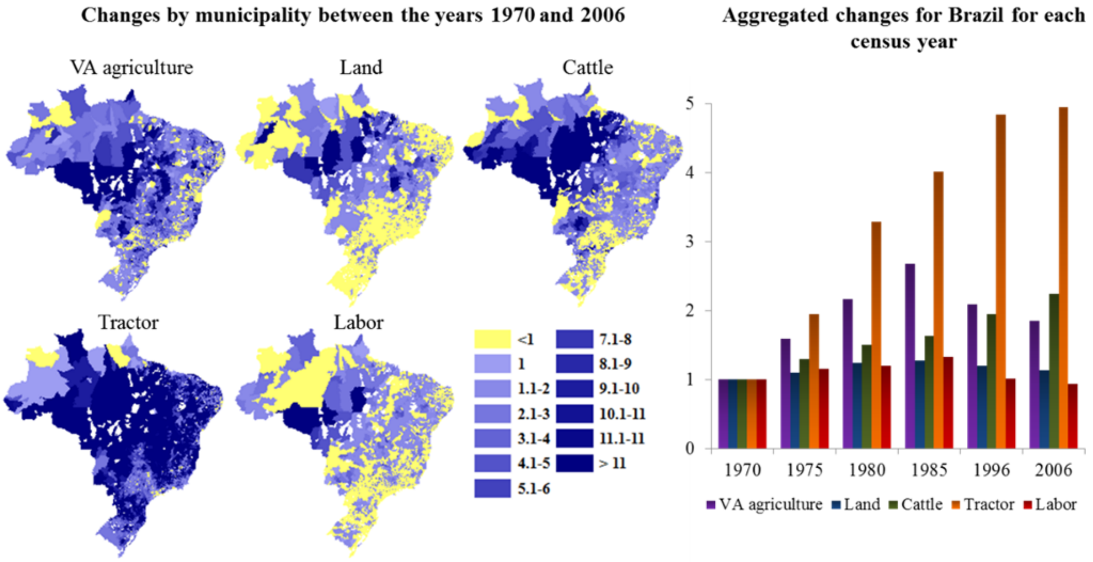
The period of time between the 1970s and the early 1980s are characterized by massive governmental interventions into agricultural commodity markets, mainly in the form of subsidized rural credits, price control mechanisms, trade barriers and general market organization (Helfand and Rezende 2004, Chaddad and Jank 2006). These measures are part of a general policy aiming at development through import substitution. The agricultural sector is also indirectly affected by a strong increase in demand resulting from government-led industrialization. From this follows a rapid process of urbanization combined with population and income growth (Pereira et al. 2012).

The debt crisis in the late 1980s puts an end to the import substitution policy and in 1985 puts an end also to the dictatorship. These changes result in necessary reductions of governmental support and thus in a sector driven by market forces (Chaddad and Jank 2006). The period in the nineties and early two thousands is then characterized by a transition process triggered by further financial problems. The Brazilian agricultural market is integrated further into the world market for agricultural commodities as a result of a reduction of export taxes and trade barriers, the elimination of price controls, a deregulation in commodity markets and the introduction of private instruments for financing the agricultural sector (Chaddad and Jank 2006). Not all farms can compete in the context of the changed market conditions (Helfand et al. 2004). Farm numbers decrease by nearly one million from 5.8 million in 1985 to 4.8 million in 1996, which is lower than the 1970 level (IBGE 2013b). On the contrary, exportable grains and the animal sector profit from the policy reforms in the 1990s and the stabilization of the fiscal situation at the beginning of the new century.

The development of the value added of the agricultural sector reflects the described historical development. Compared to the 1970 level, value added nearly triples until 1985 indicating the short-term success of the support policies (IBGE 2013d). In the following census years, the integration of the agricultural sector into the world market and the several fiscal crises lead to a decrease in real value added (IBGE 2013b).

Figure 1 illustrates the resulting changes in production patterns on the aggregate level by using data from the agricultural census of 1970, 1975, 1980, 1985, 1995 and 2006 of the Brazilian Institute for Geography and Statistics (IBGE 2013b). Data illustrated are the value added of the agricultural sector, the amount of land used for agricultural production, the amount of cattle on farms, the amount of tractors used and the amount of people employed on farms (values are normalized with their 1970 level). These are also the data used to estimate the production function later on.

Figure 1: Changes in agricultural output and input use between 1970 and 2006 (1970 = 1)



Source: Own illustration based on IBGE (2013b and 2013d)

The resulting structural changes in production processes and input use are not unilaterally distributed but the result of regionally heterogeneous developments. The maps in figure 1 indicate the spatial distribution of the aggregated values of figure 1. They show the value in 2006 normalized by their level in 1970 (1970=1). The maps in figure 3 give an orientation on the relationship between inputs. The two maps on the left-hand side display the variables in per worker terms, and the two maps on the right-hand side present them in terms of agriculturally used land. Agricultural land includes cropland, natural and planted grassland and forest. On each side, one map presents the variable in 1970 and the other one in 2006.

In the following, the structural changes are described by region using additional numbers for farm size, land titles and crop production from the agricultural census of the IBGE. Information on road infrastructure and alphabetization rates are taken from the statistical year books (IBGE 2013a) and those on subsidized credit flows from the Brazilian National Bank (Banco Central do Brasil 2013). These data are displayed graphically in Appendix A3. By identifying the heterogeneity of the regional development paths, it is possible to appraise the degree of regional heterogeneity that needs to be accommodated by the approach later on in the analysis. For orientation, figure 2 displays the regions, current states and major biomes of Brazil.

Figure 2: Brazil´s states, regions and biomes

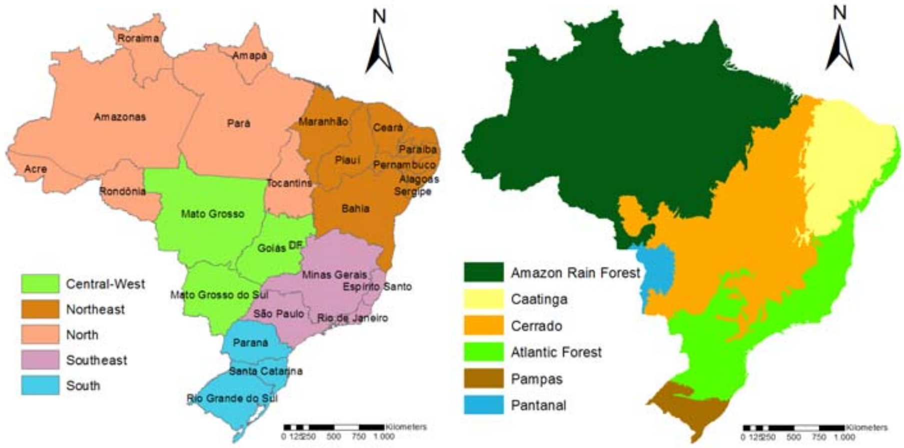
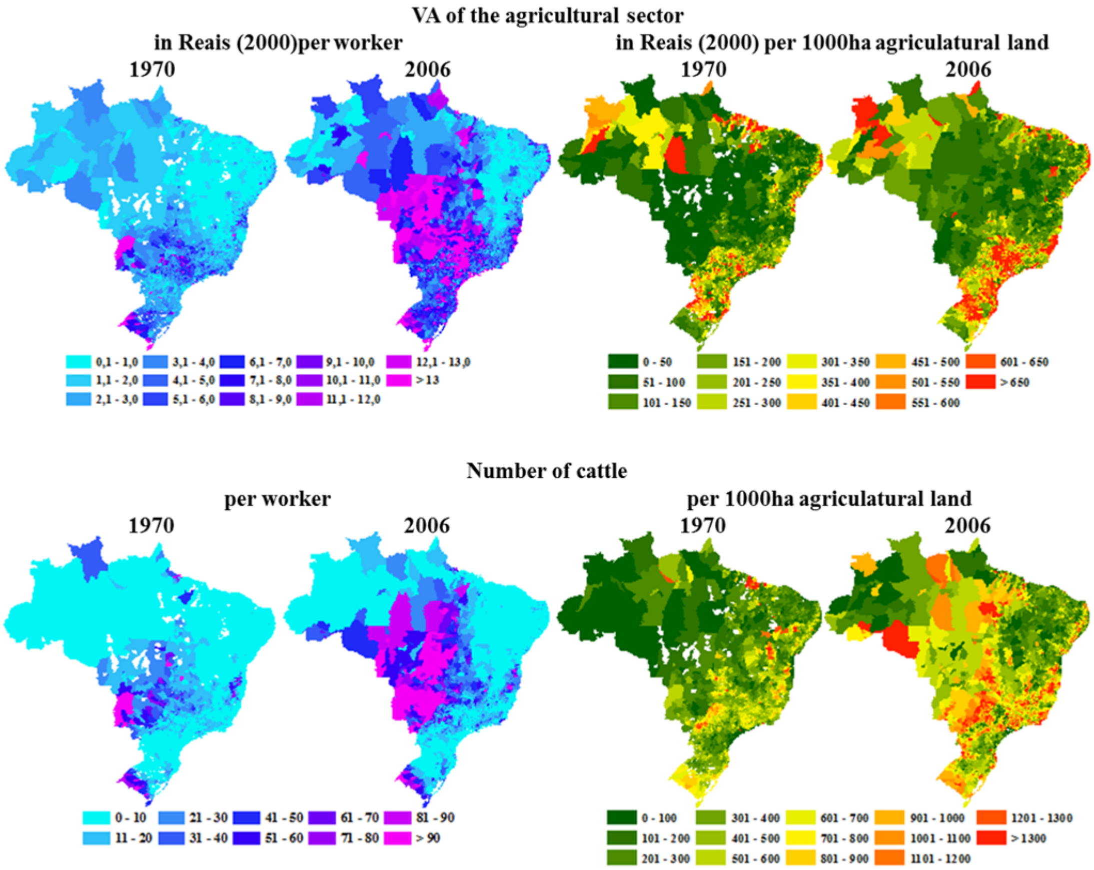
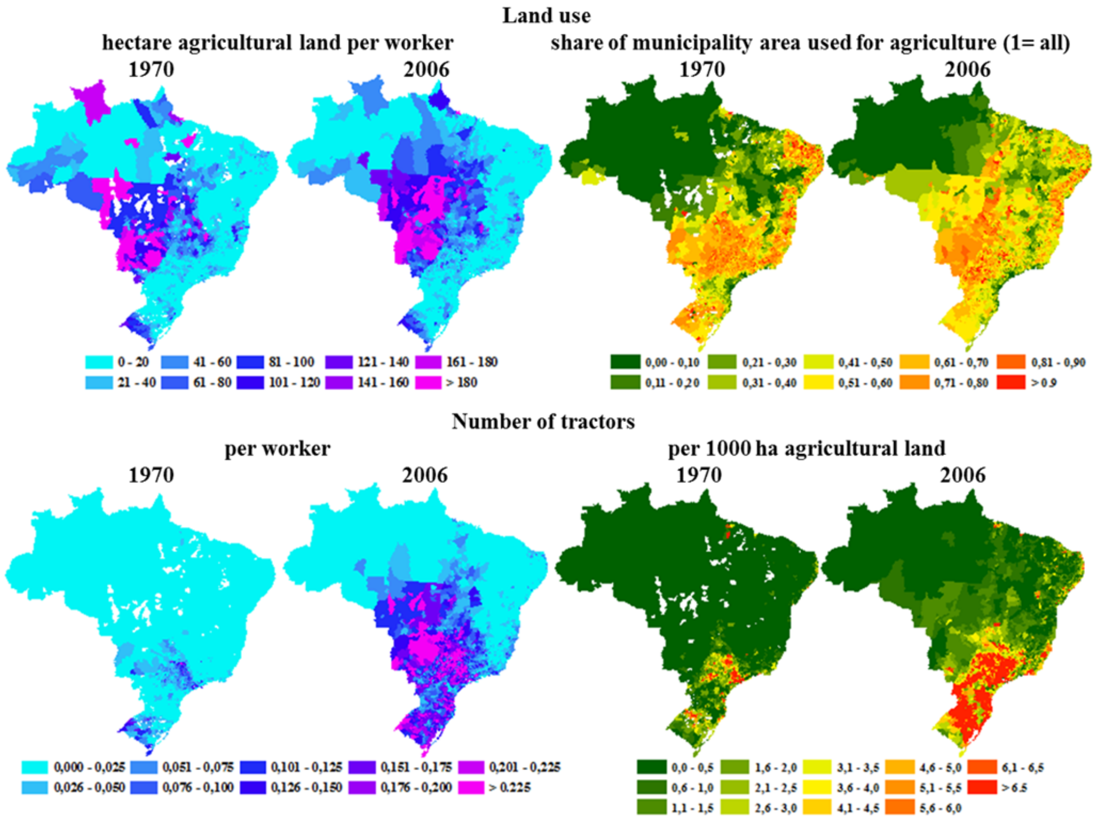


Figure 3: Relative changes of output and input use in agriculture





Source: Own illustration based on IBGE (2013b and 2013d)

The Southeast is one of the most developed regions in the country. Alphabetization rates are high, and the road infrastructure is well developed. The agricultural development in the Southeast and in particular in the state of São Paulo is characterized by a massive and continuous expansion of sugar cane production.[53] This expansion is possible due to a replacement of other crops, such as coffee, cotton, bean and rice. The mechanization of sugar production is further pushed by upcoming plans to ban the burning of sugar cane fields to avoid smoke in the cities (Martinelli and Filoso 2008). This is equivalent to banning harvesting of sugar cane by hand because without burning, it is practically impossible to harvest sugar cane.[54][55]

In addition to a change in the crop production portfolio, cropland areas increase from 9.6 million in 1970 to 13.4 million in 2006. Cropland expands for the most part into

[53] Sugar cane areas increase from 1970 to 2006 by a factor of 3.7 to over 3.5 million hectare in 2006. Particularly until the year 1985, it is massively supported by subsidized credits.

[54] Employed people on farms increase till 1985 to 4.7 million people and then decrease to 3.3 million in 2006.

[55] Unfortunatly data do not include migratory labor which is applied for the manual harvest in many regions in Brazil.

pasture areas, which shrink by nearly one half from 45 million to 28 million ha. This does not lead to a displacement of cattle production. In fact, cattle numbers are fairly constant between 1970 and 1985 in the Southeast and further increase from 35 million to 39 million heads between 1985 and 2006. However, the map in figure 3 shows a concentration of cattle production in some municipalities and thus an intensification of cattle production, meaning more cattle per land area (Cohn et al. 2014, Martha et al. (2012)). The overall development in the Southeast is thus a change in production technology and in the production portfolio and not an increase in agriculturally used area. The overall used area even shrinks in many municipalities due to an expansion of urban areas. As a result of this development, the Southeast is characterized by a fairly stable relationship between labor and land input, but tractor numbers strongly increase. Data might even underestimate this development since they do not account for the size of tractors.

In the South, the development is fairly similar. Alphabetization rates and road density are the highest in the whole country. Paraná, the state with the most grain production in the South, experienced similar development to São Paulo but in terms of soy production.[56] This development is accompanied by a decrease in other crops such as rice, beans and cotton. As a consequence, the number of employed people decrease and the number of tractors substantially increase. Additionally, cropland areas increase from 11 million ha in 1970 to 15 million ha in 2006. Pasture areas in the South only decrease after 1995, but cattle numbers continuously increase from 19.4 million ha to 27 million ha between 1970 and 2006. Thus, the South likewise experiences a change in the crop portfolio accompanied by an increase, intensification and concentration of cattle production in some municipalities. Worth mentioning is the relatively small farm size of approximately 42 ha/ farm on average in 2006 in the South which is rooted in the historical context of European immigration of small family farmers (Fausto 1999).[57]

As opposed to the South and Southeast, the Central West has never been a region of labor intensive crop production but of extensive cattle ranching in the natural

[56] 395 thousand ha in 1970 expanded to 3.5 million ha in 2006, which is half of the soy production in the South.
[57] In the South, this development is supported with the by far highest average flow of subsidized credits per agricultural land in the whole country which is rooted in the strong agrarian lobby in this region. This flow of credits peaks in 1980 and subsequently decreases. However, in 2006, it is still on average more than two times higher than, e.g., in the Southeast.

grasslands and savannahs of the Cerrado. Today, the Central West including the southern borders of the Amazon is the most growing agricultural area in Brazil. It experienced a strong increase in output (value added), which is the result of expanding mechanized grain production and increasing cattle herds. In particular, the production of soy increases continuously from 1970 to 1995 from 27 thousand ha to 3.3 million hectare. The real “boom” of soy production starts after 1995 when soy areas more than double as of the year 2006 to more than 7.7 million hectare. This is reflected in crop areas, which increase continuously until the year 1995 and then double to 12.5 million as of the year 2006. Crop areas mostly expand into natural or planted grazing areas in the Cerrado.

Thus, there is no strong transition from labor-based crop production toward mechanized crop production which results in an overall fairly stable low number of employed people but highly increasing tractor numbers. Overall, agricultural areas strongly increase by the expansion of cattle production into the Cerrado and into the southern borders of the Amazon. However, cattle numbers increase to a much greater extent than pasture areas from 20 million to 71 million between 1970 and 2006 indicating a parallel intensification of cattle production. The low numbers of output per land input indicate that parallel to the mechanized agriculture and more intensive cattle production, there are still large farm areas that are used with extensive pasture in 2006. This is reflected also in the large farm sizes in the Central West, with 332 ha per farm on average.

The rather “late” development of the Central West compared to the South and the Southeast is manifested in the development of road infrastructure, which only increases after 1985. However, due to the remoteness and size of the region, it still remains comparatively low in density today (Müller 2003, Inocêncio and Calaça 2015).

The development of the Central West reaches the borders of the Amazon. Here, deforestation for cattle production is often subsequently followed by grain production in later years. In recent years, also direct deforestation for crop production has become more common (Morton et al. 2006). Since the 90s, the Amazon experiences an increase in value added of the agricultural sector also in the more central regions. In the early census years, the development of the Amazon region suffers from problems with the validity of land titles and high rates of analphabetism. The remoteness of the Amazon and the difficult access to the region results in a poorly developed road infrastructure, which improves beginning in the 80s (Pfaff et al. 2007). This development becomes apparent in the increasing intensities of cattle production both in terms of per land area and per worker. Pasture areas continuously increase from 11 million to 27 million in 2006. Cattle numbers increase slowly between 1970 and 1985 from 2 million to 9 million cattle and then double as of the year 1995 and double again as of 2006, reaching approximately 41 million cattle.

The Northeast is fairly decoupled from the development of the agricultural expansion and intensification in the rest of the country. The coastal zone is the oldest agricultural region in the country, with historically large-scale sugar cane production. However, it suffers from the strong degradation of the formerly high agro-potential regions (FAO 1999) and a subsequently high population density (Andrade 1999). The less populated semi-arid hinterland has poor soils and suffers from droughts (Gomez 2001).

However, degraded soils can also be found in other regions of the country (FAO 1999). The nonetheless comparatively low agricultural development of the Northeast is also rooted in the generally low development of the region, resulting in an absence of off-farm opportunities in the rural areas (Carvalho & Egler 2003). Investment in road infrastructure is stagnating. Alphabetization rates are the lowest and slowest increasing in the whole country. In addition, average farm sizes are the smallest in the whole country, with only 30 ha/ farm. The decrease in farm numbers resulting from the integration of the country into the world market and an expansion of urban areas result in an interim reduction of agricultural areas. Overall, farmers are self-sufficient or produce for the local food sector in the Northeast (Sietz et al. 2006). Thus, corn and beans are the most important crops, and they already were in 1970. Few exceptions can be found in the coastal regions, where the degree of mechanization, indicated by the number of tractors per agricultural area, increases between 1970 and 2006.

