The Institute for Agricultural Economics
of the Christian-Albrechts-Universität Kiel

Essays on sustainable agriculture: studies on water, deforestation and family farming

Dissertation
submitted for the Doctoral Degree
awarded by the Faculty of Agricultural and Nutritional Sciences
of the
Christian-Albrechts-Universität zu Kiel Submitted

Submitted
Ianna Raissa Moreira Dantas (M.Sc.)
Born in Belém - Brazil

Kiel, 2022

Published with the approval of the Faculty of Agricultural and Nutritional Sciences

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Dedication

To my mother, **Socorro Moreira**, who is my biggest example of resilience and strength; to my brother and best friend **Ian Dantas**, who has always words of comfort and wisdom. To my wife, **Klara Bretschneider**, who completes me and continuously fills my life with joy.

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List of Abbreviations and Acronyms

AC	Acre
AGERP	Agência Estadual de Pesquisa Agropecuária e Extensão Rural do Maranhão (Maranhão State Agency for Agricultural Research and Rural Extension)
AIC	Akaike Information Criterion
AM	Amazonas
AP	Amapá
BASA	Banco da Amazônia (Bank of the Amazon)
BCB	Banco Central do Brazil (Central Bank of Brazil)
BI	Business Intelligence
BIC	Bayesian Information Criterion
BMBF	Bundesministerium für Bildung und Forschung (German Ministry of Education and Research)
BNDS	National Development Bank
BNDES	Banco Nacional de Desenvolvimento Econômico e Social (National Bank for Economic and Social Development)
CCI-LC	Climate Change Initiative Land Cover
CPI	Corruption Perception Index
CGE	Computable General Equilibrium
DANE	Departamento Administrativo Nacional de Estadística (National Administrative Department of Statistics)
DART	Dynamic Applied Regional Trade
DGA	Dirección General de Aguas (General Directorate of Water)
EMATER	Empresa de Assistência Técnica e Extensão Rural (Technical Assistance and Rural Extension Company)
EMPAER	Empresa Mato Grossense de Pesquisa Assistencia e Extensao Rural (Mato Grosso Company for Research, Assistance and Rural Extension)
ESA	European Space Agency
EU	European Union
FAO	Food and Agriculture Organization
FE	Fixed effects
GE	Governmental Effectiveness
GHG	Green House Gases
IBGE	Instituto Brasileiro de Economia e Estatística (Brazilian Institute of Geography and Statistics)
ICRG	International Country Risk Guide
IDAM	Instituto de Desenvolvimento Agropecuário e Florestal Sustentável do Estado do Amazonas (Institute of Agricultural Development and Sustainable Forestry of the State of Amazonas)
IFAD	International Fund for Agricultural Development
IIASA	International Institute for Applied Systems Analysis
IMAZON	Instituto do Homem e Meio Ambiente da Amazônia (Amazon Institute of People and the Environment)
IPCC	Intergovernmental Panel on Climate Change

LUC	Land Use Change
MA	Maranhão
MDGs	Millennium Development Goals
ML	Maximum Likelihood
MT	Mato Grosso
NRM	Natural Resources Management
NGO	Non-governmental organization
OECD	Organisation for Economic Co-operation and Development
PA	Pará
PRONAF	Programa Nacional de Fortalecimento da Agricultura Familiar (National Program for Strengthening Family Farming)
PTA	Public technical assistance
RO	Rondônia
RR	Roraima
RURALTINS	Instituto de Desenvolvimento Rural do Estado de Tocantins (Rural Development Institute of the State of Tocantins)
RURAP	Instituto de Desenvolvimento Rural do Amapá (Rural Development Institute of Amapá)
SAR	Spatial Lag Model
SDGs	Sustainable Development Goals
SDM	Spatial Durbin model
SDEM	Spatial Durbin Error Model
SEM	Spatial Error Model
SI	Sustainable Intensification
SLX	Spatial Lag Model of X
SNIRH	Sistema Nacional de Informações sobre Recursos Hídricos (National Water Resources Information System)
SUDAM	Superintendence of the Amazon Development
TO	Tocantins
UNDP	United Nations Development Programme
UNEP	United Nations Environment Programme
UNSD	United Nations Statistics Division
USA	United States of America
WDI	World Development Indicator
WGI	World Governance Indicators

Abstract

Essays on sustainable agriculture: studies on water, deforestation and family farming

The agricultural sector has multidimensional character for entailing social, economic, and environmental transformations crucial to sustainable development. While climate change aggravates scarcity of land and water resources, guaranteeing food security for a growing population is a global pressing challenge. However, food systems must go through pivotal modifications to double food supply under sustainable pathways. Conversely, unruled (and unsustainable) management of land and water resources results in cascading consequences to sustaining ecosystem services and biodiversity. Enhancing the understanding of anthropogenic natural resource use depends on continuous assessments. These appraisals are also crucial to implement adequate management strategies, minimizing conflicts, and designing political recommendations. This cumulative dissertation comprises three independent studies concerning fundamental topics of sustainable agriculture. Chapter 2 draws from the absence of water data, which limits the development of economic models gauging water scarcity impacts. Indeed, clear indicators, data, and conceptual definitions are key to guiding cross-country monitoring and informing priority actions. With that, the paper makes a central contribution by developing an in-depth description of national statistics, international and global water databases. The results show inconsistencies in available data content and definitions, leading to the need for data harmonization. Therefore, researchers should carefully manipulate and compare available water data, especially when deriving policy recommendations or economic conclusions. Chapter 3 concerns the relationship between deforestation data and widely used institutional indices. The paper offers empirical-based evidence about the relationship between governmental performance, public corruption perception and forest resources. Moreover, computer-intensive data management was employed to convert georeferenced raster data into a format compatible with economic statistical software and enable sample replications of large original data. Results are robust and indicate that higher government effectiveness, strong political enforcement, policy design, and lower corruption have a significant negative association with deforestation. The paper contributes to the growing literature concerning governance and forest management. Moreover, it underscores the importance of political enforcement to sustainable forest management. Chapter 4 investigates the presence of spatial spillovers as providing beneficial opportunities to family farming credit in the Brazilian Amazon. Credit rationing is argued to target wealthier farmers engaged in livestock production while neglecting those producing crops. The paper employs a spatial Durbin error model of credit acquisition for husbandry and agricultural systems in 103 microregions. To enhance the paper's discussion, 35 semi-structured interviews with key informants were conducted. Results suggest that credits are not independently distributed, being influenced by spatial characteristics of neighboring microregions. Positive spillover effects are observed for credit history for husbandry and agriculture. Microregions with steady credit acquisition enable social capital, knowledge transfer, and reduce transaction costs for credits. Negative spillovers are observed for commercial banks and production value. Given the limited amount of credits, this indicates competitiveness across microregions. Thus, results signalize potential ineffective credit allocation, where wealthier farmers have better opportunities to access markets, information, and credits. Consequently, political efforts are needed to integrate poorer and vulnerable farmers unable to benefit from social networks, stable markets, and financial investments.

Zusammenfassung

Essays über nachhaltige Landwirtschaft: Studien über Wasser, Entwaldung und Familienbetriebe

Der Agrarsektor hat einen multidimensionalen Charakter, da er soziale, wirtschaftliche und ökologische Veränderungen mit sich bringt, die für eine nachhaltige Entwicklung entscheidend sind. Während der Klimawandel die Verknappung der Land- und Wasserressourcen verschärft, ist die Gewährleistung der Ernährungssicherheit für eine wachsende Bevölkerung eine dringende globale Herausforderung. Die Lebensmittelsysteme müssen jedoch grundlegend verändert werden, um die Nahrungsmittelversorgung unter nachhaltigen Bedingungen zu verdoppeln. Umgekehrt führt eine unkontrollierte (und nicht nachhaltige) Bewirtschaftung von Land- und Wasserressourcen zu kaskadenartigen Auswirkungen auf die Erhaltung der Ökosystemleistungen und der biologischen Vielfalt. Die Verbesserung des Verständnisses der anthropogenen Nutzung natürlicher Ressourcen hängt von kontinuierlichen Beurteilungen ab. Diese Bewertungen sind auch entscheidend für die Umsetzung geeigneter Bewirtschaftungsstrategien, die Minimierung von Konflikten und die Formulierung politischer Empfehlungen. Diese kumulative Dissertation umfasst drei unabhängige Studien zu grundlegenden Themen der nachhaltigen Landwirtschaft. Kapitel 2 zeigt die aktuelle Datenlücke für Wasserdaten auf, welche die Entwicklung von Wirtschaftsmodellen, zur Messung der Auswirkungen von Wasserknappheit einschränkt. Klare Indikatoren, Daten und konzeptionelle Definitionen sind der Schlüssel zur länderübergreifenden Überwachung und zur Information über vorrangige Maßnahmen. Damit leistet der Artikel einen zentralen Beitrag, indem er eine ausführliche Beschreibung der nationalen Statistiken, sowie der internationalen und globalen Wasserdatenbanken entwickelt. Die Ergebnisse zeigen, dass die verfügbaren Dateninhalte und -definitionen inkonsistent sind, was den Bedarf an Datenharmonisierung unterstreicht. Daher sollten Forscher die verfügbaren Wasserdaten sorgfältig bearbeiten und vergleichen, insbesondere wenn sie politische Empfehlungen oder wirtschaftliche Schlussfolgerungen ableiten. Kapitel 3 befasst sich mit der Beziehung zwischen Entwaldungsdaten und weit verbreiteten institutionellen Indizes. Der Artikel bietet empirisch fundierte Beweise für die Beziehung zwischen Regierungsleistung, öffentlicher Korruptionswahrnehmung und Waldressourcen. Darüber hinaus wurde ein computergestütztes Datenmanagement eingesetzt, um georeferenzierte Rasterdaten in ein Format zu konvertieren, das mit Wirtschaftsstatistik-Software kompatibel ist und eine stichprobenartige Replikation der umfangreichen Originaldaten ermöglicht. Die Ergebnisse sind robust und weisen darauf hin, dass eine höhere Regierungswirksamkeit, starke politische Durchsetzung, die Gestaltung der Politik und eine geringere Korruption einen signifikanten negativen Zusammenhang mit der Entwaldung aufweisen. Die Studie trägt zu den zunehmenden Veröffentlichungen über Regierungsführung und Waldbewirtschaftung bei. Außerdem unterstreicht sie die Bedeutung der politischen Durchsetzung für eine nachhaltige Waldbewirtschaftung. In Kapitel 4 wird das Vorhandensein räumlicher Spillover-Effekte untersucht, die sich vorteilhaft auf die Kreditvergabe an Familienbetriebe im brasilianischen Amazonasgebiet auswirken. Es wird argumentiert, dass die Kreditrationierung auf wohlhabendere Landwirte abzielt, die in der Viehzucht tätig sind, während diejenigen vernachlässigt werden, die Ackerbau betreiben. Der Artikel verwendet ein räumliches Durbin-Error-Modell der Kreditbeschaffung für Viehzucht und landwirtschaftliche Systeme in 103 Mikroregionen. Um die Diskussion zu vertiefen, wurden 35 halbstrukturierte Interviews mit Schlüsselinformanten geführt. Die Ergebnisse deuten darauf hin, dass die Kredite nicht unabhängig verteilt sind, sondern von den räumlichen

Merkmalen der benachbarten Mikroregionen beeinflusst werden. Positive Spillover-Effekte werden bei Krediten für Viehzucht und Landwirtschaft beobachtet. Mikroregionen mit stetigem Krediterwerb ermöglichen soziales Kapital und Wissenstransfer und verringern die Transaktionskosten für Kredite. Negative Spillover-Effekte werden für Geschäftsbanken und den Produktionswert beobachtet. Angesichts des begrenzten Kreditvolumens weist dies auf die Wettbewerbsfähigkeit der Mikroregionen hin. Die Ergebnisse deuten also auf eine potenziell ineffektive Kreditvergabe hin, bei der wohlhabendere Landwirte bessere Chancen und Zugang zu Märkten, Informationen und Krediten haben. Folglich sind politische Anstrengungen erforderlich, um ärmere und gefährdete Landwirte zu integrieren, die nicht von sozialen Netzwerken, stabilen Märkten und Finanzinvestitionen profitieren können.

Chapter 1

1. General Introduction

Agriculture is certainly the most relevant sector to sustainability and climate change debates. While the scarcity of land and water resources prevail in several parts of the globe (Tubiello et al., 2008), sustaining food security and addressing climate change mitigation and adaption are acknowledged as the most alarming challenges of the 21st century (Beddington et al., 2012). In this context, agriculture intensification is perceived as an alternative to spur food production at sufficient rates to feed the growing population (Foley et al., 2011). By contrast, intensifying food systems is argued to trigger natural disruptions, biodiversity loss, and pressure on already existing local and context-specific environmental and social issues (McKenzie & Williams, 2015).

Food production involves dualistic views supporting either the need for intensive food systems (Barretto et al., 2013) following similar paths from the "green revolution" in the 1960s (Borlaug, 2007) or calling for sustainable intensification (SI). SI consists of intensifying production over existing arable lands while preserving soil quality and untouched resources (Garnett et al., 2013). Discussions about SI's potential to halt environmental degradation and increase food production date back more than 30 years. Scholars have long acknowledged conflicting perspectives on achieving sustainable agricultural intensification (Pretty, 1997). Similarly, current debates criticize the SI concept for focusing solely on production and failing to consider the multidimensional character of sustainability (Struik & Kuyper, 2017). Thus, despite the comprehensible intent to increase food production, measures should be designed in combination with environmental and social aspects compatible with local demands. Otherwise, intensifying production without sustainability concerns could lead to high environmental costs (Bennett et al., 2014).

In this context, agricultural production is not only sensitive to climatic variations (Howden et al., 2007) as well as it is a major agent of greenhouse gas (GHG) emissions (Crippa et al., 2021). Land-use systems alone contribute to about 25% of global GHG emissions, of which 10-14% refer directly to food production and 12-17% from land-use change (LUC) and deforestation (Paustian et al., 2016). In Brazil, for instance, over 70% of emissions are due to land-use conversion to food production and forest degradation (World Bank, 2010).

Furthermore, climate change affects the distribution of hydrological cycles across regions (Hagemann et al., 2013), and anthropogenic water withdrawal for industrial, domestic, and agricultural purposes significantly alters natural water dynamics (Haddeland et al., 2014). Variations in precipitation and temperatures are expected to reduce levels of land suitability and crop yield (Schmidhuber & Tubiello, 2007), raising concerns about ecosystems' capacity to supply food and energy continuously.

Agriculture plays a significant role in this process for being the biggest water user, accounting for 70% of global surface and groundwater use (Shu et al., 2021). In Mexico, for instance, almost three-quarters of available national water is addressed to agriculture, covering about 13% of the total land area (Beddington et al., 2012). This figure points to high water-intensive production systems, leading to the exacerbation of resource use and social conflicts over water rights (Reis, 2014).

In fact, the unruled (and unsustainable) management of land and water resources results in cascading consequences to sustaining ecosystem services and biodiversity (Borrelli et al., 2020) and worsening socioeconomic conflicts in several regions. Climate change is argued to aggravate food insecurity both in areas where the population is already under enormous vulnerability (Wheeler & von Braun, 2013) and in locations where communities strongly rely on local production to access food (Nelson et al., 2012). With food demand projected to double by 50% in 2030 (Bruinsma, 2003), sustainable agriculture gained momentum in international debates.

In the sustainability sphere, the 2030 agenda for sustainable development is the major international framework guiding governments and civil organizations through 17 sustainable development goals (SDGs) (FAO, 2016). The SDGs put forward 169 targets and 232 indicators to transform social, environmental, and economic development pathways (FAO, 2016). In essence, goals were further designed based on successful components of the former Millennium Development Goals (MDGs) (Mcarthur, 2013), yet proposing advantageous synergies between economic, social, and environmental domains (Costanza et al., 2016). Unlike past sustainable frameworks, the SDGs are built upon higher interactions with productive sectors and goals. This facilitates the elaboration of policies and the evaluation of synergies and trade-offs among goals (le Blanc, 2015; Matthews et al., 2017).

Sustainable agriculture is at the “heart” of the SDG framework and is crucial to promoting the 2030 agenda premises (FAO, 2021b). The agenda acknowledges the multidimensional character of sustainability, highlighting the relevance of agriculture and nutrition in all sustainable indicators and targets (Canavan et al., 2016). Moreover, poverty and hunger eradication are seen as central to achieving sustainable development (Banerjee et al., 2019). Additionally, food production is a relevant measure to alleviate hunger and malnutrition (Blesh et al., 2019), and agricultural investments are perceived to trigger direct impacts on water and land resources, air quality, and biodiversity (Streimikis & Baležentis, 2020).

The FAO (2014) outlines sustainable agriculture as promoting water, land, and biological conservation while supporting economic activities for social groups and future generations. Achieving sustainable food and agriculture would only be possible when addressing five important pillars, which have their own respective challenges to be addressed. They are namely: *i) “Increase productivity, employment and value addition in food systems,” ii) “Protect and enhance natural resources,” iii) “Improve livelihood and foster inclusive economic growth,” iv) “Enhance the resilience of people, communities and ecosystems,” and v) “Adapt governance to new challenges”* (FAO, 2021c).

These premises recognize both the importance of safeguarding natural resources and ecosystem services and the relevance of several rural groups to food production and natural resources management (NRM). Social actors are small-scale farmers, indigenous peoples, pastoralists, traditional groups, women, fishers, and family farmers, among other groups specific to local contexts. They should integrate and benefit from economic development while considering regional, cultural, and socioeconomic conditions. On top of that, the sustainable agenda refers to governance as a tool to enable farmers access to markets, offering incentives to adopt sustainable practices and stable market prices. Public action and just governance are crucial to farmers' accountability and equity and regulate private and public interests (FAO, 2021c).

Despite covering a multitude of interrelated and fundamental sustainability components, the SDG agenda proposes targets often intertwined in complex synergic and conflicting aspects. For instance, under the scope of the *"Zero Hunger"* SDG 2, agricultural systems shall go through pivotal modifications to ensure local and global food security (Lipper et al., 2020). While Target 2.3 calls for doubling the production and incomes of family farming (as well as other small-scale traditional groups), Target 2.4 aims to ensure that agricultural production follows sustainable paths, strengthening resilience and adaptation to climatic shocks (United Nations, 2018a). Such targets fuel discussions about the real potential to double production and income while preserving natural resources. Thus, fulfilling SDG targets shall be done by accounting for several interactions, acknowledging actors involved, governance aspects, and local and context-specific relations (Lipper et al., 2020).

The sustainable agriculture rhetoric is diverse and goes beyond solely food production aspects. Despite increasing agricultural investments and technological advancements to boost food production, in 2017, hunger still affected about 11% of the global population (FAO et al., 2018). Conflicts and extreme climate events have gradually led to undernourishment and hunger, a fact that might become even more critical with high food prices (Janssens et al., 2020). Thus, more than urging to intensify food production, sustainable agriculture encourages the analysis of social issues regarding hunger, malnutrition, poverty, and diet diversification, among other challenges.

Further concerns refer to the misuse of land resources as ongoing agriculture expansion leads to forest and ecosystem degradation (FAO, 2014; Hosonuma et al., 2012). In fact, LUC from forest to agricultural areas poses considerable disruptions in soil and water resources. Especially in rural areas, LUC results in socioeconomic changes in terms of economic growth, income distribution, and livelihood conditions (Müller & Zeller, 2002). Similarly, the inefficient and unregulated resources may reduce water quality and river levels and degrade aquifers (FAO, 2014). Hence, water scarcity is expected to cause unprecedented impacts in regions of water vulnerability (Dell'Angelo et al., 2018). These environmental issues underline the role of policymakers, public institutions, and governments in acting as natural resource regulators.

Meanwhile, under the sustainable frame, NRM requires clear indicators, data, and conceptual definitions to guide cross-country monitoring and inform priority actions (Gil et al., 2019). Evaluating the impacts of natural resources used on the environment and society is essential to minimize conflicts, implement adequate management strategies, and design political recommendations (Allen et al., 2018). When doing this, it is key to attain different local contexts, where measures shall be implemented according to social, economic, and political realities (Nilsson et al., 2016).

The SDG agenda brought sustainable agriculture to the center of international debates. In recent years, analyses about LUC and water resources related to socioeconomic issues have attained both political and economic interests. Nevertheless, several questions about successfully implementing sustainable NRM remain uncertain. What concerns scientific production, researchers remain diligent in improving the understanding of natural resources data, concepts, and their interaction with social interest and use.

So far, it is clear that sustainable agriculture relates multidimensional aspects of natural resources, socioeconomic, and political discourses. This cumulative dissertation embraces three independent studies of relevant topics towards a sustainable transition, namely, water resources use and the analysis of available water data and definitions, the relationship of LUC and the institutional factors, and a case study about family farming credit in the Brazilian Legal Amazon.

2. Thesis structure

This cumulative dissertation builds upon a collection of three independent scientific papers concerning distinct and relevant topics in the spectrum of sustainable agriculture discourses. This thesis is structured as follows: chapter 2 provides an extended political and economic discussion about water resources use and offers a systematic collection of existing water data. Chapter 3 concerns global land resources use under the threat of deforestation. Chapter 4 addresses a case study of family farming and credits supporting husbandry and agricultural production in the Brazilian Legal Amazon. Lastly, chapter 5 outlines the dissertation conclusions, papers contributions, shortcomings, and potential for future research.

Every chapter distills important findings and in-depth discussions to enhance the understanding of challenges and potential toward sustainable agriculture. The papers present political emphasis due to the essential role of local and national governments to set forth sustainable management and provide incentives for socioeconomic development. Moreover, the studies offer recommendations to spur future scientific contributions in the field of water and land use.

Chapter 2 investigates the availability (or the absence) of water data as a key challenge in designing political and economic strategies for sustainable water resources management. This paper is an output of the Virtual Water Values project funded by the German Ministry of Education and Research (BMBF) developed at the Kiel Institute for the World Economy (IfW). The initial goal consisted of developing a global General Equilibrium Model that explicitly accounts for water as a production factor for agriculture and industrial sectors. The model had the promising potential to simulate policy scenarios regarding climate change and LUC.

Nevertheless, data uncertainties hindered the project's development, posing several questions regarding the quality and comparability of available water data. Missing water data have critical consequences for developing economic models able to gauge restricted water use impacts in regions with alarming water scarcity. Biophysical models are likewise compromised by sparse water data, unclear definitions, and the lack of a prevailing method to obtain reliable information. Hence, the question that initially motivated this work was: “How could policies, regulations, economic and biophysical projections be designed without a consistent and robust water baseline?”.

In fact, the absence of well-documented, clear, and concise water data is long acknowledged in the scientific literature (Floerke et al., 2013; Gleick, 2003). Water scarcity affects 40% of the global population (United Nations, 2018b), climate change, population, and economic growth, and the increasing consumption of water-intensive input goods project higher water deficiency (Liu et al., 2017). Assessing how socioeconomic factors and climate change influence current and future water scarcity, and its consequences for human wellbeing, depends on knowledge about water availability and use. Assessments must be combined and consistent with local, spatially disaggregated water-use patterns. Therefore, supporting water research in economic, physical, and political fields requires consistent water data (Berritella et al., 2007; Fujimori et al., 2017).

Despite the SDG 6 efforts to assure clean water and sanitation, Ortigara et al. (2018) argue it seems unlikely that water targets might be achieved. Moreover, monitoring SDG 6 progress and its interconnectedness to other goals is jeopardized by misleading data. Similarly, robust economic analyses rely on information about water supply and consumption across different production sectors, the type of procurement source (public or private water supply), and water prices. Nevertheless, the widespread absence of data impeded assessing water use in miscellaneous industrial and agricultural activities (Liu et al., 2016).

A challenge in constructing a global water dataset draws not only from the lack of water data collection and report but also from the confusion in defining water terms. Water reports and databases do not commonly define and/or distinguish terms such as "*water use*," "*water consumption*," "*water supply*," or "*water abstraction*" and the associated aspects of water scarcity and sustainability (Gleick, 2003; Rijsberman, 2006). Thus, the paper in chapter 2 evaluates the current state of knowledge of national, international, and global water statistic databases. The study aims at addressing the following fundamental questions: "What do we know about water data availability and use;" "How reliable are global water databases;" and "How comparable are the different data sources?"

Following that, the paper offers an in-depth and structured analysis of available water data by describing what type of information is accessible, data definitions, the criteria for database consistency, and which countries having well-established water databases. By recognizing that promoting water collection and monitoring is part of a political undertaking, the work contributes to a complex discussion on how (sub-)national policymakers could improve water data collection and reporting going forward. Likewise, recommendations also target national and international organizations and researchers as a way to improve data interpretation and promote model harmonization.

It seems unrealistic to expect that the goals of improving data harmonization, collection, and even definitions will be met in the near future. However, chapter 2 contributes to raising awareness in the scientific community to improve water reporting and diminish the knowledge gap. Furthermore, the paper draws recommendations on how research and policymakers could act to enhance future assessments of water resource use.

The study in chapter 3 assesses the association between deforestation and institutional indices. The scientific literature has long investigated determinants of forest degradation in several regions (Ferretti-Gallon & Busch, 2014). In initial appraisals, biophysical factors (e.g., soil, temperature, precipitation, elevation) appeared to be the primary drivers of deforestation in numerous studies (Kissinger et al., 2012). Nevertheless, anthropogenic LUC drivers became evident over the years for posing critical uncertainties when designing conservation strategies (Rudel et al., 2009).