In summary, one can observe quite heterogeneous changes in agricultural production patterns, which lead to the existence of highly competitive mechanized agriculture and intensive cattle production in parallel to low-productivity, small family farms. They result from structural differences and from substantial changes in policies toward the sector and related market conditions. Moreover, they are the result of apparently different regional reactions toward these shocks. Few studies exist that analyze the underlying economic structure. The next section gives an overview about their findings.

3. Literature Review

This section reviews existing studies on agricultural production patterns and the dynamics of TFP growth in Brazil with respect to their relevance for the study at hand. We note the differences in data use, functional form and approach because they can trigger differences in results.

Gasques et al. (2010) calculates TFP for every Brazilian state based on a Törnquist index by using the same six agricultural censuses as this study from 1970-2006. They use the data on the state level since additional data needed for the index were derived e.g. from the Getúlio Vargas Foundation (FGV) which are only available on this spatial aggregation. They find an increase in TFP of 2.62% for the period 1970-2006. Their measured increase in TFP is continuous but slightly decreasing over the whole time period. Lower TFP growth toward 2006 is in line with the findings of Mendes et al. (2008) estimating an average TFP growth rate of 1.03 p.a. between 1985 and 2004. They estimate TFP as the residual of the production function estimation by using a fixed effects model and a Cobb-Douglas specification. Data are based on a yearly panel on the state level from the IBGE and other sources. Their results further support a decreasing variation in TFP growth rates across regions due to an increase in TFP in the non-traditional areas.

This is contrary to the findings of other papers that find a widening of the gap between the technology frontier and the average producer. Rada and Buccola (2012) estimate the Brazilian input distance frontier by using a stochastic frontier approach and thus focus on the measurement of efficiency in the sector. They use a generalized Cobb-Douglas form using the agricultural census data from three census years between 1985 and 2006 on the level of microregions and the states. The estimation of the input distance frontier allows decomposing TFP into best-technology at the productivity frontier and into technical efficiency which they define as the ratio of factor productivity at the average and at the frontier farm. They find a TFP growth rate of 2.6% but an efficiency change of -1.9%. Earlier work of Pareira et al. (2002) apply a Malmquist productivity index as a combination of indexes on technological efficiency and technological progress. They use the data of five agricultural censuses between 1970 and 1996 on the state level. They find TFP development mainly through general technology progress rather than through an increase in technological efficiency concentrated in only some regions of the country. Similarly, the recent work of Constantin et al. (2013) uses stochastic frontier analysis to estimate changes in efficiencies and a Malmquist index to analyze changes in TFP. They use data from the period 2001-2006 for 26 federal states based on the Systematic Survey of Agricultural Production and Municipal Agriculture Production from the IBGE. For the period between 2001 and 2006, they find positive changes in TFP but decreasing efficiency in the use of inputs for all grain crops.

Regarding the sources of the TFP increase, Mendes et al. (2008) argue that since 1980, infrastructure investments were reduced. This led to a reduction in the productivity and competitiveness of Brazilian agriculture, leading to a decrease in investment and thus in GDP. This argumentation is based on the finding that road investment has the highest impact on TFP followed by research, telecommunication, irrigation technologies and electricity. Rada and Buccola (2012) specify that the impact of public policies is most beneficial for the agricultural leaders, which widens the gap between the most productive and average farms. In line with Mendes et al. (2008), they find positive impacts of primary schools and road density on technological efficiency. Thus, these factors close the gap between average and frontier farms.

The current literature focuses on TFP measurement by using indices or on measurement of efficiency of input use by using stochastic frontier analysis. Only Mendes et al. (2008) estimate TFP as the residual of estimating the production function but do not display their results on the production function itself. Studies generally find increasing TFP but are ambiguous as to whether disparities between regions increase or decrease over time.

Finally, since for our model specification we discuss different functional forms of the production function, it is worth mentioning that all studies with an approach that includes an underlying production function rely on a Cobb-Douglas specification with the exception of Constantin et al. (2013). They test in their stochastic frontier model the Cobb-Douglas functional form against the translog form and prefer the latter.

The next section introduces the empirical model used to estimate the production function.

4. The Empirical Model

4.1. The production function

The empirical model of the production function needs to account for the regional heterogeneity described above. The size of Brazil almost naturally results in a large heterogeneity of natural resources, institutions, culture and technological development within the country. A further increase in the heterogeneity of production patterns between 1970 and 2006 is suggested by the data described in section 2 and by the majority of the available literature. Thus, the empirical model should allow for heterogeneity in the production function, meaning heterogeneity in the amount of input use and the productivity of inputs as a result of several factors influencing the production patterns in a region (Durlauf et al 2001). These can be very regional or local factors such as the fertility of soils or the immediate availability of infrastructure and services. However, this might be also more national factors such as a change in policy towards the sector or the development of new soy varieties by the Brazilian Corporation of Agricultural Research (EMBRAPA). These factors do not necessarily affect every region in the same way. In addition, not all of these factors are directly observable.

In a more generalized form, the described set up of heterogeneous slope parameters together with unobservable common factors can be represented by random coefficient models or latent factor models which are discussed e.g. in Pesaran and Smith (1995), Hsiao (2003), Hsiao and Pesaran (2004), Pesaran (2006) and Coakley et al. (2006). In the following we rely on the representation of a latent factor model by Eberhardt and Teal (2014) because they explicitly apply this approach to the production function of the agricultural sector. A similar application to the agricultural sector can be found in Exenberger et al. (2014).

They assume that the production function in log linearized form is a linear heterogeneous panel model. y_{it} represents the total agricultural output of municipality i at time t in logs and x_{it} the set of observable inputs(to the econometrician) in logs. We use municipalities as the unit i since it is the smallest observable spatial unit in our data set. Thus, the log linearized production function in municipality i can be written as follows:

i = 1,…,N; where i is the individual municipality and N is the total number of municipalities

t = 1,…,T; where t is the individual year and T is the total number of years

m=1,…,M; where m is the individual input and M is the total number of observable inputs

$$y_{it} = \sum_{m=1}^{M} \beta'_{mi} x_{mit} + u_{it} \qquad u_{it} = \alpha_i + \lambda'_i f_t + \varepsilon_{uit}, \;\; \varepsilon_{uit} \sim iid(0, \sigma_{ui}^2) \qquad (1)$$

$$x_{mit} = \pi_{mi} + \delta'_{mi} g_{mt} + \rho_{mi} f_{mt} + \varepsilon_{mit}, \;\; \varepsilon_{mit} \sim iid(0, \sigma_{mi}^2) \qquad (2)$$

$$f_t = e'_i f_{t-1} + \varepsilon_{it} \qquad f_{mt} \subset f_t \qquad g_t = \kappa'_i g_{t-1} + \varepsilon_{it} \qquad (3)$$

x_{it} is a M x 1 vector of observed individual inputs and the ith cross section unit at time t. β_i is the M x 1 vector of the associated technology parameters to be estimated. All β_{mi} are assumed to be constant over time and are allowed to differ between municipalities. The mean effect of each β_m over municipalities are the main parameters of interest since in the Cobb-Douglas specification they represents the elasticities of output of each input indicating the productivity of each input.

We assume that there is a set of factors that influence output beyond the use of individual inputs. This set of factors is unobservable and therefore enters the error term u_{it} . It can be further divided into a combination of municipality-specific factor levels α_i and a set of common factors f_t represented by the s-dimensional vector $f_t = (f_{1t,} f_{2t}, \dots, f_{st})$[58] associated with a s-dimensional vector of factor loading λ'_i that can differ across municipalities (Pesaran and Tosetti 2011, Eberhardt and Teal 2013). Thus, $\lambda'_i f_t$ captures effects to which all municipalities are exposed to but to which they react differently (Eberhardt and Teal 2011).

Equation 2 captures the endogeneity introduced in the framework by Eberhardt and Teal (2013). It implies that the choice of profit maximizing inputs is not independent but influenced by a set of factors. This is obvious because in reality, farmers choose

[58] including all relevant common factors f_{ct} with c = 1,…s where c is the individual common factor and s is the total number of relevant common factors

their inputs based on their knowledge about local and global circumstances. The factor demand is thus driven by sets of common latent factors g_{mt} and f_{mt} (equation2). We differentiate between g_{mt} and f_{mt} to point out that part of the common latent factors, here f_{mt}, can be a subset of the factors driving output (Eberhardt and Teal 2013) whereas other factors, here g_{mt}, only drive input choice. This setting also allows for the fact that factors are common to all municipalities, such as global shocks. However, the factor loading ρ_{mi} and δ'_{mi}, meaning the reaction of factor demand in each municipality to these shocks, can be heterogeneous across municipalities. However, if $\lambda'_i \neq 0$ and $\rho_{mi} \neq 0$, the error and the regressor are correlated (Coakley et al. 2006). Thus, for estimation, this implied endogeneity complicates the estimation of the technology parameters β_{mi} (Eberhardt and Teal 2013).

As stated earlier, it is further plausible that similar regions face similar local factors and similar factor loadings of global factors. Thus, cross-section correlation in the effect of unobservable factors and input choices are possible (Eberhardt and Teal 2013).

Equation 3, indicates that these factors are persistent over time, which includes the possibility of non-stationarity in the factors ($e = 1, \kappa = 1$) and thus also in the observable inputs (Eberhardt and Teal 2013, Bond and Eberhardt 2013). Non-stationarity emerges almost naturally in the data because variable series might incorporate a certain persistence of time (Nelson and Plosser 1982, Granger 1997, Lee et al.1997, Rapach 2002, Bai and NG, 2004, Pedroni 2007, Canning and Pedroni 2008, Eberhardt and Teal 2014). In particular, the influence of (technology) shocks is expected to be non-stationary (Coackley et al. 2006).

Summarizing, the formulation of Eberhardt and Teal (2013) is very flexible in the way that it allows for heterogeneity in technology parameters (here the productivity of inputs), error cross-section dependence, non-stationarity and dependence between x_{it} and u_{it} induced by latent common factors.

The model so far contains the underlying functional form of a Cobb-Douglas production function. The Cobb-Douglas specification imposes constant factor shares and implies that each input is substitutable by another input by the factor 1. The elasticities of substitution indicate how easy one input can be substituted by another input or whether inputs function as complements in a production system. Cobb Douglas thus imposes that each input is substitutable by another input by factor 1. However, the input setting in agriculture differs from e.g. the manufacturing sector. Land is the fundamental input factor for agricultural production and it can never be fully substituted. It is not possible to produce cattle without land inputs, nor does land produce grains without any seeding and harvesting activities. However, it is likely that, e.g., an increasing use of machinery and fertilizer increases the productivity of other factors such as land. Likewise, it changes factor shares in production by decreasing, for example, the share of labor. In the same way, an increase in cattle numbers often results in an intensification of production, which means a switch from grazing to grain fed production. This increases the productivity of one animal but requires additional machinery, e.g., for producing the grain feed. Thus, we cannot be sure whether the Cobb-Douglas functional form is the most suitable to estimate production function for the Brazilian agricultural sector.

The translog functional form offers a solution in the absence of correct information on the specific functional form (Cristensen et al. 1978). With the translog specification as a second-order approximation to an arbitrary functional form, factor shares and output elasticities become functions of the quantities of inputs used, and thus, factor shares are allowed to vary across countries and over time (Martin and Mitra 2000). In addition, elasticities of substitution are allowed to vary between inputs. Consequently, we presume a better accommodation of the described development of the Brazilian agricultural sector by the translog functional form which is supported by the results of Constantin et al. (2013). Thus, in contrast to the vast majority of the current literature on agricultural development in Brazil, this paper estimates the production function by using the translog functional form in addition to the Cobb-Douglas specification. The suitability of the translog form for the agricultural sector is supported by other studies in the field, e.g., by Debertin and Pagoulatos (1978) for US agriculture, by Martin and Mitra (2001) using cross-country agricultural data of the World Bank and by Tzouvelekas (2000) for Greek farmers.

Thus, we also consider a translog specification of the above model. The translog production function with neutral technical change has the following form (equation 4) [59]:

$$y_{it} = \sum_{m=1}^{M} \beta_{mi} x_{mit} + \frac{1}{2} \sum_{m=1}^{M} \sum_{k=1}^{M} \beta_{mki} x_{mit} x_{kit} + u_{it} \qquad (4)$$

$$\epsilon_{mit} = \frac{\partial y_{it}}{\partial x_{mit}} = \beta_{mi} + \sum_{k=1}^{M} \beta_{mki} x_{kit} \qquad (5)$$

$$\sigma_{mki} = \sum_{f=1}^{F} \frac{H_{fi} x_{fi} |H_{mki}|}{x_{mi} x_{ki} |H_i|} \qquad (6)$$

For identification of equation 4, symmetry, monotonicity and diminishing marginal productivities are required (Tzouvelekas 2000), which implies $\beta_{mki} = \beta_{kmi}$ for all *m, k* (Youngs´s theorem), positive marginal products of each input and $0 < \beta_{im} < 1\ \forall m$ (Hatziprokopiou et al. 1996). ϵ_{mit} in equation 5 delivers the final elasticity of output of input *m* of municipality *i* at time *t.* The elasticity of substitution σ_{mki} between inputs can be derived by using equation 6 applying the bordered Hessian Matrix. F=m+1 is the order of the bordered Hessian matrix of the first- and second-order partial derivatives, $|H|$ is the determinant of the bordered Hessian matrix and $|H_{mk}|$ is the cofactor of H_{mk} in H (Tzouvelekas 2000). Inputs j and k are substitutes, independent or complements as σ_{mki} is greater, equal to or less than zero, respectively (Tzouvelekas 2000).

Given that the model framework presented here is the correct model to represent the agricultural sector in Brazil, for the estimation, heterogeneity of technology parameters, endogeneity of input choice, cross-section correlation and non-stationarity need to be addressed. The following section introduces the estimation strategy for both the Cobb-Douglas and the translog specifications.

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[59] We maintain the assumption of heterogeneous production functions and thus allow for municipality specific parameters. If this formulation is to be estimated with neutral technological change, the formulation of the error term remains as in equation 1 and 2. For estimating the production function with non-neutral technological change, it requires an explicit estimate of the technical change (t) to be incorporated into the production function estimate to estimate the parameters γ_{i1}, γ_{i2} and θ_{ij} of the following production function with scale augmenting and non-neutral technical change:
$y_{it} = \sum_{m=1}^{M} \beta_{mi} x_{mit} + \frac{1}{2} \sum_{m=1}^{M} \sum_{k=1}^{M} \beta_{mki} x_{mit} x_{kit} + \gamma_{i1} t + \frac{1}{2} \gamma_{i1} t^2 + \sum_{m=1}^{M} \theta_{ij}\, x_{mit} t + u_{it}$. And accordingly $\epsilon_{mit} = \frac{\partial y_{it}}{\partial x_{mit}} = \beta_{mi} + \sum_{k=1}^{M} \beta_{mki} x_{kit} + \theta_{ij} t$ (adaptation of latent common factor model to the translog including non-neutral technical change based on Tzouvelekas 2000)

4.2. Estimation Strategy

The endogeneity of input choice represents a major challenge for the choice of the estimation strategy since it directly influences the major result of interest, the estimation of the elasticities of output of different inputs. One strategy to account for the effect of factors driving input choice would be to incorporate them into the regression equation and to quantify their effect e.g. by using interaction terms. In fact, Pesaran and Tosetti (2011) write the model of equation 1 by differentiating between observable and unobservable factors and Exenberger et al. (2014) explicitly estimate the effect of climate change. However, depending on the analysis, these additional factors are not always analyzed regarding their impact on the solution of the economic theory model and this strategy can lead to a large augmentation of the regression equation (Eberhardt and Teal 2013, 2010). The additional variables can also be endogenous if they are driven by initial conditions (Durlauf et al. 2005). Despite the methodological problem, the dataset for the Brazilian agricultural sector does not incorporate sufficient information to allow incorporating all possible factors.

An additional strategy is instrumentation in panel models via the GMM estimators of Arello and Bond (1991) and Blundell and Bond (1999). However, they are invalid if heterogeneous technology parameters apply because they assume common technology parameters (Eberhardt and Teal 2014). If $\rho_{mi} \neq 0$, it is also not sufficient to correct for cross-section correlation in the error term (e.g., with the Driscoll and Kraay (1998) estimator) because the input choice would still be endogenous. Eberhardt and Teal (2010, 2013, 2014) argue against these approaches and favor an integrated consideration of parameter heterogeneity into the cross-country empirics, which also accounts for the time-series properties of the data and cross-section correlation (see, also, Coakley et al. 2006, Kapetanios et al. 2011, Pesaran 2006).

This paper follows the estimation strategy of Eberhardt and Teal (2013) and (2014), who estimate a production function for the agricultural sector and the manufacturing sector, respectively, and consider different estimators that integrate the flexible properties of the model setup to different degrees. The estimators differ essentially regarding their underlying assumptions on the commonality of technology parameters, the effect of the latent factors on input choice and the evolution of the latent factors (Eberhardt and Teal 2014). The comparison of estimator properties and estimation results together with post-estimation diagnostics helps to choose the optimal estimator for the data and setup in this paper. In the following, we introduce the different estimators used.

As a first estimator, we apply the standard pooled OLS estimator with year dummies (POLS), which implies parameter homogeneity (Coakley et al. 2006) and thus common technology parameters in all municipalities ($\beta_i = \beta$). It further assumes exogenous input choice, which means no impact of latent factors on input choices ($\rho = 0$). Differences in the levels of latent factors are assumed to be random, and the evolution of the latent factors is captured by common year effects and thus constant and common across municipalities (Eberhardt and Teal 2010). Consequently, also cross-section independence and homogeneous cointegration are implied. Thus, the equation estimated by OLS reduces to:

$$y_{it} = \alpha + \tau_t + \beta x_{it} + e_{it}, \quad e_{it} \sim iid(0, \sigma^2), \quad i = 1, \dots, N, \quad t = 1, \dots, T \quad (7)$$

As a second estimator, we apply the two-way fixed effects estimator (2FE), which includes time and regional fixed effects. As the POLS estimator, the 2FE estimator assumes homogeneous technology parameters and cointegration and common factor evolution captured by common year effects (Eberhardt and Teal 2014). However, as opposed to the POLS, it allows the intercept to differ both by unit and time period (Coakley et al. 2006), which means heterogeneous levels of common factors across regions but equal evolution of common factors across municipalities. The estimator further assumes cross section independence.[60] The equation estimated with two-way fixed effects is:

$$y_{it} = \alpha_i + \alpha_t + \beta x_{it} + e_{it}, \quad e_{it} \sim iid(0, \sigma^2) \quad (8)$$

As the next set of estimators, we use estimators based on the mean group (MG) estimation procedure, which is introduced by Pesaran and Smith (1995) for estimation of latent coefficient models (see Coakley et al. 2006 for a review). All estimators using the MG estimation procedure allow, in contrast to POLS and 2FE, for heterogeneity in technology parameters. This is because they follow the same principle methodology. First they estimate a group-specific (in our case municipality

[60] we run the 2FE estimation with two-way demeaned data as described in Coakley et al. 2006, meaning a regression of $y_{it} - \bar{y}_i - \bar{y}_t + \bar{y}$ on $x_{it} - \bar{x}_i - \bar{x}_t + \bar{x}$ where $\bar{y}_t = N^{-1} \sum_{i=1}^{N} y_{it}$, $\bar{y}_i = T^{-1} \sum_{t=1}^{T} y_{it}$ and $\bar{y} = (NT)^{-1} \sum_{t=1}^{T} \sum_{i=1}^{N} y_{it}$ (equivalent for x)

specific) OLS regression and second average the estimated coefficients across groups (Eberhardt 2012). Thus, the MG estimator is defined as the simple average of the OLS estimator $\widehat{\beta_1}$. Thus, as a first step, OLS estimates are derived for each panel unit and then, as a second step, the aggregate estimate of β is derived as follows (Hsiao and Pesaran 2004)[61]:

$$unweighted\ average\ \overline{\widehat{\beta}_{MG}} = N^{-1} \sum_{i=1}^{N} \widehat{\beta}_i$$

$$value\ added\ weighted\ average\ \overline{\widehat{\beta}_{MG}} = \sum_{i=1}^{N} \frac{VA_i}{\sum_{i=1}^{N} VA_i} \widehat{\beta}_i \tag{9}$$

The unweighted average is the standard implementation of the MG estimator. It allows for individual production functions for each municipality but the final estimate of $\widehat{\beta}_{MG}$ is an average about all individual production functions. In our case we want to derive a meaningful and representative estimate of the productivity of inputs for the Brazilian agricultural sector. Since municipalities differ largely in size and importance in the sector we derive the average over municipalities weighting each municipality by their contribution to the total agricultural value added of the country. In addition, when displaying the results, we calculate these weighted averages for each larger region in Brazil in order to analyze the differences in factor productivity across regions.

The classical MG estimator by Pesaran and Smith (1995) assumes that the factor loadings of the unobserved common factors contained in both the equations for input and output are zero on average (Coakley et al. 2006). Otherwise, the latent factors would influence input choice on average. We cannot be sure whether the productivity of inputs changes when the factor loadings of the unobserved common factors are non-zero. Thus, results on the estimated productivity of inputs might be biased if factor loadings of the unobserved common factors are non-zero on average. Thus, the classical MG estimator allows for heterogeneous technology parameters but assumes on average homogenous factor loading of latent common factors and common evolution of common factors to all panel units.

Since we cannot be sure whether the factor loadings are indeed zero on average, we consider three variations of the MG estimator. These variations allow for heterogeneous factor loadings by augmenting the regression equation of the OLS

[61] Standard errors reported in the averaged regression results are constructed following Pesaran and Smith (1995), thus testing the significant difference of the average coefficient from zero.

regression on the municipality level. The goal of the augmentation is to approximate or explicitly model the latent factors in the regression equation. The averaging over municipalities remains the same for all variations according to equation 9. The variations differ in their assumption about the evolution of the latent common factors. The basic approach is proposed already by Pesaran and Smith (1995), Bond and Eberhardt (2013) propose the augmented mean group (AMG) estimator and Pesaran (2006) propose the common correlated effects mean group estimator (CCEMG)[62].

The basic Pesaran and Smith (1995) approach augments the regression equation with a panel unit specific linear trend. This allows for differential impact of unobservable factors across municipalities whilst imposing linearity on their evolution (Eberhardt et al. 2013).[63] The regression equation for the first stage municipality specific OLS is then:

$$y_{it} = \alpha + \beta x_{it} + c_i t + e_{it}, \quad e_{it} \sim iid(0, \sigma^2) \tag{10}$$

In contrast, the AMG and the CCEMG estimators allow for an unrestricted evolution of common factors (Eberhardt and Teal 2014), which involves the possibility of non-stationary common factors (Bond and Eberhardt 2013, Kapetanios et al. 2011). The AMG estimator includes a common dynamic effect in the panel-unit specific regression (derived by equation 11). In addition to the common dynamic effect $\hat{\mu}_t^\circ$, Bond and Eberhardt (2013) include a linear time trend t, similar to the Pesaran and Smith (1995) MG estimator, to capture the omitted idiosyncratic processes that evolve in a linear fashion over time. The common dynamic effect is constructed from the coefficient of T-1 period dummies in first differences ΔD_t of a pooled OLS regression in first differences (equation 9a) and represents the levels-equivalent average evolution of unobserved common factors across the panel units (Bond and Eberhardt 2013). The idea of the AMG estimator is to obtain an explicit rather than implicit estimate for f_t assuming that the pooled estimate is some function $h(\cdot)$ of the unobserved common factors f_t: $\hat{\mu}_t^\circ = h(\lambda f_t)$, where $\hat{\mu}_t^\circ$ is the common or mean evolution of the unobservables in levels across panel groups over time from

[62] Kapetanios et al. (2011) extend the work of Pesaran (2006) with the case that the unobservable common factors follow unit root processes.
[63] Thus, it implies stationary latent common factors and require a cointegrated relationship between inputs and outputs (Eberhardt and Teal 2014).

estimating $\Delta y_{it} = b'\Delta x_{it} + \lambda'_i \Delta f_t + \Delta u_{it}$ (Eberhardt and Teal 2014).[64] The regression equation for the first stage OLS is then as in equation 12:

$$\Delta y_{it} = b'\Delta x_{it} + \sum_{t=2}^{T} c_t \Delta D_t + e_{it} \qquad \rightarrow \hat{c}_t \equiv \hat{\mu}_t^{\circ} \qquad (11)$$

$$y_{it} = a_i + b'_i x_{it} + c_i t + d_i \hat{\mu}_t^{\circ} + e_{it} \qquad \rightarrow \hat{b}_{AMG} = N^{-1} \sum_i \hat{b}_i \qquad (12)$$

The CCEMG estimator augments the regression equation with cross-section averages of the dependent and independent variables as additional regressors to capture unobserved common factors with heterogeneous factor loadings (Pesaran 2006)[65]. It assumes that the common factors form part of the municipality-specific cointegration relation, which is then captured by the augmented regression model (Bond and Eberhardt 2013, Pedroni 2001).[66] The regression equation for OLS on the municipality level is then:

$$y_{it} = \alpha_i + \beta_i x_{it} + c_{1i}\bar{y}_t + c_{2i}\bar{x}_t + e_{it}, \quad e_{it} \sim iid(0, \sigma^2) \qquad (13)$$

Both the CCEMG and the AMG estimator presume that by incorporating the latent common factors (or modeled proxies for them) into the regression equation and by allowing for heterogeneous factor loads, the endogeneity problem is solved (Pesaran 2006, Coakley et al. 2006, Kapetanios et al. 2011, Bond and Eberhardt 2013). Appendix A1 shows the intuition of these estimators in more detail exemplarily for the CCEMG estimator. Pesaran (2006) shows for the CCEMG estimator that this also solves the problem of cross-section dependence if the cross-section dependence arises from the presence of unobserved common factors, now explicitly included in the regression equation. Pesaran and Tosetti (2011) further show that the problem of spatial spillovers is also accommodated by the CCEMG estimator since the CCEMG

[64] Thus, the second-stage regression could also be rewritten as $y_{it} = a_i + b'_i x_{it} + \lambda_i h(\bar{\lambda} f_t) + u_{it}$, and the factor d_i represents the implicit factor loading on common latent factors (Eberhardt and Teal 2014). Because the AMG estimator delivers an explicit estimate for f_t, it is the only estimator that allows an estimation of the translog production function with non-neutral technological change.

[65] As proposed by Eberhardt and Teal 2013 we test for the idea that the average of the factor loadings across countries might be non-zero, but driven by systematic differences. We test two different weight matrices additional to the arithmetic means in the CCEMG estimator (See Eberhardt and Teal 2013 Technical Appendix for a general description of the construction of the weight matrices). The first weight matrix tested follows the idea of commonality between regions due to commonality in the agro-climatic circumstances. It uses data on suitability for crop production by IIASA and additionally differentiates rural and urban areas. The second weight matrix adresses the idea commonality resulting from neighborhood and spatial proximity by using an inverse distance spatial weight matrix. However, different weight matrices had only very minor impact on results. We therefore only present results derived by arithmetic means.

[66] Although $\bar{y}_t$ and e_{it} are not independent, their correlation goes to zero as $N \rightarrow \infty$ (Coakley et al. 2006)

estimator is *"most effective in dealing with error cross-section dependencies, irrespective whether they arise from spatial spillovers or are due to the presence of unobserved common factors."* They show that the CCEMG estimator is robust to possible serial correlations in the errors and time variations in the degree and the nature of cross section error dependence. The model setup can accommodate a fixed number of strong factors (such as global shocks) and an infinite number of weak factors (such as local spillovers) (Chudik et al. 2011). Thus, estimates for means of heterogeneous β_i are consistent for the model setup of equation 1-3, even with non-stationary variables, cointegrated or structural breaks (Chudik et al. 2011, Kapetanios et al. 2011, Pesaran and Tosetti, 2011, Bond and Eberhardt 2013).

To compare estimator performances, residuals are tested for cross-section correlation by using the Pesaran (2004) CD test on cross-section correlation. This is based on the assumption that most common latent factors cause cross-section correlation as a result of similarity in reaction to these factor caused by similarities between regions. Thus, with a present cross-section correlation in the residuals we cannot be sure whether the cross section correlation is driven by unobserved common factors driving only output[67] or whether it is driven by unobservable factors which also drive input choice ($\rho_{mi} \neq 0$). Thus, with cross section correlation, the estimator accounts insufficiently for unobservable common factors and thus does not sufficiently address the endogeneity problem when estimating the productivity of inputs. Thus, indirectly, by investigating whether residuals are essentially white noise or subject to cross-section correlation, it is tested whether the endogeneity concern resulting from those latent factors which cause cross-section correlation is addressed by the estimator (Eberhardt and Teal 2014).[68] In addition, residuals are tested regarding the presence of non-stationarity by applying several panel unit root tests. Non-stationary residuals would result in an overestimation of the precision of parameter estimates (Bond and Eberhardt 2013).

[67] If only the error term would be affected without endogeneity in input choice ($\rho_{mi} \neq 0$) a correction of the error term would be sufficient to solve the problem.

[68] The Pesaran 2004 CD test has the advantage of not depending on the choice of a spatial weight matrix such as tests on spatial autocorrelation (e.g., Moran's I Moran (1984)). In addition, it has reasonable small sample properties compared to the Breusch Pagan Lagrange Multiplier test (Breusch and Pagan 1980), which is likely to exhibit substantial size distortions for N large and T small (which is the case for the present Brazil dataset)(Pesaran 2004).

Table 1 Summary of estimator properties

		factor loadings $\boldsymbol{\lambda}$		
		homogeneous	heterogeneous	
Evolution of factors $\boldsymbol{\beta}$		unrestricted	linear	unrestricted
technology $\boldsymbol{\beta}$	homogeneous	**POLS, 2FE**		
	heterogeneous		**MG**	**AMG, CCEMG**

Summarizing we estimate the technology parameters associated with individual inputs (β) in order to derive the elasticitiy of output of different inputs (input productivity)[69] and the elasticities of substitution between inputs by testing different estimators. Table 1 summarizes the estimator properties.

4.3. Empirical Implementation

For estimating the production function with different estimators (equation 4-12), we use panel data for 3607 Brazilian municipalities for six years, namely, 1970, 1975, 1980, 1985, 1996 and 2006. Some municipalities were grouped together according to data of the IBGE (2013c) to accommodate changes in municipality numbers and borders over time. All data were provided by the IBGE and downloaded from the SIDRA[70] and IPEA[71] data webpages. We use the value added of the agricultural sector to indicate value of agricultural output, the dependent variable y_{it}. Values are normalized with inflation data of the World Bank for the year 2000 (The World Bank 2013). The included inputs are (proxies for) labor, agricultural capital stock and land under cultivation, which represent the m observed inputs x_{mit} to produce output y_{it}. For labor, we use data on all people officially and permanently employed on farms. Thus, family work, temporary or illegal workers are not included in the dataset. Capital inputs are approximated with the number of tractors on farms and the number of cattle on farms, the most important livestock to produce meat and milk products in Brazil. For land under cultivation, we use the total amount of productive land per farm in hectare including permanent and annual cropland, natural grassland, pasture, natural forest and planted forest. Thus, illegal land use or land not declared in the agricultural census is not included.

[69] For the Cobb-Douglas production function this directly derives the elasticities of output, for the translog functional form elasticities of output are derived based on equation 5 and elasticities of substitution based on equation 6.
[70] Sistema IBGE de Recuperação Automática (SIDRA) http://www.sidra.ibge.gov.br/
[71] Instituto de Pesquisa Econômica Aplicada (IPEA) http://www.ipeadata.gov.br/

All data are specified in natural logs. For the Cobb-Douglas estimation, variables are specified in per worker terms. Because the translog production function can be viewed as a Taylor series approximation around the sample mean (Friedlaender and Spady 1981), for the translog estimation, all data are normalized around the sample mean prior to logarithmic transformation to define the point of approximation (Tzouvelekas 2000). (See Appendix A2 for a detailed data overview).

It is still necessary to discuss the issue that for the estimation of the AMG and the CCEMG estimator, a problem particular to the dataset at hand emerges. The Brazilian census data are only available for six years. However, because the MG estimator starts with an OLS regression for each municipality, the number of degrees of freedom of the estimator is reduced to T-1, which means a maximum of five repressors including an intercept. With land, capital and cattle in per worker terms as inputs in the regression equation, this setting does not permit the inclusion of both the time trend and the common dynamic effect or the cross-section averages into the regression equation, disregarding a translog specification.

In order to be able to use these estimators, and thus the inclusion of the time trend and the common dynamic effect (for the AMG estimator) or the cross-section averages (for the CCEMG estimator), municipalities are grouped into clusters to run the first stage OLS regressions. These first stage regressions then represent POLS regressions and thus imply homogenous factor loadings and technology parameters for all municipalities within a cluster. The assumption of homogenous factor loadings and technology parameters is more likely to be valid for very similar municipalities. Thus, municipalities are clustered by using an Euclidian distance matrix based on four municipality characteristics: the x and y coordinates[72], the information to which state a municipality belongs[73], the suitability of the municipality for crop production[74] and the degree of urbanization of each

[72] Closer municipalities are more likely to have similar production patterns.
[73] Municipalities in one state are subject to the same state policies.
[74] Similar biophysical characteristics will require similar production technologies. Suitability data are provided in raster format by FAO/IIASA (2010) and present a suitability index representing the suitability of the cell for the cropping of a particular feedstock. For the creation of the suitability variable, we create the mean suitability out of the 8 most important cash crops in Brazil, which we define as those with more or close to 1 million hectare (sugar, soy, corn, cassava, beans, rice, wheat, and cotton). Additionally, we include the suitability for grazing based on raster data from Haberl et al 2006. The resulting mean suitability raster has seven suitability classes, where 1 means not suitable and 7 very suitable. We then calculate the mean suitability for each municipality.

municipality[75]. Based on the Euclidian distance measure, we group the most similar municipalities in clusters of four municipalities and obtain 901 clusters.[76] The second-stage mean group estimation is consequently based on these 901 first-stage cluster regressions.

Summarizing, equation 4-12 are estimated by using several estimators that differ in their properties regarding the commonality of factor loadings and technology parameters and the evolution of latent common factors. The suitability of the estimators is tested regarding their ability to account for latent common factors driving input and output by testing for cross-section correlation and stationarity of the error terms. For those estimators that satisfy these conditions in the estimate of the production function using the Cobb-Douglas specification, the translog specification is tested. The next section presents the results.

5. Results

5.1. Estimators and functional form

Before interpreting the results in detail, they need to be evaluated regarding their ability to address the model setup of section 3 and regarding the appropriateness of the underlying functional form. This section first compares the different estimates based on their results on the CD-Pesaran test statistic. Stationary residuals proved to be delivered by all estimators.

Table 2 summarizes the regression results for all estimators. As a first step, the regression results for the Cobb-Douglas specification are analyzed. Column one presents the result of estimating equation 7 with POLS, and column two presents the results for estimating equation 8 with two way fixed effects. The results of the Pesaran CD test clearly indicate that the estimators imposing one homogenous production function for the whole country result in cross-section correlation in the error term.

[75] Urban areas might offer different infrastructures and services for production than those of purely rural areas. The degree of urban area is determined with NOAA night light data, from which one can identify the pixels lid, which we define as settled pixels. We then calculate for each municipality the share of area settled.

[76] As a robustness check, we group only neighboring municipalities into clusters. However, the cluster based on more commonality variables performed better according to the residual diagnostics.

However, allowing for heterogeneous production functions across municipalities is not sufficient to control for latent common factors driving input and output. The results of column three of the MG estimation with a linear time trend of equation 10 and 9 show cross section correlation in the error term as well. This result may be driven by the restrictive assumption of linear evolution of the latent common factors in the context of strong structural changes in the Brazilian economy.

The next estimators permit an unrestrictive evolution of the influence of latent common factors. Column four displays the result for the AMG estimation of equation 11-12, and column five displays the result of the CCEMG estimation of equation 13. The common dynamic effect is the result of estimating $\hat{\mu}_t^{\circ}$ in equation 11. Although the test statistic of the Pesaran CD test improves, the AMG estimator still shows significant cross section correlation in the error term. In other analyses such as that of Eberhardt and Teal (2013), the AMG estimator is appropriate for estimating the

Table 2 Regression Results Brazil

		1	2	3	4	5	6	7	8
	Functional form			**Cobb-Douglas**				**Translog**	
independent variables, in logs, for CD estimation parameters in per worker terms	**Land**	**0.254*****	**0.243*****	**0.297*****	**0.274*****	**0.253*****	**0.219*****	**0.350*****	**0.194*****
		(0.0412)	(0.0784)	(0.0345)	(0.0184)	(0.0198)	(0.0347)	(0.135)	(0.0389)
	Cattle	**0.105*****	**0.300*****	**0.110*****	**0.241*****	**0.256*****	**0.236*****	**0.358*****	**0.296*****
		(0.0346)	(0.0663)	(0.0304)	(0.0173)	(0.0185)	(0.0268)	(0.0998)	(0.0328)
	Tractor	**0.276*****	**0.0481*****	**0.294*****	**0.104*****	**0.100*****	**0.185*****	**0.176*****	**0.167*****
		(0.00592)	(0.0110)	(0.0150)	(0.00776)	(0.00808)	(0.0164)	(0.0561)	(0.0191)
	Labor	**0.365**	**0.4089**	**0.299**	**0.381**	**0.291**	**0.274*****	**0.170***	**0.302*****
		calculated by substracting other input elasticities from unity					(0.0229)	(0.0997)	(0.0254)
	Land^2						**-0.0567**	**-0.00890**	**-0.0259**
							(0.0723)	(0.133)	(0.0817)
	Cattle^2						**-0.0154**	**-0.0253**	**0.0375**
							(0.0425)	(0.0790)	(0.0475)
	Tractor^2						**0.0282*****	**0.0169**	**0.0221*****
							(0.00722)	(0.0147)	(0.00803)
	Labor^2						**0.0293**	**-0.0315**	**0.0431**
							(0.0334)	(0.0635)	(0.0389)
	LandxCattle						**0.117**	**0.164**	**0.224****
							(0.0949)	(0.173)	(0.109)
	LandxTractor						**-0.0166**	**-0.00269**	**-0.00127**
							(0.0266)	(0.0542)	(0.0295)
	LandxLabor						**0.0745**	**0.0102**	**0.109**
							(0.0793)	(0.147)	(0.0867)
	CattlexTractor						**-0.027**	**0.253**	**-0.215**
							implied by homogeneity restriction		
	CattlexLabor						**-0.109***	**-0.108**	**-0.175****
							(0.0600)	(0.106)	(0.0681)
	TractorxLabor						**-0.0522****	**-0.120****	**-0.0181**
							(0.0230)	(0.0472)	(0.0255)
	common dynamic effect (CDE)				**0.936*****		**0.893*****	**0.983*****	
					(0.0285)		(0.0312)	(0.208)	
	time trend			**-0.000556**	**0.00583*****		**-0.0516*****	**0.0447*****	
				(0.00105)	(0.000688)		(0.00694)	(0.00966)	
	CDE^2							**-0.244**	
								(0.381)	
	CDExLand							**-0.238**	
								(0.212)	
	CDExCattle							**-0.155**	
								(0.164)	
	CDExTractor							**-0.00110**	
								(0.0882)	
	CDExLabor							**0.0474**	
								(0.163)	
	Constant	**0.545*****	**-1.32e-09**	**0.385*****	**0.361*****	**1.100**	**-0.421*****	**-0.475*****	**1.912***
		(0.0177)	(0.000465)	(0.0257)	(0.0134)	(8.264)	(0.0272)	(0.0706)	(1.094)
cross section correlation test	P value of Pesaran CD test	0.000	0.000	0.000	0.000	0.687	0.002	0.018	0.920
	CD test statistics (see notes)	35.594	55.524	93.590	27.381	-0.487	2.957	2.104	-1.407
	mean absolute correlation (see notes)	0.407	0.407	0.411	0.342	0.346	0.375	0.413	0.372
Stationarity	test statistics in Appendix	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Wald test translog							0.001	0.549	0.008
Root mean squared error		0.102	0.456	0.191	0.055	0.048			
Observations		21 641	21 641	21 641	21 641	21 641	21 641	21 641	21 641
Number of municipalities		3 607	3 607	3 607	3 607	3 607	3 607	3 607	3 607
Number of clusters					901	901	901	901	901

Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentesis. Estimation 1 includes time dummies, estimation 2 is conducted with two times demeaned data (as descriped in Coakley et al. 2004. Results from all MG type estimators are unweighted means. All variables are in logs. For the CD estimations, variables are specified in per worker terms. For the translog estimations, variables are normalized with their sample mean.