According to Rudel et al. (2009), for decades, scholars and forestry professionals diverged about the influences of socioeconomic factors on tropical deforestation. Nevertheless, population growth and economic incentives are currently seen to facilitate agricultural expansion toward forest areas (Geist & Lambin, 2002). Only recently understanding the linkages between weak governance and forest degradation received more attention. In fact, institutional factors are argued to impact forest resources through various mechanisms (Kissinger et al., 2012). Corruption stands as the most immediate example, acting by facilitating illegal logging activities (Amacher, 2006) and using the public mechanism to pursue private gains (Galinato & Galinato, 2012).

So far, the effects of physical and infrastructural variables over land-use change have been well-documented; however, very few studies investigate the relations of weak institutions in forest conservation (Agrawal, 2007). Notwithstanding the advancement in high-resolution land use data, assessing its association with socioeconomic variables is still in progress. The absence of robust institutional data is undoubtedly a limitation to this type of analysis. With that, chapter 3 aims to shed light on the relationship between institutional factors and LUC at the global level.

According to Chomitz & Gray (1996), to refine previous quantitative LUC studies, models should follow an economic framework, apply spatially disaggregated data, and account for economic, physical, and political determinants. Empirical estimations improve substantially when simultaneously employing anthropogenic, biophysical, and institution variables (Barrett et al., 2006). Moreover, studies based on remote sensing data, deforestation, and explanatory variables are available on the same spatial resolution, which facilitates continuously assessing their effects. The headway of high-resolution LUC data has enabled assessing the association between socioeconomic variables and deforestation (Marcos-Martinez et al., 2017).

For that aim, the paper employs high-resolution explicit disaggregated global land use data into an econometric model, accounting for biophysical, structural, and institutional factors. Land use data refer to maps from 1992 and 2015 provided by the European Space Agency’s (ESA) Climate Change Initiative Land Cover (CCI-LC) (Defourny et al., 2009). Data for biophysical factors refer to crop suitability indices of the Global Agro-Ecological Zones model (FAO, 2021a) developed by IIASA and FAO. The index represents a harmonized aggregation of biophysical attributes related to production suitability.

Subsequently, the infrastructural variable refers to the accessibility index from (Nelson, 2008), informing the presence of transportation systems and cities around the pixel. Well-structured areas with direct access to markets (or other cities and regions) provide a series of off-farm opportunities which ease the pressure on agricultural production (Müller & Zeller, 2002). Lower transportation costs due to road systems enable in and outflow of production, inputs, commodities, services, and consumers. Using such harmonized indexes enables accounting for relevant biophysical and structural elements while controlling for collinearity among predictor variables.

Furthermore, institutional factors refer to the Corruption Perception Index (CPI) from Transparency International and the World Bank Government Effectiveness (GE) index. Both indexes are available at the country level and represent well-documented quantifications of institutional and political elements. By following the economic model for land use proposed by von Thünen (1826) and employing a logistic model, the study provides empirical evidence of the relationship between forest degradation and institutional factors for the globe and several country groups. Moreover, chapter 3 presents a critical discussion of the available institutional indices and offers suggestions to refine social indicators for natural resources management.

Chapter 4 addresses spatial direct, and spillover effects on rural credit to family farmers engaged in husbandry and agricultural production in the Legal Brazilian Amazon rainforest.

Family farming represents the majority of farms worldwide (Medina et al., 2015), responsible for producing more than half of the global food (IFAD, 2011). Over 1.5 billion people live in small rural households whose economic and social development depend on agricultural production. Thus, family farmers are seen as the forefront of promoting meaningful advancements to the sustainability agenda (Abraham & Pingali, 2020; United Nations, 2018a).

Family farmers comprise highly diverse groups with several performances in the agricultural sector, directly sustaining food security in rural areas (Graeub et al., 2016). In Sub-Saharan Africa, for instance, where severe hunger, poverty, and malnutrition prevail, family farmers are responsible for supplying 80% of the food (Abraham & Pingali, 2020). Nevertheless, there is considerably little information about this group's diversity (Pokorny & Jong, 2015), and it is unclear what challenges and benefits family agriculture bears across several regional contexts (Medina et al., 2015).

In Brazil, family farmers were recognized as an important social category only in 1995 with the creation of the National Program for Strengthening Family Farming (PRONAF) (Guanziroli et al., 2013). PRONAF is a governmental program granting credit lines with low interest rates (Kumar, 2005), allowing income transfers to economically vulnerable family farmers (de Castro & Teixeira, 2012; Zeller & Schiesari, 2020). PRONAF investments aim to support input acquisition, technology, information and income transfer, and job generation while promoting sustainable development and production in marginalized rural areas (Medina et al., 2015).

By contrast, despite strong aspirations, studies point to the underperformance of PRONAF in reducing the inequality gap (Helfrand et al., 2009), and credits are highly uneven across Brazil (Zeller & Schiesari, 2020). Moreover, states composing the Legal Amazon received the lowest concentration of PRONAF contracts over the years (Grisa et al., 2014). Credit rationing has been observed for prioritizing farmers specialized in monocultures with technology, financial resources, and market access (Grisa et al., 2014; Resende & Martins Mafra, 2016). With that, it is argued that PRONAF investments did not integrate vulnerable producers and have instead supported monoculture expansion in the Amazon (Maia et al., 2020; Mattei, 2011).

The credit market literature comprises well-established theories discoursing reasons for credit rationing. In rural contexts, credit rationing is a common process (Ghosh et al., 2000) and is explained by means of supply and demand mechanisms (Jaffe & Modigliani, 1969), lenders' information asymmetry (Stiglitz & Weiss, 1981), among others. By understanding that credit rationing is inherent to loan markets (Bester & Hellwig, 1987), chapter 4 does not analyze whether there is a clear selection among farmers but investigates possible inefficiencies in PRONAF credit provision.

Following that, chapter 4 undertakes a spatial Durbin error model regression to assess direct and spillover effects of credit values per hectare for husbandry and agriculture production in 103 microregions composing the Brazilian Legal Amazon. PRONAF data from 2012 to 2019 are provided by the Central Bank of Brazil (BCB, 2021), differentiating loans intended for husbandry and agricultural activities. Production statistics are provided by the most recent Brazilian agricultural census referring to the harvest year 2017 (IBGE, 2017).

Available production variables are highly aggregated, limiting their inclusion and assessments in econometric models. As an alternative to the absence of data, we conducted 35 semi-structured interviews with key informants from banks, technical assistants, and researchers specializing in family farming in the Legal Amazon to uphold and enhance the paper's discussion and explanation of the findings. Hence, chapter 4 represents the first contribution to identifying the spatial dependence of credit distribution and potential spillovers in the Amazon. Moreover, interviews with key informants offer a valuable description of challenges and insightful contributions to the literature.

3. Study relevance

Overall, the three independent contributions go about specific challenges highly relevant to the headway of sustainable agriculture research.

Chapter 2 draws from the water data challenge, centering the potential for future research. The paper sets out available global, international, and national water databases, their structure, and definitions. Aiming for data harmonization, the study sets forth key elements to attain when using available water information and possibilities to enhance water reporting. Notwithstanding the acknowledgment of water data issues, a comprehensive and concise data analysis and systematic collection of databases were still to be addressed. Chapter 2 is particularly relevant to policy analysts and modelers when gauging existing water statistics and how comparable their data contents are.

Still, to underline the relevance of chapter 2, the extensive water data collection and in-depth analysis resulted in a cross-country database of water use and withdrawal for industrial sectors. We used the self-built water database to explicitly model blue water as a production factor in industries in the Dynamic Applied Regional Trade (DART)[1] model.

More specifically, chapter 3 provides a methodological contribution to applying georeferenced high-resolution land use data into an econometric model. Spatial data analysis can evaluate land uses from a fine data resolution, supporting a broader understanding of deforestation processes and their driving forces (Müller & Zeller, 2002). The study performs an empirical analysis of institutional factors' effects on deforestation and discourses possibilities to refine land-use models further. Such assessments are particularly relevant when designing strategies for biodiversity conservation (Rudel et al., 2009). Moreover, this is the first study to employ high-resolution data while accounting for biophysical, infrastructural, and institutional factors in a cross-country setting.

Chapter 4 is a regional study assessing spatial dependence in credit provision for family farmers in the Brazilian Legal Amazon. The study's relevance stands out for various reasons: Family farmers account for 82% of productive units in the Legal Amazon (IBGE, 2017), spurring job generation and economic activities in rural areas (Guanziroli et al., 2013). Nevertheless, they face considerable barriers to integrating markets and accessing land and inputs (Medina et al., 2015). Furthermore, while the Brazilian Amazon remains in the spotlight of scientific and political debates over climate change and sustainability, natural resource degradation through agricultural systems remains rampant (Nobre et al., 2016). There are very few studies about family farming and sustainable progress in the region (Martins and Pereira, 2012) able to inform current challenges under the lens of PRONAF. Therefore, understanding

[1] The Model is own by the Kiel Institute for the World Economy. The database, assumptions, and detailed description of the data manipulation are available upon request.

the challenges of family farming and credit acquisition in the Legal Amazon is still to be addressed (Pokorny et al., 2010).

Following that, the study is relevant to the sustainability debates in Brazil but also provides a novel and insightful case study of the spatial dependence of PRONAF in the region. Furthermore, the extensive semi-structured interviews enhance the discussion and support a critical analysis of PRONAF in the Amazon.

References

Abraham, M., & Pingali, P. (2020). Transforming smallholder agriculture to achieve the SDGs. In *The role of smallholder farms in food and nutrition security* (pp. 173–209). Springer, Charm.

Agrawal, A. (2007). Forests, governance, and sustainability: common property theory and its contributions. *International Journal of the Commons*, *1*(1), 111–136.

Allen, C., Metternicht, G., & Wiedmann, T. (2018). Initial progress in implementing the Sustainable Development Goals (SDGs): a review of evidence from countries. *Sustainability Science*, *13*(5), 1453–1467. https://doi.org/10.1007/s11625-018-0572-3

Amacher, G. S. (2006). A challenge for economists interested in forest policy design. *Journal of Forest Economics*, *12*(2), 85–89.

Banerjee, O., Cicowiez, M., Horridge, M., & Vargas, R. (2019). Evaluating synergies and trade-offs in achieving the SDGs of zero hunger and clean water and sanitation: An application of the IEEM Platform to Guatemala. *Ecological Economics*, *161*, 280–291. https://doi.org/10.1016/j.ecolecon.2019.04.003

Barrett, C. B., Gibson, C. C., Hoffman, B., & McCubbins, M. D. (2006). The complex links between governance and biodiversity. *Conservation Biology*, *20*(5), 1358–1366.

Barretto, A. G. O. P., Berndes, G., Sparovek, G., & Wirsenius, S. (2013). Agricultural intensification in Brazil and its effects on land-use patterns: An analysis of the 1975-2006 period. *Global Change Biology*, *19*(6), 1804–1815. https://doi.org/10.1111/gcb.12174

BCB. (2021). *Central Bank of Brazil*. Retrieved December 10, 2021 from https://www.bcb.gov.br/

Beddington, J., Asaduzzaman, M., Clark, M., Fernández, A., Guillou, M., Jahn, M., Erda, L., Mamo, T., van Bo, N., Nobre, C. A., Scholes, R., Sharma, R., & Wakhungu, J. (2012). *Achieving food security in the face of climate change Final report from the Commission on Sustainable Agriculture and Climate Change*. www.ccafs.cgiar.org/commission

Bennett, E. M., Carpenter, S. R., Gordon, L. J., Ramakutty, N., Balvanera, P., Campbell, B. M., & Spierenburg, M. (2014). Resilient thinking for a more sustainable agriculture. *The Solutions Journal*, *5*(5), 65–75.

Berritella, M., Hoekstra, A. Y., Rehdanz, K., Roson, R., & Tol, R. S. J. (2007). The economic impact of restricted water supply: A computable genera; equilibrium analysis. *Water Research*, *41*, 1799–1813.

Bester, H., & Hellwig, M. (1987). Moral Hazard and Equilibrium Credit Rationing: An Overview of the Issues. In G. Bamberg & K. Spreman (Eds.), *Agency Theory, Information, and Incentives* (pp. 135–166). Springer.

Blesh, J., Hoey, L., Jones, A. D., Friedmann, H., & Perfecto, I. (2019). Development pathways toward “zero hunger.” *World Development*, *118*, 1–14. https://doi.org/10.1016/j.worlddev.2019.02.004

Borlaug, N. (2007). Feeding a hungry world. *Science*, *318*(5849), 359.

Borrelli, P., Robinson, D. A., Panagos, P., Lugato, E., Yang, J. E., Alewell, C., Wuepper, D., Montanarella, L., & Ballabio, C. (2020). Land use and climate change impacts on global soil erosion by water (2015-2070). *Proceedings of the National Academy of Sciences*, *117*(36), 21994–22001. https://doi.org/10.1073/pnas.2001403117/-/DCSupplemental

Bruinsma, J. (2003). *World Agriculture: Towards 2015/2030: An FAO perspecive* (1st ed.). Routledge.

Canavan, C. R., Graybill, L., Fawzi, W., & Kinabo, J. (2016). The SDGs Will Require Integrated Agriculture, Nutrition, and Health at the Community Level. *Food and Nutrition Bulletin*, *37*(1), 112–115. https://doi.org/10.1177/0379572115626617

Chomitz, K. M., & Gray, A. (1996). Roads, Land Use , and Deforestation : A Spatial Model Applied to Belize. *The World Bank Economic Review*, *10*(3), 487–512. https://mygeohub.org/resources/1131/download/Tool_introduction_and_users_guide.pdf

Costanza, R., Daly, L., Fioramonti, L., Giovannini, E., Kubiszewski, I., Mortensen, L. F., Pickett, K. E., Ragnarsdottir, K. V., de Vogli, R., & Wilkinson, R. (2016). Modelling and measuring sustainable wellbeing in connection with the UN Sustainable Development Goals. *Ecological Economics*, *130*, 350–355. https://doi.org/10.1016/j.ecolecon.2016.07.009

Crippa, M., Solazzo, E., Guizzardi, D., Monforti-Ferrario, F., Tubiello, F. N., & Leip, A. (2021). Food systems are responsible for a third of global anthropogenic GHG emissions. *Nature Food*, *2*(3), 198–209. https://doi.org/10.1038/s43016-021-00225-9

de Castro, E. R., & Teixeira, E. C. (2012). Rural credit and agricultural supply in Brazil. *Agricultural Economics*, *43*(3), 293–302. https://doi.org/10.1111/j.1574-0862.2012.00583.x

Defourny, P., Schouten, L., Bartalev, S., Bontemps, S., Caccetta, P., de Wit, A. J. W., di Bella, C., Gérard, B., Giri, C., & Gond, V. (2009). Accuracy Assessment of a 300 M Global Land Cover Map:The GlobCover Experience. *Proceedings of the 33rd International Symposium on Remote Sensing of Environment*.

Dell'Angelo, J., Rulli, M. C., & D'Odorico, P. (2018). The Global Water Grabbing Syndrome. *Ecological Economics*, *143*, 276–285. https://doi.org/10.1016/j.ecolecon.2017.06.033

FAO. (2014). *Building a common vision for sustainable food and agriculture. Principles and approaches*.

FAO. (2016). Food and Agriculture. Key to achieving the 2030 Agenda for Sustainable Development. In *FAO*.

FAO. (2021a). *Global Agro-Ecological Zones*. Retrieved November 03, 2021 from http://www.fao.org/nr/gaez/about-data-portal/agricultural-suitability-and-potential-yields/en/#

FAO. (2021b). *Sustainable Development Goals*. Retrieved November 03, 2021 from https://www.fao.org/sustainable-development-goals/indicators/241/en/

FAO. (2021c). *Sustainable Food and Agriculture*. Retrieved September 02, 2021 from https://www.fao.org/sustainability/background/en/

FAO, IFAD, UNICEF, WFP, & WHO. (2018). *The State of Food Security and Nutrition in the World 2018. Building Climate Resilience for Food Security and Nutrition*.

Ferretti-Gallon, K., & Busch, J. (2014). What Drives Deforestation and What Stops it? A Meta-Analysis of Spatially Explicit Econometric Studies. *SSRN Electronic Journal*, *April 2014*. https://doi.org/10.2139/ssrn.2458040

Floerke, M., Kynast, E., Baerlund, I., Eisner, S., Wimmer, F., & Alcamo, J. (2013). Domestic and industrial water uses of the past 60 years as a mirror of socio-economic development: A global simulation study. *Global Environmental Change*, *23*, 144–156.

Foley, J. A., Ramankutty, N., Brauman, K. A., Cassidy, E. S., Gerber, J. S., Johnston, M., Mueller, N. D., O'Connell, C., Ray, D. K., West, P. C., Balzer, C., Bennett, E. M., Carpenter, S. R., Hill, J., Monfreda, C., Polasky, S., Rockström, J., Sheehan, J., Siebert, S., … Zaks, D. P. M. (2011). Solutions for a cultivated planet. *Nature*, *478*(7369), 337–342. https://doi.org/10.1038/nature10452

Fujimori, S., Hanasaki, N., & Masui, T. (2017). Projections of industrial water withdrawal under shared socioeconomic pathways and climate mitigation scenarios. *Sustainability Science*, *12*(2), 275–292. https://doi.org/10.1007/s11625-016-0392-2

Galinato, G. I., & Galinato, S. P. (2012). The effects of corruption control, political stability and economic growth on deforestation-induced carbon dioxide emissions. *Environment and Development Economics*, *17*(1), 67–90.

Garnett, T., Appleby, M. C., Balmford, A., Bateman, I. J., Benton, T. G., Bloomer, P., Burlingame, B., Dawkins, M., Dolan, L., Fraser, D., Herrero, M., Hoffmann, I., Smith, P., Thornton, P. K., Toulmin, C., Vermeulen, S. J., & Godfray, H. C. J. (2013). Sustainable intensification in agriculture: Premises and policies. *Science*, *341*(6141), 33–34. https://doi.org/10.1126/science.1234485

Geist, H. J., & Lambin, E. F. (2002). Proximate Causes and Underlying Driving Forces of Tropical DeforestationTropical forests are disappearing as the result of many pressures, both local and regional, acting in various combinations in different geographical locations. *BioScience*, *52*(2), 143–150.

Ghosh, P., Mookherjee, D., & Ray, D. (2000). Credit rationing in developing countries: an overview of the theory. In *Readings in the theory of economic development* (Vol. 7, pp. 383–401).

Gil, J. D. B., Reidsma, P., Giller, K., Todman, L., Whitmore, A., & van Ittersum, M. (2019). Sustainable development goal 2: Improved targets and indicators for agriculture and food security. *Ambio*, *48*(7), 685–698. https://doi.org/10.1007/s13280-018-1101-4

Gleick, P. H. (2003). Water Use. *Annual Review of Environment and Resources*, *28*, 275–314.

Graeub, B. E., Chappell, M. J., Wittman, H., Ledermann, S., Kerr, R. B., & Gemmill-Herren, B. (2016). The State of Family Farms in the World. *World Development*, *87*, 1–15. https://doi.org/10.1016/j.worlddev.2015.05.012

Grisa, C., Wesz Junior, V. J., & Buchweitz, V. D. (2014). Revisitando o Pronaf: Velhos questionamentos, novas interpretações. *Revista de Economia e Sociologia Rural*, *52*(2), 323–346. https://doi.org/10.1590/s0103-20032014000200007

Guanziroli, C., Buainain, A., & Sabbato, A. (2013). Family farming in Brazil: Evolution between the 1996 and 2006 agricultural censuses. *Journal of Peasant Studies*, *40*(5), 817–843. https://doi.org/10.1080/03066150.2013.857179

Haddeland, I., Heinke, J., Biemans, H., Eisner, S., Flörke, M., Hanasaki, N., Konzmann, M., Ludwig, F., Masaki, Y., Schewe, J., Stacke, T., Tessler, Z. D., Wada, Y., & Wisser, D. (2014). Global water resources affected by human interventions and climate change. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(9), 3251–3256. https://doi.org/10.1073/pnas.1222475110

Hagemann, S., Chen, C., Clark, D. B., Folwell, S., Gosling, S. N., Haddeland, I., Hanasaki, N., Heinke, J., Ludwig, F., Voss, F., & Wiltshire, A. J. (2013). Climate change impact on available water resources obtained using multiple global climate and hydrology models. *Earth System Dynamics*, *4*(1), 129–144. https://doi.org/10.5194/esd-4-129-2013

Helfrand, S., Rocha, R., & Vinhais, H. (2009). Pobreza e desigualdade de renda no Brasil rural: uma análise da queda recente. *Pesquisa e Planejamento Econômico*, *39*(1), 59–80.

Hosonuma, N., Herold, M., de Sy, V., de Fries, R. S., Brockhaus, M., Verchot, L., Angelsen, A., & Romijn, E. (2012). An assessment of deforestation and forest degradation drivers in developing countries. *Environmental Research Letters*, *7*(4). https://doi.org/10.1088/1748-9326/7/4/044009

Howden, S. M., Soussana, J.-F., Tubiello, F. N., Chhetri, N., Dunlop, M., & Meinke, H. (2007). Adapting agriculture to climate change. *Proceedings of the National Academy of Sciences*, *104*(50), 19691–19696. www.pnas.orgcgidoi10.1073pnas.0701890104

IBGE. (2017). *Censo agropecuário 2017: Agricultura Familiar. Instituto Brasileiro de Geografia e Estatística*. Retrieved August 02, 2021 from https://sidra.ibge.gov.br/pesquisa/censo-agropecuario/censo-agropecuario-2017#caracteristicas-produtores.

IFAD. (2011). Rural Poverty Report 2011. New realities, new challenges: new opportunities for tomorrow ' s generation. In *Rurual Poverty Report*. http://www.ifad.org/rpr2011/report/e/rpr2011.pdf. Accessed on 11.11.2021

Jaffe, D. M., & Modigliani, F. (1969). A theory and test of credit rationing. *American Economic Review*, *59*(5), 850–872.

Janssens, C., Havlík, P., Krisztin, T., Baker, J., Frank, S., Hasegawa, T., Leclère, D., Ohrel, S., Ragnauth, S., Schmid, E., Valin, H., van Lipzig, N., & Maertens, M. (2020). Global hunger and climate change adaptation through international trade. *Nature Climate Change*, *10*(9), 829–835. https://doi.org/10.1038/s41558-020-0847-4

Kissinger, G., Herold, M., & Sy, V. de. (2012). Drivers of Deforestation and Forest Degradation: A Synthesis Report for REDD+ Policymakers. In *Lexeme Consulting* (Issue August). https://doi.org/10.1126/science.1239402

Kumar, A. (2005). Access to Financial Services in Brazil. In *Directions in Development. The World Bank*. https://doi.org/https://doi.org/10.1596/0-8213-5716-6

le Blanc, D. (2015). Towards Integration at Last? The Sustainable Development Goals as a Network of Targets. *Sustainable Development*, *23*(3), 176–187. https://doi.org/10.1002/sd.1582

Lipper, L., DeFries, R., & Bizikova, L. (2020). Shedding light on the evidence blind spots confounding the multiple objectives of SDG 2. *Nature Plants*, *6*(10), 1203–1210. https://doi.org/10.1038/s41477-020-00792-y

Liu, J., Liu, Q., & Yang, H. (2016). Assessing water scarcity by simultaneously considering environmental flow requirements, water quantity, and water quality. *Ecological Indicators*, *60*, 434–441. https://doi.org/10.1016/j.ecolind.2015.07.019

Liu, J., Yang, H., Gosling, S. N., Kummu, M., Flörke, M., Hanasaki, N., Wada, Y., Zhang, X., & Zheng, C. (2017). Water scarcity assessments in the past , present , and future. *Earth's Future*, 1–15. https://doi.org/10.1002/eft2.200

Maia, A. G., Eusébio, G. dos S., & da Silveira, R. L. F. (2020). Can credit help small family farming? Evidence from Brazil. *Agricultural Finance Review*, *80*(2), 212–230. https://doi.org/10.1108/AFR-10-2018-0087

Marcos-Martinez, R., Bryan, B. A., Connor, J. D., & King, D. (2017). Agricultural land-use dynamics: assessing the relative importance of socioeconomic and biophysical drivers for more targeted policy. *Land Use Policy*, *63*, 53–66.

Mattei, L. (2011). Evolução do crédito do PRONAF para as categorias de agricultores A e A/C entre 2000 e 2010. In SOBER (Ed.), *Congresso da Sociedade Brasileira de Economia, Administração e Sociologia Rural*.

Matthews, J. H., White, M., Bahije, S., Grantham, T., Guillaume, G., Holmgren, T., Kerres, M., Krahl, D., Lahham, N., Lundqvist, J., Marré, F., Marta, S., Rodriguez, D. J., Thiem, M., Timmerman, J., Unver, O., van de Guchte, C., Vlaanderen, N., & Whiting, L. (2017). *A thirst for food resilience: Integrating UNFCCC and SDG policies for food and agriculture* (Issue 11).

Mcarthur, J. W. (2013). Own the Goals What the Millennium Development Goals Have Accomplished. *Foreign Aff.*, *92*(152).