Residual diagnostics: stationarity tests: I(0) - stationary, I(1) - non-stationary. Cross section correlation tests conduceted with Pesaran (2004) CD test with H0: no cross section correlation. The mean absolut correlation is the sample estimate of the pair-wise correlation of residuals. The CD statistic is based on the pair-wise correlation coefficients and is exactly zero (under H0) for fixed values of T and N, under a wide class of panel data models, so long as the unconditional means of y_{it} andx_{it} are time-invariant and their innovations are symmetrically distributed (Pesaran 2004).

Table 3 Regression Results Regions

Region		1 Central West	2 North-east	3 North	4 South-east	5 South
independent variables, in logs	**Land**	**-0.244**	**0.174*** **	**-0.0603**	**0.270*** **	**0.281*** **
		(0.149)	(0.0519)	(0.128)	(0.0792)	(0.0911)
	Cattle	**0.826*** **	**0.359*** **	**0.256** **	**0.246*** **	**0.0250**
		(0.134)	(0.0450)	(0.106)	(0.0641)	(0.0757)
	Tractor	**0.164**	**0.0853*** **	**0.178*** **	**0.206*** **	**0.284*** **
		(-0.0374)	(0.0239)	(0.0659)	(0.0368)	(0.0529)
	Labor	**0.295*** **	**0.414*** **	**0.320*** **	**0.205*** **	**0.261*** **
		(0.0940)	(0.0366)	(0.121)	(0.0479)	(0.0588)
	Land^2	**-0.394**	**0.226**	**0.0980**	**-0.244**	**-0.515**
		(0.527)	(0.192)	(0.229)	(0.384)	(0.499)
	Cattle^2	**0.347**	**0.308** **	**0.132**	**-0.107**	**-0.379**
		(0.348)	(0.132)	(0.0832)	(0.202)	(0.255)
	Tractor^2	**0.0745**	**0.0224**	**0.0712**	**0.0663** **	**0.0227**
		(0.0693)	(0.0227)	(0.0439)	(0.0335)	(0.0410)
	Labor^2	**-0.0916**	**0.178**	**-0.213**	**-0.0241**	**0.182**
		(0.269)	(0.121)	(0.251)	(0.162)	(0.138)
	LandxCattle	**0.264**	**-0.178**	**-0.353**	**1.158** **	**1.026**
		(0.801)	(0.266)	(0.255)	(0.461)	(0.662)
	LandxTractor	**-0.0459**	**0.0611**	**0.206**	**-0.215***	**0202**
		(0.204)	(0.0760)	(0.139)	(0.120)	(0.176)
	LandxLabor	**0.681**	**0.260**	**-0.127**	**0.114**	**0.488**
		(0.615)	(0.230)	(0.421)	(0.379)	(0.421)
	CattlexTractor	**-0.906**	**-0.503**	**-0.010**	**-0.345**	**-0.198**
		implied by homogeneity restriction				
	CattlexLabor	**0.108**	**-0.265**	**0.344***	**-0.505***	**-0.697** **
		(0.560)	(0.199)	(0.189)	(0.287)	(0.313)
	TractorxLabor	**-0.0374**	**-0.110**	**-0.148**	**0.102**	**-0.132**
		(0.210)	(0.0675)	(0.180)	(0.104)	(0.134)
	Constant	**-0.229**	**0.744**	**-0.114** **	**-0.123***	**-0.0695**
		(0.847)	(1.056)	(0.0535)	(0.0629)	(0.0598)
cross section correlation test	P value of Pesaran CD test	0.929	0.946	0.949	0.938	0.946
	CD test statistics (see notes)	-1.471	-1.612	-1.640	-1.539	-1.611
	mean absolute correlation (see notes)	0.394	0.361	0.355	0.379	0.389
Stationarity	test statistics in Appendix	I(0)	I(0)	I(0)	I(0)	I(0)
p valueWald test translog		0.784	0.001	0.164	0.009	0.014
Observations		1 386	7 656	960	8208	3654
Number of clusters		57	319	40	342	152

Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors in parentesis. Results are unweighted means. Variables are in logs and normalized with their sample mean.

Residual diagnostics: stationarity tests: I(0) - stationary, I(1) - non-stationary. Cross section correlation tests conduceted with Pesaran (2004) CD test with H0: no cross section correlation. The mean absolut correlation is the sample estimate of the pair-wise correlation of residuals. The CD statistic is based on the pair-wise correlation coefficients and is exactly zero (under H0) for fixed values of T and N, under a wide class of panel data models, so long as the unconditional means of yit andxit are time-invariant and their innovations are symmetrically distributed (Pesaran 2004).

model setup of equation 1-3. On the one hand, the clustering of municipalities in groups with homogenous production functions may not be appropriate when using the AMG estimator. On the other hand, the cross section correlation may disappear once the more flexible translog functional form is used.

For the Cobb-Douglas specification, only the CCEMG estimator is able to deliver error terms without cross section correlation. Comparing the parameter values of the CCEMG estimator with the 2FE estimator indicates that the differences in estimation results is not very large for the land variable but ~0.04 for the cattle variable and ~0.05 for the tractor variable. Although showing cross section correlation in the error term, the AMG estimator delivers very similar results to the CCEMG estimator for all variables.

As a next step, it needs to be tested whether Cobb-Douglas is the appropriate functional form for the Brazilian agricultural sector. Table 2 displays the result of the translog regressions based on AMG estimation with non-neutral technical change in column 6, neutral technical change in column 7 and CCEMG estimation in column 8. The Pesaran CD test statistic further improves on the AMG estimation in translog form. When allowing for non-neutral technical change, with a p value of 0.018 in model 7, cross-section correlation in the error term is rejected if we accept a lower significance level of 5%. The more flexible functional form is not able to deliver a rejection of cross-section correlation at a higher significance level by using the AMG estimator. This indicates that the clustering of the municipalities in subgroups is indeed not working satisfactorily for this estimator.[77]

In terms of the Pesaran CD test, results on the CCEMG estimator improve substantially for the translog specification compared to the Cobb-Douglas specification. The F test on the translog estimation parameters additionally confirms that they are jointly significantly different from zero. Thus, as suspected, the translog functional form needs to be preferred over the Cobb-Douglas specification for the data at hand. In addition, on the aggregate level, the production function is well behaved because $0 < \beta_j < 1$, and marginal products are positive.

[77] Other clustering was tested by grouping only municipalities together that share a common border, but the results change for the worse.

The next section interprets the result of the preferred CCEMG estimation in translog form.

5.2. Interpretation of results

For the interpretation of results on the regional level we use results of the estimated parameters on the regional level, the final elasticities of output of each input and the elasticities of substitution between inputs.

Table 3 displays the estimation results for each region based on the CCEMG estimation in translog form. For all regions, the p values of the Pesaran CD test shows no cross section correlation in the error term. Results in table 3 are based on unweighted averages of the CCEMG estimator and thus the significance of the parameter estimates and the related standard errors are displayed in the regression table.

In addition to the regression table we calculate the final elasticities of output by using equation 5 (based on results of table 3 which correspond to results of table 2 column 8). We do this first for each municipality cluster and then aggregate over regions according to equation 9. Since we aim at a representative result for the productivity of each input in the regions, this time we weight results by their contribution to the agricultural value added in the region. As such, we account for the large differences in sizes and economic activity across municipalities within one region.

Figure 4 displays the calculated elasticities of output for the different inputs based on the estimation in column 1-5 in table 3 (which corresponds to column 8 in table 2).

In the same manner we calculate the value added weighted elasticities of substitution between inputs. Figure 5 displays the calculated elasticities of substitution between inputs for the different regions.

For the calculation of the value added weighted elasticities of output and the elasticities of substitution between inputs we use all estimated parameters on the cluster level, independently whether they are significant on the aggregated regional level. One could choose only those parameters which are significant on the regional level according to the estimates displayed in table 3. However, results of this alternative strategy differ only marginally.[78]

As a confirmation of the regional heterogeneity in agricultural productivity, results on the regional level differ compared to overall results for Brazil. Therefore, we first comment on the results on the national level. However, since we are particularly interested in the regional heterogeneity we go into the details of the interpretation of results region by region later on in this chapter. The first order parameters are all significant on the national level (Land 0.194***, cattle 0.296***, tractor 0.167***, labor 0.302***). We find also a significant second order parameter of tractor input (Tractor^2 0.0221***) indicating that a higher degree of mechanization increases the productivity of tractor input in Brazil. We also find that high cattle numbers increase the productivity of land input (LandxCattle 0.244**), showing that intensive cattle production, which is an indicator for very modern cattle production in Brazil, further increases productivity of land. In contrast, we find that high labor numbers decrease the productivity of cattle input (CattlexLabor -0.175***). Since modern cattle production has proportionally very low labor input, a high labor input in livestock systems indicates a low level of development and thus low productivity of cattle input.

On the regional level, results differ in the sense that not all first order parameter are significant (e.g. land in the Central West or Cattle in the Southeast). Even though not significant, the Central West and the North obtain negative parameter estimates for Land input which results in a violation of the assumption of positive marginal products for a well behaved production function. We interpret this result as a consequence of the relative low number of observations for these two regions and their remoteness with large municipality sizes. Thus, the data quality for these two

[78] The estimation of the significance of the parameter estimates of each mean group estimator are based on the calculation of the variance with $V(\hat{\beta}^{MG}) = \frac{1}{N(N-1)}\sum_{i=1}^{N}(\hat{\beta}_i - \bar{\beta})^2$. Thus, it is based on the significance of a parameter resulting from the regional aggregation and not the significance of the parameter in the auxiliary first stepp POLS estimation according to equation 13 for each municipality cluster. Thus, by using only the significant final parameters on the regional level one would miss out significant second order parameters of the translog function at the cluster level. By using all estimated parameters independent of their significance level we have the risk of influencing the final elasticities of output and elasticities of substitution with unsignificant parameters. However, since for the translog estimation we have to normalize data with the sample mean on the cluster level before taking the natural logs (see section 4.1.), the influence of the second order parameters of the translog function on the final elasticities of output is rather small if parameter estimates are small which is mostly the case for the unsignificant parameters. We test both options and find little difference in the results.

regions is probably lower than for the two other regions and results need to be interpreted with caution.

In addition, for these two regions, the Wald Test on the joint significance of the second order translog parameter estimates show a joint non-significance of these parameters for the Central West (p = 0.783) and the North (p=0.163). For the Southeast, we only find a joint significance at a lower significance level (0.014). Only for the regions with the higher number of observations, the Southeast (p= 0.009) and the Northeast (p=0.001), we find a clear joint significance of the second order parameters. However, when looking at the regional level, this is mostly due to the high variance of the estimates across municipalities. Thus, we do not interpret this result as a negation of the translog functional form but as a result of the heterogeneity of the relationship between input productivity across municipality combined with low numbers of observations. With increased observation numbers, some general conclusions for the relationship between input pairs can be drawn (see detailed interpretation for the Northeast and the Southeast.)

A further confirmation of the preferability of the translog specification, the assumption of an elasticity of substitution of 1 between all inputs is rejected by the variety of resulting elasticities of substitution across input combinations and regions. In the following, we interpret results by region.

Figure 4: Estimated Elasticities of Output for Different Inputs (based on VA weighted means)

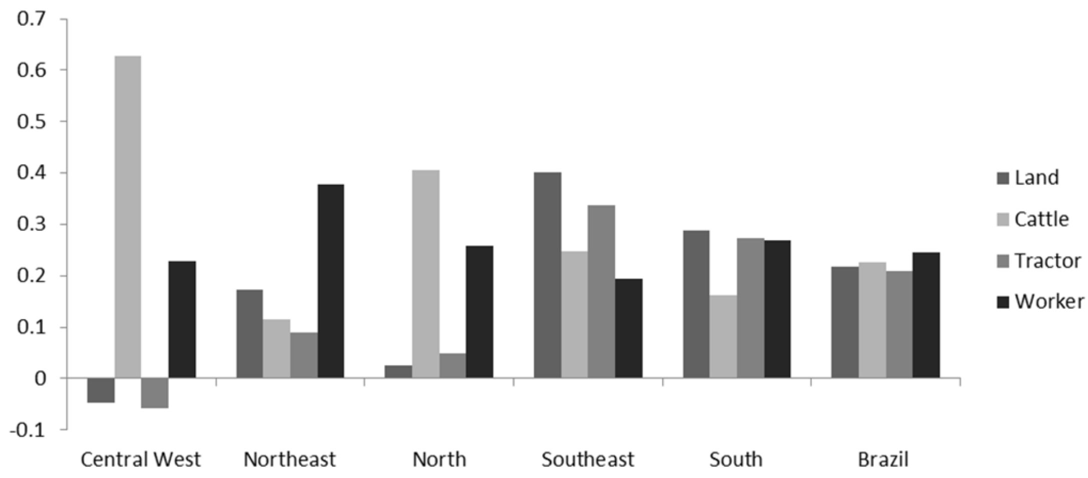
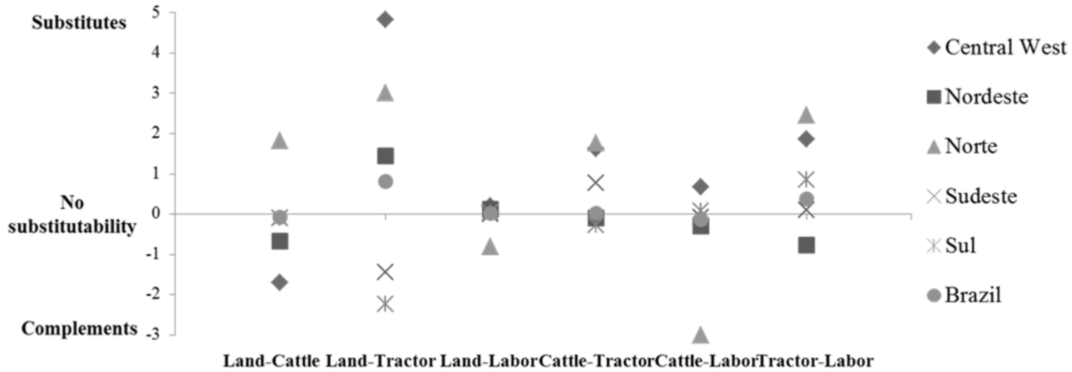


Figure 5: Estimated Elasticities of Substitution Between Inputs (based on VA weighted means)



In the Southeast, the output elasticity of land (weighted elasticity of output 0.401) is the highest compared to all other regions. The high elasticity is driven by a high estimate of the first order land parameter. Here, land has a high productivity resulting from fertile soils (FAO/IIASA 2010) but also from other favorable factors such as close distances to markets, which implies proximity to infrastructure and other services (Land 0.270***). In addition, we find a significant increase of land productivity from increased cattle input (LandxCattle 1.158**) indicating that a high cattle density increases the productivity of land. We find a slightly negative impact of a high number of tractors on the productivity of land (LandxTractor -0.215*) even though at a low significance level. One would expect that a high technology input increases the productivity of land. However, in the Southeast tractor numbers are already high in the 1970 and over the years, many small tractors are replaced by few large tractors with larger capacities. Thus, a high tractor input per land area can in some areas indicate a low technological development. Unfortunately our data only allow accounting for tractor numbers and not tractor sizes. Nonetheless, we find an output elasticity of tractor input (weighted elasticity of output 0.337) which is higher than the Brazilian average (weighted elasticity of output 0.208) showing the technological development of tractors used for production in the region (Tractor 0.206***) and also a small scale effects resulting from a high degree of mechanization (Tractor^2 0.066**).

For the elasticities of substitution of land with other inputs it is important to recall that the land variable used here includes cropland, grassland and forest. Thus, the change from grassland to cropland in many municipalities in the Southeast did not result in a reduction of overall land use but allowed a different combination of land with other inputs depending on the present production system. Consequently, the elasticity of substitution between land and cattle (-0.09) and land and labor (-0.001) is almost zero in the Southeast indicating that the structural change in the region did only result in a very weak substitutability between these inputs.

Output values increased due to a mechanization of crop production and an expansion of crop production into grazing land which resulted in a strong increase of tractor numbers. Thus, tractor and land function as complements (-1.45). In addition, the expansion of mechanized crop production into cattle grazing areas is reflected in a positive elasticity of substitution between cattle and tractors (0.77). However, intensification of cattle production and the mechanization of crop production did not allow a substantial decrease in labor input. This is reflected in an elasticity of substitution of almost zero for labor input with cattle (-0.07) or tractor input (0.09). However, one might expect at least for the introduction of mechanized crop production instead of manual crop production to reduce the overall demand for labor, particularly in harvesting time. We suspect that results do not reflect this process because of the labor data considered here. Problems with the labor data emerge for other regions too. The data in the agricultural census of the IBGE only include permanently employed people on farms. Thus, migratory workers which were often used for the manual sugar cane harvest are probably not included into the data since they are often not permanently employed on the farms. Consequently the substitution of this part of the labor force by tractors is not or not fully included in the data and results.