McKenzie, F. C., & Williams, J. (2015). Sustainable food production: constraints, challenges and choices by 2050. *Food Security*, *7*(2), 221–233. https://doi.org/10.1007/s12571-015-0441-1

Medina, G., Almeida, C., Novaes, E., Godar, J., & Pokorny, B. (2015). Development Conditions for Family Farming: Lessons From Brazil. *World Development*, *74*, 386–396. https://doi.org/10.1016/j.worlddev.2015.05.023

Müller, D., & Zeller, M. (2002). Land use dynamics in the central highlands of Vietnam: A spatial model combining village survey data with satellite imagery interpretation. *Agricultural Economics*, *27*(3), 333–354. https://doi.org/10.1016/S0169-5150(02)00073-7

Nelson, A. (2008). *Estimated travel time to the nearest city of 50,000 or more people in year 2000*. Global Environment Monitoring Unit - Joint Research Centre of the European Commission. Retrieved March 02, 2020 from https://forobs.jrc.ec.europa.eu/products/gam/

Nelson, G., Cai, Z., Hassan, R., Godfray, C., Santos, M., & Swaminathan, H. (2012). *Food security and climate change: A report by the high level panel of experts on food security and nutrition*.

Nilsson, M., Griggs, D., & Visbeck, M. (2016). Map the interactions between Sustainable Development Goals. *Nature*, *534*(7607), 320–322. https://doi.org/10.1038/534320a

Ortigara, A. R. C., Kay, M., & Uhlenbrook, S. (2018). A Review of the SDG 6 Synthesis Report 2018 from an Education, Training, and Research Perspective. *Water*, *10*(1353).

Paustian, K., Lehmann, J., Ogle, S., Reay, D., Robertson, G. P., & Smith, P. (2016). Climate-smart soils. *Nature*, *532*(7597), 49–57.

Pokorny, A. B., & Jong, W. de. (2015). Smallholders and Forest Landscape Transitions : Locally Devised Development Smallholders and forest landscape transitions : locally devised development strategies of the tropical Americas. *International Forestry Review*, *17*(1), 1–19.

Pretty, J. N. (1997). The sustainable intensification of agriculture. *Natural Resources Forum*, *21*(4), 247–256. https://doi.org/10.1111/j.1477-8947.1997.tb00699.x

Reis, N. (2014). Coyotes, Concessions and Construction Companies: Illegal Water Markets and Legally Constructed Water Scarcity in Central Mexico. *Water Alternatives*, *7*(3), 542–560.

Resende, C. M., & Martins Mafra, R. L. (2016). Desenvolvimento rural e reconhecimento: Tensões e dilemas envolvendo o pronaf. *Revista de Economia e Sociologia Rural*, *54*(2), 261–280. https://doi.org/10.1590/1234.56781806-947900540204

Rijsberman, F. R. (2006). Water scarcity: Fact or fiction? *Agricultural Water Management*, *80*(1-3 SPEC. ISS.), 5–22. https://doi.org/10.1016/j.agwat.2005.07.001

Rudel, T. K., Defries, R., Asner, G. P., & Laurance, W. F. (2009). Changing drivers of deforestation and new opportunities for conservation. *Conservation Biology*, *23*(6), 1396–1405. https://doi.org/10.1111/j.1523-1739.2009.01332.x

Schmidhuber, J., & Tubiello, F. N. (2007). Global food security under climate change. *Proceedings of the National Academy of Sciences*, *104*(50), 19703–19708.

Shu, R., Cao, X., & Wu, M. (2021). Clarifying Regional Water Scarcity in Agriculture based on the Theory of Blue, Green and Grey Water Footprints. *Water Resources Management*, *35*(3), 1101–1118. https://doi.org/10.1007/s11269-021-02779-6

Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American Economic Review*, *71*(3), 393–410.

Streimikis, J., & Baležentis, T. (2020). Agricultural sustainability assessment framework integrating sustainable development goals and interlinked priorities of environmental, climate and agriculture policies. *Sustainable Development*, *28*(6), 1702–1712. https://doi.org/10.1002/sd.2118

Struik, P. C., & Kuyper, T. W. (2017). Sustainable intensification in agriculture: the richer shade of green. A review. In *Agronomy for Sustainable Development* (Vol. 37, Issue 5). Springer-Verlag France. https://doi.org/10.1007/s13593-017-0445-7

Tubiello, F., Schmidhuber, J., Howden, M., Neofotis, P. G., Park, S., Fernandes, E., & Thapa, D. (2008). Climate change response strategies for agriculture: challenges and opportunities for the 21st century. *Agriculture and Rural Development Discussion Paper*, *24*, 1–75. http://documents.worldbank.org/curated/en/2008/01/10680765/climate-change-response-strategies-agriculture-challenges-opportunities-21st-century

United Nations. (2018a). *Sustainable Development Goal 2*. Retrieved September 10, 2021 from https://sdgs.un.org/goals/goal2.

United Nations. (2018b). *Sustainable Development Goal 6*. Retrieved September 10, 2021 from https://sustainabledevelopment.un.org/sdg6

von Thünen, J. H. (1826). *Der isolierte Staat in Beziehung auf Nationalökonomie und Landwirtschaft*.

Wheeler, T., & von Braun, J. (2013). The future of species under climate change: Resilience or decline? In *Science* (Vol. 341, Issue 6145, pp. 504–508). American Association for the Advancement of Science. https://doi.org/10.1126/science.1237190

World Bank. (2010). *The Hague Conference on Agriculture, Food Security and Climate Change Opportunities and Challenges for a Converging Agenda: country examples. Conference edition*.

Zeller, M., & Schiesari, C. (2020). The unequal allocation of PRONAF resources: Which factors determine the intensity of the program across Brazil? *Revista de Economia e Sociologia Rural*, *58*(3). https://doi.org/10.1590/1806-9479.2020.207126

Chapter 2

Economic Research on the Global Allocation of Scarce Water Resources Needs Better Data

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Abstract

Water sustainability is central to modern political and academic debates. Despite increasing efforts to promote regional and global integrated water management, climate change, population, and economic growth, and increasing consumption of water-intensive goods project higher water deficiency. Robust economic analyses rely on information about water supply and consumption across different production sectors, type of procurement source (public or private water supply), and water prices. Nevertheless, developing current and future economic water assessments and indicators is impeded by the absence of data. Despite the lack of official national statistics on water withdrawal and consumption, as mall number of international and global databases have been constructed and attempt to combine available national water information into databases. Water databases do not commonly define and/or distinguish terms such as water use, water consumption, water supply, or water abstraction, and the associated aspects of water scarcity and sustainability. They comprise variable data quality, provided by numerous sources, and estimated values. This paper evaluates the current state of knowledge of national statistics, international and global water databases. We describe the data collection methods, identify basic concepts and definitions of water terms, followed by the criteria of consistent water databases. We inform about data availability across regions, and present the data content and definitions of national, international, and global water databases. The results show inconsistencies of data content and definitions, suggesting no evidence of data harmonization among databases. Therefore, our study cautions researchers to be careful when manipulating and comparing the available water data, especially when deriving policy recommendations or economic conclusions. In the long run, the headway of water research and political assessments depend on political enforcements to refine the meaningfulness of water data and support water collection, reporting, and monitoring. Alternatively, in the short- and medium-run, water data challenges can be addressed by joint research efforts for water data harmonization.

Keywords: Water data; water sustainability; water use; water withdrawal; water economics; water scarcity; water policy.

1. Introduction

Water is essential for life and to human and environmental sustenance. Freshwater accounts for a very small share of water resources and is the base for human activities, encompassing drinking, irrigation, and industrial use (Jackson et al., 2001). As water and population are unevenly distributed across the globe, some regions bear higher impacts as water becomes scarce (Berritella et al., 2007; Zeng et al., 2013). Climate change, population and economic growth, and the increasing consumption of water-intensive input goods project higher water deficiency (Liu et al., 2017). In its introductory statement on Sustainable Development Goal (SGD) 6, the United Nations Development Program (2019) (UNDP) states: *"Water scarcity affects more than 40 percent of people, an alarming figure that is projected to rise as temperatures do"*. This statement raises concerns as water scarcity is accompanied by and interacts with other scarce natural resources such as fertile land, and with a multitude of ecosystems, which strongly influence human wellbeing and poverty. Due to the complexity and multidimensional character of water challenges, water resource management deserves special and integrated treatment (Ait-Kadi, 2016).

Despite increasing efforts to promote regional and global integrated water management, the target of water sustainability may not be achieved (United Nations, 2018). This is especially due to the absence of data, which directly influences the results of water indicators, research outcomes (Ortigara et al., 2018; United Nations, 2018), and impacts economic assessments of water resources. Economic development through industrialization depends on sufficient water supplies. At the same time, ecosystem services are often negatively affected as water consumption increases (Rijsberman, 2006), and climate change is likely to affect the amount, temporal, and the spatial distribution of water (Liu et al., 2017). How these combined and interacting factors influence current and future water scarcity, and its consequences for human wellbeing, depend on knowledge about water availability and use. Assessments need to be combined and consistent with local, spatially disaggregated water use patterns. Therefore, supporting water research in economic, physical, and political fields require consistent water data (Berrittella et al., 2007; Fujimori et al., 2017; United Nations, 2018).

From an economic perspective, water is an essential production factor (Hertel & Liu, 2014). Agriculture is the biggest water user, where 70% of all freshwater withdrawal is supplied to irrigation purposes, followed by industry (20%), and municipal matters (10%) (United Nations, 2009). Local water scarcity is potentially alleviated by virtual water trade mechanisms (Oki et al., 2017). Water economics enables the assessment of the impact of production, as well as economic and political interventions on water resources in the context of international food and industrial trade (Calzadilla et al., 2010). Computable General Equilibrium (CGE) models, for instance, are used to study water availability, use, and management in the context of international trade by reallocating water using market mechanisms (Calzadilla et al., 2016). Spatially disaggregated water data are core to the development of such economic models. Furthermore, robust economic analyses rely on information about water supply and consumption across different production sectors, type of procurement source (public or private water supply), and water prices. Nevertheless, assessing water use in miscellaneous industrial and agricultural activities is impeded by the widespread absence of data (Liu et al., 2016). Despite the lack of official national statistics on water withdrawal and consumption, a small number of international and global databases (EUROSTAT; FAO; WaterGap model (Floerke et al., 2013); OECD; The World's Water; UNSD) have been constructed and attempt to combine available national water information into databases. A challenge in constructing a global water dataset draws from the confusion in defining water terms. Water reports and databases do not commonly define and/or distinguish terms such as water use, water consumption, water supply, or water abstraction, and the associated aspects of water scarcity and sustainability (Gleick, 2003; Rijsberman, 2006).

This paper evaluates the current state of knowledge of national statistics on water as well as international and global water databases, and addresses some fundamental questions: What do we know about water data availability and use? How reliable are global water databases? How comparable are the different data sources? The paper is structured as follows: Chapter 2 presents the systematic methods for data search; Chapter 3 displays the data analysis by identifying basic concepts and definitions of water terms, followed by the criteria a consistent water database should adhere to; Chapter 4 sets out the results of the data search, by informing the content and definitions of currently available national, international, and global water databases. Chapter 5 discusses challenges and potentials to the development of meaningful research and political water assessments. Finally, Chapter 6 draws implications for water research and political actions related to water data.

2. Data collection methods

Acquiring water data has long been acknowledged as an issue in the scientific literature. Historical water reports are often non-existent or incomplete (Floerke et al., 2013) and lack definitions and details about the data collection process. Following from these concerns, Gleick (2003) provides a comprehensive discussion about water data limitations. The issues range from the absence of a prevailing collection method, including standardized source and collection period reporting, to dubious data definitions and geographical disparities of collection. In this sense, industrialized countries are known as water data-rich (Ortigara et al., 2018) as they often have a developed structure of data collection for industrial and agricultural sectors.

Our approach aims to identify a globally consistent database on water consumption and withdrawal, which is the basis for the analysis of water allocation in agriculture and industry. Further aspects of water (e.g. sanitation, water quality, affordable drinking water) are not considered, as well as single official and unofficial water or environmental reports and water projections. Based on the above-mentioned literature, we selected a set of criteria and apply a three-steps search method.

The first step in our search for data consists of searching for global water data references, both in scientific and non-scientific sources. Here we follow the first phase of the methodological framework for extensive literature review and evaluation (Schlichter & Kraemmergaard, 2010). The phase defines the types of publications to be considered, where to find them, the period of publication, and keywords. From the scientific literature, we consider studies about biophysical and economic water use published in peer-reviewed journals. The procedure is done through academic search engines: google scholar and Web of Science. Papers from the year 2000 onwards are considered by using the following keywords: *water withdrawal, water consumption, water use, industrial water, water statistics, water scarcity, water and CGE*. We look specifically at the type and source of water data used in the selected papers. This allows us to add additional articles that are referenced as data sources in these studies. Articles using simulated data are excluded, as our interest is finding collected water data. The enquiry of non-scientific sources, in turn, is likewise done through search engine (google). We consider governmental and research water initiatives and organizations engaged in water data collection and reporting. The same set of keywords (except “water and CGE”) is used. As an attempt to evaluate the characteristics of reported water data, the period is not restricted.

As the second step, we scrutinize the selected databases according to the following criteria:

A) Global coverage: the data set should cover all countries across the world.

B) Documentation of definitions: Definitions of water data are necessary and should be well documented to assure consistency when comparing country level withdrawal and consumption.

C) Disaggregated industrial sectors: Reporting water data for different industrial sectors enables assessing the trade-offs of water allocation within and across nations and production activities. Therefore, the aimed consistent global database should convey water use for individual sectors.

D) Up-to-date data: The use of outdated water information may jeopardize water studies by not depicting the current status of water resources and water use. Therefore, we look for up-to-date databases ranging from 2010-2020.

E) Reliability: Transparency in communicating the years of data collection and reporting, and information regarding the entity responsible to collect the data.

Subsequently, since no databases fully meet the aforementioned criteria, as the third step, we search for official online national water statistics of water consumption and withdrawal. Similar to the first step, we exclude single official and unofficial water or environmental reports, and water estimations. The latter are disregarded for not representing a prominent platform for water data reporting, namely, an online easily accessible platform for water data, reporting and monitoring. Due to (human) resource constraints, the data search is pursued in a pre-selected sample of countries. We list the major economies of every region to be the focus of the data search (see Table 2.3). The language capacity of our inquiry encompasses English, Spanish, German, Portuguese, and French. Similar to the first step, we make use of searching engines with the following keywords: *Water withdrawal, water consumption, water use, industrial water, water statistics*; together with the respective country’s name. This enables us to spot the countries with national water statistics. Subsequently, for the remaining countries, we search for water data on online platforms of environmental ministries and statistical offices. For the nations with no indication of water statistics, we further examine the country-specific references of the global water databases from the first step. Hence, we are able to track back the existence of water statistics and further details about the entity responsible for reporting national water data, and the types of data sources (e.g. single reports, open access statistics, official statements). Additionally, we consider the scientific literature on national studies. We replicate the scientific search done in the first step as a way to find country-specific water studies, which could potentially reference national water databases.

The criteria applied in the first step do not entirely fit the third step since the latter targets only the occurrence of national water statistics. Moreover, national water reporting systems are highly heterogeneous and differ on the desired frame for water reporting. Nevertheless, we provide and compare the main characteristics, definitions, and national institutions responsible to manage water data in the results section.

3. Analysis

The analysis presented here is twofold. Section 3.1 highlights the issue of water definitions, describes various forms of water allocation, and discusses the relevant characteristics of water use and values. Section 3.2 assesses the consistency of global water databases, and aspects of data search for national statistics.

3.1. Defining water terms

Water is a dynamic resource occurring in temporally and spatially variable cycles that provide services to the environment and society (Rijsberman, 2006). The hydrological cycle is composed of blue and green water. Blue water is the share of precipitation that goes to aquifers, lakes, and composes surface and groundwater resources (Savenije, 2000). This is the main source to sustain human needs, industrial production, and irrigation agriculture. Originated from Falkenmark (1995), the term green water is the part of precipitation intercepted by vegetation, stored into the soil, transpired back to the atmosphere, or temporally available for vegetation growth (Quinteiro et al., 2015). In fact, green water is essential to 60-70% of the world's food production (Rost et al., 2008). Accounting for both blue and green water resources is crucial to the completeness of reports and accuracy of water use projections (Liu et al., 2009). However, water indicators and reports have widely neglected green water in their composition (Zeng et al., 2013).

Water use is determined by interrelated factors such as water type (blue and green), seasonal variability, technology level, and population density, among others. For instance, water withdrawals for domestic and energy purposes are higher in regions with high population density (Huang et al., 2018). During cropping seasons, drought regimes call for irrigation in the western USA, eastern China, and India. In this period, irrigation agriculture requires large amounts of water for food and biomass production (Rio Carrillo & Frei, 2009; Wada et al., 2014). Assessing the global spatial distribution of production activities and water withdrawals from 1971 to 2010, Huang et al. (2018) observe increasing withdrawal rates. The authors found that 68% of withdrawals are designated to irrigation, followed by electricity (11%), households (9%), manufacturing (7%), and less than (5%) to mining and livestock production. Assessing water issues required a broader knowledge about water use patterns along with various production processes. Nevertheless, the absence of water data and contrasting water definitions create conceptual confusion and hinder concise data collection (Gleick, 2003). Similarly, defining water categories guides data collection, the development of reports, data documentation, and water assessments.

The term water use often refers to water consumption or withdrawal. However, these two categories are very different. Following Gleick (2003), here we define water use as a general term referring to any type of water manipulation. Water withdrawal varies enormously over countries and production activities, it denotes the amount of water removed from a natural source and appointed to human activities (Gleick, 2003; Rijsberman, 2006). In industries, water is withdrawn by means of private infrastructure and supplied by public procurement (Hertel & Liu, 2014). A portion of withdrawals is lost and returns to the hydrological cycle before entering the production processes. The remaining is split into a share that is directly consumed into production, and the water that is further discharged back to the natural water system. Therefore, consumption, or consumptive use, refers to the share of water withdrawal that does not return to the hydrological cycle. In agriculture, consumptive use, also denoted as water depletion (Liu et al., 2009), is the amount of irrigated water captured by plants and not available for further reuse (Hertel & Liu, 2014).

Water need and demand are interrelated terms; the first is subjectively oriented and refers to the minimum amount of water to sustain a certain activity, while the latter describes the amount of water desired by potential users, usually larger than the minimum requirement of water. Especially in regions facing limited water resources, demand is a considerable policy matter (Banda et al., 2007). Understanding how users behave towards different water prices can support policy makers designing instruments to regulate water use (Strand & Walker, 2005). This follows the principle that water demand responds to price signals, where water prices lead to more efficient water allocation between competing users (Rogers et al., 2002). Nevertheless, this strategy is arguable as price information are imperfect or unobserved, and when price demand elasticity is very low (Banda et al., 2007; Gaudin, 2006). Moreover, studies have also shown various water demands are price unresponsive (Gaudin et al., 2001; Martínez-Espiñeira & Nauges, 2004). For instance, Scheierling et al., (2006) discusses that pricing policies to reduce irrigation water use might come with negative consequences, as large prices would inflict minor water use reduction, but would rather affect agricultural income and wealth. Similar effect is observed by Berbel & Gómez-Limón (2000) where water demands respond only after farm incomes decrease up to 40%.

Furthermore, there are other water-related terms non-uniformly defined in the literature: water conservation, efficiency, and productivity. Gleick (2003) describes water conservation as the reduction in water losses triggered by technology development, or institutional efforts to promote behavioral changes. Water efficiency is a precise measure of conservation, representing the relationship of the amount of water used relative to the minimum requirement to accomplish an activity. Maximum water-use efficiency holds if water use converges to its minimum water requirement (Gleick, 2003). Lastly, water productivity is defined as the unit ratio of output and water use (Gleick, 2003). Units may be either physical (e.g. volumes, tons) or economic terms (e.g. dollar value of output or service) (Gleick, 2003).

In water economics, defining withdrawal and consumption is especially necessary to study water values (Gibbons, 1986). In general terms, water values rise when the supply of water is lower than its relative demand (Ward & Michelsen, 2002). For decades, water was seen as abundant, with no active economic and political mechanisms to regulate resource uses. This concept has gradually changed as water supply has fallen short in many countries (Gibbons, 1986), resulting in multifold conflicts over water between competitive users and geographical regions (Gibbons, 1986; Ward & Michelsen, 2002).

From the geographical dimension, water is used instream or off-stream. The former refers to the activities occurring on the water stream (e.g. navigation, hydropower generation, recreation); while the latter is the removal of water from the natural cycle to sustain further activities (e.g. agriculture, industry, municipal water demand). Quantity, quality, and time are other dimensions that likewise influence the analysis of water use (Gibbons, 1986; Turner et al., 2004). Analyses based purely on the quantitative aspects of water use are somewhat limited. Water is not necessarily consumed during the process of being used and can even be reused several times, which also generates utility to users. In fact, the proportion of water consumed as a portion of withdrawals varies tremendously across uses. Reusing water stems from competitive and complementary relationships with other uses, meaning that reusing water is expected to trigger serious effects to subsequent uses (Gibbons, 1986; Ward & Michelsen, 2002).

3.2. Selection process for water database

Table 2.1 sets out the list of water data references found on the first step of data search. These datasets represent the most cited sources for water data in scientific research and the databases found on non-scientific sources. The references do not follow a common data structure and differ from reporting collected (empirical) data and estimates. Generally, there are two main categories of water studies: those based on statistical water records of empirical data on withdrawal and availability; and those based on simulated water accounts derived from hydrological models (Hanasaki et al., 2012). The latter are likewise based on empirical evidence to obtain realistic estimation results. All references from Table 2.1 are examined to identify detailed characteristics of the data. We exclude sources that do not contain collected data on water withdrawal and consumption. In this matter, although applied as databases, two references contain model estimates for water withdrawal and consumption: H08 (Hanasaki et al., 2012; Hanasaki et al., 2017), and PCR-GLOBWB (Sutanudjaja et al., 2018; Van Beek et al., 2011); or comprise a set of own methods to derive an alternative character of water consumption (Water footprint). Likewise, EXIOBASE builds the water accounts based on data from FAO and Water footprint to estimate water consumption in agriculture; and the WaterGAP model (Floerke et al., 2013) to account for water in industrial sectors (Stadler et al., 2018). Such references are excluded for not representing a database of collected data on water consumption and withdrawal.

Subsequently, Table 2.2 describes water databases according to the consistency criteria. None of the databases meets all consistency criteria. From the global coverage criterion, we define two groups: global and international water databases. The latter is here defined as those composed of countries belonging to a specific group. This is the case of EUROSTAT, reporting data from members of the European Union; and the Organization for Economic Cooperation and Development (OECD) comprising data from the signatory OECD countries. All databases from Table 2.2 present a glossary with their own data definitions. Data on single industrial sectors (e.g. manufacture, electricity, services), however, are presented only by EUROSTAT, OECD, and the WaterGap model. The remaining databases treat industrial water as an aggregation of various industrial sectors. The number and type of industrial sectors in the aggregation is specific to every database.

Another important criterion involves up-to-date data. As an attempt to report the most recent information for freshwater withdrawal and consumption, databases make use of reporting and data acquiring strategies, for instance information from of national correspondents (FAO, 2021). However, we identified that both World's Water and WaterGap model only account for data from 2000 or even earlier. Up-to-date data is directly related to the reliability criterion. In this sense, we draw attention to the importance of distinguishing the year reports are updated, and the year the data refer to. To better exemplify, the updated report of the World's Water database dates from 2013, however, the observations in the report range from 1975 to 2010. Indeed, the constraints to acquire water data are known and water databases are composed of data from various years. Nevertheless, transparency is required when communicating the sources of each data point. Knowing the sources enables following back every detail of the data, such as definitions, collection method, and the organizations responsible for data collection. Our search asserts that both the World's Water and WaterGap databases lack complete information of data sources, and do not provide further details to prove for reliability.

Table 2.1. List of water references and respective country coverage

Water data references	Country coverage
EUROSTAT	EU members
EXIOBASE	Global
FAO-AQUASTAT	Global
H08	Global
OECD*	OECD, EU, G7, G20
PCR-GLOBWB	Global
UNSD	Global
Water footprint	Global
WaterGap model	Global
World's Water	Global

*OECD (35), EU (28), Euro area (17), G7, G20
Sources: EUROSTAT: https://ec.europa.eu/eurostat/web/environment/water
EXIOBASE: https://www.exiobase.eu/ (Stadler et al., 2018)
FAO-AQUASTAT: http://www.fao.org/aquastat/en/
H08:(Hanasaki et al., 2012; Hanasaki et al., 2017)
OECD: https://stats.oecd.org/BrandedView.aspx?oecd_bv_id=env-data-en&doi=data-00602-en
PCR-GLOBWB:(Sutanudjaja et al., 2018; Van Beek et al., 2011)
UNSD: https://unstats.un.org/unsd/envstats/qindicators.cshtml
Water footprint: https://waterfootprint.org/en/resources/waterstat/
WaterGap model: http://watclim.cesr.de/; (Floerke et al., 2013)
World’s Water: http://worldwater.org/wp-content/uploads/2013/07/ww8-table2.pdf

Furthermore, we analyze global and international water databases from Table 2.2 according to their data content and definitions, by applying the following water categories: Water withdrawal, water use, and procurement source. The two first categories were chosen for representing the most common data reported in water databases, while the last category informs about the differentiation between public and private water supply. Additionally, withdrawal data are also distinguished in agriculture, industry, municipal, surface, groundwater and total freshwater withdrawal. Therefore, we examine the definitions of all data categories. Moreover, sectoral aggregation is included because it informs whether data are available for single industrial sectors (e.g. manufacturing, electricity) or in an aggregated manner. Lastly, we provide information about period and collection interval. These categories describe, respectively, the years data are reported, and the frequency of water collection.

Table 2.2. Water databases and criteria for a consistent global database: Global coverage, definitions, industrial sectors, up-to-date data, and reliability

Databases	Criteria				
	Global coverage	Definitions	Single sectors	Up-to-date	Reliability
EUROSTAT		x	x	x	x
FAO-AQUASTAT	x	x		x	x
OECD		x	x	x	x
UNSD	x	x		x	x
WaterGap model	x	x	x		
World's Water	x	x			

Following from the lack of consistency on global water databases, we look for water statistics at the national level. We search specifically for official online national water statistics that report water consumption and withdrawal data. Due to human capacity, we could not search for water statistics in all countries, but had to prioritize according to the following criteria: size and economic importance/relevance in a region (e.g. Nigeria, China, Saudi Arabia, Germany, USA); the relevance in terms of water scarcity (e.g. Tanzania, Israel, Spain, India, Saudi Arabia, Chile); and countries that have comprehensive water statistics (The Netherlands, Denmark, Australia). Table 2.3 sets out the selected countries we intended to gather data from. Given the extensive data and literature search, we believe we did not overlook a country with comprehensive water statistics.

We came across several official websites and single water reports but could not find water statistics for all countries. For instance, the *"Direción General de Aguas" (DGA)*[2] is a public authority responsible to manage the water resources in Chile. The DGA reports an extensive list of data referring to water rights, water market, characteristics of water resources, among others. However, we did not find data on water withdrawals and consumption. We also examined the *"Escenarios Hídricos 2030 Chile"*[3], which is a big national collaboration of public and private entities to promote dialog and agreement towards water issues. The initiative developed an extensive report accounting for aspects of water in Chile, as well as definitions of water terms. Similarly, in Mexico, the government created CONAGUA[4], which is an authority responsible to promote sustainable water resources management and water security. We could not find freely-accessible water consumption and withdrawal information. We further consulted the 2011 water statistical report released by CONAGUA. The report contains various aspects of water resources and use in Mexico. In Colombia, the national department of statistics (DANE- *Departamento Administrativo Nacional de Estadística*)[5] is the official agency to manage national data. Despite accounting for environmental statistics, water data are not reported. Similarly, for countries like South Africa[6], Tanzania[7], Japan[8], and Morocco[9], we identified statistical reports but did not find comprehensive online water statistics platforms. Respectively for India[10] and Russia[11], we came across governmental water reports, which did not contain the targeted data, and we were not able to assess them due to language limitations. Our search on Nigeria, Uganda, Bangladesh, and Argentina was not successful. For the

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[2] Chilean governmental general water authority https://dga.mop.gob.cl/Paginas/default.aspx

[3] Escenarios Hídricos 2030. We looked into the 2018 report "Radiografía del Agua: Brecha y riego hídrico en Chile". Source: htpp:// escenarioshidricos.cl/publicaciones/

[4] CONAGUA website: https://www.gob.mx/conagua
The 2011 water report: http://www.conagua.gob.mx/CONAGUA07/Publicaciones/Publicaciones/SGP-1-11-EAM2011.pdf

[5] DANE website: https://www.dane.gov.co/

[6] Statistics South Africa: http://www.statssa.gov.za/?page_id=595
South Africa 2010 water report: https://www.statssa.gov.za/publications/D04058/D04058.pdf

[7] The National Environment Statistics Report, 2017 contains several aspects of water management in Tanzania: https://www.nbs.go.tz/nbs/takwimu/Environment/NESR_2017.pdf

[8] Japan Water Agency (Independent Administrative Corporation) website: https://www.mlit.go.jp/tochimizushigen/mizsei/water_resources/contents/corporation.html
For reports of the Ministry of Land, Infrastructure, Transport and Tourism: htpp://www.mlit.go.jp/en/index.html

[9] The annual reports from the General Division of Statistic encompass general information of water use across productive sectors: https://www.hcp.ma/Bookcases-des-Annuaires-Statistiques-du-HCP_a2071.html

[10] The report "River Basin Atlas of India" contains noteworthy information of water resources in India. However, it does not contain empirical data on water use. Source: Government of India Ministry of Water Resources http://nwm.gov.in/?q=surface-water-2

[11] FAO reports water withdrawals from Russia based on the Federal Agency of water resources 2018 report. The reference is available only in Russian, which hinder our analysis due to language capacity. Source: http://www.mnr.gov.ru/docs/proekty_pravovykh_aktov/proekt_gosudarstvennogo_doklada_o_sostoyaii_i_ob_okhrane_okruzhayushchey_sredy_rossiyskoy_federatsi/

remaining countries of Table 2.3, the water statistics are further analyzed based on the definitions of water data content and the institutions engaged to collect and report water data.

Table 2.3. Regional selection of countries as targets of further water data search

Region	Countries
Africa	Egypt, Morocco, Nigeria, South Africa, Tanzania, Tunisia, Uganda
Asia	Bangladesh, China, India, Japan, South Korea
Middle-East	Saudi Arabia, Israel, Palestine
North America	Canada, USA
Central America	Mexico
South America	Argentina, Brazil, Chile, Colombia
Oceania	Australia, New Zealand
Europe	Croatia, Denmark, France Germany, Ireland, The Netherlands, Poland, Portugal, Spain, Sweden, United Kingdom, Russia

4. Results

The results are described for global and national databases. Section 4.1 contains the analysis of global and international water databases, by highlighting their data content and definitions. Section 4.2 presents water national statistics across region and describes the type of data reported and definitions.

4.1. Global and international databases

Table 2.4 presents the data structure of global and international databases. Water withdrawal is the most readily available water information across the databases. In addition to presenting the total amount of water withdrawal, FAO and UNSD differentiate between surface and groundwater withdrawal. However, withdrawal data reported by both UNSD is based on FAO. The exchange of data information occurs among all databases. For instance, according to the data glossaries, OECD reports European water accounts from EUROSTAT. FAO is the main statistical database for water resources and management in agriculture. FAO*s* data quality is highly diverse, however, no other database presents similar crop and country coverage for water resources (Berrittella et al., 2007). Distinguishing between surface and groundwater withdrawal is important since both sources have particular characteristics and compete with different users (Hertel & Liu, 2014). Surface water availability varies with climatic conditions (e.g. precipitation and vegetation cover) (Hertel & Liu, 2014), and is the dominant source for irrigation (Wada et al., 2013). Groundwater is less vulnerable to climatic variation and is recharged according to precipitation (Hertel & Liu, 2014).

Water use is less frequently reported. This information is available only in EUROSTAT, WaterGap model and the World's Water databases. However, special attention should be given to the term "use", as it might be applied with different meanings, either referring to consumption or general terms of water manipulation. This distinction is key to understand the specific definition of water terms to avoid confusion. Seldom available is the differentiation of procurement sources. Water is either supplied by a public procurement or self-abstracted. Such information is available in the OECD and the EUROSTAT data platforms. For instance, industrial water is largely self-supplied as companies invest in the private infrastructure of water caption (Hertel & Liu, 2014; Rio Carrillo & Frei, 2009). This informs how sectors are reliant on the public water supply system.

Table 2.4. Informational content of global water databases, type of data available, timeframe coverage and collection period

Database	Withdrawal			Use	Procurement source	Aggregated industrial sectors	Period	Collection interval
	Total	Surface	Ground					
EUROSTAT	x	x	x	x	x		2009-2018	yearly
FAO-AQUASTAT	x	x	x			x	1960-2015	5 years
OECD*	x				x		1970-2018	yearly
UNSD**	x	x	x			x	1990-2016	yearly
WaterGap model	x			x			various	irregular
World's Water	x			x		x	various	yearly

*Data partly sourced from EUROSTAT.
**Data partly sources from National Statistics, OECD, and EUROSTAT.

Concerning industrial water, data are often reported as an aggregation of various sectors. Each database aggregates sectors differently, which hampers comparison among them. In other words, relating industrial water withdrawal among FAO, UNSD, and World's Water is not possible due to diverse sectoral aggregation. Disaggregated industrial water accounts (e.g. manufacturing, cooling and electricity, and services) are provided by OECD, EUROSTAT, and the WaterGap model, yet with own classifications.

Although the period category in Table 2.4 indicates a large sample of years, water observations are not available for all years and all categories. For instance, the manufacturing water supply in EUROSTAT for The United Kingdom is only available for the year 2011, or Switzerland for 2012. Databases have to deal with lack of data and, therefore, make use of mechanisms to impute and estimate water quantities. The WaterGap model is an exception to this spotty coverage because it is not a water database engaged to collect or report data. Instead, the WaterGap model acquires data from various sources in the development of the model. The water literature heavily uses the model as a database due to its sectoral and country coverage.

Using water data in a coherent way depends on concise comprehension of how data are composed and defined. Table 2.5 contains the definitions of water categories that are used in the selected international and global water databases. Water withdrawal is divided into production sectors that receive water and the type of source water is abstracted from. FAO breaks down withdrawal into industry, agriculture, and municipal activities. Industry encompasses thermoelectric cooling and nuclear power plants, dairy and meat industries, and industrial processing of harvested agricultural products (excludes hydropower). Agriculture, in turn, considers water withdrawn for irrigation, livestock, and aquaculture purposes. In the FAO accounts, water in industries and agriculture is only self-supplied, while the municipal category refers to the water provided by the public system for domestic activities, and industrial purposes. Water is abstracted from surface and groundwater resources. FAO also differentiates the amount of water taken from such resources. Surface withdrawal is defined as the water extracted from rivers, lakes, and reservoirs (including returned water). Groundwater withdrawal, in turn, is defined as the removal of water from groundwater resources. Total freshwater withdrawal is the sum of surface and groundwater withdrawals, subtracting water that is made available by other means (e.g. desalination and municipal treatment).

In contrast to FAO, the OECD presents water withdrawal for single industrial sectors, such as mining, cooling and electricity, and for irrigation agriculture. The data only refers to water removed from a public procurement, and there is no differentiation between surface and groundwater resources. Water use is defined as the “use of water by agriculture, industry, energy production and households, including in-stream uses such as fishing, recreation, transportation and waste disposal”. This definition does not sufficiently clarify whether “use” refers to a general term of water manipulation, or to a specific water category. Apart from withdrawal quantities, there is no additional data available in the OECD.

Table 2.5. Definitions of selected water categories used in international and global water databases

Global databases	Water withdrawal						Water use	Public private ratio
	Industry	Agriculture	Municipal	Surface withdrawal	Groundwater withdrawal	Total freshwater withdrawal		
EUROSTAT	Process of taking water from a source. Surface and groundwater water collected for use by households and enterprises. Includes public and private water supply for mining, manufacturing, constructions, households, agriculture, forestry, fishing, and services.			Removal of water from natural or artificial waterways containing freshwater, including lakes, rivers, streams and canals.	Process of removing freshwater from underground sources, either temporarily or permanently.	Percentage of its long-term annual average available water from renewable ground freshwater resources	Water actually used by end users (e.g. households, services, agriculture, industry) within a territory for a specific purpose such as domestic use, irrigation or industrial processing.	Public: Water supplied by economic units engaged in collection, purification and distribution of water. Private: Abstraction of water by the user for own final use.
FAO-AQUASTAT	Self-supplied withdrawal for thermoelectric cooling and nuclear power plants; water for dairy and meat industries and industrial processing of harvested agricultural products. Does not include hydropower.	Self-supplied water withdrawal for irrigation, livestock and aquaculture purposes.	Withdrawal for the direct use by population. It is usually computed as the total water withdrawn by the public distribution network (includes industrial public supply).	Water extracted from rivers, lakes and reservoirs. Includes withdrawal of primary and secondary (water previously withdrawn and returned) renewable surface water resources.	Water extracted from aquifers. Includes renewable primary, secondary groundwater, and water from over-abstraction of renewable groundwater or from fossil groundwater.	Sum of surface and groundwater subtracting (desalinated water, direct use of treated municipal wastewater, direct use of agricultural drainage water).	*No data*	*No data*
OECD	Freshwater removed from ground or surface water resources (permanently or temporarily) and conveyed to a place of use. Refer to public water supply for irrigation, industrial processes and cooling of electric power plants. Includes mining and drainage, excludes hydroelectricity generation.			*No data*	*No data*	*No data*	Use of water by agriculture, industry, energy production and households. Includes in-stream uses (e.g. fishing, recreation, transportation, and waste disposal).	*No data*
UNSD	Water removed from any water source (surface water sources, such as rivers, lakes, reservoirs or rainwater; and groundwater sources) either permanently or temporarily. Includes abstraction by the water supply industry for distribution and direct abstraction by other activities for own use.			Water removed from any surface sources (permanently or temporarily).	Water removed from any groundwater source (permanently or temporarily).	*No data*	*No data*	*No data*
WaterGap model	Total amount of water that is taken from the terrestrial part of the water cycle.			*No data*	*No data*	*No data*	Part of the withdrawal that does not return to the terrestrial water cycle.	*No data*
World's Water	Water removed from a source for use. Includes water use for power plant cooling and industrial production.	Water abstraction for irrigation and livestock	Household, municipal, commercial and governmental water use.	*No data*	*No data*	*No data*	Withdrawal and use are synonyms.	*No data*

EUROSTAT presents information for all water categories. Withdrawal is defined as the process of taking water from surface and groundwater resources. Data are available for single industrial sectors such as mining, manufacturing, construction, and services, both by public and self-supplied water. Surface withdrawal refers to the removal of water from surface resources, such as lakes, rivers, streams, and canals, while groundwater is the *"process of removing freshwater from underground sources, either temporarily or permanently"*. Public procurement is the network unit that collects, purifies, and distributes water to various activities. Private supply is the abstraction of water by the user for their own final use. EUROSTAT also provides data for water use, defining the data as water "*actually used by end users*". In general terms, the definition is not sufficient to assert whether the data refers to water consumption or any other category of water utilization.

Water abstraction in the UNSD database is defined as the amount of water removed from a surface or groundwater resource permanently or temporarily. Data are not differentiated between industry, agriculture, and domestic sectors, but represent the sum of yearly withdrawal quantities of sectors altogether. The sectoral aggregation is not clear, because it is obtained from numerous sources. In fact, there are several notes throughout the UNSD data reports concerning data quality, and that data definitions and estimation methods vary substantially. Yearly surface and groundwater abstraction numbers are available and refer to the water temporarily or permanently removed from surface and groundwater resources.

The WaterGap model defines withdrawal as the removal of water from the water cycle, and use as the water that does not return to the terrestrial cycle. The World's Water database breaks down water withdrawals into industry (water withdrawal for power plant cooling and industrial production), agriculture (irrigation and livestock), and municipal sectors (household, municipal, commercial, and governmental water use). There is no clear specification for industrial processes; neither there is a differentiation of surface and groundwater resources, nor public and self-supplied water. Water use, however, corresponds to a general term implying water manipulation, and here applied as a synonym of withdrawal.

4.2. National Statistics

Table 2.6 sets out countries (from the preselected list) that have an established national water statistical system. Even in industrialized nations with comprehensive water statistics, elements such as water reporting, collection period, and definitions vary significantly. The institutions responsible to collect, monitor and report water statistics are predominantly governmental agencies, but in some countries also scientific research institutes report (e.g. The United States of America), and independent agencies (e.g. Portugal and New Zealand).

We identified water statistics mostly from European countries. Detailed sectoral data are also available for Oceania and North America. Latin America, Asia and Africa are underrepresented, as we could only identify official online national water statistics for few countries from these regions. Table 2.6 displays some of the water categories reported by every national database, followed by their definitions. For instance, Canada reports statistics on water use and water withdrawal for various industrial sectors, both on national and county level. In the Canadian database, water withdrawal is defined as the amount of water extracted from water bodies, either surface or groundwater resources; whereas water use is generally related to the utilization of water to support economic activities and residential sectors. The Canadian water statistics also report water consumption, water discharge, and other categories. For simplification, these terms are not presented, yet the level of detail on definitions and sectoral disaggregation is noticeable. The data structure and definitions of water categories of the USA statistics are very similar to the Canadian water statistics. Data are collected every five years, available at the country and state levels, differentiating industrial sectors and type of procurement. Likewise, water use is not defined as a synonym of consumption; rather it is related to production activities, such as aquaculture, hydropower generation, irrigation, domestic purposes, among others.

Out of the selected Latin American countries, the only water statistics platform found was from Brazil. Water withdrawal and consumption are available for various industrial sectors that are supplied by the public water system. The definition of withdrawal is similar to the previous sources. Consumption is the part of the water withdrawal that does not return to the hydrological cycle, which also corresponds to the definitions presented in the aforementioned databases.

Similarly, Australia and New Zealand have detailed water statistics, covering various productive sectors, and surface as well as groundwater resources. Australia differentiates public and self-supplied water. Water use is defined as the sum of distributed water, self-supplied water, and reused water, therefore suggesting that use refers to various types of water manipulation. In turn, water consumption is the subtraction of instream water use and the distribution of water to other sectors from total water use. In the New Zealand database, the definitions *per se* are not available. The information about water use suggests that the database distinguishes between consumptive and non-consumptive water use, where consumptive use is the water use not returned to its original stream.

Water statistics from Africa are available for Egypt and Tunisia. Egypt statistics presents yearly water consumption and water produced for non-residential units (e.g. city councils, industrial plants, and water companies). Nevertheless, detailed information of definitions and the collection process are not provided. Similarly, Tunisian statistics reports data for water supply and use but further details are not available.

In Asia, water statistical systems are found for China and South Korea. Chinese statistics report water supply and use from 2000 to 2014, both at the country and city levels. The accounts are presented for agriculture, households, and industry. Water supply is defined as the water removed from different water resources (synonym of withdrawal). Water use is the water provided for different activities. There is no differentiation of water consumption and discharge, and water use across activities sums the total water supply. For South Korea, the Statistical Information Service reports water supply and consumption at the district level. Information on water supply is represented by the amount of private and public water works (water utilities) in every district, and the amount of water supplied (m^3 per day) by water works. Water supply data is available from 2008 to 2018. Water consumption is reported in thousand cubic meters per year (from 1991 to 2018). The South Korean water statistics does not provide data definitions, which hampers further analysis or comparison to other databases.

In the Middle-East, we found water statistics for all three selected countries. Saudi Arabia reports water statistics for consumption, supply, and various aspects of desalinated water. Water consumption and use are treated as synonyms and are defined as the water withdrawal that does not return to its original source. Data are available for agriculture, industries, and municipal uses. Water supply is the main source of drinking water. It includes water purification, a public system to distribute water to households, water preserved in bottles, and water taken from wells located close to households. Israeli statistics report data on water consumption and water production. Water production is defined as "pumping water" to main consumers. However, the glossary does not present the definition of water consumption. For the Palestinian statistics, consumption and withdrawal are synonyms. Although the definition of withdrawal refers to water removal for various economic activities, data refer only to water in the domestic sector.

Water statistics are well documented in Europe, but every national water reporting system presents particular structures of data collection and reporting. In various online water platforms, explicit definitions are not readily available, at least in English. This is the case of Czech Republic, Denmark, Ireland, and The United Kingdom. Nevertheless, Denmark Statistics provides details regarding the collection and reporting process. Water data are differentiated by public and self-supplied water; accounts are available for water supply, discharge, extraction, and consumption for agriculture, domestic, and various industrial sectors. Information privately provided by the Danish Statistics indicate that water use and consumption are treated as synonyms. European countries displayed in Table 2.6 have different water definitions. In the Dutch statistics, water use is the combination of self-abstracted water, and water provided by external procurements (similar to the Spanish statistics). The Swedish statistics, however, regards water use as the sum of the water abstracted and purchase but subtracting water that returns to the hydrological cycle. In the Dutch statistics, water use also accounts for leakages, which is similar to the definition of water extraction in the German statistics.

Table 2.6. Informational content, definitions, and institutions of national water statistical systems

Region	Information content	Definitions	Institution
North America			
Canada	Water use in industries and household	**Water Withdrawal:** Water extracted from water bodies. **Water use:** Water withdrawn from water resources to support society in economic and residential sectors.	Governmental Agency
USA	Water use, withdrawal, public supply, domestic, thermoelectric, industrial, mining, aquaculture and irrigation, livestock	**Withdrawal for each category of use:** total amount of water removed from the water source for a particular use. **Water use:** water that is used for a specific purpose.	Scientific Institution
South America			
Brazil	Water use in industries, irrigation, hydropower generation	**Water Withdrawal:** Water extracted from water resources. **Water consumption:** Water withdrawal that does not return to the hydrological cycle.	Governmental Agency
Oceania			
Australia	Water use, consumption in various productive sectors	**Total water use:** Sum of distributed water use, self–extracted water use and reuse. **Water consumption:** Total water use minus in–stream water use and distributed water supplied to other users.	Governmental Agency
New Zealand	Water use and consumption	**Water use:** Distinguished between consumptive and non-consumptive water use. **Consumptive uses:** Water uses in which water is not returned to its original stream.	Governmental Agency Independent Research Institute
Africa			
Egypt	Water consumption in companies, water produced	*No definitions reported*	Governmental Agency
Tunisia	Total water use and supply	*No definitions reported*	Governmental Agency
Asia			
China	Water supply and use.	**Water supply:** Water removed from different water resources. **Water use:** Water provided to different activities.	Governmental Agency
South Korea	Total water consumption, water supply	*No definitions reported*	Governmental Agency
Middle- East			
Saudi-Arabia	Water consumption, water use, supply	**Water consumption:** Quantity of water consumed (used) in a corporation, which does not return to its original source after being withdrawn. **Water supply**: Main Source of drinking water including: distributed water, bottles, wells, purification, public power network.	Governmental Agency
Israel	Water production and consumption	**Water Production:** Pumping water. **Water Consumption:** No definition reported	Governmental Agency
Palestine	Water supply and consumption for the domestic sector, agriculture supply	**Water consumption:** Water withdrawn from groundwater or surface resource for industrial, domestic and irrigation purposes or for any other use.	Governmental Agency

Europe			
Croatia	Water supply and water utilization	**Water supply:** Water used in supplying enterprises/trade companies, irrespective of whether it was used for own purposes or sold to other users. **Water utilization:** Water used by a reporting unit for its own purposes in the period of one year.	Governmental Agency
Czech Republic	Public water supply	**Water Production:** Pumping the water. **Water Consumption:** Carrying water to the main consumers.	Governmental Agency
Denmark	Water supply, discharge, consumption	**Water use:** Same as water consumption. **Water supply:** Water abstracted by public waterworks – loss in handling of the water.	Governmental Agency
France	Water withdrawal	**Water withdrawal:** all abstractions related to activities generated by agriculture, industry (including energy), drinking water supply, or others.	Governmental Agency
Germany	Water extraction, public and non-public water extraction	**Public supply:** Water daily distributed.	Governmental Agency
Ireland	Domestic metered public water consumption	*No definitions reported*	Governmental Agency
The Netherlands	Water use and abstraction	**Water use** (including leakage): Combination of 'self-abstracted/produced and used water' added to the amount produced and supplied by others, for the distinguished water types.	Governmental Agency
Poland	Consumption of water for needs of the national economy and population during the year	**Water consumption:** Water used by the plants for production, exploitation, administration purposes or for social and living needs of employees (excludes water delivered to residential buildings located in the plant).	Governmental Agency
Portugal	Water withdrawal, water supply, water consumption	**Water Withdrawal:** Water used from surface and ground water for various activities. **Water supply:** Distribution of water to various activities. **Water Consumption:** Water provided to registered consumers.	Autonomous Public Agency
Spain	Water supply for various economic activity	**Water use:** Water used (from self and public supply) that has an entry into the industrial establishment to provide for the needs of the productive process. **Water Consumption:** Water that, after being used, does not return to the environment.	Governmental Agency
Sweden	Water withdrawal and use	**Water use:** Abstracted water added to purchased water minus returned water (water returned without use).	Governmental Agency
United Kingdom	Public and self-supply of water for England and Wales	*No definitions reported*	Non-ministerial Office

Sources:
Statistics Canada: https://www.statcan.gc.ca/eng/about/about?MM=as
United States Geological Survey: https://www.usgs.gov/media/images/categories-water-use
Brazilian National Water Agency: https://www.ana.gov.br/
Australian Government Bureau of Meteorology: http://www.bom.gov.au/water/waterinaustralia/
Australian Bureau of Statistics:
https://www.abs.gov.au/AUSSTATS/abs@.nsf/Lookup/4610.0Explanatory%20Notes12015-16?OpenDocument
New Zealand Ministry for the Environment: https://www.mfe.govt.nz/
New Zealand Institute of Economic Research: https://nzier.org.nz/
Egypt Data Portal: https://egypt.opendataforafrica.org/xbeofib/clean-water-produced-consumed-by-use-egypt-2007-2013
Tunisian Statistics: http://www.ins.tn/en/themes/environnement#sub-378

China Statistical Yearbook: http://www.stats.gov.cn/tjsj/ndsj/2015/indexeh.htm
South Korea Statistical Information Service: htpp://kosis.kr/eng/index/index.do
Saudi Arabia General Authority for Statistics: htpp://www.stats.gov.sa/en
Israel – Central Bureau of Statistics: https://www.cbs.gov.il/en/Pages/default.aspx
State of Palestine: http://pcbs.gov.ps/site/lang__en/771/default.aspx
Croatian Bureau of Statistics: https://www.dzs.hr/default_e.htm
Czech Statistical Office:
https://vdb.czso.cz/vdbvo2/faces/en/index.jsf?page=statistiky#katalog=30842
Statistics Denmark: https://www.statbank.dk/statbank5a/default.asp?w=1680
French Ministry of Ecological Transition (Ministère de la transition Écologique) - EAU France: www.data.eaufrance.fr
Glossary:www.glossaire-eau.fr/sites/default/files/glossaire_eau_biodiv_en_20210608.pdf?v=1623167652
German Federal Office of Statistics: https://www.destatis.de/DE/Home/_inhalt.html
Ireland Central Statistics Office: https://www.cso.ie/en/
Dutch Central Statistical Office (CBS):
https://opendata.cbs.nl/statline/portal.html?_la=nl&_catalog=CBS
Statistics Poland: https://bdl.stat.gov.pl/BDL/start
Statistics Portugal: https://www.ine.pt/xportal/xmain?xpid=INE&xpgid=ine_main
Spanish Institute of Statistics: https://www.ine.es/en/index.htm
Statistics Sweden: https://www.scb.se/en/
UK Office for National Statistics: https://www.ons.gov.uk/

These differences imply that combining and comparing such data requires a careful analysis of the definitions. The Polish statistics, for instance, define water consumption as general means of water manipulation. It does not seem to consider returned water and leakages. From that, comparing water consumption between Poland and Spain would not be possible, because the Spanish statistical system computes water consumption as the volumes of water used in various activities, and does not return to the hydrological cycle after use. Additionally, Portuguese water consumption would also not allow any comparison as it refers to the water provided or supplied to registered consumers.