In the South, land is slightly less productive than in the Southeast (weighted elasticity of output 0.289) but still above the Brazilian average (weighted elasticity of output 0.217) which is influenced by the well-developed infrastructure and close markets in the coastal zone but also by less productive soils in the Pampas, visible in the high first order land parameter (Land 0.281***). The smaller farm structure and highest education levels in the South compared to the Southeast seem to increase labor productivity (weighted elasticity of output 0.268 / Labor 0.261***) but slightly decrease tractor productivity (weighted elasticity of ouput 0.274/ Tractor 0.284***). The latter may be caused by the fact that smaller fields require smaller tractors which, by unit, might be less productive than the tractors used on the larger fields in the Southeast. Productivity of cattle (weighted elasticity of output 0.161) likewise lacks behind compared to the Southeast which can be explained with the later intensification of cattle production in the South (Silva Neto and Basso 2005). However, the first order unweighted parameter of cattle is even lower and not significant (Cattle 0.025), indicating that intensive cattle production is concentrated and productive only in few municipalities in the South which is in line with the maps of section 2.

Elasticities of substitution are similar to those of the Southeast: cattle and worker are no substitutes for land (-0.098/ 0.047) and land and tractor (-2.232) complement each other. In contrast to the Southeast, the elasticity of substitution between cattle and tractor (-0.269) is slightly negative indicating a weak complementarity. This can be explained by two factors. First, the municipalities in the South are larger than in the Southeast. Thus, a displacement of extensive cattle production by mechanized crop production might result in an intensification of cattle production in the same municipality. In contrast, due to the smaller size of municipalities in the Southeast, this leads to an intensification of cattle production in the neighboring municipalities. Thus, we observe parallel existence of intensive cattle production and mechanized crop production within one municipality in the South. In contrast, we observe a separated use of cattle and tractor in neighboring municipalities in the Southeast. Thus, results show a complementary use of cattle and tractor in the South and a substitutability of cattle by tractors in the Southeast. Second, in contrast to the Southeast, the South specialized in soy and corn production instead of sugar cane production. Both crops are important for intensive grain fed cattle breeding and thus might locate closer to the intensive cattle areas than sugar cane fields in the Southeast.

Furthermore, in the South results reflect a certain degree of substitutability between labor and tractor input (0.850). This reflects the fact that migratory workers are traditionally less common in the South due to the varying crop portfolio and smaller farm sizes. Thus, more workers were continuously employed on farms and are thus included in the data set. The increase of mechanized crop production allows a substitution of manual work and thus labor by tractors.

In the Central West, the output elasticity of land (weighted elasticity of output -0.046) and tractor input (weighted elasticity of output -0.058) are negative, which violates the assumption of non-negative marginal products as the basis for assuming profit-maximizing farmers. However, when estimating the Central West separately, the negative first order parameters are not significant (Land -0.244 / Tractor 0.164). Nevertheless, results for the Central West may be problematic, which can be partly caused by the low number of observations for this region (57 clusters). Nonetheless, the results are interpretable with the regionally extensive use of pasture and the late expansion of soy production. Thus, in the early census years, land was essentially abundant for cattle ranching because the varieties for the poor Cerrado soils were not yet developed. In addition, the transportation infrastructure was poorly developed and several planted pasture areas were severely degraded (Müller 2003). Accordingly, results indicate a very high output elasticity of cattle (weighted elasticity of output 0.627 / Cattle 0.826***), indicating the importance of cattle production in the whole period of analysis.

The expansion of highly mechanized soy production accelerated only after the regime shift in 1985. This expansion is triggered by the high demand for soy on the world market and by technological development particularly in the Cerrado area. This technological development enabled the cultivation of soy in formerly inhospitable agro-ecosystems (Müller 2003). Investments in transportation infrastructure facilitated market access (Müller 2003).

The development described above with an overall increase in land use by a spatial expansion of cattle production and a subsequently introduction of mechanized soy production and intensification of cattle production reflects in the elasticities of substitution. In the Central West, land and cattle are complements (-1.710) reflecting the parallel increase of both inputs. In contrast, tractor and land result to be substitutes (4.828). This results from the development path of a subsequent introduction of highly mechanized soy production in extensive cattle areas. Not all of these extensively used grazing areas are suitable for crop production. In addition, particularly in the State of Mato Grosso do Sul, several areas are highly degraded and are not usable anymore for crop production. Positive elasticities of substitution of cattle with tractors (1.624) are in line with this subsequent development. The also positive elasticity of substitution between labor and cattle (0.670) and labor and tractor (1.854) reflect that the Central West strongly increases its cattle production and mechanized crop production by holding labor input on a very low level.

In the North, the output elasticity of land input is very low (weighted elasticity of output 0.173), which reflects the low fertility of Amazon soils, the remoteness of the region resulting in long distances to markets and the very low development of transportation infrastructure. The unweighted first order parameter is even negative but not significant (-0.060). However, at the borders of the Amazon, one can observe a similar development as in the Central West. Particularly for cattle ranching, forest areas are cleared. Cattle ranching starts on a relatively intensive level compared to other areas since natural grassland does not exist and all grazing cattle production requires planting of pasture. This is reflected in the relatively high elasticity of output of cattle in the North (weighted elasticity of output 0.405 / Cattle 0.256**). The productivity of labor is relatively high (weighted elasticity of output 0.259 / Labor 0.295***) compared to the most developed areas. However, as for most other areas, we expect a data problem in the labor data. In the early census years, the region was very poorly developed which might result in a low quality of the data. However, this problem is not particular for the labor variable. Particular for the Amazon is a labor force that works partly illegally to deforest the areas which we expect not to be included in the data set (Gutierres-Velez and MacDicken 2008).

The elasticities of substitution are mostly more extreme meaning more far away from zero than in the other regions. We interpret this as a result of the dynamic in the region in the last two decades due to a subsequent expansion of cattle and soy production. Cattle breeding expand in areas where there has been only natural forest before, whereas soy bean production at the Southern borders expands mostly into grazing areas only few years after the areas have been cleared. As a result, land and cattle (1.831) and land and tractor (3.010) are "easy" substitutes indicating that not all cleared areas are used for cattle production and not all grazing areas are suitable for crop production. In addition, as the land variable includes used forest areas, the implementation of cattle ranching or cropping might allow an abandonment of managed forest since crop production and cattle breeding results to be more profitable. Labor and land (-0.819) and labor and cattle (-2.981) are complements reflecting the increasing use of labor for the increased cattle production. The expanding soy production is less labor intensive than cattle production and thus allows a substitution of labor by tractors (2.453). In line with this development, cattle is substitutable by tractors (1.753) in the North.

Results for the Northeast reflect the dominance of small, minimally productive family farms. The elasticity of output of land input is low (weighted elasticity of output 0.173) compared to the southern regions which also mirror the poor soils of the Caatinga adjacent to the relatively fertile coastal area (Land 0.174***). The same holds for the low productivity of cattle (weighted elasticity of output 0.114). However, we find here a stronger effect of the calculation of the final output elasticities. The unweighted first order parameter of cattle is higher (Cattle 0.359***) and we observe a scale effect of intensive cattle production (Cattle ^2 0.308**). However, the maps in section 2 indicate that this intensive and productive cattle production is concentrated in only few municipalities of the Northeast. The elasticity of output of tractor input is very low (weighted elasticity of output 0.089/Tractor 0.0853***), however, tractors are also barely existent in many municipalities. What strikes out is the high elasticity of output of labor input (weighted elasticity of output 0.378/ Labor 0.414***). This is counterintuitive since due to the low overall development of the sector and region, one would expect a relatively low productivity of labor and thus a low output elasticity of labor as well. Underlying the assumption that inputs get paid their marginal product, this is supported by lower agricultural wages in the Northeast (FGV). We interpret this counterintuitive result again as a problem of the labor data which becomes the most evident in this region. The Northeast has a lot of small subsistence farmers or family farmers that supply to the local food market which do not employ labor. The work is done mostly by low skilled family members which are not captured by the census data as employed labor. Thus, the amount of labor, even though already the highest in the whole country, seem to be still highly underestimated. In addition, labor data in the Northeast will have a bias towards skilled labor since most low skilled work is done by family members. In the other regions, labor includes both high skilled and low skilled workers since both types of work are done by employed labor. This data problem can only be overcome by more differentiated labor data which are only available since the last census.

As a result of the low technological development and structural change in the whole census period, elasticities of substitution between inputs are mostly close to zero in the Northeast (Land-Cattle 0.677, Land-Labor 0.111, Cattle-Tractor 0.095, Cattle-Labor 0.288). One can observe a positive elasticity of substitution and thus substitutability between land and tractor (1.438). This is affected by the decrease in agricultural land at the coastal zone due to a strong urbanization process. In addition, close to the markets and due to the more fertile soils at the coast, a few exceptions of mechanized crop production can be found for example in Maranhao resulting in a certain substitutability between tractor and labor (0.767) (Müller 2003).

Summarizing, it is evident that results confirm the strong heterogeneity of production patterns in the Brazilian agricultural sector. The flexible functional form captures not only different levels of development between regions but also different development path. In particular, the translog functional form is able to accommodate the expansion of mechanized agriculture in areas with labor intensive agriculture in the South and the Southeast. Similarly, it is able to accommodate the expansion in areas with extensive cattle production in the Central West. In addition, the parallel expansion of cattle numbers and the intensification of cattle production in both regions are revealed. It further captures the stagnation of development in the Northeast and the increasing crop production and rising cattle herds in the Amazon forest. Thus, by allowing for regional differences in production functions, a variety in production systems and development levels can be reflected with the elasticities of output and elasticities of substitution between inputs. However, we identify different problems in the labor data. In addition, some results on the elasticities of substitution between inputs seem to be affected by municipality size. The next section summarizes the effect of factors influencing output not yet included in the productivity of inputs and elasticities of substitution.

5.3. Additional factors influencing output

The change from labor-based agriculture to mechanized agriculture is the basic idea of technological development in the agricultural sector. The estimation of the production function on the municipality level and the flexible functional form allow the ability to capture differences in input productivity and substitutability between inputs. These differences are an indicator for suitability of input (such as fertility of the soil or capacity of tractors). However, they are also an indicator for different technologies and levels of development of the agricultural system. The size of the output elasticity reflects the productivity of an input in the present agricultural system. Thus, the majority of the differences in technological development, resulting from regional differences in, e.g., climate, infrastructure, governmental support, education, etc., are already accommodated in the estimated production function as long as they individually influence the productivity of inputs.

It remains to measure the effect of factors on output that goes beyond the individual productivity of inputs analyzed in this study. These are effects of factors that can shift the production function beyond their influence on factor-specific productivity. It measures the part of the equation that cannot be explained by the use of the individual inputs considered here (Eberhardt and Teal 2014). Normally, the part of the production function not explainable by individual input use is referred to as "total factor productivity". However, in this context it can be misleading since it is often used as a synonym for overall technical progress even though there are several studies pointing out that it may not represent a measurement of technological progress at all (Baier, Dwyner and Tamura 2006, Caselli, 2008). They point out that such measurement includes all kind of factors that can shift the production possibility frontier like input factors not considered in the analysis or local and global political or climate shocks. In order to avoid confusion also with other approaches to measure total factor productivity we therefore refer in the following to additional factors influencing output which are captured in the residual to point out that we implicitly measure most of the technological progress already in the elasticities of output of the main inputs. The residual captures the factors that influence output beyond the productivity of individual inputs considered in this analysis.

For measuring these additional factors, the well-known approach of growth accounting (e.g., Abramowitz 1956, Kendrick 1956 or Solow 1957) is used. This approach decomposes value-added growth into contributions of inputs and other factors (Eberhardt and Teal 2014). Thus, based on the translog specification and a previous estimation of the production function using the CCEMG estimator[79], the change in the residuals on the municipality level can be estimated as follows:[80]

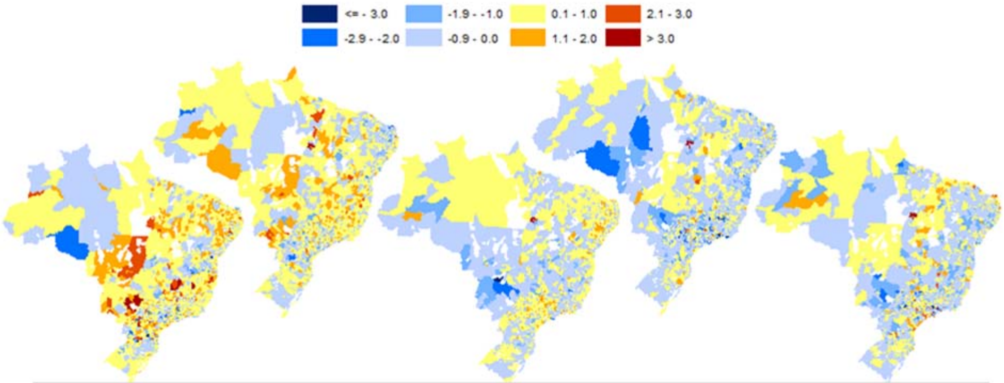
$$\Delta u_{it} = \Delta y_{it} - \sum_{m=1}^{M} \beta_{mi} \Delta x_{mit} - \sum_{m=1}^{M} \sum_{k=1}^{M} \beta_{mki} \Delta(x_{mit} x_{kit}) \qquad (10)$$

Results in figure 6 indicate the percentage change in the residuals for each municipality based on the first stage POLS regression on the cluster level of model 8

[79] Or any other MG-type estimator.
[80] This measurement also includes the effect of the cross sectional means of the dependent and independent variables used in the CCEMG estimator.

in table 2. The table below indicates the related value added weighted mean of the percentage change in the residual for Brazil and the large regions.

Figure 6: Percentage change in additional factors influencing output



	1970-1975	1975-1980	1980-1985	1985-1995	1995-2006
Brazil	0.23	0.11	-0.01	-0.41	-0.27
Central-West	0.56	0.40	-0.49	-0.09	-0.32
Northeast	0.27	0.06	0.12	-0.52	-0.21
North	0.16	0.16	-0.01	-0.31	-0.16
Southeast	0.20	0.22	0.05	-0.48	-0.31
South	0.20	0.22	0.05	-0.48	-0.31

The mean results are close to zero and decrease slightly over time (see results for Brazil and major regions in figure 6). Thus, on average, shocks do not substantially shift the production possibility frontier. This indicates that most of the policy shocks such as the opening of the economy or changes in the available technology are already captured in the individual factor productivities. Nonetheless, the slight downward slope of aggregate growth in the effect of unobservable factors may result from decreasing governmental support for the sector since the 80s (-0.01% 1980-1985, -0.41% 1985-1996 on average for Brazil). Less subsidized credits and a lower protection of prices increased cost of production and decreased the potential return from production.

The maps indicate that on the local municipality level, additional factors affect output approximately between -3% and 3% (indicated by the colors of the map). The local results may suffer from the low degree of freedom on this level of analysis. They are nonetheless useful to illustrate some examples of local development. Figure 2 with the map on the federal states in section 2 gives an orientation for the location of the federal states. The maps illustrate that the municipalities in the state of Mato Grosso and Mato Grosso do Sul are the first to suffer under the decrease in support policies between 1980 and 1985 (Central West 1980-1985: average -0.49% but municipalities in Mato Grosso do Sul with <-3%). At this time, land use is highly inefficient in many regions in the Central-West, and the lack of infrastructure and market protection still impedes the later expansion of mechanized agriculture. In the transition period, even more municipalities struggle under rigorous market conditions and exhibit negative impacts on output. However, the production regions of sugar cane in São Paulo and of soy in Paraná already profit from the opening of the markets and still experience positive impacts on output beyond individual factor productivity (Southeast 1980-1985: average 0.05% but municipalities in São Paulo with > 2.5%). This is also the case for the municipalities in the Cerrado that introduce mechanized soy production. This growth in the Cerrado gains more momentum in the time between 1995 and 2006, during which the soy sector expands substantially (municipalities in Tocantins, Goiás and Mato Grosso with > 2.5% 1980-2006). Bonelli (2001) indicates that municipalities that successfully implement highly modern soy production are subject to a relatively well-developed transportation infrastructure and gain technical assistance. In addition, they received adequate financing possibilities and were close to the related processing industries (Bonelli 2001). In areas where these factors are not present, the maps indicate that several municipalities experience negative impacts on output until 2006. This is particularly true for areas in Mato Grosso do Sul, where severely degraded pasture areas remain (FAO 1999).

In addition to the development in the Central West, the stabilization of the whole economy creates a more favorable environment for all export-oriented crop-producing regions. This appears in the maps in the form of more municipalities with positive impacts on output beyond individual factor productivity in the traditional areas of the Southeast and the South but also at the coastal line of the Northeast.

The importance of transportation infrastructure in the Northeast is particularly highlighted by the “Corredor de Exportação Norte” in the 90s. This transportation corridor to the Itaqui harbor in Maranhão substantially improved the transportation of soybeans to the Itaqui harbor (Müller 2003). Locally, this effect becomes visible in positive effects on output beyond the productivity of individual inputs (1996-2006 increase in relevant municipalities of 1-3%). Thus, here it becomes evident that the residual captures infrastructure as a potential “input” into the production function not considered in the measurement of the production function in this study. Infrastructure may be indirectly included in the productivity of e.g. land as results for the Southeast and the South suggest, however, examples like Maranhão suggest an effect on output beyond that. In a similar way, a continuous improvement of the road infrastructure seems to boost development in other regions such as in the Amazon (Pfaff et al. 2007). In the state of Roraima, a continuous increase in paved and unpaved roads similarly positively impact on output values beginning in 1975 (since 1975 > 1% in several municipalities of Roraima).

In addition, results indicate that the severe structural and biophysical problems in the Northeastern hinterland negatively affect output values beyond the low estimated productivity of individual inputs after 1985 (1985-1996 average -0.52%).

Summarizing, the measurement of additional factors influencing output shows part of the factors already relevant for the measurement of the heterogeneous productivity of observable inputs Thus, although aggregate values on the regional level are very close to zero, the national shocks of the regime shift and the related changes in policy and markets cause shifts in the production function on the local level that go beyond the productivity of individual inputs. The results also indicate the relevance of local and regional factors. Infrastructure and other factors that facilitate the implementation of an export-oriented, mechanized crop production result in a positive shift. A deeper analysis of these factors is subject to future work since data an e.g. infrastructure are not systematically available on the municipality level as for the census data.

6. Conclusions

The aim of this paper is to derive an estimate of the production function of the Brazilian agricultural sector in order to deliver a basis of information for future development. In the context of a looming increase in demand for agricultural products from Brazil, the potential for intensification is of particular importance. The results contribute to the methodological discussion on estimation of production functions and highlight strong regional differences in development of the agricultural sector.

We estimate the production function of the Brazilian agricultural sector by applying an approach that allows for changing factor shares and elasticities of output over time and regions. In addition, it simultaneously accommodates technology heterogeneity, variable time-series properties and the potential for correlated latent common factors across municipalities influencing input and output heterogeneously. The results highlight the importance of flexible functional forms for production function estimation in agriculture. For the production function, even though the second order parameters are not jointly significantly different from zero for all specifications, the results clearly rejected constant and equal substitutability between all inputs of one. Elasticities of substitution between inputs vary for different types of inputs and between regions. Apparently different development path and technological development in the regions result in production regimes that allow varying substitutability between inputs.