5. Discussion

Our study investigates the state of the arts of global, international, and national water databases accounting for water withdrawal and consumption. We provide an approach for water data search, followed by the analysis of data definitions and consistency. The need for water data and improvement of water statistics are widely acknowledged (Floerke et al., 2013; Gleick, 2003; Ortigara et al., 2018; Rijsberman, 2006; United Nations, 2018; Zeng et al., 2013). In the political sphere, the United Nations have placed increasing efforts to improve the SDG 6 data monitoring and reporting. There are considerable data challenges to progress towards the SDG 6 targets for sanitation, water quality, resources management, and water use (Ortigara et al., 2018; United Nations, 2018). Nevertheless, this paper does not focus on the SDG debates. Rather, the analysis of water data centers on potential for future (economic) water research.

Water data are the basis to develop assessments and indicators, and to understand the status of water resources and management (Gleick, 2003; Rijsberman, 2006). Empirical water data are likewise essential to the development of hydrological (Hanasaki et al., 2012) and economic models, in order to obtain more robust scenario results. Nevertheless, the knowledge gap is pronounced as water statistics have very different reporting structures and often deal with obsolete data (Floerke et al., 2013). Our research indicates that few countries report own water statistics and water categories are aggregated and defined differently across databases.

Additionally, as of now, there is no prevailing method or framework to collect, monitor, and report water data. Databases must also deal with the challenge of missing data. They are constantly improving their mechanisms to acquire water accounts, and even estimate and impute data. The lack of data poses difficulties to compare observations across databases, a problem excacerbated by the fact that it is difficult to control for the differences in sectoral aggregation and definitions.

Water in agriculture is better documented than in industrial sectors. Despite of highly variable data quality, FAO reports water categories on the global level since the 1960s. However, assessing the impact of energy production, mining, manufacturing, food processing, and services in water resources is only possible with a meaningful understanding of sectoral amounts of water used, consumed, and discharged. Industrial water use concerns the intake of water by manufacturing, thermals, mines, and electricity generation (Dupont & Renzetti, 2001). Thermoelectric plants encompass nuclear and fossil fuel energy facilities (Inhaber, 2010). Water is used in various processes in the industrial production chain. Besides being part of the final output, water is used for cooling and for steam production as an intermediate input (Dupont & Renzetti, 2001). In power plants and manufacturing facilities, water is reused to reduce effluent steam, recapture raw materials, and reduce energy costs (Dupont & Renzetti, 2001). Water and energy are intrinsically related as water is essential to energy production, and distributing water across services requires energy. In the USA, for instance, energy production demands way more water than any other industrial sector (Inhaber, 2010). In general terms, power generation is one of the biggest water-demanding sectors (Rio Carrillo & Frei, 2009). However, the amount of water that is consumed within the production system represents a small share of total industrial abstractions. The main reason for this discrepancy is that water is mainly utilized for cooling purposes, and is subsequently discharged back into the cycle to potential downstream uses (Hertel & Liu, 2014).

Looking at the complexity of water flows in industries, detailed water data could potentially refine the analyses from volumes to water values. Economic assessments would be able to identify the water values to upstream and downstream users, as well as the opportunity costs of water in various production activities. Considering solely total water withdrawal or supply limits the understanding of the real utilization and value of water within the production processes. The available industrial water databases, however, show insufficient evidence of water consumption and discharges and often report industries as an aggregation of various industrial sectors altogether. Moreover, as there are insufficient policy enforcements to regulate water, industries mostly capture water by their own structural means. Therefore, prices are often non-existent.

From a political science perspective, Berg (2020) provides an extensive analysis of data that is used to support policy action. He asserts that improving data quality is crucial as reliable information could help policy makers and analysts to potentially avoid inefficient investments and inadequate operational incentives. Reliability here means that decision-makers are informed about the whole process of data collection, communication, and storage. Enhancing data reliability strengthens the collaboration of private and public initiatives involved in water utility management, but also supports the development of key performance indicators and benchmarking to regulate operations in developing nations.

Nevertheless, acquiring water data from low income countries is challenging due to several reasons: records and registers might have been destroyed during conflicts; data might be stored in “information silos” and in a hard way to access; collecting and cataloging water data might not be a priority when compared to other public services; low human resources to improve data reporting into information systems; management boards might avoid transparency to conceal operational disruptions and corruption (Berg, 2020). These reasons suggest that the lack of data is both a financial problem to establish a systematic structure of data collection and reporting, and also an intentional way to avoid transparency and, therefore, maintaining corruption, and the gains of those who benefit from investment in the water sector (Berg, 2020). In fact, the lack of data does not incentivize policy makers to improve inefficient utilities as society is not informed about the problems and inadequate practices (Berg, 2007).

A way to respond to this problem would be establishing data collection and reporting procedures as a condition to obtain investment funds from development agencies, governments, and other funding initiatives in general (Berg, 2020). Systematic data collection enables benchmarking strategies, which are instruments to compare the performance of water utilities and indicators at the local level and across nations over years (Berg, 2007). In regions with limited technical resources, training community-based organizations to collect water data represents an alternative to monitoring water utilities and resource management (Berg, 2020). A good practice would be providing data to a central operation that is able to analyze the data content and sources, in a way to enhance data accuracy (Berg, 2020).

Improving the procedures to collect and report water data, or even successfully applying the above-mentioned suggestions is unlikely to be implemented in the near future. Yet, reliable data are key to understand and interpret limited information about water availability and use. Definitions of water categories are essential when assessing the consistency and comparing data from various sources. Following from that, our study selects two important water categories (consumption and withdrawal) and investigates the data treatment in terms of definitions and data reporting. For that, we analyze the scientific literature, and global and national databases. Despite structural and conceptual differences in the data sets, the exchange of data is common among international and global databases. In fact, they mostly rely on national statistics to acquire data. The definitions of different water categories provided in previous chapters, indicate that comparing, or even combining various water accounts is difficult and often misleading. The definitions of water categories are diverse, either regarding how numbers are composed of or what they represent. Given the differences in definitions, there is no evidence of data harmonization among international and global databases.

Harmonization supports interpretation, access, monitoring, and reporting of data (Porter et al., 2014). Collaborative research initiatives for model harmonization have allowed comparing and improving biophysical and economic models to assess food security, hunger, and food price volatility (Porter et al., 2014). Additionally, Fuchs et al., (2013) harmonized various data sources to develop accurate historical land change data in Europe. Following such initiatives unfolds the potential for water modelers to likewise develop water data harmonization. Water economic research relies on data for different productive sectors at the local and global levels. The absence of data is a reality. Moreover, the state of the arts of water databases suggests that there is little consistency in defining water categories, and various methods for data collection trigger uncertainty when comparing data. Such issues call for policy enforcements to improve data collection at the national level, and possibly together with national statistical agencies. Nevertheless, implementing water data collection depends on political efforts particularly from sovereign estates. Such endeavor is not likely to be met in the short or medium run. Alternatively, joining efforts of modellers to develop meaningful ways of dealing with water data problems, would facilitate data interpretation and collaboration of institutions worldwide.

This study provides a list of global and national water databases, their reporting structure, definitions, and organizations responsible for data management. We show that data are treated differently across databases, and that even in the pre-selected countries, lack of data is evident and low-income nations are underrepresented. Nevertheless, this paper can be potentially used as a “starting point” to initiate water reporting in places where water statistic system is still missing. Moreover, throughout the paper we discuss essential aspects to bear in mind when communicating water data.

Meanwhile, databases undergo ongoing improvements of water data especially to estimate missing values. However, when using and comparing the currently available water data, it is key to critically analyze what each number actually represents, understand to which level data are comparable, and think carefully about how they can be used to estimate reliable results.

6. Conclusion

Following the knowledge gap often pointed out in the water literature and the difficulties of acquiring water data to support studies in various fields, we assess the state of the arts of water databases at global, international, and national levels. This paper distills important information regarding water data availability across regions, and presents the structure of databases as well as data compositions and definitions. We address the importance of clarifying water definitions, and promoting a concise report and monitoring, especially when employing the currently available data for policy and research assessments. The overall conclusion is that there are considerable inconsistencies of available data, which hamper comparison across databases.

In times where water is present in many political debates, evaluating the global interplay of water resources and scarcity requires refined water models, which in turn rely on water data. In the long run, headway of water research and political assessments depend on political enforcements to refine the meaningfulness of water data and support water collection, reporting, and monitoring. However, lack of data transparency and weak governmental enforcement to establish water utility monitoring may also be intentional due to economic interest of those controlling water resources. Alternatively, in the short and medium run, water data challenges can be addressed by joint research efforts for water data harmonization. Following from that, developing model comparison exercises would not only contribute to international research cooperation, improve communication about water issues internationally and among policy makers, refine evaluation of uncertainties, improve integration of assessments, compare water models, and support the implementation of policy relevant water issues.

It is unrealistic to expect the goals of improving data harmonization, collection, and even definitions will be met in the near future. However, this paper contributes to raising awareness in the scientific community on the need to improve water reporting and diminish the knowledge gap, and further investigate the potentials to improve water data reporting. Moreover, our study cautions researchers to be careful when manipulating and comparing the available water data. Especially when deriving policy recommendations or economic conclusions based on the *status quo* databases, the use of the data requires a critical analysis of what data actually represent and how they can be translated into realistic findings.

References

Ait-Kadi, M. (2016). Water for development and development for water: Tralizing the Sustainable DEvelopment Goals (SDGs) Visiom. *Aquatic Procedia*, *6*, 106–110.

Banda, B. M., Farolfi, S., & Hassan, R. M. (2007). Estimating water demand for domestic use in rural South Africa in the absence of price information. *Water Policy*, *9*(5), 513–528.

Berbel, J., & Gómez-Limón, J. A. (2000). The impact of water-pricing policy in Spain: an analysis of three irrigated areas. *Agricultural Water Management*, *43*(2), 219–238.

Berg, S. V. (2007). Conflict resolution: benchmarking water utility performance. *Public Administration and Development: The International Journal of Management Research and Practice*, *27*(1), 1–11.

Berg, S. V. (2020). Performance Assessment Using Key Performance Indicators (KPIs) for Water Utilities: A Primer. *Water Economics and Policy*, *6*(02), 2050001.

Berritella, M., Hoekstra, A. Y., Rehdanz, K., Roson, R., & Tol, R. S. J. (2007). The economic impact of restricted water supply: A computable genera; equilibrium analysis. *Water Research*, *41*, 1799–1813.

Berrittella, M., Hoekstra, A. Y., Rehdanz, K., Roson, R., & Tol, R. S. J. (2007). The economic impact of restricted water supply : A computable general equilibrium analysis. *Water Re*, *41*, 1799–1813. https://doi.org/10.1016/j.watres.2007.01.010

Berrittella, M., Rehdanz, K., Roson, R., & Tol, R. S. J. (2005). The Economic Impact of Water Pricing: A Computable General Equilibrium Analysis. *Rep. FNU-96, Res. Unit Sustainability and Global Change, Hamburg University*. Hamburg.

Berrittella, M., Rehdanz, K., Roson, R., & Tol, R. S. J. (2008). The economic impact of water taxes: A computable general equilibrium analysis with an international data set. *Water Policy Not Known*, 1–14. https://doi.org/10.2166/wp.2008.003

Calzadilla, A., Rehdanz, K., Roson, R., Sartori, M., & Tol, R. S. J. (2016). Review of GCE Models of Water Issues. In *Computable General Equilibrium Models* (pp. 101–123).

Calzadilla, A., Rehdanz, K., & Tol, R. S. J. (2008). Water scarcity and the impact of improved irrigation management : A CGE analysis. *Kiel Working Paper, No. 1436*.

Calzadilla, A., Rehdanz, K., & Tol, R. S. J. (2010). The economic impact of more sustainable water use in agriculture: A computable general equilibrium analysis. *Journal of Hydrology*, *384*(3–4), 292–305. https://doi.org/10.1016/j.jhydrol.2009.12.012

Dupont, D. P., & Renzetti, S. (2001). The role of water in manufacturing. *Environmental and Resource Economics*, *18*(4), 411–432. https://doi.org/10.1023/A:1011117319932

El Kharraz, J., El-Sadek, A., Ghaffour, N., & Mino, E. (2012). Water scarcity and drought in WANA countries. *Procedia Engineering*, *33*, 14–29.

EUROSTAT. (2020). EUROSTAT. Retrieved February 13, 2020, from https://ec.europa.eu/eurostat/statistics-explained/index.php/Water_statistics

EXIOBASE. (2020). EXIOBASE Database. Retrieved June 10, 2020, from https://www.exiobase.eu/

Falkenmark, M. (1995). *Land-water linkages: a synopsis. In: land and water integration and river basin management*. Rome, Italy.

FAO. (2020). Food and Agriculture Organization of the United Nations. AQUASTAT Core Database. Retrieved January 1, 2020, from http://www.fao.org/nr/water/aquastat/data/query/ index.html

FAO. (2021). The AQUASTAT methodology. Retrieved November 11, 2019 from http://www.fao.org/aquastat/en/overview/methodology

Floerke, M., Kynast, E., Baerlund, I., Eisner, S., Wimmer, F., & Alcamo, J. (2013). Domestic and industrial water uses of the past 60 years as a mirror of socio-economic development: A global simulation study. *Global Environmental Change*, *23*, 144–156.

Fuchs, R., Herold, M., Verburg, P. H., & Clevers, J. G. P. W. (2013). A high-resolution and harmonized model approach for reconstructing and analysing historic land changes in Europe. *Biogeosciences*, *10*(3), 1543–1559. https://doi.org/10.5194/bg-10-1543-2013

Fujimori, S., Hanasaki, N., & Masui, T. (2017). Projections of industrial water withdrawal under shared socioeconomic pathways and climate mitigation scenarios. *Sustainability Science*, *12*(2), 275–292. https://doi.org/10.1007/s11625-016-0392-2

Gaudin, S. (2006). Effect of price information on residential water demand. *Applied Economics*, *38*(4), 383–393.

Gaudin, S., Griffin, R. C., & Sickles, R. C. (2001). Demand specification for municipal water management: evaluation of the Stone-Geary form. *Land Economics*, *77*(3), 399–422.

Gibbons, D. C. (1986). *The economic value of water*. Washington, D.C.: Resources for the Future.

Gleick, P. H. (2003). Water Use. *Annual Review of Environment and Resources*, *28*, 275–314.

Hanasaki, N., Fujimori, S., Yamamoto, T., Yoshikawa, S., Masaki, Y., Hijioka, Y., Kainuma, Y., Kanamori, Y., Matsui, T., Katahashi, K., Kanae, S. (2012). A global water scarcity assessment under shared socio-economic pathways - Part 2: Water availability and scarcity. *Hydrology and Earth System Sciences Discussions* (Vol. 9). https://doi.org/10.5194/hessd-9-13933-2012

Hanasaki, N., Yoshikawa, S., Pokhrel, Y., & Kanae, S. (2017). A global hydrological simulation to specify the sources of water used by humans. *Hydrology and Earth System Sciences Discussions*, *08*, 1–53. https://doi.org/10.5194/hess-2017-280

Hertel, T. W., & Liu, J. (2014). Implications of water scarcity for economic growth. *ENV/EPOC-17*, 1–48.

Huang, Z., Hejazi, M., Li, X., Tang, Q., Vernon, C., Leng, G., Liu, Y., Döll, S., Eisner, S., Gerten, D., Hanasaki, N., Wada, Y. (2018). Reconstruction of global gridded monthly sectoral water withdrawals for 1971-2010 and analysis of their spatiotemporal patterns. *Hydrology and Earth System Sciences*, *22*(4), 2117–2133. https://doi.org/10.5194/hess-22-2117-2018

Inhaber, H. (2010). Water Use in Renewable and Conventional Electricity Production. *Energy Sources*, *26*(3), 309–322.

Jackson, R B; Carpenter, S R; Dahm, C N; McKnight, D M; Naiman, R J; Postel, S L; Running, S. W. (2001). Water in a changing world. *Ecological Applications*, *11*(4), 1027–1045. https://doi.org/10.1890/0012-9623(2005)86[249b:IIE]2.0.CO;2

Liu, J., Hertel, T., & Taheripour, F. (2016). Analyzing Future Water Scarcity in Computable General Equilibrium Models. *Water Economics and Policy*, *2*(4). https://doi.org/10.1142/S2382624X16500065

Liu, J., Yang, H., Gosling, S. N., Kummu, M., Flörke, M., Hanasaki, N., Wada, Y., Zhang, X., Zheng, C., Alcamo, J., Oki, T. (2017). Water scarcity assessments in the past, present, and future. *Earth's Future*, 1–15. https://doi.org/10.1002/eft2.200

Liu, J., Zehnder, A. J. B., & Yang, H. (2009). Global consumptive water use for crop production : The importance of green water and virtual water, *45*(March), 1–15. https://doi.org/10.1029/2007WR006051

Martínez-Espiñeira, R., & Nauges, C. (2004). Is all domestic water consumption sensitive to price control? *Applied Economics*, *36*(15), 1697–1703.

OECD. (2019). Organization for Economic Cooperation and Development. (OECD). Water database. Retrieved October 10, 2019 from https://www.oecd.org/water/

Oki, T., Yano, S., & Hanasaki, N. (2017). Economic aspects of virtual water trade. *Environmental Research Letters*, *12*(4).

Ortigara, A. R. C., Kay, M., & Uhlenbrook, S. (2018). A Review of the SDG 6 Synthesis Report 2018 from an Education, Training, and Research Perspective. *Water*, *10*(1353).

Porter, C. H., Villalobos, C., Holzworth, D., Nelson, R., White, J. W., Athanasiadis, I. N., Janssen, S., Ripoche, D., Cufi, J., Raes, D., Zhang, M., Knapen, R., Sahajpal, R., Boote, K., Jones, J. W. (2014). Harmonization and translation of crop modeling data to ensure interoperability. *Environmental Modelling and Software*, *62*, 495–508. https://doi.org/10.1016/j.envsoft.2014.09.004

Quinteiro, P., Dias, A. C., Silva, M., Ridoutt, B. G., & Arroja, L. (2015). A contribution to the environmental impact assessment of green water flows. *Journal of Cleaner Production*, *93*, 318–329. https://doi.org/10.1016/j.jclepro.2015.01.022

Rijsberman, F. R. (2006). Water scarcity: Fact or fiction? *Agricultural Water Management*, *80*(1-3 SPEC. ISS.), 5–22. https://doi.org/10.1016/j.agwat.2005.07.001

Rio Carrillo, A. M., & Frei, C. (2009). Water: A key resource in energy production. *Energy Policy*, *37*(11), 4303–4312. https://doi.org/10.1016/j.enpol.2009.05.074

Rogers, P., De Silva, R., & Bhatia, R. (2002). Water is an economic good: How to use prices to promote equity, efficiency, and sustainability. *Water Policy*, *4*(1), 1–17.

Rost, S., Gerten, D., Bondeau, A., Lucht, W., Rohwer, J., & Schaphoff, S. (2008). Agricultural green and blue water consumption and its influence on the global water system. *Water Resources Research*, *44*(9), 1–17. https://doi.org/10.1029/2007WR006331

Savenije, H. H. G. (2000). Water scarcity indicators; the deception of the numbers. *Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere*, *25*(3), 199–204. https://doi.org/10.1016/S1464-1909(00)00004-6

Scheierling, S. M., Loomis, J. B., & Young, R. A. (2006). Irrigation water demand: A meta-analysis of price elasticities. *Water Resources Research*, *42*(1).

Schlichter, R. B., & Kraemmergaard, P. (2010). A comprehensive literature review of the ERP research field over a decade. *Journal of Enterprise Information Management*, *23*(4), 486–520.

Stadler, K., Wood, R., Bulavskaya, T., Södersten, C. J., Simas, M., Schmidt, S., Usubiaga, A., Acosta-Fernández, J., Kuenen, J., Bruckner, M., Giljum, S., Lutter, S., Merciai, S., Schmidt, J. H., Theurl, M. C., Plutzar, C., Kastner, T., Eisenmenger, N., Erb, K., Koning, A., Tukker, A. (2018). EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional Input-Output Tables. *Journal of Industrial Ecology*, *22*(3), 502–515. https://doi.org/10.1111/jiec.12715

Strand, J., & Walker, I. (2005). Water markets and demand in Central American cities. *Environment and Development Economics,* 313–335.

Sutanudjaja, E. H., Van Beek, R., Wanders, N., Wada, Y., Bosmans, J. H. C., Drost, N., van der Ernt, R. J., Hoch, J. M., Jong, K., Karssenberg, D., López, P. L., Peßenteiner, S., Schmitz, O., Straatsma, M. W., Vannametee, E., Wisser, D., Bierkens, M. F. P. (2018). PCR-GLOBWB 2: A 5 arcmin global hydrological and water resources model. *Geoscientific Model Development*, *11*(6), 2429–2453. https://doi.org/10.5194/gmd-11-2429-2018

The World's Water. (2020). World Water database. Retrieved November 15, 2019, from https://www.worldwater.org/water-data/

Turner, K., Georgiou, S., Clark, R., & Brouwer, R. (2004). *Economic valuation of water resources in agriculture: From the sectoral to a functional perspective of natural resource management*. (Food and Agriculture Organization, Ed.). Rome, Italy.

United Nations. (2009). *Water in a changing world. The United Nations World Water Development Report 3*. Paris and London.

United Nations. (2018). *Sustainable Development Goal 6: Synthesis Report on Water and Sanitation*. *United Nations*. https://doi.org/10.1126/science.278.5339.827

United Nations Development Program. (2019). https://www.undp.org/content/undp/en/home/sustainable-development-goals/goal-6-clean-water-and-sanitation.html. Retrieved September 18, 2019, from https://www.undp.org/content/undp/en/home/sustainable-development-goals/goal-6-clean-water-and-sanitation.html

UNSD. (2020). United Nation Statistics Division. Water portal. Retrieved February 28, 2020, from https://unstats.un.org/unsd/envstats/qindicators.cshtml

Van Beek, L. P. H., Wada, Y., & Bierkens, M. F. P. (2011). Global monthly water stress: 1. Water balance and water availability. *Water Resources Research*, *47*(7). https://doi.org/10.1029/2010WR009791

Wada, Y., Wisser, D., & Bierkens, M. F. P. (2014). Global modeling of withdrawal, allocation and consumptive use of surface water and groundwater resources. *Earth System Dynamics*, *5*(1), 15–40. https://doi.org/10.5194/esd-5-15-2014

Wada, Y., Wisser, D., Eisner, S., Floerke, M., Gerten, D., Haddeland, I., Hanasaki, N., Masaki, Y., Portmann, F. T., Tessler, Z., Schewe, J. (2013). Multimodel projections and uncertainties of irrigation water demand under climate change. *Geophys. Res. Lett*, *40*, 4626–4632.

Ward, F. A., & Michelsen, A. (2002). The economic value of water in agriculture: Concepts and policy applications. *Water Policy*, *4*(5), 423–446. https://doi.org/10.1016/S1366-7017(02)00039-9

Water footprint. (2020). The Water Foot Print Portal. Retrieved October 10, 2019 from https://waterfootprint.org/en/resources/waterstat/

Zeng, Z., Liu, J., & Savenije, H. H. G. (2013). A simple approach to assess water scarcity integrating water quantity and quality. *Ecological Indicators*, *34*, 441–449. https://doi.org/10.1016/j.ecolind.2013.06.012

Chapter 3

Global deforestation revisited: The role of weak institutions[12]

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Abstract

Linking weak governance and forest degradation has received increasing attention in scientific and political spheres. Deforestation remains a global matter as a major agent of greenhouse gas (GHG) emissions, for endangering the lives of several plant and animal species, and for triggering political disputes involving land tenure and rural violence. Political factors are acknowledged to have a direct impact on forest resources management. Corruption and weak governance are able to deflect policies to private interests, and encourage illegal logging and unlawful allowances to forest degradation even in protected areas. However, the effects of corruption and weak institutions in forest management are still uncertain. This paper offers empirical-based evidence about the relationship between institutional factors and forest cover conversion. The role of weak institutions is explored by employing a logistic model of recent high-resolution global remote sensing data from the European Space Agency (ESA) Climate Change Initiative Land Cover (CCI-LC) from 1992 and 2015. We assess the cross-country associations of the Corruption Perception Index (CPI) and the World Bank Government Effectiveness (GE) index while controlling for physiographic and structural variables. Results are robust and show, as expected, that difficult access areas pose considerable barriers to forest conversion, and regions of high agricultural suitability are more likely to be converted from forests to agricultural fields. Furthermore, higher government effectiveness with stronger political enforcement, policy design, and lower corruption perception are significantly related to a lower probability of deforestation. Further elaborating governance and corruption indicators with emphasis on forest management/conservation can potentially improve the accuracy of local and cross-country quantitative land use studies. Our findings support the continuous understanding of weak institutions in deforestation debates. The paper highlights the need to fight corruption and to build strong institutions into effective policy strategies.

Keywords: global deforestation, corruption, political stability, land-use change, drivers of deforestation, weak institutions

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1. Introduction

Deforestation is a major agent of greenhouse gas (GHG) emissions (Margono et al., 2014) and threatens ecosystem services and lives of several plant and animal species (Houghton, 2012). Forest degradation also triggers social issues ranging from repressing indigenous rights and cultures, to rural violence and spreading diseases (Rich, 1994).

In scientific and political spheres, linking weak governance and deforestation has received increasing attention (Bonfin et al., 2011; Laurance et al., 2011; Meehan & Tacconi, 2017). Institutional factors are argued to impact the state of forest resources through various mechanisms (Kissinger et al., 2012). Corruption is a common claim of weak governance (Galinato and Galinato, 2012), able to encourage illegal logging (Amacher, 2006) either in protected areas or by obtaining unlawful allowances to pursue them (Sundström, 2016). Corruption is facilitated by political instability and occurs when deflecting policies to private interests (Galinato and Galinato, 2012).

Nevertheless, it is still uncertain what the effects of corruption and weak institutions in forest management are (Obydenkova et al., 2016). Only a few studies empirically investigate the role of governance and corruption in forest conservation (Agrawal, 2007). Sundström (2016), for instance, provides an extensive literature review evaluating the macro and micro-level empirical studies looking into the effects of corruption and weak governance in forest management. The findings underline the threats of bribery in forest management.

Analyzing the correlation between corruption and deforestation, Koyuncu and Yilmaz (2009) employed a cross-country quantitative model of deforestation data from the World Development Indicator (WDI) tables and three corruption indexes: Corruption Perception Index (CPI), International Country Risk Guide (ICRG) index, Business Intelligence (BI) index. The results show a significant correlation between corruption and deforestation. This analysis is further refined in Koyuncu and Yilmaz, (2013), where the authors found a significant negative association between private forest ownership and CPI, and the World Governance Indicators (WGI). According to Müller and Zeller, (2002) population growth, market and technical progress, socioeconomic development, and political and institutional factors are determinants of anthropogenic land-use change (LUC).

To further refine these quantitative LUC studies, models should be accompanied by spatially disaggregated data to capture differences in local land features, account for a wide range of land-use factors (e.g., economic, physical, social, and political determinants), and follow an economic framework (Chomitz and Gray, 1996). Empirical estimations substantially improve when simultaneously accounting for anthropogenic, biophysical, and institution variables (Barrett et al., 2006). In parallel, spatial data analyses are able to evaluate land uses from a fine data resolution, which supports a broader understanding of deforestation processes and their driving forces (Müller and Zeller, 2002).

Early quantitative assessments of deforestation have primarily focused on biophysical variables, especially due to data availability (Veldkamp and Lambin, 2001). Land characteristics (e.g., slope, temperature, soil and forest type, erosion, and distance to water) are included in most studies and showed a direct impact on deforestation (Ferretti-Gallon and Busch, 2014). Nevertheless, the inclusion of socioeconomic variables in quantitative deforestation studies is still challenging. It is mainly because variables are not available in a low spatial resolution but often only on the national level.

There is a growing number of studies investigating the influences of socioeconomic variables in the forest sector, enhancing the understanding of forest management dynamics towards demographics, economic growth, and agricultural profits, among other variables. Valuable contributions are from Marcos-Martinez et al. (2017), who assess forest transition in Australia, Rogelja and Shannon (2017), who analyze anti-corruption policy in Serbia; Lu et al. (2021), who investigate forest transition in China, and Sommer (2017), who looks into petty and grand corruption in forest loss.

In this context, and to the best of our knowledge, this is the first study to explore the cross-country associations of available international corruption and governance indicators in an analysis using global high-resolution deforestation data. In a logistic model, this study employs recent global remote sensing data from the European Space Agency (ESA) Climate Change Initiative Land Cover (CCI-LC) from 1992 and 2015 (Bontemps et al., 2013) with CPI and the World Bank Government Effectiveness (GE) index. While studies often consider a land cover dataset of a single year to assess LUC drivers, our analysis stands out for accounting cross-country high-resolution land cover data over a period of time.

2. Modeling approach

2.1. Theoretical model of land use

The model proposed by von Thünen (1826) remains the predominant quantitative spatial economic model of land use, able to assess the influence of prices, technology, and natural characteristics on site-specific land use (Liu and Villoria, 2015). von Thünen (1826) suggests that the adopted production activity generates the highest economic land rent. This rationale purports that deforestation may increase if pasture and crop production provide more economic returns (Ferretti-Gallon and Busch, 2014).

To estimate land rents, we follow the directions proposed by Chomitz and Gray, (1996) and further revised by Liu and Villoria, (2015). We consider two types of land uses: Deforested land use (e.g. for agricultural production) and forest. In location i, let Y_i denote output per unit of area by using input, I_i. S_i represents a bundle of factor endowment regionally fixed. These are rainfall, slope, soil fertility, and other land characteristics affecting the productivity of I_i. Assuming a Cobb-Douglas Technology, β is the elasticity of yields to input usage, and the production function is defined as in equation (1).

$$Y_i = S_i I_i^{\beta} \ , 0 < \beta < 1 \tag{1}$$

P_i and C_i denote site-specific output and input prices, respectively. When prices are available, standard profit maximization subjected to 1 produces optimal input demand:

$$I_i^* = \left[\frac{C_i}{P_i S_i \beta}\right]^{\frac{1}{\beta-1}} \tag{2}$$

The optimal demand Y^* is obtained by substituting (2) into (1):

$$Y_i^* = S_i^{\frac{1}{1-\beta}} \left[\frac{C_i}{P_i \beta}\right]^{\frac{\beta}{\beta-1}} \tag{3}$$

The potential rent of site i under agricultural land use is given by: $R_i = P_i Y_i^* - C_i I_i^*$. The expression can be further rearranged by inserting equations (2) into (3):

$$R_i = \left(P_i S_i C_i^{-\beta}\right)^{\frac{1}{1-\beta}} \frac{(1-\beta)}{\beta} \tag{4}$$

Comparing land rents from different plots and production activities would gauge conversion incentives across different production processes. However, data on prices and land rents are non-existent (Villoria and Liu, 2015). To circumvent data issues, Chomitz and Gray (1996) proposed a reduced form of equation 4 to assess price and productivity determinants. They depart from von Thünen's assumption that farm gate prices are predominantly affected by transport costs to markets (determined by physical distance) (Villoria and Liu, 2015).

Equation 5 depicts input and output prices as functions of market accessibility. A_i measures the traveling time from plot i to the market. γ and δ are semi-elasticities of prices to changes in distance, indicating the percentage change in price given a unitary change in market access. The intercepts are represented by p and c. Input prices tend to increase insofar as markets are farther from production areas. The approach presented by Villoria and Liu (2015) uses of the market remoteness index from (Verburg et al., 2011), where they rank cities according to traveling time to major markets. The scores range from 0 to 100, denoting inaccessible areas and areas with easy market access, respectively.

$$\begin{aligned} P_i &= exp(p + \gamma A_i)\,, \gamma > 0 \\ C_i &= exp(c + \delta A_i)\,, \delta < 0 \end{aligned} \tag{5}$$

The price term is ruled out when inserting equation (5) into (4),. Equation (6) is given after taking logs, grouping similar terms, and adding an error term.

$$log(R_i) = \alpha_0 + \alpha_1 A_i + \alpha_2 log(S_i) + \varepsilon_i \tag{6}$$

The semi-elasticity of land rents to changes in market access and $\alpha_2 = (1-\beta)^{-1}$ is $\alpha_1 = (\gamma - \beta\delta)(1-\beta)^{-1}$, which is expected to be higher than zero ($\alpha_1 > 0$). In the present model, when forest land rents are smaller than land rents of alternative land uses, the land remains forest. Conversely, when land rents for alternative land uses are higher, the land will be deforested to enable other land uses (e.g., agricultural production). Therefore, deforestation takes place if $R_{i\,other\,land\,use} > R_{i\,forest}$. This allows for a latent variable R_i to a binary outcome $Z_i = 1\left[R_{i\,other\,land\,use} > R_{i\,forest}\right]$, assuming 1 when deforestation is observed and 0 otherwise. This variable can be obtained based on global grids of land use and allows estimating the parameter of the model in equation 6 by using a discrete choice model:

$$P(Z_i = 1|A_i, S_i) = \Lambda(\alpha_0 + \alpha_1 A_i + \alpha_2 log(S_i) + \varepsilon_i) \tag{7}$$

The estimate $\Lambda(.)$ is the logistic distribution, $P(Z_i = 1|A_i, S_i)$ the probability of observing i being deforested for alternative land uses, given the distances to markets A_i, and natural traits S_i.

The partial effect of A_i on $P(Z_i = 1)$ indicates the probability of deforesting a parcel given a change in market distance conditions.

$$\frac{\partial P(Z_i = 1)}{\partial A_i} = \lambda[\alpha_0 + \alpha_1 A_i + \alpha_2 log(S_i)]\alpha_1 \tag{8}$$

The probability distribution function varies by plot, which allows the estimation of partial effects of market remoteness on the probability of deforestation for different geographic aggregates. The elasticity of the probability of deforestation to changes in market remoteness is given by:

$$\epsilon_i = \frac{\partial P(Z_i = 1)}{\partial A_i} \times \frac{A_i}{P(Z_i = 1)} = \lambda[\alpha_0 + \alpha_1 A_i + \alpha_2 log(S_i)] \times \alpha_1 \times \frac{A_i}{P(Z_i = 1)}$$

2.2. Model specification and sampling design

We assess the correlation between a dichotomous dependent variable of forest land cover by employing a logistic regression model. We identify one anthropogenic LUC process: Forest areas converted to other land use classifications. The logistic regression model of forest land cover is specified as follows:

$$Log\ \left(\frac{P_i}{1 - P_i}\right) = \sum \beta_j\, x_{ij} + \varepsilon_i$$

Where i denotes the i-th observation in the sample, P is the probability of the outcome, β_j represents the regression coefficients of the explanatory variables x_j. The logistic coefficients are estimated using the maximum likelihood method. The probability that forest areas will be converted into other activities is given as P=P[y_i=1], while the probability that such areas will remain in their natural state is P=P[y_i=0]. The probability function of this binary characteristic is f(y)=$P^y(-P)^{1-y}$ where y can take the values of 0 and 1. The probability that forest areas will be converted into other land activities is P_i and 1- P_i if otherwise.

The data preparation consisted primarily of converting all georeferenced raster data (land cover, biophysical and accessibility variables) into a format compatible with economic statistical software[13]. Afterwards, pixels were matched by coordinates and merged to the CPI and GE scores per county. The original sample[14] is a large file with 58,627,795 observations, which is not processable by the software processing capacity.

According to Gallego (2005), selecting a sample size for the analysis is valid when studying large areas with fine resolution. With that, sapling percentages of the original sample is a practical strategy that would not result in accuracy loss (Czaplewski, 2003). Following that, we base our analysis on 15%, 10% and 5% random sample selections without replacement, so all the pixels had the same probability of being selected.

After selecting the samples, computer-intensive sampling with replication techniques is useful when managing large complex datasets for variance estimation (Stapleton, 2008). Hence, we apply a pixel replacement bootstrapping with 1000 replications for each random

[13] Raster data converted into STATA (.dta) files.

[14] Descriptive statistics available in the supplementary material.

sample selected. This allows resampling the original dataset several times to observe how consistent regression associations are. To generate the main results of this paper, we use the 10% sample (5,841,577 observations), and the other samples are used as a robustness check[15].

The CPI and GE are highly correlated (correlation 97%), so their effects are accounted separately to control for multicollinearity. To estimate country fixed-effects (FE), we use a dummy variable approach with the USA as a reference. This is because the USA presents average deforestation rate and has major economic relevance. In the country binary regression, marginal effects refer to the strength of variables associations compared to the reference country.

Applying the trajectory analysis method to the same database, Liu et al. (2018) reveal that the land classification of a pixel might change several times and even transition back to a previous land cover type. For simplicity, our analysis does not account for the dynamics of land cover transition. Thus, we observe a single transition from forest in 1992 to other land uses in 2015, and assess the statistical variable responses for this conversion. Our analysis does not include transitions between different forest types, such as natural forest converted to managed forest or forest plantations.

3. Data

3.1. Dependent variable: global deforestation between 1992 and 2015

The dependent variable is derived from the global land cover time series maps from 1992 and 2015 provided by the European Space Agency (ESA) Climate Change Initiative Land Cover (CCI-LC) (Defourny et al., 2009). Every pixel informs the land cover classification in a resolution of 300m surface reflectance. The land cover classes from the CCI-LC were summarized according to the Intergovernmental Panel on Climate Change (IPCC) land categories, except for the case of shrubland which we associate with grassland (e.g., Caatinga in Brazil) (Table 3.1).

The first step consists of extracting all pixels classified as forests in the year 1992. Subsequently, we analyze the land cover classification for the same set of pixels in 2015. Pixels remaining forest assume the value of y_i=0, and pixels presenting other land cover types take the value of y_i=1.

The result is a binary dataset of forest and deforested areas between 1992 and 2015, where pixels determine the observations for the regression analysis. The amount of pixels of a country depends on its forest area size. Thus, countries with considerably larger forest areas (e.g., Russia) have consequently more pixels, a fact that is beneficial to the country size representation in the sample. The availability of annual data from 1992 to 2015 allows for assessing the drivers of deforestation for this specific period in time. This is a major difference from other studies (e.g., Chomitz and Gray, 1996; Koyuncu and Yilmaz 2009, 2013) which consider a land cover data set of one year and analyze the probability of each pixel having a non-forest land cover.

[15] All estimations available in the supplementary material.

Table 3.1. Land cover classes and codes according to the IPCC and European Space Agency (ESA) Climate Change Initiative Land Cover (CCI-LC) maps.

IPCC Land Cover Classes	Land Cover codes	Classification used in ESA-CCI LC maps
1 Agriculture	10, 11, 12	Rainfed cropland
	20	Irrigated cropland
	30	Mosaic cropland (>50%)/natural vegetation (tree, shrub, herbaceous cover) (<50%)
2 Forest	50	Tree cover, broadleaved, evergreen, closed to open*
	60, 61, 62	Tree cover, broadleaved, deciduous, closed to open*
	70, 71, 72	Tree cover, needleleaved, evergreen, closed to open*
	80, 81, 82	Tree cover, needleleaved, deciduous, closed to open*
	90	Tree cover, mixed leaf type (broadleaved and needleleaved)
	100	Mosaic tree and shrub (>50%)/ herbaceous cover (<50%)
	160	Tree cover, flooded, fresh or brackish water
	170	Tree cover, flooded, saline water
3 Grassland	110	Mosaic herbaceous cover (>50%)/ tree and shrub (<50%)
	130	Grassland
4 Wetland	180	Shrub or herbaceous cover
	220	Permanent snow and ice
5 Settlement	190	Urban areas
6 Other	120, 121, 122	Shrubland
	140	Sparse (Lichens and mosses)
	150, 151, 152, 153	Sparse vegetation (tree, shrub, herbaceous cover)
	200, 201, 202	Bare areas
	210	Water bodies

Note: *(>15%)
Adapted from (ESA, 2014).

3.2. Explanatory variables: biophysical, infrastructural and institutional factors

3.2.1. Suitability for agricultural production

Biophysical conditions are represented by crop suitability indices of the Global Agro-Ecological Zones model (FAO, 2021), developed by the International Institute for Applied Systems Analysis (IIASA) and FAO. This variable informs pixel suitability for agricultural production by considering a harmonized set of physiographic variables (e.g., soil type, slope, temperature, moisture, among others). Data are provided as a global raster dataset where every pixel contains values ranging from one to nine. Observations scoring 1 are highly suitable for agricultural production, whereas a score of 9 purports low suitability for agricultural activities.

3.2.2. Accessibility

Infrastructural factors are represented by accessibility data from Nelson (2008), where the global map informs the travel time to the nearest city. The map has a resolution of 30 arc seconds and accounts for cities with a minimum amount of 50,000 inhabitants. Access purports the travel time to a location of interest by using land or water transportation. It includes road and rail networks, navigable rivers, major water bodies, shipping lanes, national borders, and urban areas, among other elements. Higher scores represent areas of difficult access, while lower scores are driven by the presence of a combination of factors enabling land accessibility.

3.2.3. Institutional factors

The Corruption Perception Index (CPI) and the World Bank Government Effectiveness (GE) index are institutional factors. The CPI was developed to enhance understanding of public sector corruption in 183 countries. Corruption is defined as the "abuse of entrusted power for private gain" (Transparency International, 2011), classified into grand and petty corruption.

CPI is an average of various corruption indicators at the country level. Grand corruption refers to the actions done by governmental levels (e.g., policy distortions), which benefit leaders and various public figures at the expense of public goods. Petty corruption, in turn, is defined as the abusive actions of low and mid-level public officials towards citizens. We employ the index values from 2011, which rank corruption on a scale from zero to ten, where zero is very high, and ten is very low corruption.

Furthermore, the World Bank GE index was developed by Kaufmann et al. (2008) and measured the perceptions with regard to the quality of several government services to civil society. The index includes the quality of policy formulation and implementation, the governmental ability and credibility to enforce such policies, and evaluates how governmental services are independent of political pressures. The GE index is a country score ranging from -2.5 to +2.5, meaning the lowest and highest level of governmental effectiveness, respectively. Data refer to the year 2011 and is available for 214 countries.

3.3. Descriptive statistics

Approximately 4.5% of the observations converted from forest to other land cover classes in the time between 1992 and 2015. The biophysical and infrastructural factors are provided at the pixel level, whereas the institutional variables are available at the county level. Thus, for all pixels of a specific country, we assigned the values of both CPI and GE index (Table 3.2).

Table 3.2. Descriptive statistics

Variable Name	Variable description	Mean	Std. dev
Deforestation	=1 converted from forest to other LU classes, 0 otherwise	0.04	0.2
Deforestation Rate	Country rate of forest conversion	0.04	0.03
Ln Deforestation Rate	Log of deforestation rate	-3.38	0.58
Infrastructural Factor			
Accessibility	Higher values indicate increasing difficulty in accessing land	1076	1360
Ln Accessibility	Log of accessibility	6.14	1.44
Biophysical Factor			
Suitability	1 (highly suitable), 9 (low suitability) for agricultural production	6.26	2.08
Ln Suitability	Log of suitability	6.14	1.44
Institutional Factors			
Corruption Perception Index	Country-level 0 (Highly corrupt), 10 (very clean)	4.17	2.49
Government Effectiveness	Country-level -2.5 (low effectiveness) to 2.5(high effectiveness)	0.09	1.02

Note: Sample 10% (N=5,841,577)

Comparing forest pixels in 1992 and 2015 shows that all countries presented forest cover loss (forest pixel conversion). For a selection of countries, Table 3.3 sets out the number of pixels remaining forest, those that changed to other land cover classifications, and the conversion rate (in percentage points). Higher levels of pixel conversion took place in South America (e.g. Argentina, Brazil, and Bolivia). Although converted pixels are a proxy for deforestation, pixel conversion rates do not represent actual deforestation levels.

Table 3.3. Net change in land cover (pixels) and percentage, 1992-2015 (sample 10%).

	Remaining Forest	Converted pixels	Change of pixels (%)
South America			
Argentina	35,845	9,899	21.6
Bolivia	62,037	5,789	8.5
Brazil	424,437	43,069	9.2
Colombia	73,311	2,285	3
Peru	84,786	1,395	1.6
North America			
Canada	731,695	17,377	2.3
Mexico	73,268	1,395	4.4
USA	379,371	13,385	3.4
Africa			
Dem. Rep. Congo	186,660	4,654	2.43
Ghana	6,014	178	2.8
Nigeria	14,745	502	3.3
Tanzania	31,753	3,105	8.9
Sudan	5,108	24	0.5
Europe			
Austria	6,224	356	5.4
Finland	48,931	1,460	2.9
France	17,574	1,217	6.48
Germany	14,581	846	5.48
Russia	1,889,356	48,685	2.5
Spain	17,273	1,356	7.28
Asia			
Bangladesh	1,223	49	3.8
China	191,918	9,407	4.7
India	55,204	2,309	4
Indonesia	104,692	9,560	8.4
Myanmar	30,131	1,431	4.5
Philippines	7,618	606	7.4
Oceania			
Australia	79,575	6,821	7.9
New Zealand	8,787	760	7.9
Papua New Guinea	37,534	1,390	3.6

See appendix for the complete list of countries

4. Results

The model results[16] provide evidence that the relationship of all variables is robust and with significant associations with deforestation at the 1 percent level ($p<0.01$) (Table 3.4). Institutional factors are negatively related to deforestation, indicating an inverse relationship between deforestation and higher levels of political transparency perception and government effectiveness. Thus, higher scores of institutional indices are associated with a lower likelihood of forest land conversion. Likewise, infrastructural and biophysical variables present a significant relationship at a 1 percent level ($p<0.01$).

Table 3.4. Bootstrapped logistic regressions and marginal effects of deforestation (1992-2015) of Corruption Perception Index and Government Effectiveness index (10% sample).

Dependent Variable: Deforestation	(1) Logistic (CPI)	Marginal Effects	(2) Logistic (GE)	Marginal Effects
Constant	-2.1345***		0.821***	
	(0.00612)		(0.03722)	
Suitability	-0.11136***	-.00404***	-0.101***	-0.0036***
	(.00094)	(0.00003)	(0.00094)	(0.00003)
Accessibility	-0.00002***	-.0000108***	-0.0003***	-0.00001***
	(0.000002)	(0.00001)	(0.000002)	(0.000001)
CPI	-0.02058***	-.00074***		
	(0.00081)	(0.00003)		
GE			-15.193***	-0.5446***
			(0.1848)	(0.00648)
# of Observations	5,841,577		5,783,501	

Notes: Bootstrapped results of 1000 replications with the 10% sample. Model (1): Wald chi2 (3)= 32003.85; pseudo R2= 0.0239; Pearson chi2(322225)= 506535.97; Prob>chi2=0.000. Model (2): Wald chi2 (3)=36181.25; pseudo R2=0.0279; Pearson chi2(246277)=417386.26; Prob>chi2=0.000. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In the country fixed effect estimation, institutional factors are not included as their informational content is at the country level, a fact that could lead to multicollinearity problems (Table 3.5)[17]. Positive coefficients imply, *ceteris paribus*, a higher propensity to forest conversion when compared to the USA. This is the case in countries like Brazil, Canada, Russia, Tanzania, Indonesia, and Australia. Negative coefficients, in turn, purport lower likelihood of forest conversion when compared to the USA. This effect is observed in Peru, Ghana, Nigeria, and Finland. The fixed effect estimation does not measure of corruption on deforestation, but rather highlights that forest in some countries are more likely to be deforested than in other countries.

[16] Results for 15% and 5% samples are consistent to the 10% sample and are available in the supplementary material.
[17] Complete list of countries is provided in the supplementary material.

Table 3.5. Country dummy logistic regression and marginal effects of deforestation (1992-2015), with the United States of America as reference.

Dependent Variable: Deforestation	Logistic Country	Marginal effects			Marginal Effects
Constant	-0.48***		***Europe***		
	(0.0125)		Austria	0.189***	0.006***
Ln Accessibility	-0.34***	-0.0105***		(0.055)	(0.002)
	(0.0018)	(0.00005)	Finland	-0.189***	-0.005***
Suitability	-0.018***	-0.0005***		(0.028)	(0.0007)
	(0.0012)	(0.00004)	France	0.233***	0.007***
South America				(0.0312)	(0.001)
Argentina	2.145***	0.183***	Germany	-0.026	-0.0007***
	(0.0146)	(0.002)		(0.037)	(0.001)
Bolivia	1.35***	0.079***	Russia	0.394***	0.012***
	(0.0170)	(0.001)		(0.0107)	(0.0003)
Brazil	1.56***	0.093***	Spain	0.507***	0.019
	(0.0109)	(0.001)		(0.0298)	(0.001)
Colombia	0.507***	0.079***	***Asia***		
	(0.0234)	(0.001)	Bangladesh	-0.23	-0.006***
Peru	-0.067**	-0.002***		(0.155)	(0.003)
	(0.0288)	(0.0008)	China	0.43***	0.015***
North America				(0.0141)	(0.0006)
Canada	0.282***	0.009***	India	-0.0074	-0.0002***
	(0.0124)	(0.0004)		(0.023)	(0.0007)
Mexico	0.373***	0.013***	Indonesia	1.369***	0.08***
	(0.0198)	(0,0008)		(0.0142)	(0.0013)
Africa			Myanmar	0.623***	0.025***
Dem. Rep. Congo	0.021	0.0006***		(0.028)	(0.0015)
	(0.0176)	(0.0005)	Philippines	0.91***	0.043***
Ghana	-0.162**	-0.004***		(0.043)	(0.003)
	(0.0769)	(0.002)	***Oceania***		
Nigeria	-0.325***	-0.0008***	Australia	1.146***	0. 06***
	(0.0479)	(0.001)		(0.015)	(0.001)
Tanzania	1.28***	0.0733***	New Zealand	1.150***	0.061***
	(0.0211)	(0.001)		(0.039)	(0.0032)
Sudan	-1.713***	-0.025	Papua New Guinea	0.770***	0.034***
	(0.209)	(0.001)		(0.0291)	(0.0017)
# of Observations	5,836,521				

Notes: LR chi2 (117) =168406.56; pseudo R2= 0.0831; Pearson chi2(459180) = 532060.83; Prob > chi2 =0.000. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Coefficients and marginal effects provide a statistical measure to assess the direction and the strength of the associations with the dependent variable and the reference country (Figure 3.1). Argentina has the strongest marginal effect, followed by Brazil, Indonesia, Cambodia, Bolivia, and Tanzania. The weakest effects are presented mostly by negative associations, as for Sudan, Finland, Ghana, Peru, and Nigeria.