In addition to the over-restrictive functional form, the results negate the existence of one homogenous production function for the whole Brazilian agricultural sector. All estimators imposing homogeneity in technology parameters and evolution of latent common factors deliver residuals with cross section correlation. This follows intuitively given the fundamentally different regional production regimes and development paths. The different sizes of estimated productivity of inputs reflect different levels of regional development and thus confirm the effect of latent factors on input choice. Therefore, the results are in line with Eberhardt and Teal (2013), who reject a homogenous production function for cross-country analysis. This paper demonstrates that the concept of regional heterogeneity in agricultural production functions holds also for within-country analysis, at least for countries as diverse as Brazil. The use of a translog specification instead of the Cobb-Douglas specification even demonstrates that heterogeneity is also contained in elasticities of substitution between inputs and the evolution of factor shares. This further enhances the idea that heterogeneity in production functions are the result of regional and local circumstances driving, e.g., the applicability of available technologies.

Results show a strong heterogeneity in the productivity of inputs. Thus, the potential for further intensification of production will differ between regions as well. We find favorable conditions in particular in the South and the Southeast with high education levels, fertile soils, closeness to markets, highly developed infrastructure and last but not least governmental support. This results in a comparably high productivity of all inputs and in particular of land. In addition, these conditions increase output beyond the productivity of each input.

A mechanization of crop production and thus intensive crop production is also existent in areas of highly mechanized soy production in Mato Grosso and Maranhão. Both regions gained from the development of plant varieties suitable for the Cerrado, which was supported by the publicly financed EMPRAPA. Thus, the strong public investment of the Brazilian state into agricultural research within the EMPRAPA research centers directly affects expansion of agricultural production and intensification of land use by allowing the conversion of extensive pasture into intensively used cropland in the savannah biome of the Cerrado.

Moreover, the analysis of additional factors driving output reveals that for both local centers of highly mechanized crop production, transportation infrastructure was the key factor that triggered the successful expansion of soy production (Bonelli 2001, Müller 2003). Both states are still in regions with a strong heterogeneity in productivity of inputs which result in a much lower productivity of inputs on the aggregate level for the Central-West and the Northeast. In many areas of the Central-West and in the Northeast, there are still considerable deficiencies in transportation infrastructure as well as in technical assistance, adequate financing possibilities and related processing industries (Müller 2003).

Results show however for the Central-West that, despite some low productive regions, intensification of both cattle production and crop production is an ongoing process. The influence of such deficiencies becomes much more evident in the very low productivities of inputs in the Northeast. In addition, the elasticities of substitution mirror the minor changes in the Northeastern agricultural structure since 1970ties. The unfavorable combination of low education, low off-farm employment possibilities, low soil fertility, unequal land distribution and minimal governmental support seem to impede further development. The modernization of the agricultural sector in the Northeast is thus a major challenge to achieve a strong increase in agricultural output without increasing agricultural areas in the Savannahs of the Central-West or the Amazon Forest. The ongoing expansion of agricultural areas in these biomes highlights the importance to increase production on the already used areas. Results for the Amazon even reveal an increased dynamic in the expansion of agricultural areas. Here, agricultural expansion has particular severe effects on carbon pools and biodiversity.

Overall, the results confirm findings of Strassburg et al. (2014) who see a strong potential for increasing production on the existing agricultural areas particularly in the Cerrado. The results indicate strong deficits in some local areas and suggest that infrastructure is a key factor to trigger modernization of production techniques and thus to generally boost output values and to cause the necessary changes in factor shares and factor productivity. Eberhardt and Teal (2013) conclude that heterogeneity detected in regional production functions indicates why technology transfers can fail. In line with their argumentation, agricultural policies and publicly financed research efforts need to be revised in terms of their ability to promote agricultural development for example in the Northeast. Moreover, the detected regional heterogeneous development paths highlight the need for regional or even local agricultural policies in general. These local policies need to address the deficits in infrastructure but also in the availability of production techniques suitable for the local conditions. They further need to address deficits in general, structural factors such as financing of the sector, extension services and education. The high demand for agricultural production from Brazil on the one hand and the valuable biomes at risk on the other hand demand a focus on the elimination of local inefficiencies in the use of inputs. Thus, to realize non-expansion scenarios, such as those of Strassburg et al. (2014), an efficient use of land is fundamental.

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Appendix A1

This appendix presents the intuition behind the CCEMG estimator. Several studies indicate that the CCE estimators are able to accommodate the model setup introduced in section 3 (Coakley et al. 2006, Kapetaios et al. 2011, Pesaran 2006). In the following, we describe the intuition behind the CCEMG estimator as explained in Eberhardt et al. (2013):

First, equation 2 needs to be rewritten with x_{it} as the vector of all observable inputs x_{mit} (assume this accordingly for the parameters) and f_t as the vector of all factors influencing input and output at time t

$$x_{it} = \pi_i + \delta_i' g_t + \rho_i' f_t + \epsilon_{xit} \text{ and } u_{it} = \alpha_i + \lambda_i' f_t + \varepsilon_{uit} \qquad \text{(A1)}$$

If the basic assumption of the random coefficient models ($\beta_i' = \beta + \eta_i \, with \, \eta_i \sim iid(0, \sigma_\beta^2)$) does not hold and thus the influence of the unobservable factors is on average non-zero ($\bar{\rho} \neq 0$), ($\bar{\lambda} \neq 0$), the estimate of β is biased. The intuition of the CCEMG estimator to account for this can be indicated as follows based on Eberhardt et al. (2013):

Insert equation 2 in equation 1:

$$y_{it} = \beta_i' x_{it} + \alpha_i + \lambda_i' f_t + \varepsilon_{uit} \qquad \text{(A2)}$$

The averaged version of this equation is given as:

$$\overline{y_t} = \bar{\beta}\overline{x_t} + \bar{\alpha} + \bar{\lambda} f_t \qquad given \; \varepsilon_{uit} \to 0 \; as \; N \to \infty \qquad \text{(A3)}$$

This can be rewritten as a function of f_t with cross-section averages defined as

$$\overline{y_t} = N^{-1} \textstyle\sum_{i=1}^{N} y_{it} \quad and \quad \overline{x_t} = N^{-1} \textstyle\sum_{i=1}^{N} x_{it} \qquad \text{(A4)}$$

$$f_t = \bar{\lambda}^{-1}(\overline{y_t} - \bar{\alpha} - \bar{\beta}\overline{x_t}) \qquad \text{(A5)}$$

$$f_t = \bar{\lambda}^{-1}\overline{y_t} - \bar{\lambda}^{-1}\bar{\alpha} - \bar{\lambda}^{-1}\bar{\beta}\overline{x_t} \qquad \text{(A6)}$$

This implies that as the cross-section dimension becomes large, the unobservable common factors f_t can be captured by a combination of cross-sectional averages of y and x.

Inserting this into equation 1 yields:

$$y_{it} = \beta_i' x_{it} + \alpha_i + \lambda_i' \bar{\lambda}^{-1}(\overline{y_t} - \bar{\alpha} - \bar{\beta}\overline{x_t}) + \varepsilon_{uit} \qquad \text{(A7)}$$

$$y_{it} = \beta_i' x_{it} + \theta_{1i} + \theta_{2i}\overline{y_t} + \theta_{3i}\overline{x_t} + \varepsilon_{it} \quad \text{(A8)}$$

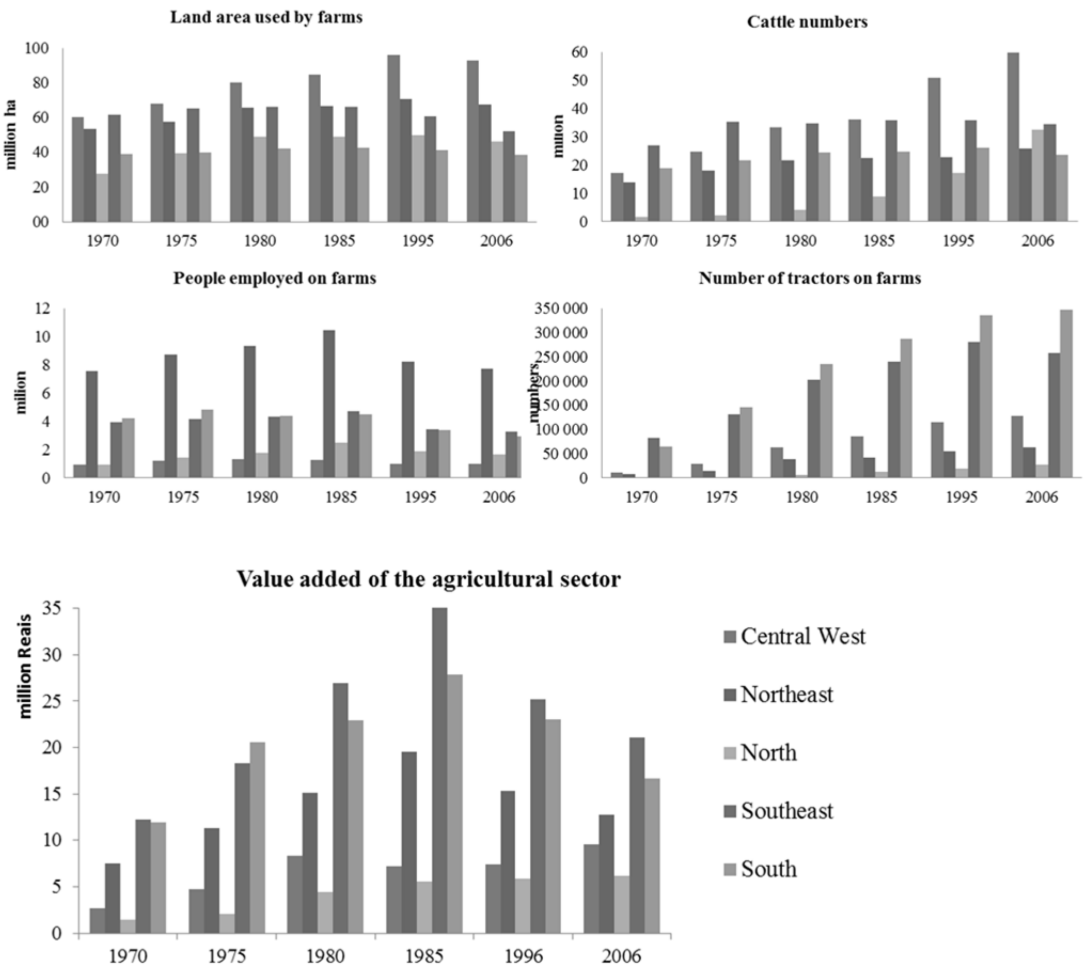
To allow this setting to capture heterogeneity of factor loadings, the intercept and factor loadings of the cross-section averages of x and y, $\theta_{1i}, \theta_{2i}, \theta_{3i}$, must be municipality specific (Eberhardt et al. 2013).

Appendix A2 Data Overview

Table A1 Sample distribution of raw data

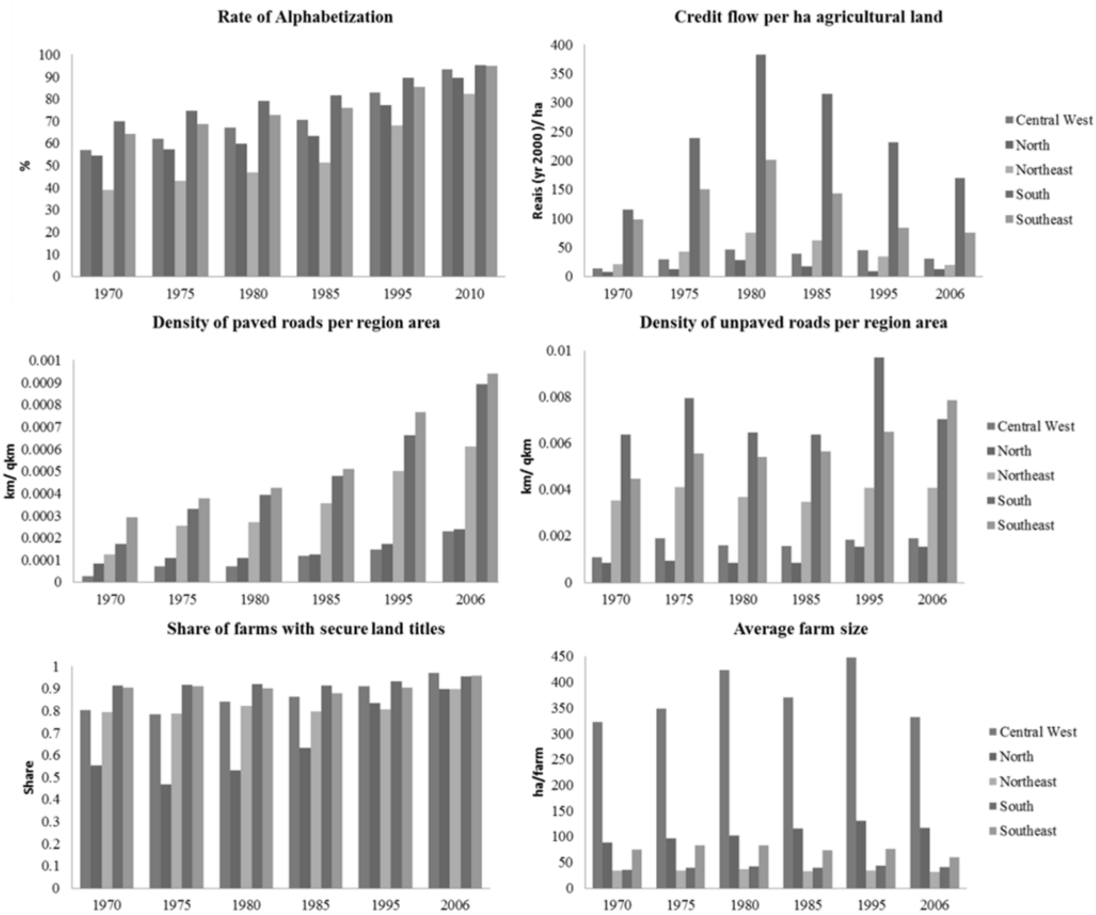
Estimation Data Brazil	mean	median	Std. Dev.	Min	Max
Land (ha)	80 289	29 215	314 027	1	14 200 000
Cattle (heads)	36 016	13 874	149 488	1	11 500 000
Tractor (numbers)	150	37	419	1	15 506
Labor (numbers)	5 315	3 079	8 545	2	324 440
Value added of agriculture (Reais 2000)	18 498	9 112	37 020	3	1 718 435

Figure A1: Regional and temporal distribution of dependent and independent variables



Note: Data on land used on farms, cattle, employed people and tractor numbers are obtained from the Agricultural Census (IBGE 2013b). Land used includes all cropland, natural pasture, planted pasture, planted forest and natural forest. Value added of the agricultural sector is downloaded from the ipeadata.gov.br webpage but originated in the (IBGE 2013d). Value added is provided in real values of the year 2000.

Figure A2: Additional statistics of the data used for interpretation



Note: Rate of Alphabetization, paved and unpaved roads from Statistical Yearbooks (IBGE 2013a). Flow of credits are credits of the program "credito rural" of the Banco Central do Brasil. Credits are averaged over the last five years and represent total credits to both crop and livestock production, investment and commercialization. Reais are normalized to Reais of the year 2000 (The World Bank 2013) and are weighted by the total agricultural area (all cropland, pasture and forest of farms obtained from the Agricultural Census (IBGE 2013b). Areas with secure land titels are defined as those areas where the farmer is the official owner, tenant or partner. Areas with insecure land titles are those areas where the farmer is an occupier. Data on the legal status of the land is obtained from the Agricultural Census (IBGE 2013b). Farm sizes are also obtained from the Agricultural Census (IBGE 2013b).

Appendix A3: Unit Root Test Statistics.

The following tables show the unit root test results related to the regression results in table 2. Tests have as the null hypothesis that all the panels contain a unit root.

Table A2

	Cobb-Douglas									
	1 POLS		2 2FE		3 MG		4 AMG		5 CCEMG	
unit root test	Z	p	Z	p	Z	p	Z	p	Z	p
Harris-Tzavalis	-82.553	0.000	-83.792	0.000	-150.000	0.000	-110.000	0.000	-97.995	0.000
Harris-Tzavalis trend	-52.427	0.000	-56.311	0.000	-65.735	0.000	-66.134	0.000	-56.280	0.000
Harris-Tzavalis no constant	-96.249	0.000	-240.000	0.000	-340.000	0.000	-240.000	0.000	-220.000	0.000
IPS	-16.872	0.000	-15.534	0.000	-50.745	0.000	-30.806	0.000	-26.972	0.000
Fisher type lag = 0	-48.699	0.000	-46.426	0.000	-132.078	0.000	-73.328	0.000	-85.704	0.000
Fisher type lag = 1	-37.324	0.000	-36.459	0.000	-119.232	0.000	-68.032	0.000	-58.362	0.000

Table A3

	Translog					
	6 AMG		7 AMG		8 CCEMG	
unit root test	Z	p	Z	p	Z	p
Harris-Tzavalis	-130.000	0.000	-140.000	0.000	-130.000	0.000
Harris-Tzavalis trend	-69.160	0.000	-81.224	0.000	-64.015	0.000
Harris-Tzavalis no constant	-300.000	0.000	-320.000	0.000	-290.000	0.000
IPS	-42.395	0.000	-43.269	0.000	-40.376	0.000
Fisher type lag = 0	-104.449	0.000	-106.281	0.000	-97.553	0.000
Fisher type lag = 1	-93.341	0.000	-93.259	0.000	-83.474	0.000

Paper: 5

NIGHT LIGHTS AND REGIONAL GDP[81]

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Abstract:

Based on evidence from national data, Henderson, Storeygard and Weil (AER 2012) suggest that growth of night lights can proxy reliably for growth of regional GDP in low-income countries where GDP data is frequently lacking or of poor quality. Based on evidence from regional data in two large emerging economies, Brazil and India, we suggest, by contrast, that the relationship between night lights growth and observed GDP growth varies significantly—in both statistical and economic terms—across regions. We find little evidence for this regional variation to be caused by measurement errors of GDP, or by urban-rural divide.

Keywords: night lights, regional GDP, stability of lights elasticities, emerging economies, developed economies

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[81] Updated version (January 2014) of Bickenbach, F. Bode, E., Nunnenkamp, P. and Söder, M. (2014). Night Lights and Regional GDP. Kiel Working Paper, Kiel Institute for the World Economy, Kiel.

1. Introduction

Numerous recent studies exploit the positive cross-section correlation between the levels of night lights intensities, measured by satellites from outer space, and levels of GDP. By approximating GDP by night lights data, which is globally available at a grid of less than one square kilometer, these studies have been able to address a variety of interesting and relevant issues especially at subnational levels in low- and middle-income countries.[82] These issues could not be addressed otherwise because data on GDP is unavailable or unreliable.

In a recent paper, Henderson et al. (2012) go one step further by suggesting that the growth rate of night lights intensities is a useful proxy for the growth rate of GDP as well.[83] They show for a sample of more than 100 low- and middle-income countries that there is a significant and stable positive relationship between growth of night lights intensities and of *observed* GDP at the county level. Their estimates suggest that a one percent faster growth of night lights intensity is associated with a roughly 0.3 percent faster growth of observed GDP. They also show that this estimate is not significantly biased by changes of measurement errors of observed GDP. This suggests that changes of night lights intensities are a useful proxy of changes of *true* GDP as well. They may substitute for true GDP growth when GDP data is unavailable, or may help correct observed GDP data measured with error.