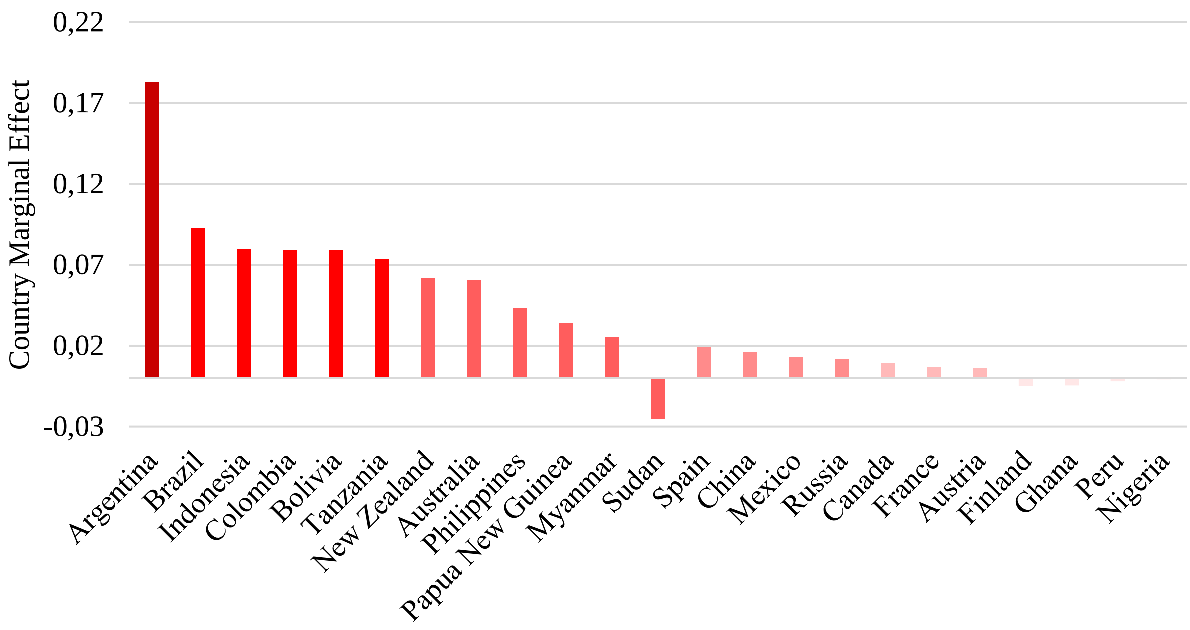

Figure 3.1. Strength of logistic marginal effects of countries presenting statistical significance

Furthermore, we use additional robustness checks to test CPI and GE effects for eight groups of countries[18] (Table 3.6). These groups are net exporters of agricultural products (FAOSTAT, 2021), countries with the highest deforestation rates (FAO, 2015), European Union (EU), North America, Latin America, South America, Africa, and Asia. Effects are generally similar to previous regressions; however, the African region (Table 3.6 (15, 16)) shows a significant positive effect between institutional factors and deforestation.

[18] List of countries across groups:
Net exporters of agricultural products: Argentina, Australia, Brazil, China, Canada, Chile, Germany, France, India, Indonesia, Italy, Mexico, New Zealand, Poland, Russia, Spain, Thailand, United States of America, Turkey.
Highest deforestation rate: Brazil, Australia, Mexico, United Republic of Tanzania, Zimbabwe, Argentina, Bolivia, Mozambique, Peru, Sudan, Venezuela, Colombia, Mali, Laos, China, Canada, Ecuador, Philippines, Guatemala.
EU: Austria, Belgium, Croatia, Czechia, Estonia, Finlandia, France, Germany, Hungary, Italy, Latvia, Lithuania, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden
North America: Canada, The United States of America, Mexico
Latin America: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Guyana, Paraguay, Nicaragua, Peru, Suriname, Uruguay, Venezuela, Mexico, Guatemala, Dominican Republic, Honduras, Nicaragua, El Salvador, Costa Rica, Panama, Belize
South America: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Guyana, Paraguay, Peru, Suriname, Uruguay, Venezuela
Africa: Benin, Botswana, Central African Republic, Chad, Democratic Republic of the Congo, Equatorial Guinea, Ethiopia, Gabon, Ghana, Guinea, Guinea-Bissau, Kenya, Madagascar, Malawi, Mali, Mozambique, Namibia, Nigeria, Republic of the Congo, Senegal, Sierra Leone, Somalia, South Africa, South Sudan, Sudan, Togo, Uganda, Namibia, United Republic of Tanzania, Zambia, Zimbabwe
Asia: China, India, Indonesia, Pakistan, Bangladesh, Japan, Philippines, Vietnam, Turkey, Iran, Thailand, Myanmar, South Korea, Laos, Malaysia, Nepal, North Korea, Sri Lanka, Kazakhstan, Cambodia, Azerbaijan, Kyrgyzstan, Georgia, Mongolia, Bhutan

Table 3.6. Bootstrap logistic regressions and marginal effects of deforestation (1992-2015), Corruption Perception Index, and Government Effectiveness for country groups: net agricultural exporters, countries with high deforestation rates, European Union, North America, Latin America, South America, Africa, and Asia.

Dependent Variable: Deforestation	(3) Net Agr. Exporters	Marginal Effects	(4) Net Agr. Exporters	Marginal Effects
Constant	-1.7790***		1.955495	
	(0.0081)		(.0495203)	-.0050519
Suitability	-0.1625***	-0.0056***	-.1488863	(0.00003)
	(.0010715)	(0.00004)	(.0010385)	
Accessibility	-0.0002036***	-7.05e-06***	-.0002206	-7.49e-06
	(2.77e-06)	(0.000001)	(2.83e-06)	(0.00001)
CPI	-.03751***	-0.0012***		
	(0.001)	(0.00003)		
GE			-19.50856	-.6619478
			(.2422201)	(.0079)
# of Observations	4,275,269		4,275,269	

Model (3) Wald chi2(3)= 37233.99; pseudo R2=0.0292; Pearson chi2(126383) =277050;Prob>chi2=0.0000.
Model (4) Wald chi2(3)= 38347.53; pseudo R2=0.0339; Pearson chi2(91476) =176178; Prob > chi2=0.0000

Dependent Variable: Deforestation	(5) High deforestation	Marginal Effects	(6) High deforestation	Marginal Effects
Constant	-1.7790***		-1.955***	
	(0.0081)		(0.0495)	
Suitability	-0.1625***	-0.0056***	-0.1488***	-0.0050***
	(0.0010)	(0.00004)	(0.0010)	(0.00003)
Accessibility	-0.0002***	-7.05e-06***	-0.00022***	-7.493-06***
	(2.77e-06)	(0.000001)	(2.83e-06)	(0.000001)
CPI	-0.0375***	-0.0012***		
	(0.0010)	(0.00003)		
GE			-19.508***	-0.6619***
			(0.2422)	(0.0079)
# of Observations	4,275,269		4,275,269	

Model (5) Wald chi2(3) =37233.99; Peudo R2=0.0292; Pearson chi2(126383)=277050; Prob > chi2=0.0000
Model (6) Wald chi2(3) =38347.53; Peudo R2=0.0339; Pearson chi2(91476)=176178.32; Prob > chi2=0.0000

Dependent Variable: Deforestation	(7) EU	Marginal Effects	(8) EU	Marginal Effects
Constant	-2.1530***		-8.2598***	
	(0.0377)		(0.2991)	
Suitability	-0.0574***	-0.0028***	-0.0859***	-0.0041
	(0.0055)	(0.00027)	(0.0051)	(0.00025)
Accessibility	-0.0026***	-0.0001***	-0.0031***	-0.00015***
	(0.00023)	(0.00001)	(0.00021)	(0.00001)
CPI	-0.0270***	-0.0013***		
	(0.0058)	(0.00029)		
GE			27.939***	1.3572***
			(1.3844)	(0.0663)
# of Observations	192,397		192,397	

Model (7) Wald chi2(3) =679.25; Peudo R2=0.0107; Pearson chi2(13073) =22094.99; Prob > chi2=0.0000
Model (8)Wald chi2(3)=1153.62;Pseudo R2=0.0156; Pearson chi2(6616) =12793.15; Prob > chi2=0.0000

Dependent Variable: Deforestation	(9) North America	Marginal Effects	(10) North America	Marginal Effects
Constant	-2.431***		-0.200***	
	(0.0281)		(0.1339)	
Suitability	-0.0455***	-0.0012***	-0.0580***	-0.0015***
	(0.0031)	(0.00008)	(0.00327)	(0.00009)
Accessibility	-0.00007***	-2.03e-06***	-0.0001***	-2.70e-06***
	(6.22e-06)	(0.000001)	(6.33e-06)	(0.000001)
CPI	-0.0964***	-0.0025***		
	(0.0033)	(0.00009)		
GE			-13.026***	-0.3472***
			(0.6090)	(0.01628)
# of Observations	1,218,480		1,218,480	

Model (9) Wald chi2(3) =2178.82; Peudo R2=0.0065; Pearson chi2(30825) =39795.21; Prob > chi2=0.0000
Model (10)Wald chi2(3)=1711.25;Pseudo R2=0.0054; Pearson chi2(22606) =30673.38; Prob >chi2=0.0000

Table 3.6. (continued)

Dependent Variable: Deforestation	(11) Latin America	Marginal Effect	(12) Latin America	Marginal Effect
Constant	-0.7453***		5.0731***	
	(0.01456)		(0.17527)	
Suitability	-0.1462***	-0.0053***	-0.1503***	-0.0054***
	(0.00196)	(0.00007)	(0.00189)	(0.00007)
Accessibility	-0.00134***	-0.00004***	-0.00133***	-0.00004***
	(0.00001)	(0.000001)	(0.00189)	(0.000001)
CPI	-0.0676***	-0.00246***		
	(0.0038)	(0.00014)		
GE			-30.8705***	-1.1235***
			(0.00001)	(0.03359)
# of Observations	1,007,309		1,007,309	

Model (11) Wald chi2(3) =18252.44; Peudo R2=0.1083; Pearson chi2(155249)=2065590; Prob > chi2=0.0000
Model (12) Wald chi2(3)=18565.77;Pseudo R2=0.1106; Pearson chi2(88856)=1833124 ;Prob >chi2=0.0000

Dependent Variable: Deforestation	(13) South America	Marginal Effects	(14) South America	Marginal Effects
Constant	-0.5019***		-6.7879***	
	(0.0163)		(0.2230)	
Suitability	-0.0942***	-0.00311***	-0.1085***	-0.0035***
	(0.0021)	(0.00007)	(0.0020)	(0.00007)
Accessibility	-0.0014***	-0.00004***	-0.00142***	-0.00004***
	(0.00001)	(0.000001)	(0.00001)	(0.000001)
CPI	-0.1565***	-0.0051***		
	(0.0043)	(0.00016)		
GE			-40.009***	-1.320***
			(1.1407)	(0.03857)
# of Observations	895,123		896,123	

Model (13) Wald chi2(3) =17524.9; Peudo R2= 0.1267; Pearson chi2(142774)=2778968;Prob > chi2=0.0000
Model (14) Wald chi2(3) =16617.11; Peudo R2= 0.1280; Pearson chi2(85468)=2618194.3;Prob > chi2=0.0000

Dependent Variable: Deforestation	(15) Africa	Marginal Effects	(16) Africa	Marginal Effects
Constant	-3.1083***		7.7304***	
	(0.0298)		(0.221)	
Suitability	-0.0144***	-0.00034***	-0.01011***	-0.0002***
	(0.0039)	(0.000009)	(0.0039)	(0.00009)
Accessibility	-0.00322***	-0.00007***	-0.00278***	-0.00006***
	(0.00004)	(0.000001)	(0.00005)	(0.00001)
CPI	0.3548***	0.0084***		
	(0.0078)	(0.0002)		
GE			51.8744***	-1.23057***
			(1.1685)	(0.0295)
# of Observations	591,603		565,089	

Model (15) Wald chi2(3) =7418.28; Peudo R2=0.0728; Pearson chi2(74972) =217998.40; Prob > chi2=0.0000
Model (16)Wald chi2(3)=7893.95;Pseudo R2=0.0803; Pearson chi2(57243) =145710.15; Prob > chi2=0.0000

Dependent Variable: Deforestation	(17) Asia	Marginal Effects	(18) Asia	Marginal Effects
Constant	-0.3034***		1.3206***	
	(0.02467)		(0.1059)	
Suitability	-0.2162***	-0.0096***	-0.2252***	-0.01050***
	(0.0035)	(0.0001)	(0.00355)	(0.00017)
Accessibility	-0.0023***	-0.0001***	-0.0020***	-0.00009***
		(0.000001)	(0.00003)	(0.000001)
CPI	-0.1562***	-0.0069***		
	(0.0039)	(0.0001)		
GE			-10.826***	-0.5048***
			(0.5249)	(0.0242)
# of Observations	591,642			
Model (17) Wald chi2(3)=10140.43;Peudo R2=0.0591;Pearson chi2(63094) = 418158.92; Prob > chi2=0.0000				
Model (18) Wald chi2(3)=8514.32;Peudo R2=0.0546;Pearson chi2(37110) =195984.05; Prob > chi2=0.0000				

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

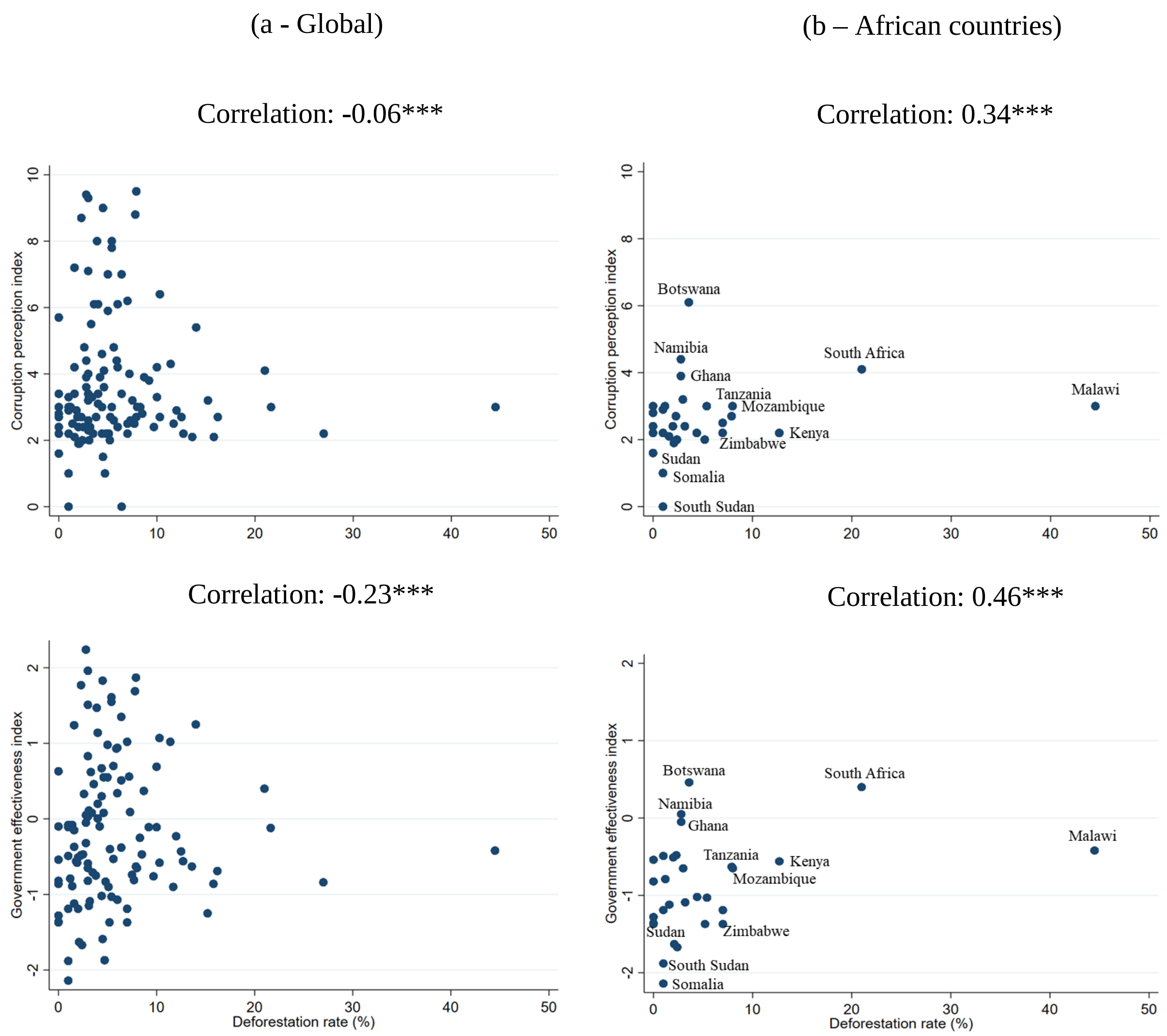

Figure 3.2. Scatterplots and significant correlation coefficients (*** p<0.01) between deforestation rate and Corruption Perception Index and Government Coefficient Index for the Globe and African countries.

The distribution and correlation between institutional factors and deforestation show a general negative association between them; however, for the African region, the correlation coefficient is positive (Figure 3.2)[19].

In our sample, various African countries report similar CPI and GE scores while having very different levels of pixel conversion. For instance, Malawi (CPI 3 and GE -0.42) and Zambia (CPI 3.2 and GE -0.62) have very similar CPI and GE scores while reporting 44% and 3% of pixel conversion, respectively. Botswana, in turn, has considerably higher institutional scores (CPI 6.1 and GE 0.46), yet with the same level of pixel conversion (3.6%).

5. Discussion

5.1. Deforestation and institutions in scientific studies

Regression results suggest that biophysical and infrastructural variables are in line with the literature. In an extensive meta-analysis of deforestation drivers, Ferretti-Gallon and Busch (2014) assert that these variables are employed in most studies and have a direct relation with deforestation. Similar to von Thünen's (1826) economic model, areas of difficult access pose considerable barriers to land conversion when compared to areas of higher accessibility (e.g., solid logistic infrastructure and networks to acquire agricultural inputs and production outflow). Additionally, regions of high agricultural suitability are of interest to land owners and other actors involved in agricultural activities and able to decide over land uses.

In parallel, when analyzing political indices, the CPI effects are similar to Koyuncu and Yilmaz (2013), where higher values of CPI are significantly related to lower deforestation. Our logistic regressions are robust and show that higher CPI scores lead to significantly lower likelihood of deforestation. Similarly, GE results suggest that higher effective governance, strong law enforcement, and policy design respond to lower deforestation, fact that is also observed in Umemiya et al. (2010). Such results remained overall consistent for country groups and sample sizes.

Notwithstanding the consistency of results, the regression for African countries reported opposite effects. We observe that various African countries have similar CPI and GE scores but with variant deforestation rates. This implies that institutional factors have no clear association with deforestation for this country group. This can be potentially explained by the fact that using cross-country perception indicators (e.g., CPI) or specialist-based evaluations (e.g., GE index) might not capture further aspects of local natural resources management (Sundström, 2016).

Corruption acts differently across sectors, and the status of natural resources is not entirely uniform in the national territory (Barrett et al., 2006). Thus, general perceptions of government performance and corruption may be influenced by cultural perspectives not fully comparable among countries. Nevertheless, despite capturing public corruption perception and potentially suffering from personal bias, Lisciandra and Migliardo (2017) point out that corruption has a latent character. Hence, CPI is still a valid measure because perceptions might be the only way to enable cross-country assessments.

Furthermore, Umemiya et al. (2010) describe the conceptual limitations when accounting for indicators that are not developed within the frame of deforestation, like the CPI and GE. However, while using CPI, Irland (2008) points out that corruption affects forests due to weak

[19] After checking and removing possible outliers (e.g., Malawi) the correlation remains.

legislation to protect natural resources, when governments lack structural capacity and efficient policy design and political enforcement to protect forests. Additionally, Amacher et al. (2012) argue that bribery in logging inspections directly influences forest concessions, which is spurred by governmental incentives for private gain. Corruption also represents poorly-designed regulations, inadequate monitoring, uneven distribution of power (Contreas-Hermosella, 2001), and bribery (promoting the overuse of resources regardless of scarcity and optimal land returns) (Sundström, 2016).

Our results are consistent with the growing literature devoted to assessing the effects of several forms of corruption over forest resources. Moreover, the association between governmental efficiency and corruption perception remained highly significant and consistent across model specifications. Although both institutional indicators were not developed to consider the frame of the forest sector in every country, they capture relevant political aspects that translate in forest and natural resource management. Hence, our results point to a robust relationship between efficient governance, policy enforcement, and lower corruption mechanisms to be significant to forest land cover maintenance. Certainly, further developing institutional indicators to include aspects of natural resources conservation and forest management would enhance scientific research on national and cross-country land-use analyses.

Despite growing literature investigating the role of weak governments in the forestry sector (Amacher et al., 2012; Contreas-Hermosella, 2001; Sundström, 2016), most studies are based on country-level and time-series analyses. Only very few studies apply cross-country models (Koyuncu and Yilmaz, 2013) but do not account for high-resolution LUC data from two distinct periods of actual land cover change. Our approach combines cross-country high-resolution LUC data with a spatiotemporal change to assess available international indicators for corruption perception and government effectiveness.

Furthermore, as seen in Marcos-Martinez et al. (2018, 2017), our research is part of a growing literature applying computer-intensive data management, able to convert and import the large georeferenced dataset into statistical software. The approach here employed tests for model robustness, and accounts for several country groups. This can potentially encourage future research basing land-use analyses on high-resolution LUC data with socioeconomic and political variables.

5.2. Research caveats

Despite evidence from the literature that land cover might convert several times and transitions back to forest areas (Lu et al. 2021), we do not explore the dimension of deforestation and land transitions. In our model, it is not possible to assert when deforestation occurred, nor differentiate between natural forest, managed forests or forest plantations. This is because the underlying land cover data do not allow to differentiate between managed and unmanaged forest.

Furthermore, the use of a cross-section analysis was motivated by very modest variations in both CPI and GE indices overtime. Additionally, both physiographic and structural variables are available only for a single year. Thus, our model assesses the association between different levels of CPI and GE and deforestation, rather than a change in corruption levels on deforestation.

5.3. Policy Implications

The main policy implications derived from our paper is to provide empirical evidence on the role of weak institutions and corruption as drivers of deforestation. It highlights the need to include the fight against corruption and building strong institutions into effective policy strategies for forest conservation and sustainable forest management. Our results suggest a major need for such policy strategies particularly for countries in South America and South East Asia.

6. Conclusion

Overall quantitative results show that higher government effectiveness, strong political enforcement, policy design, and lower corruption perception have a significant negative association with deforestation. Such institutional effects remain consistent when testing for country groups and various sampling sizes and replications. Only when testing for African countries, the relationships do not hold.

Further elaborating governance and corruption indicators with emphasis on natural resource management might be a plausible headway for local and cross-country quantitative LUC studies. Additionally, accounting for land transition and governance in a spatiotemporal manner would enhance insights into the dynamics of political aspects in forest management.

The scientific contribution of our study is twofold: firstly, it offers empirical-based evidence about the relationship between governmental performance over forest resources. While applying a cross-country analysis, our findings are consistent with the existing literature. Results endorse that weak government, inefficient regulations and facilitated corruption lead to a high probability of forest conversion. Secondly, it supports future cross-country high-resolution LUC research able to integrate large data with institutional variables. An interesting future research question would be to investigate the role of corruption for deforestation patterns with high rates of regrowth and multiple conversion events.

By providing evidence of the associations between governance and deforestation, our findings potentially contribute to international debates, highlighting the need for policy strategies for forest conservation and sustainable forest management.

References

Agrawal, A. (2007). Forests, governance, and sustainability: common property theory and its contributions. *International Journal of the Commons*, *1*(1), 111–136.

Amacher, G. S. (2006). A challenge for economists interested in forest policy design. *Journal of Forest Economics*, *12*(2), 85–89.

Amacher, G. S., Ollikainen, M., & Koskela, E. (2012). Corruption and forest concessions. *Journal of Environmental Economics and Management*, *63*(1), 92–104. https://doi.org/10.1016/j.jeem.2011.05.007

Barrett, C. B., Gibson, C. C., Hoffman, B., & McCubbins, M. D. (2006). The complex links between governance and biodiversity. *Conservation Biology*, *20*(5), 1358–1366.

Bonfin, P., du Preez, M. L., Standing, A., & Williams, A. (2011). REDD Integrity: Addressing governance and corruption challenges in schemes for Reducing Emissions from Deforestation and Forest Degradation (REDD). *U4 Report*, *1*.