While Henderson et al. establish this stable GDP-lights growth nexus at the country level they suggest that lights growth may proxy for GDP growth at any spatial resolution. This suggestion paves the way for addressing another set of important questions for less developed countries, namely those related to recent local or regional economic dynamics in these countries. Henderson et al. exemplify this by showing for sub-Saharan Africa that, against conventional wisdom, coastal areas have not grown faster than landlocked areas, primate cities have not grown faster

[82] Examples of these studies are Alesina et al. (2013), who show that ethnic inequality within countries (Gini index of average per-capita lights intensities across the homelands of ethnic groups) hinders aggregate economic development (country-level GDP); Gennaioli et al. (2013), who find that night lights are related to human capital in a similar way as regional per-capita income for a large cross-country sample of regions; Michalopoulos and Papaioannou (2013), who find a positive association between more complex pre-colonial institutions and current night lights intensity within African countries; Hodler and Raschky (2014), who find that leaders of countries with poor institutions use foreign aid for favoritism, indicated by higher effects of foreign aid on per-capita lights intensities at the leaders' birthplaces; or Small et al. (2011), who find that Zipf's law holds for night lights all over the world.

[83] In a similar vein, Chen and Nordhaus (2011) argue that changes of night lights have informational value for countries with poor quality of national income accounts.

than hinterlands, and malarial areas have not caught up in growth dynamics to nonmalarial areas in spite of extensive antimalarial campaigns.

In this paper, we complement Henderson et al. by investigating the GDP-lights growth nexus at the subnational level where it is arguably most valuable for economic research. Adopting Henderson et al.'s empirical approach, we exemplify for two large emerging economies, India and Brazil, that the relationship between the growth of lights and that of *observed* GDP is unstable across regions. The corresponding parameter estimates are roughly similar to those reported by Henderson et al. for some regions but are very small or even negative for other regions. The relationship remains unstable even if we control, as far as possible, for potential biases from measurement errors of GDP. In addition to this, we show that the relationship is similarly unstable across regions within some of the most advanced economies, the United States and Western Europe, even though GDP data is arguably of highest quality in these countries and measurement errors of GDP are therefore particularly small. Taken together, this evidence suggests that the relationship between the growth of lights and of *true* GDP observed at the country level does not carry over to subnational levels as easily as suggested by Henderson et al.

2. Instability of the long-term relationship between regional GDP and night lights intensity growth

2.1. Empirical approach and data

The main purpose of this section is estimating—and assessing the stability of—the long-term GDP-lights growth nexus for emerging economies, exemplified by India and Brazil, and highly developed economies, exemplified by the United States and Western Europe. Estimates for the corresponding short-term nexus from panel data are given in the Appendix. Following Henderson et al., we hypothesize that the long-term relationship between growth of night lights intensity and of *true* regional GDP can, for a cross section of subnational administrative units, henceforth called counties[84] and indexed by $i = 1, \ldots, I$, be formalized for predictive purposes as

[84] While we call these local units counties for expositional convenience here, we will use the smallest administrative units for which GDP data is available in the empirical implementations: districts in India, municipalities in Brazil, counties in the US and NUTS3 regions in Western Europe.

$$y_i^* = \beta_0 l_i + u_i, \qquad u_i = \alpha + \varepsilon_i \qquad (1)$$

where y_i^* is the (unobservable) growth rate of true GDP in county i over a given period of time, l_i the contemporaneous growth rate of the night lights intensity, β_0 the parameter of main interest and u_i the error term that comprises some national growth component, α, as well as an idiosyncratic component, ε_i, that may be heteroscedastic across regions but is uncorrelated with the growth of night lights. If β_0 is significant and stable across regions, night lights intensity could be considered a feasible proxy of true GDP for subnational units.

Since true GDP growth is unobservable, it has to be replaced by observed GDP growth, y_i, which Henderson et al. (2012: 1005) assume to deviate only randomly from true GDP growth, i.e., $y_i = y_i^* + \eta_i$. η_i reflects county-specific changes of all kinds of measurement errors of GDP over the growth period. These errors may be heteroscedastic but are assumed to be uncorrelated with l_i. Substituting this equation into (1) gives the so-called "long-difference" regression model,

$$y_i = \beta_0 l_i + u_{i0}, \qquad u_{i0} = \alpha + \varepsilon_{i0}, \qquad (2)$$

which Henderson et al. estimate for a cross section of 113 low- and middle-income countries (see Henderson et al. 2012, Table 4, column 3). $\varepsilon_{i0} = \varepsilon_i - \eta_i$ in (2) is assumed to have zero mean and county-specific variances. We adopt (2) as our baseline model and estimate it for Indian, Brazilian, U.S. and Western European counties.[85] We then test for stability of β_0 across administratively or economically defined subsets of counties, which we call regions.[86] We add a set of interaction terms between lights growth, l_i, and dummies for all (but one) regions, D_r,

[85] Like Henderson et al., we average the initial and final GDP and lights densities of these growth rates over two years to mitigate the effects of outliers. The GDP growth rate, for example, is calculated as $y_i = [\ln(YD_{iT}+YD_{iT-1}) - \ln(YD_{it+1}+YD_{it})]/(T-t-1)$, where YD denotes GDP density (per km²) and T and t are, respectively, the last and the first year for which we have data for region i. Unlike Henderson et al., we use compound growth rates because time periods for which data is available differ across counties, notably in India and Western Europe.

[86] For the case of Western Europe these regions are actually countries (EU Member States).

$r = 2, \ldots, R$, to (2),[87] and test if the parameters of these interaction terms are jointly zero. We use a χ^2 test that is robust to heteroscedasticity (Wooldridge 2002: 57-58).[88]

Anticipating the results of these tests, which clearly reject parameter stability for all four countries, we note that the baseline model, and consequently the tests, may be too restrictive. The region-specific estimates of β_0 may be biased by changes of measurement errors of GDP that vary systematically across regions or are spatially correlated with l_i (or, for that matter, with omitted variables correlated with l_i). We try to control for these possible biases as far as possible by extending the baseline model (2) successively in two ways. First, we control for region-specific changes of measurement errors of GDP by adding dummies to model (2) for all (but one) regions, D_r, $r = 2, \ldots, R$. And second, we control for measurement errors correlated across space with lights intensities by adding the spatial lag of lights growth as an additional control variable. For the latter purpose, we hypothesize that the measurement error in (2), η_i, actually takes the form $\eta_i = \gamma_i l_i + \eta_{i0}$ where η_{i0} has expected value of zero and county-specific variances, and the parameter γ_i is correlated across counties, i.e., tends to be more similar in counties close-by than in those further away. We approximate the term $\gamma_i l_i$ by a spatial lag of lights growth, defined as $Wl_i = \Sigma_{j\neq i} w_{ij} l_j$. We choose the spatial weights, w_{ij}, to be based on inverse squared geographical distances.[89]

In addition to measurement errors, the regional dummies and the spatial lag might also capture the effects of omitted structural growth determinants. In fact, Berliant and Weiss (2013) suggest similar extensions to account for omitted structural variables such as electricity prices. Unfortunately, we are not aware of a way to discriminate effectively between measurement errors and omitted variables. However, if β_0 turns out to be stable in the extended models, we can be more confident of the general usefulness of lights intensity growth as a proxy of true GDP growth at the subnational level.

[87] In these unrestricted regressions, the parameter β_0 will report the GDP-lights growth nexus in the reference region, whereas the parameters of the interaction terms will report deviations of the respective regions from the reference region.

[88] We use Huber/White robust covariances. χ^2 tests based on spatial heteroscedasticity and autocorrelation consistent (HAC) covariances (Kelejian and Prucha 2007) yield even stronger results (lower p-values).

[89] More precisely, $w_{ij} = [1/D_{ij}^2] / \Sigma_j[1/D_{ij}^2]$, where D_{ij} is the Euclidean geographic distance between counties i and j.

The night lights data, which is described in detail in Henderson et al. (2012), range from zero (unlit pixels) to 63 (top-coded pixels).[90] For India, we use an unbalanced dataset of real GDP (1999–2000 prices) for 519 districts published by the Planning Commission.[91] The data typically starts in 1999 and extends to 2004 or later. We assess the stability of the lights elasticity across five Indian regions, East India, North India, Northeast India, South India, and West India.[92] For Brazil, we use data on real GDP (2000 prices) for 4,820 municipalities in 1999–2010 (balanced), published by the Instituto Brasileiro de Geografia e Estatística, and test for parameter stability across five statistical regions, Norte, Nordeste, Sudeste, Sul and Centro-Oeste. For the United States, we use data on personal income (current prices) in the 3,079 mainland counties 1992–2010 (balanced), published by the Bureau of Economic Analysis (BEA), and test for parameter stability across the eight regions defined by the BEA. Finally, for Western Europe, we use GDP data (current prices) for the 871 NUTS3 regions in 13 countries[93] over the period 1995–2010 (unbalanced), published by Eurostat, and test for parameter stability across countries.

2.2. Stability of long-term lights elasticities in emerging economies

This section shows that the long-term relationships between night lights growth and both observed and true GDP growth differ significantly—in both statistical and economic terms—across Indian and Brazilian regions.

Table 1 summarizes the results for India. Column (1), which reports the results of the baseline model (2), estimated under the null hypothesis of parameter stability, indicates that the country-wide long-term GDP-lights growth nexus is positive and

[90] While even high-income countries have a high share of unlit pixels, there are few pixels with low light intensity of one or two in both high- and low-income countries. Likewise, top-coded pixels with light intensity of 63 are few and restricted to metropolitan areas. See, e.g., Henderson et al. (2012: Table 1). Our main results are not affected by controlling for changes of the shares of unlit or top-coded pixels per county (see Section B.4).

[91] http://planningcommission.nic.in/plans/stateplan/ssphd.php?state=ssphdbody.htm.

[92] East India comprises all counties (districts) of the states of Bihar, Jharkhand, Orissa and West Bengal; North India those of Chhattisgarh, Haryana, Himachal Pradesh, Madhya Pradesh, Punjab, Uttar Pradesh and Uttarakhand; Northeast India those of Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram and Sikkim; South India those of Andra Pradesh, Karnataka, Kerala and Tamil Nadu; and West India those of Maharashtra and Rajasthan.

[93] The 13 Western European countries are Austria, Belgium, Germany, Denmark, Finland, France, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden and the United Kingdom. Luxembourg is excluded from the regressions in this section because it comprises a single NUTS3 region. It is included, however, in the panel estimations of short-term elasticities provided in the Appendix. Greece is excluded because Greek data may not be as reliable as the Penn World Tables data quality grade of B suggests. The questionable reliability is, among others, indicated by the poor data on public debt reported to the EU Commission during the financial crisis.

significant. The point estimate for β_0, 0.107, is much lower than the estimates of around 0.3 reported by Henderson et al. (2012, Tables 3 and 4), though. Column (2) reports the results for the unrestricted model that allows the GDP-lights growth nexus to vary across regions. East India is the reference region. β_0 is estimated to be considerably higher than the national average in East India (0.13) and North India (0.18 = 0.13+0.05) but to be even negative in West India (–0.161 = 0.13–0.291). The χ^2 test ("Parameter stability") clearly suggests rejecting parameter stability for β_0 across regions at an error probability of virtually zero (χ^2=54.6, 4 degrees of freedom). The R^2 (0.128) is almost double that of the baseline model (0.067). When we control for the effects of measurement errors by adding region dummies (column 3), the χ^2 statistic drops by half (to 26.3) but is still highly significant.

Table 1: Stability of long-term elasticity of GDP with regard to lights for India across five regions

	(1)		(2)		(3)		(4)	
	Parameter	(SE)	Parameter	(SE)	Parameter	(SE)	Parameter	(SE)
l	0.107***	(0.02)	0.130***	(0.05)	0.067	(0.05)	0.065	(0.05)
*l*_North			0.050	(0.05)	0.111*	(0.06)	0.112*	(0.06)
*l*_Northeast			-0.090	(0.06)	-0.026	(0.06)	-0.020	(0.06)
*l*_South			-0.030	(0.13)	-0.112	(0.19)	-0.111	(0.19)
*l*_West			-0.291***	(0.06)	-0.204***	(0.07)	-0.202***	(0.07)
W*l*							0.300***	(0.10)
Constant	0.039***	(0.00)	0.038***	(0.00)	0.033***	(0.00)	0.033***	(0.00)
Parameter stability [p-value]			54.6***	[0.00]	26.3***	[0.00]	26.2***	[0.00]
Region-specific constants	no		no		yes		yes	
R^2	0.067		0.128		0.184		0.187	
Observations	519		519		519		519	

Notes: Cross-section OLS regressions. Dependent variable: Average annual GDP density growth. *l*: Average annual lights intensity growth. *l*_<region>: Interactions between *l* and region dummies (reference region in columns 2–4: East India). W*l*: Spatially lagged *l* (spatial weights: inverse squared distances, row-standardized). Constant: Country-wide intercept in columns (1) and (2); intercept for East India in columns (3) and (4). Parameter stability: Heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms *l*_<region> are jointly zero. (SE): White-robust standard errors; *** p<0.01, ** p<0.05, * p<0.1.

The statistic does not drop further when we also add the second control, the spatial lag of lights growth (column 4). The parameter of the spatial lag is positive and significant but hardly affects the regional estimates of β_0. Rather than the effects of measurement errors, it appears to capture the effects of omitted structural variables in the first place. Notice that β_0 still varies widely across Indian regions in columns (3) and (4), ranging from almost 0.2 in North India to negative values in West and South

India.[94] Moreover, it is not significantly different from zero in most of the Indian regions. This suggests that the growth of night lights may not proxy too well for true GDP growth within India.

The results for Brazil (Table 2) are very similar to those for India. The baseline estimate of β_0 is 0.147 (column 1), which is somewhat higher than the corresponding estimate for India but still considerably lower than that reported by Henderson et al. The R^2 of 0.045 is even lower than that for India. As for India, we observe highly significant regional differences in β_0 for Brazil (reference region: Norte). The χ^2 test statistic for the baseline model is 132.4 (column 2), its error probability being virtually zero (4 degrees of freedom). β_0 for Norte is, for example, significantly higher than that for Sul but significantly lower than that for Centro-Oeste. Our major finding is again invariant to our attempts to eliminate the effects of measurement errors. Region-specific constants reduce parameter heterogeneity to some extent but not sufficiently (column 3), while the spatial lag (column 4) affects neither the estimates of β_0 nor the stability test notably. Again, a stable relationship between night lights growth and true GDP growth does not appear to exist across Brazilian regions.

Table2: Stability of long term elasticity of GDP with regard to lights for Brazil across five regions

	(1)		(2)		(3)		(4)	
	Parameter	(SE)	Parameter	(SE)	Parameter	(SE)	Parameter	(SE)
l	0.147***	(0.01)	0.235***	(0.02)	0.136***	(0.03)	0.135***	(0.03)
*l*_Nordeste			-0.078***	(0.02)	-0.038	(0.04)	-0.036	(0.04)
*l*_Sudeste			-0.168***	(0.03)	0.079*	(0.04)	0.081*	(0.04)
*l*_Sul			-0.197***	(0.02)	-0.072**	(0.03)	-0.067*	(0.04)
*l*_Centro-Oeste			0.133***	(0.05)	0.136*	(0.08)	0.136*	(0.08)
W*l*							-0.130	(0.09)
Constant	0.030***	(0.00)	0.030***	(0.00)	0.041***	(0.00)	0.041***	(0.00)
Parameter stability [p-value]			132.4***	[0.00]	25.6**	[0.01]	24.5**	[0.01]
Region-specific constants	no		no		yes		yes	
R^2	0.045		0.092		0.120		0.121	
Observations	4,820		4,820		4,820		4,820	

Notes: Cross-section OLS regressions. Dependent variable: Average annual GDP density growth. *l*: Average annual lights intensity growth. *l*_<region>: Interactions between *l* and region dummies (reference region in columns 2–4: Norte). W*l*: Spatially lagged *l* (spatial weights: inverse squared distances, row-standardized). Constant: Country-wide intercept in columns (1) and (2); intercept for Norte in columns (3) and (4). Parameter stability: Heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms *l*_<region> are jointly zero. (SE): White-robust standard errors; *** p<0.01, ** p<0.05, * p<0.1.

[94] State-level regressions that are not reported here indicate that β_0 is negative (though insignificant) in 9 of the 23 Indian states in our sample. Only Andhra Pradesh (South) and Haryana (North) exhibit positive point estimates of 0.3 or higher.

2.3. Stability of long-term lights elasticities in developed economies

In spite of the significant regional heterogeneity we observe for India and Brazil, Henderson et al.'s main hypothesis of the stability of the relationship between night lights growth and *true* GDP growth might still hold, if our extensions of the baseline model did not succeed in eliminating the biases from measurement errors of GDP. In this subsection, we therefore pursue an additional way to assess the importance of possible biases from measurement errors. We reestimate the baseline and the extended models for those countries where GDP is arguably of highest quality.[95] If it is indeed only measurement errors of GDP that cause the estimates of β_0 to vary across regions, we should find little or at least significantly less regional variation of β_0 in countries like the United States or Western Europe where measurement errors are minimal.

Table 3: Stability of long-term elasticity of GDP with regard to lights for United States across eight BEA regions

	(1)		(2)		(3)		(4)	
	Parameter	(SE)	Parameter	(SE)	Parameter	(SE)	Parameter	(SE)
l	0.164***	(0.02)	0.365***	(0.08)	0.312***	(0.07)	0.312***	(0.07)
*l*_Great Lakes			-0.480***	(0.08)	-0.205**	(0.08)	-0.205**	(0.08)
*l*_Mideast			-0.204*	(0.12)	0.160	(0.12)	0.160	(0.12)
*l*_New England			-0.217	(0.13)	-0.238*	(0.14)	-0.238*	(0.14)
*l*_Plains			-0.265***	(0.08)	-0.158**	(0.07)	-0.158**	(0.07)
*l*_Rocky Mountains			-0.007	(0.10)	-0.095	(0.10)	-0.095	(0.10)
*l*_Southeast			-0.191**	(0.08)	-0.125*	(0.07)	-0.124*	(0.07)
*l*_Southwest			-0.120	(0.09)	-0.157*	(0.09)	-0.157*	(0.09)
W*l*							-0.060	(0.06)
Constant	0.038***	(0.00)	0.039***	(0.00)	0.042***	(0.00)	0.042***	(0.00)
Parameter stability [p-value]			140.4***	[0.00]	17.4**	[0.01]	17.4**	[0.01]
Region-specific constants	no		no		yes		yes	
R²	0.048		0.092		0.124		0.124	
Observations	3,079		3,079		3,079		3,079	

Notes: Cross-section OLS regressions. Dependent variable: Average annual GDP density growth. *l*: Average annual lights intensity growth. *l*_<region>: Interactions between *l* and region dummies (reference region in columns 2–4: Far West). W*l*: Spatially lagged *l* (spatial weights: inverse squared distances, row-standardized). Constant: Country-wide intercept in columns (1) and (2); intercept for Far West in columns (3) and (4). Parameter stability: Heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms *l*_<region> are jointly zero. (SE): White-robust standard errors; *** p<0.01, ** p<0.05, * p<0.1.

Table 3 shows that the qualitative results for the United States closely resemble those for the emerging market economies, however. β_0 varies widely across BEA regions (column 2; reference region: Far West). And the region specific constants (column 3) and the spatial lag (column 4) mitigate parameter instability but do not remove it.

[95] While India and Brazil are rated C for data quality on the A-D scale of the Penn World Tables, more advanced OECD countries are mostly rated A. See the online appendix of Chen and Nordhaus (2011: Table SI-4).

The stability tests clearly suggest rejecting parameter stability across BEA regions in all specifications. Essentially the same holds for Western Europe (Table 4).

These results suggest that the regional heterogeneity of β_0 in Brazil and India cannot be attributed to measurement errors of GDP due to poor data quality in the first place. The relationship between *true* GDP and lights growth may in fact not be as stable across regions within countries than across countries.

Table 4: Stability of long term elasticity of GDP with regard to lights for Western Europe across 13 countries.

	(1)		(2)		(3)		(4)	
	Parameter	(SE)	Parameter	(SE)	Parameter	(SE)	Parameter	(SE)
l	0.105***	(0.04)	0.129***	(0.04)	0.126	(0.08)	0.126	(0.08)
l_Belgium			0.296*	(0.16)	-0.297	(0.20)	-0.298	(0.19)
l_Germany			-0.439***	(0.03)	0.142	(0.09)	0.141	(0.09)
l_Denmark			0.135	(0.15)	-0.549**	(0.25)	-0.550**	(0.25)
l_Spain			0.701***	(0.09)	-0.181	(0.12)	-0.181	(0.12)
l_Finland			-0.061	(0.09)	-0.112	(0.17)	-0.113	(0.17)
l_France			-0.061	(0.04)	-0.400***	(0.17)	-0.401***	(0.12)
l_Ireland			0.839***	(0.10)	-0.344**	(0.17)	-0.344**	(0.16)
l_Italy			-0.018	(0.06)	0.578	(0.48)	0.580	(0.48)
l_Netherlands			0.962***	(0.15)	0.392	(0.27)	0.391	(0.27)
l_Portugal			0.206***	(0.04)	-0.131	(0.13)	-0.131	(0.13)
l_Sweden			-0.177**	(0.08)	-0.203	(0.12)	-0.204*	(0.12)
l_UK			0.179	(0.12)	-0.112	(0.17)	-0.112	(0.17)
Wl							0.115	(0.14)
Constant	0.021***	(0.00)	0.022***	(0.00)	0.023***	(0.00)	0.023***	(0.00)
Country-specific constants	no		no		yes		yes	
Parameter stability [p-value]			657.6	[0.00]	62.4	[0.00]	62.4	[0.00]
R^2	0.009		0.407		0.573		0.573	
Observations	871		871		871		871	

Notes: Cross-section OLS regressions. Dependent variable: Average annual GDP density growth. l: Average annual lights intensity growth. l_<region>: Interactions between l and country dummies (EU-15 countries except Greece and Luxembourg; reference region in columns 2–4: Austria). Wl: Spatially lagged l (spatial weights: inverse squared distances, row-standardized). Constant: Country-wide intercept in columns (1) and (2); intercept for Austria in columns (3) and (4). Parameter stability: Heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms l_<country> are jointly zero. (SE): White-robust standard errors; *** p<0.01, ** p<0.05, * p<0.1.

2.4. Robustness: Additional results on long term elasticities and panel estimates for short term elasticities

Our main result, the instability of the GDP-lights growth nexus, is robust to several modifications of the regression models and treatments of extreme observations on night lights.[96] The χ^2 tests still reject parameter stability for all four economies when we control for the average annual changes of the shares of unlit (light intensity ≤ 2)

[96] The detailed results of these robustness checks, which are not reported here for the sake of brevity, are available from the authors upon request.

and top-coded pixels (light intensity = 63), or when we drop all counties with more than 10% of top-coded pixels in the first year of observation from the samples. Going more into detail, Appendix 1 shows that the parameter instability is not just due to parameter differences between urban and rural counties. While parameter stability across *urban* regions is not rejected for Brazil, if urban regions are defined narrowly, it is rejected for all definitions of urban regions in India.

Parameter stability is also rejected across NUTS1 regions within individual Western European countries. Results for the largest of these countries, France, Germany and the United Kingdom, indicate that the differences in the estimates of β_0 between the European countries are not just due to differences in data quality between these countries.[97]

Finally, parameter stability is clearly rejected for the short-term GDP-lights growth nexus. Appendix 2 gives a brief description of the panel fixed-effects estimation approach employed for this purpose and presents the detailed results for India, Brazil, the United States and Western Europe.

3. Conclusions

If there were a stable relationship between the growth of night lights intensity and that of true regional GDP, night lights intensity measured from outer space could serve as a valuable proxy of economic growth at the subnational level in low- and middle-income countries where GDP data is frequently lacking or of poor quality. While Henderson et al. (2012) find that this relationship is stable at the country level, we find that it is rather unstable at the regional level within countries. We exemplify for two large emerging economies, India and Brazil, that the relationship between the growth of GDP and of night lights intensity varies widely and significantly across Indian and Brazilian regions. We also show that this regional instability is not caused by biases from measurement errors of GDP. It does not disappear if measurement errors of GDP are controlled for as far as possible. In addition to this, the regional instability is of similar magnitude in highly developed economies like the United States or Western Europe where GDP data is arguably of highest quality and

[97] The detailed results are available upon request. We do not test for parameter stability within the smaller countries because these tests are less reliable due to the small numbers of regional observations.

measurement errors should correspondingly be much smaller. The relationship between the growth of night lights and of *true* GDP obviously does not carry over from the country level to subnational levels as easily as suggested by Henderson et al.

The relationship between night lights and GDP growth may differ across regions for a variety of reasons. One reason may be the urban-rural divide. Our results suggest that the regional differences may, at least in some countries (e.g., Brazil), be ameliorated by focusing on urban regions only. Generally, however, the urban-rural divide is not the only or even most important reason for instability. Another reason may be omitted structural variables such as electricity prices (Berliant and Weiss 2013), land use, industry composition or cultural or institutional factors. One may, in fact, succeed in stabilizing the relationship between night lights and GDP growth by adding such control variables to Henderson et al.'s univariate model. This will deprive their basic idea of much of its merits, however. Rather than being a sufficient predictor on its own, night lights growth will be merely one out of potentially many variables that contribute to predicting GDP growth. Most of these variables will not be observable for subnational units in low- and middle-income countries.

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Appendix 1: Stability among urban or rural areas

To test if the parameter instability within Brazil (table 3) and India (table 2) originates from systematic differences in the lights-GDP growth nexus between urban and rural counties, we split the sample of all counties into two subsamples, urban and rural, and run separate tests of parameter stability across regions for each of these two subsamples.

We distinguish urban from rural counties by means of light intensities rather than population or income density to account for the fact that statistical data on the latter may be unavailable or unreliable. We classify a county to be urban if its brightest pixel (of approximately 1 sqkm) exceeds a predefined threshold light intensity.[98] By varying the threshold light intensity, we are able to test parameter stability for a broad variety of different definitions of urban counnties.

Figure A1: Stability of long-term elasticity of GDP with regard to lights for urban and rural counties in Brazil across five regions

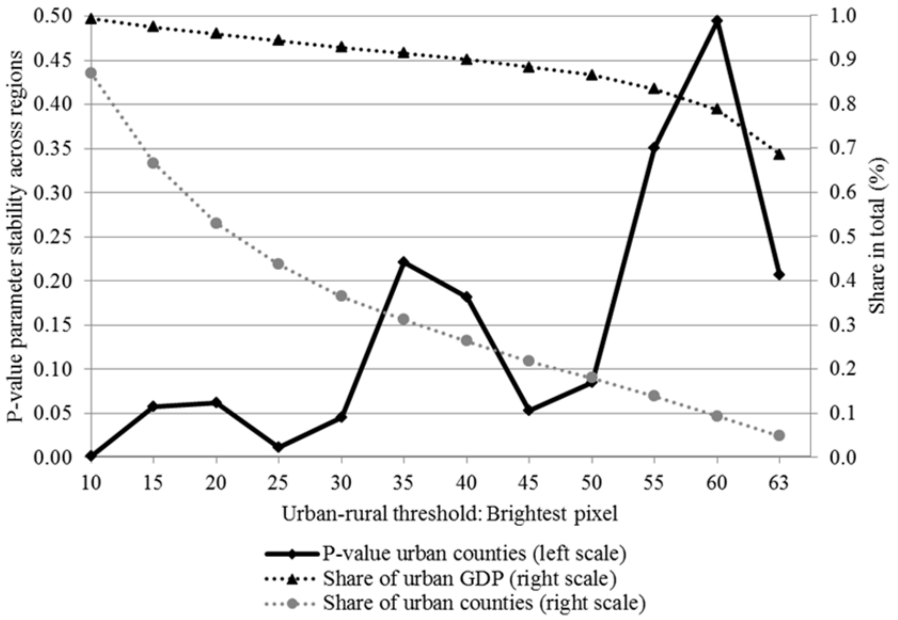
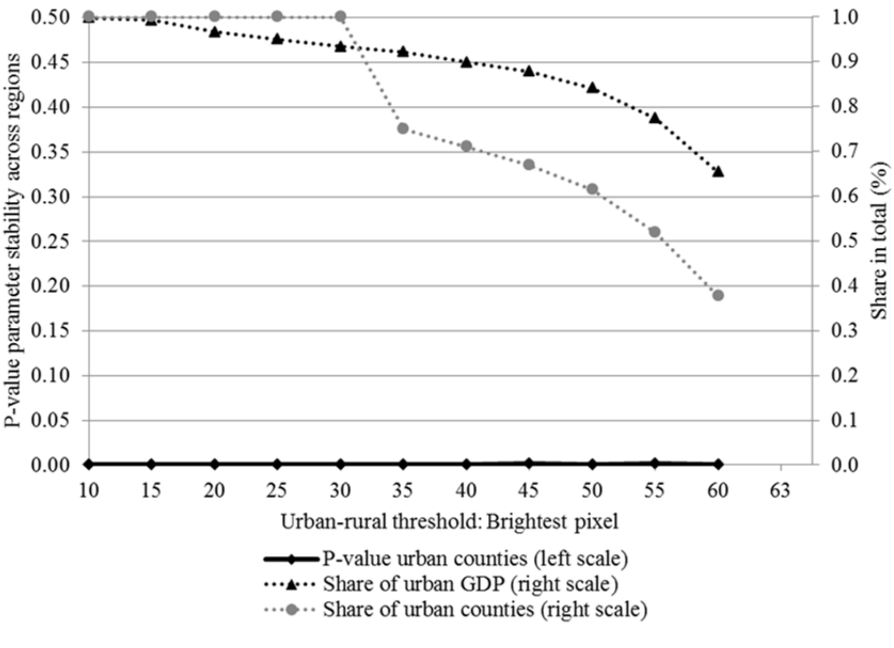


Figure A1 depicts the main results for Brazil. The horizontal axis gives the threshold light intensity for the brightest pixel. The value of 40, for example, refers to a regression of GDP growth on night light growth and region-specific constants for the subsample of 1,267 Brazilian counties that feature at least one pixel with light

[98] We alternatively classified a county to be urban if the share of unlit pixels (light intensity = 0) in this county is below a predefined threshold. The results, available from the authors upon request, are very similar to those reported below.

intensity of 40 or more in the first year of the sample period. The dotted lines in Figure A1 indicate that this subsample represents about one fourth of all Brazilian counties and 90% of the Brazilian GDP. Lower thresholds imply broader, higher thresholds narrower definitions of urban counties. The solid line in Figure A1 reports the p-value of the parameter stability test across regions. It indicates that parameter stability is not rejected at the 5% level for sufficiently narrowly defined urban counties. Parameter stability for corresponding subsamples of rural counties is always rejected at p-values below 0.001, by contrast, which is why we do not report them in Figure A1. Taken together, this indicates that there is a stable relationship between lights growth and GDP growth among urban counties in Brazil, which account for the lion's share of national GDP. Thus, the parameter instability we detect in Table 2 originates from differences between rural areas and possibly also from differences between rural and urban areas.

Figure A2: Stability of long-term elasticity of GDP with regard to lights for urban and rural counties in India across five regions



This result does not hold for India, however. Figure A2, which is constructed in a similar way as Figure A1, shows that parameter stability is rejected for urban counties as well, irrespective of how wide or narrow urban is defined. The p-values of the test statistics are below 0.001 for all threshold light intensities. Likewise, the result does not hold either for the US or Western Europe. The p-values of the test statistics for urban areas in these countries, which are not reported here in detail, are also below 0.001 for all threshold light intensities. In summary, the instability of the lights-GDP growth nexus we report in this paper may be due to the urban-rural divide in some countries but is not due to this divide in general.

Appendix 2: Stability of short-term elasticities

In this appendix, we report the estimation results for the short-term relationship between observed GDP and night lights intensity as well as the corresponding tests of parameter stability across regions. We estimate essentially the same model as Henderson et al. (2012: Table 2) for panels of annual data for districts in India, municipalities in Brazil, counties in the United States and NUTS3 regions in Western Europe. More specifically, we estimate, separately for each country,

$$\ln Y_{it} = \alpha + \beta_0 \ln L_{it} + \delta_i + \delta_t + u_{it}, \qquad \text{(A1)}$$

where $\ln Y_{it}$ and $\ln L_{it}$ denote the natural logs of GDP and night lights intensity in county i and year t, δ_i and δ_t county- and year-fixed effects, α a global intercept, β_0 the elasticity of GDP with respect to night lights and u_{it} the error term that may be heteroscedastic. We estimate equation (A1) using the panel fixed effect estimator, accounting for heteroscedasticity in the errors by clustering the standard errors at the county level. We test the stability of β_0 across regions in the same way as in the cross-section growth regressions in Section 2: We add a set of interaction terms between lights, $\ln L_{it}$, and dummies for all (but one) regions, D_r, $r = 2, \ldots, R$, to equation (A1), and test if the parameters of these interaction terms are jointly zero by means of a robust χ^2 test (based on the clustered covariances).

The results for India, Brazil, the United States and Western Europe are shown in Tables A1 – A4. Stability of the parameter β_0 is clearly rejected in all four cases.

Table A1: Stability of short-term elasticity of GDP with regard to lights for India across five regions

	(1)		(2)	
	Parameter	(SE)	Parameter	(SE)
ln*L*	0.056***	(0.01)	-0.003	(0.01)
ln*L*_North			0.100***	(0.02)
ln*L*_Northeast			0.118***	(0.04)
ln*L*_South			0.111***	(0.04)
ln*L*_West			-0.089***	(0.03)
Mean of district fixed effects	3.679***	(0.01)	3.665***	(0.01)
Parameter stability [p-value]			**92.2**	**[0.00]**
District fixed effects	Yes		Yes	
Year fixed effects	Yes		Yes	
R^2 (within)	0.689		0.699	
Number of districts	521		521	
Observations	3,833		3,833	

Notes: Panel fixed effects regressions. Dependent variable: ln*Y*. ln*L*: Lights intensity. ln*L*_<region>: Interactions between ln*L* and region dummies (reference region in column 2: East India). Parameter stability: Heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms ln*L*_<region> are jointly zero. (SE): Robust standard errors clustered by counties; *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Stability of short-term elasticity of GDP with regard to lights for Brazil across five regions

	(1)		(2)	
	Parameter	(SE)	Parameter	(SE)
ln*L*	0.065***	(0.01)	0.131***	(0.02)
ln*L*_Nordeste			-0.046***	(0.02)
ln*L*_Sudeste			-0.074***	(0.02)
ln*L*_Sul			-0.129***	(0.02)
ln*L*_Centro-Oeste			-0.031	(0.03)
Mean of municipality fixed effects	4.083***	(0.00)	4.103***	(0.01)
Parameter stability [p-value]			**129.7**	**[0.00]**
Municipality fixed effects	Yes		Yes	
Year fixed effects	Yes		Yes	
R^2 (within)	0.499		0.504	
Number of municipalities	4,830		4,830	
Observations	57,702		57,702	

Notes: Panel fixed effect regressions. Dependent variable: ln*Y*. ln*L*: Lights intensity. ln*L*_<region>: Interactions between ln*L* and region dummies (reference region in column 2: Norte). Parameter stability: Heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms ln*L*_<region> are jointly zero. (SE): Robust standard errors clustered by counties; *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Stability of short-term elasticity of GDP with regard to lights for the United States across eight BEA regions

	(1) Parameter	(SE)	(2) Parameter	(SE)
ln$L$	0.104***	(0.01)	0.099***	(0.01)
ln$L$_Great_Lakes			-0.027**	(0.01)
ln$L$_Mideast			0.054***	(0.02)
ln$L$_New_England			-0.082***	(0.02)
ln$L$_Plains			-0.017	(0.01)
ln$L$_Rocky_Mountains			0.015	(0.02)
ln$L$_Southeast			0.030**	(0.01)
ln$L$_Southwest			0.036	(0.02)
Mean of county fixed effects	4.776***	(0.01)	4.770***	(0.01)
Parameter stability [p-value]			**106.8**	**[0.00]**
County fixed effects	Yes		Yes	
Year fixed effects	Yes		Yes	
R^2 (within)	0.911		0.911	
Number of counties	3,079		3,079	
Observations	58,488		58,488	

Notes: Panel fixed effect regressions. Dependent variable: ln$Y$. ln$L$: Lights intensity. ln$L$_<region>: Interactions between ln$L$ and region dummies (reference region in column 2: Far West). Parameter stability: Heteroscedasticity-robust χ^2 test of the hypothesis that all interaction terms ln$L$_<region> are jointly zero. (SE): Robust standard errors clustered by counties; *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Stability of short-term elasticity of GDP with regard to lights for Western Europe across 14 countries

	(1) Parameter	(SE)	(2) Parameter	(SE)
ln$L$	0.161***	(0.01)	0.233***	(0.02)
ln$L$_Belgium			-0.058***	(0.02)
ln$L$_Germany			-0.107***	(0.01)
ln$L$_Denmark			-0.171***	(0.02)
ln$L$_Spain			0.430***	(0.06)
ln$L$_Finland			-0.143***	(0.03)
ln$L$_France			-0.100***	(0.02)
ln$L$_Ireland			0.594***	(0.07)
ln$L$_Italy			0.011	(0.04)
ln$L$_Luxembourg			0.017	(0.01)
ln$L$_Netherlands			-0.107***	(0.02)
ln$L$_Portugal			0.067**	(0.03)
ln$L$_Sweden			-0.152***	(0.02)
ln$L$_UK			-0.424***	(0.03)
Mean of NUTS3 region fixed effects	-0.161***	(0.05)	0.023	(0.05)
Parameter stability [p-value]			**1378**	**[0.00]**
NUTS3 region fixed effects	Yes		Yes	
Year fixed effects	Yes		Yes	
R^2 (within)	0.704		0.732	
Number of NUTS3 regions	1,015		1,015	
Observations	13,803		13,803	

Notes: Panel fixed effect regressions. Dependent variable: ln$Y$. ln$L$: Lights intensity. ln$L$_<region>: Interactions between ln$L$ and country dummies (reference in column 2: Austria). Parameter stability: χ^2 test of the hypothesis that all interaction terms ln$L$_<region> are jointly zero. (SE): Robust standard errors clustered by counties; *** p<0.01, ** p<0.05, * p<0.1.

Eidesstattliche Erklärung

Ich erkläre hiermit an Eides statt, dass ich meine Doktorarbeit „Essays on the Challenges of Global Land Change Science“ selbstständig und ohne fremde Hilfe angefertigt habe und dass ich alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen meiner Arbeit, besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert habe.

Mareike Söder

Kiel, Februar 2014

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2014/2015	Lecturer at the University of Applied Science Westküste on Environmental Economics;
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