Bontemps, S., Defourny, P., Radoux, J., Van Bogaert, E., Lamarche, C., Achard, F., Mayaux, P., Boettcher, M., Brockmann, C., Kirches, G., Zülkhe, M., Kalogirou, V., & Arino, O. (2013). Consistent global land cover maps for climate modeling communities: Current achievements of the ESA's land cover CCI. *ESA Living Planet Symposium*, *2013*(September), 9–13.

Chomitz, K. M., & Gray, A. (1996). Roads, Land Use , and Deforestation : A Spatial Model Applied to Belize. *The World Bank Economic Review*, *10*(3), 487–512. https://mygeohub.org/resources/1131/download/Tool_introduction_and_users_guide.pdf

Contreas-Hermosella, A. (2001). Illegal activities and corruption in the forest sector. In *State of the World's Forest* (pp. 76–89). Food and Agriculture Organization of the United Nations.

Contreras-Hermosilla, A. (2000). *The underlying causes of forest decline*. CIFOR.

Czaplewski, R. L. (2003). Can a sample of Landsat sensor scenes reliably estimate the global extent of tropical deforestation? *International Journal of Remote Sensing*, *24*(6), 1409–1412. https://doi.org/10.1080/0143116021000057135

Defourny, P., Schouten, L., Bartalev, S., Bontemps, S., Caccetta, P., de Wit, A. J. W., di Bella, C., Gérard, B., Giri, C., & Gond, V. (2009). Accuracy Assessment of a 300 M Global Land Cover Map:The GlobCover Experience. *Proceedings of the 33rd International Symposium on Remote Sensing of Environment*.

ESA. (2014). *Land Cover CCI - Product User Guide. Version 2.0*.

FAO. (2001). *State of the World's Forests 2001*.

FAO. (2015). *Global Forest Rresources Assessment 2015*.

FAO. (2021). *Global Agro-Ecological Zones*. Retrieved December 10, 2021 from http://www.fao.org/nr/gaez/about-data-portal/agricultural-suitability-and-potential-yields/en/#

FAOSTAT. (2021). *The Food and Agriculture Organization Corporate Statistical Database website*. Retrieved October 15, 2021 from http://www.fao.org/faostat/en/#rankings/major_commodities_exports

Ferretti-Gallon, K., & Busch, J. (2014). What Drives Deforestation and What Stops it? A Meta-Analysis of Spatially Explicit Econometric Studies. *SSRN Electronic Journal, April 2014*. https://doi.org/10.2139/ssrn.2458040

Galinato, G. I., & Galinato, S. P. (2012). The effects of corruption control, political stability and economic growth on deforestation-induced carbon dioxide emissions. *Environment and Development Economics*, *17*(1), 67–90.

Gallego, F. J. (2005). Stratified sampling of satellite images with a systematic grid of points. *ISPRS Journal of Photogrammetry and Remote Sensing*, *59*(6), 369–376. https://doi.org/10.1016/j.isprsjprs.2005.10.001

Houghton, R. A. (2012). Carbon emissions and the drivers of deforestation and forest degradation in the tropics. *Current Opinion in Environmental Sustainability*, *4*(6).

Irland, L. C. (2008). State failure, corruption, and warfare: Challenges for forest policy. *Journal of Sustainable Forestry*, *27*(3), 189–223. https://doi.org/10.1080/10549810802219963

Kaufmann, D., Kraay, A., & Mastruzzi, M. (2008). Governance matters VII: Aggregate and individual governance indicators, 1996-2007. *World Bank Policy Research Working Paper, 4654*.

Kissinger, G., Herold, M., & Sy, V. de. (2012). Drivers of Deforestation and Forest Degradation: A Synthesis Report for REDD+ Policymakers. In *Lexeme Consulting* (Issue August). https://doi.org/10.1126/science.1239402

Koyuncu, C., & Yilmaz, R. (2009). The impact of corruption on deforestation: a cross-country evidence. *The Journal of Developing Areas*, 213–222.

Koyuncu, C., & Yilmaz, R. (2013). Deforestation, corruption, and private ownership in the forest sector. *Quality & Quantity*, *1*, 227–236.

Laurance, W. F., Kakul, T., Keenan, R. J., Sayer, J., Passingan, S., Clements, G. R., Villegas, F., & Sodhi, N. S. (2011). Predatory corporations, failing governance, and the fate of forests in Papua New Guinea. *Conservation Letters*, *2*, 95–100.

Liu, J., & Villoria, N. (2015). *LANDPARAM : A tool to compute land use change parameters* (pp. 1–8).

Liu, X., Yu, L., Sia, Y., Zhang, C., Lu, H., Yu, C., & Gong, P. (2018). Identifying patterns and hotspots of global land cover transitions using the ESA CCI land cover dataset. *Remote Sensing Letters*, *9*(10), 972–981. https://doi.org/10.1080/2150704X.2018.1500070

Lu, L., Marcos-Martinez, R., Xu, Y., Huang, A., Duan, Y., Ji, Z., & Huang, L. (2021). The spatiotemporal patterns and pathways of forest transition in China. *Land Degradation and Development*, *32*(18), 5378–5392. https://doi.org/10.1002/ldr.4115

Marcos-Martinez, R., Bryan, B. A., Connor, J. D., & King, D. (2017). Agricultural land-use dynamics: Assessing the relative importance of socioeconomic and biophysical drivers for more targeted policy. *Land Use Policy*, *63*, 53–66. https://doi.org/10.1016/j.landusepol.2017.01.011

Marcos-Martinez, R., Bryan, B. A., Schwabe, K. A., Connor, J. D., & Law, E. A. (2018). Forest transition in developed agricultural regions needs efficient regulatory policy. *Forest Policy and Economics*, *86*, 67–75. https://doi.org/10.1016/j.forpol.2017.10.021

Margono, B. A., Potapov, P. V., Turubanova, S., & Stolle, F. (2014). Primary forest cover loss in Indonesia over 2000–2012. *Nature Climate Change*. https://doi.org/10.1038/NCLIMATE227

Meehan, F., & Tacconi, L. (2017). A framework to assess the impacts of corruption on forests and prioritize responses. *Land Use Policy, 60*, 113–122.

Müller, D., & Zeller, M. (2002). Land use dynamics in the central highlands of Vietnam: A spatial model combining village survey data with satellite imagery interpretation. *Agricultural Economics*, *27*(3), 333–354. https://doi.org/10.1016/S0169-5150(02)00073-7

Nelson, A. (2008). *Estimated travel time to the nearest city of 50,000 or more people in year 2000*. Global Environment Monitoring Unit - Joint Research Centre of the European Commission. Retrieved September 04, 2021 from https://forobs.jrc.ec.europa.eu/products/gam/

Obydenkova, A., Nazarov, Z., & Salahodjaev, R. (2016). The process of deforestation in weak democracies and the role of intelligence. *Environmental Research*, *148*, 484–490.

Rich, B. (1994). *Mortgaging the Earth: The World Bank, Environmental Impoverishment, and the Crisis of Development*.

Rogelja, T., & Shannon, M. A. (2017). Structural power in Serbian anti-corruption forest policy network. *Forest Policy and Economics*, *82*, 52–60. https://doi.org/10.1016/j.forpol.2017.05.008

Sommer, J. M. (2017). Grand and petty corruption: a cross-national analysis of forest loss in low- and middle-income nations. *Environmental Sociology*, *3*(4), 414–426. https://doi.org/10.1080/23251042.2017.1348569

Stapleton, L. M. (2008). Variance estimation using replication methods in structural equation modeling with complex sample data. *Structural Equation Modeling*, *15*(2), 183–210. https://doi.org/10.1080/10705510801922316

Sundström, A. (2016). Understanding illegality and corruption in forest governance. *Journal of Environmental Management*, *181*, 779–790.

Transparency International. (2011). *What is public sector corruption?* Retrieved June 10, 2020 from https://www.transparency.org/en/blog/what-is-public-sector-corruption

Veldkamp, A., & Lambin, E. F. (2001). Editorial: Predicting land-use change. *Agriculture, Ecosystems and Environment*, *85*(1–3), 1–6. https://doi.org/10.1016/S0167-8809(01)00199-2

Verburg, P. H., Ellis, E. C., & Letourneau, A. (2011). A global assessment of market accessibility and market influence for global environmental change studies. *Environmental Research Letters*, *6*(3), 034019.

Villoria, N., & Liu, J. (2015). Using continental grids to improve our understanding of global land supply responses: Implications for policy-driven land use changes in the Americas. *GTAP Working Paper, 81*.

von Thünen, J. H. (1826). *Der isolierte Staat in Beziehung auf Nationalökonomie und Landwirtschaft*.

Appendix

Table A3.1. List of countries by region in the sample

Africa	Latin America	Oceania	Europe	Asia	North America
Algeria	Argentina	Australia	Austria	Azerbaijan	Canada
Angola	Belize	New Zealand	Belarus	Bangladesh	Mexico
Benin	Bolivia	Papua New	Bulgaria	Cambodia	USA
Bhutan	Brazil	Guinea	Croatia	China	
Botswana	Chile	Solomon Islands	Czechia	Georgia	
Cameroon	Colombia		Estonia	India	
C. African Rep.	Costa Rica		Finland	Indonesia	
Chad	Cuba		France	Iran	
Dem. Rep. of	Dominican		Germany	Japan	
Congo	Rep.		Greece	Kazakhstan	
Equatorial Guinea	Ecuador		Hungary	Kyrgyzstan	
Ethiopia	El Salvador		Italy	Laos	
Gabon	Guatemala		Latvia	Malaysia	
Ghana	Guyana		Lithuania	Mongolia	
Guinea	Honduras		Macedonia	Morocco	
Guinea-Bissau	Nicaragua		Norway	Myanmar	
Kenya	Panama		Poland	Nepal	
Liberia	Paraguay		Portugal	North Korea	
Madagascar	Peru		Serbia	Pakistan	
Malawi	Uruguay		Romania	Philippines	
Mali	Venezuela		Russia	South Korea	
Mozambique	Suriname		Slovakia	Sri Lanka	
Namibia			Slovenia	Taiwan	
Nigeria			Spain	Thailand	
Rep. of Congo			Sweden	Turkey	
Senegal			Ukraine	Vietnam	
Sierra Leone			Bosnia and		
Somalia			Herzegovina		
South Africa					
South Sudan					
Sudan					
Togo					
Uganda					
Tanzania					
Zambia					
Zimbabwe					

Table A3.2. List of countries by region, net change in land cover

	Remaining Forest	Change to other land uses	Change of pixels (%)
Africa			
Algeria	1,762	33	1.80
Angola	73,030	2,373	3.10
Benin	2,575	9	0
Bhutan	3,242	17	0
Botswana	3,379	128	3.6
Cameroon	35,715	534	1.4
Central African Rep.	50,038	233	0
Chad	3,789	210	5.2
Dem. Rep. of Congo	18,666	4,654	2.4
Equatorial Guinea	2,406	53	2.1
Ethiopia	17,304	421	2.3
Gabon	23,904	291	1.2
Ghana	6,014	178	2.8
Guinea	14,070	239	1.6
Guinea-Bissau	1,971	92	4.4
Kenya	6,457	943	12.7
Liberia	4,078	733	15.2
Madagascar	23,351	1,342	5.4
Malawi	1,964	1,575	44.5
Mali	1,398	6	0
Mozambique	45,090	3,884	7.9
Namibia	6,227	185	2.8
Nigeria	14,745	502	3.2
Rep. of Congo	186,660	4,654	1.0
Senegal	4,144	72	1.0
Sierra Leone	1,591	126	7.0
Somalia	1,427	18	1.0
South Africa	7,161	1,911	21.0
South Sudan	20,958	424	1.0
Sudan	5,108	24	0
Togo	1,295	4	0
Uganda	4,120	91	2.0
Tanzania	31,753	3,105	8.0
Zambia	43,766	1,592	3.0
Zimbabwe	8,974	683	7.0
Latin America			
Argentina	35,845	9,899	21.63
Belize	1,835	126	6.0
Bolivia	62,037	5,789	8.5
Brazil	424,437	43,069	9.2
Chile	25,249	433	1.6

Colombia	73,311	2,285	3.0
Costa Rica	3,002	83	2.6
Cuba	3,727	63	1.6
Dominican Republic	1,727	55	3.0
Ecuador	16,239	316	1.9
El Salvador	1,170	6	0
Guatemala	6,842	1,330	16.2
Guyana	19,986	301	1.4
Honduras	7,025	421	5.6
Nicaragua	6,461	858	11.7
Suriname	14,479	170	1.0
Panama	4,434	159	3.4
Paraguay	16,581	6,206	27.0
Peru	84,786	1,395	1.6
Uruguay	1315	75	5.0
Venezuela	49,628	1,292	2.0
Ocenaia			
Australia	79,575	6,821	7.8
New Zealand	8,787	760	7.9
Papua New Guinea	37,534	1,390	3.5
Solomon Islands	1032	8	0
Europe			
Austria	6,224	356	5.4
Belarus	12,569	805	6.0
Bosnia and Herzegovina	3,704	304	7.5
Bulgaria	4,988	163	3.1
Croatia	3,166	248	7.2
Czechia	3,827	240	5.9
Estonia	4,725	543	10.3
Finland	48,931	1,460	2.8
France	17,574	1,217	6.4
Germany	14,581	846	5.4
Greece	3,396	233	6.4
Hungary	1,951	90	4.4
Italy	10,293	992	8.7
Latvia	6,168	740	10.0
Lithuania	3,056	182	5.6
Macedonia	1,159	52	4.2
Norway	22,788	1,078	4.5
Poland	13,559	476	3.3
Portugal	3,953	297	6.0
Serbia	3,198	55	1.0
Romania	9,790	290	2.8
Russia	1,889,356	4,8685	2.5
Slovakia	3301	103	3.0
Slovenia	1,888	111	5.0

Spain	17,273	1,356	7.0
Sweden	60,616	2,365	3.0
Ukraine	10,314	351	3.0
Turkey	19,323	1,237	6.0
Asia			
Azerbaijan	1,053	113	9.69
Bangladesh	1,223	49	3.80
Cambodia	8,328	1,573	15.8
China	191,918	9,407	4.6
Georgia	4,046	196	4.6
India	55,204	2,309	4.0
Indonesia	104,692	9,560	8.3
Iran	1999	286	12.5
Japan	29,520	1,200	3.9
Kazakhstan	6,059	336	5.25
Kyrgyzstan	1,006	159	13.6
Laos	11,127	567	4.8
Malaysia	18,889	2,438	11.4
Mongolia	10,444	1,201	10.3
Morocco	1,761	29	1.6
Myanmar	30,131	1,431	4.5
Nepal	7,032	385	5.1
North Korea	9,822	494	4.7
Pakistan	2,429	203	7.7
Philippines	7,618	606	7.3
South Korea	5,356	927	14.0
Sri Lanka	2,028	271	10.0
Taiwan	2,310	118	4.0
Thailand	11,455	601	4.0
Vietnam	10,639	1,493	12.0
North America			
Canada	731,695	17,377	2.3
Mexico	73,268	1,395	4.4
USA	379,371	13,385	3.4

Table A3.3. Complete list country dummy logistic regression and marginal effects of deforestation (1992-2015), as the United States of America as reference

Dependent Variable: Deforestation	Logistic Country	Marginal effects	country	Logistic Country	Marginal effects
Constant	-0.488***		South Sudan	-1.402***	-0.0237***
	(0.0161)			(0.0508)	(0.0004)
Suitability	-0.0181***	-0.0005***	Sudan	-2.860***	-0.0297
	(0.00126)	(0.00004)		(0.209)	(0.0004)
Ln Accessibility	-0.346***	-0.0105***	Sri Lanka	-0.0631	-0.0018***
	(0.00182)	(0.00005)		(0.0669)	(0.0019)
Zimbabwe	-0.402***	-0.0102***	Spain	-0.638***	-0.0146
	(0.0423)	(0.0008)		(0.0313)	(0.0005)
Zambia	-0.996***	-0.0197***	South Korea	-0.0325	-0.0009***
	(0.0287)	(0.0003)		(0.0387)	(0.0011)
Vietnam	0.251***	0.0086***	South Africa	0.662***	0.0278***
	(0.0307)	(0.001)		(0.0295)	(0.0016)
Venezuela	-0.704***	-0.0157***	Somalia	-1.869***	-0.0265***
	(0.0311)	(0.0004)		(0.238)	(0.001)
Uruguay	-0.726***	-0.016***	Solomon Islands	-2.685***	-0.0293***
	(0.120)	(0.0018)		(0.355)	(0.0007)
Ukraine	-1.469***	-0.0241***	Slovakia	-1.609***	-0.025***
	(0.0565)	(0.0004)		(0.101)	(0.0006)
Uganda	-1.713***	-0.0257***	Slovenia	-1.012***	-0.0198***
	(0.107)	(0.0006)		(0.0987)	(0.0011)
Turkey	-0.731***	-0.0161***	Sierra Leone	-0.274***	-0.0073***
	(0.0322)	(0.0004)		(0.0943)	(0.0022)
Togo	-3.783***	-0.0308***	Republic of Serbia	-2.179***	-0.0279***
	(0.501)	(0.0003)		(0.137)	(0.0005)
Thailand	-0.628***	-0.0144***	Senegal	-1.760***	-0.026***
	(0.0439)	(0.0007)		(0.120)	(0.0006)
Tanzania	0.140***	0.0045***	Russia	-0.753***	-0.0208***
	(0.0228)	(0.0007)		(0.0137)	(0.0003)
Taiwan	-1.067***	-0.0204***	Romania	-1.508***	-0.0244***
	(0.0993)	(0.001)		(0.0610)	(0.0004)
Sweden	-0.988***	-0.0197***	Portugal	-0.671***	-0.0151***
	(0.0248)	(0.0003)		(0.0621)	(0.001)
Suriname	-1.472***	-0.0242***	Poland	-1.646***	-0.0253***
	(0.0784)	(0.0005)		(0.0491)	(0.0003)
Philippines	-0.234***	-0.0064***	Malawi	1.924***	0.1506***
	(0.0448)	(0.0011)		(0.0366)	(0.0054)

Peru	-1.214***	-0.0223***	Madagascar	-0.209***	-0.0058***
	(0.0300)	(0.0003)		(0.0309)	(0.0007)
Paraguay	1.614***	0.1084***	Macedonia	-1.072***	-0.0205***
	(0.0197)	(0.0023)		(0.143)	(0.0015)
Papua New Guinea	-0.376***	-0.0096***	Lithuania	-0.976***	-0.0194***
	(0.0303)	(0.0006)		(0.0778)	(0.0009)
Panama	-0.839***	-0.0176***	Liberia	0.794***	0.0356***
	(0.0820)	(0.0001)		(0.0423)	(0.002)
Pakistan	-0.386***	-0.0098***	Latvia	-0.132***	-0.0037***
	(0.0753)	(0.0016)		(0.0413)	(0.0011)
Norway	-0.794***	-0.017***	Laos	-0.399***	-0.0101***
	(0.0341)	(0.0004)		(0.0450)	(0.0009)
North Korea	-0.857***	-0.0179***	Kyrgyzstan	0.627***	0.0259***
	(0.0484)	(0.0006)		(0.0866)	(0.0046)
Nigeria	-1.471***	-0.0242***	Kenya	0.406***	0.015***
	(0.0488)	(0.0003)		(0.0375)	(0.0016)
Nicaragua	0.394***	0.0145	Kazakhstan	-0.412***	-0.0104***
	(0.0388)	(0.0017)		(0.0578)	(0.0012)
New Zealand	0.00397	0.0001***	Japan	-1.528***	-0.0247***
	(0.0401)	(0.0012)		(0.0332)	(0.0002)
Nepal	-0.650***	-0.0148***	Italy	-0.562***	-0.0133**
	(0.0547)	(0.0009)		(0.0361)	(0.0006)
Namibia	-0.979***	-0.0194***	Iran	0.142**	0.0046***
	(0.0758)	(0.0009)		(0.0652)	(0.0022)
Mozambique	-0.171***	-0.0048***	Indonesia	0.223***	0.0075***
	(0.0212)	(0.0005)		(0.0167)	(0.0006)
Morocco	-2.240***	-0.0281***	India	-1.154***	-0.0216***
	(0.188)	(0.0006)		(0.0252)	(0.0002)
Mongolia	0.706***	0.0303***	Hungary	-1.285***	-0.0226***
	(0.0333)	(0.0019)		(0.109)	(0.0009)
Mexico	-0.774***	-0.0168***	Honduras	-0.440***	-0.011***
	(0.0218)	(0.0003)		(0.0520)	(0.001)
Mali	-3.025***	-0.0299***	Guyana	-1.198***	-0.0218***
	(0.409)	(0.0006)		(0.0596)	(0.0005)
Malaysia	0.430***	0.0161***	Guinea-Bissau	-0.819***	-0.0173***
	(0.0252)	(0.0011)		(0.108)	(0.0015)
Guinea	-1.912***	-0.0268***	Dem. Rep. of Congo	-1.125***	-0.0218***
	(0.0669)	(0.0003)		(0.0196)	(0.0002)
Guatemala	0.579***	0.0233***	Rep. of Congo	-1.393***	-0.0236***
	(0.0330)	(0.0017)		(0.0516)	(0.0004)

Greece	-0.725***	-0.016***	Colombia	-0.640***	-0.0147***
	(0.0691)	(0.001)		(0.0249)	(0.0004)
Ghana	-1.309***	-0.0228***	China	-0.716***	-0.0162***
	(0.0774)	(0.0006)		(0.0168)	(0.0002)
Germany	-1.172***	-0.0216***	Chile	-1.653***	-0.0255***
	(0.0384)	(0.0003)		(0.0503)	(0.0003)
Georgia	-0.768***	-0.0166***	Chad	-0.635***	-0.0145***
	(0.0746)	(0.0011)		(0.0722)	(0.0012)
Gabon	-1.733***	-0.0259***	Central African Republic	-2.660***	-0.0299***
	(0.0604)	(0.0003)		(0.0671)	(0.0001)
France	-0.914***	-0.0186***	Canada	-0.864***	-0.0199***
	(0.0326)	(0.0004)		(0.0151)	(0.0002)
Finland	-1.335***	-0.0232***	Cameroon	-1.907***	-0.027***
	(0.0296)	(0.0002)		(0.0457)	(0.0002)
Ethiopia	-1.387***	-0.0235***	Cambodia	0.800***	0.036***
	(0.0510)	(0.0004)		(0.0304)	(0.001)
Estonia	-0.120**	-0.0034***	Myanmar	-0.524***	-0.0126***
	(0.0473)	(0.0012)		(0.0300)	(0.0005)
Equatorial Guinea	-1.486***	-0.0242***	Bulgaria	-1.322***	-0.0229***
	(0.141)	(0.001)		(0.0807)	(0.0006)
El Salvador	-3.705***	-0.0307***	Brazil	0.423***	0.0153***
	(0.449)	(0.0003)		(0.0138)	(0.0005)
Ecuador	-1.490***	-0.0243***	Botswana	-0.817***	-0.0173***
	(0.0587)	(0.0004)		(0.0919)	(0.0012)
Dominican Rep.	-1.367***	-0.0233***	Bosnia and Herzegovina	-0.516***	-0.0124***
	(0.138)	(0.0011)		(0.0614)	(0.0011)
Czechia	-1.069***	-0.0204***	Bolivia	0.205***	0.0068***
	(0.0685)	(0.0007)		(0.0190)	(0.0007)
Cuba	-2.007***	-0.0272***	Bhutan	-2.721***	-0.0294***
	(0.128)	(0.0005)		(0.244)	(0.0005)
Croatia	-0.740***	-0.0162***	Costa Rica	-1.398***	-0.0235***
	(0.0674)	(0.001)		(0.114)	(0.0009)
Benin	-3.751***	-0.0308***	Austria	-0.958***	-0.0192***
	(0.379)	(0.0003)		(0.0562)	(0.0006)
Belize	-0.265***	-0.0071***	Argentina	0.999***	0.04932***
	(0.0932)	(0.002)		(0.0171)	(0.0012)
Belarus	-0.722***	-0.0159***	Angola	-0.976***	-0.0196***
	(0.0387)	(0.0006)		(0.0245)	(0.0003)
Bangladesh	-1.385***	-0.0234***	Algeria	-2.276***	-0.0282***
	(0.155)	(0.001)		(0.176)	(0.0005)

Azerbaijan	-0.0795 (0.101)	-0.0023*** (0.002)
# of Observations	5,836,*521*	

Notes: LR chi2 (117) =168406.56; pseudo R2= 0.0831; Pearson chi2(459180) = 532060.83; Prob > chi2 = 0.0000. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A3.4. Descriptive statistics of original database and random samples (15%, 10%, 5%)

Sample	**Original**		**15%**		**10%**		**5%**	
Variable Name	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Deforestation	0.04	0.2	0.04	0.2	0.04	0.2	0.04	0.02
Infrastructural Factor								
Accessibility	1073	1359	1072.5	1358.4	1076	1360	1071.4	1358.1
Ln Accessibility	6.13	1.44	6.14	1.44	6.14	1.44	6.13	1.44
Biophysical Factor								
Suitability	6.25	2.08	6.25	2.08	6.26	2.08	6.25	2.08
Ln Suitability	1.74	0.48	1.74	0.48	1.74	0.48	1.74	0.48
Institutional Factors								
CPI	4.17	2.49	4.17	2.49	4.17	2.49	4.17	2.49
GE	0.2	0.012	0.2	0.012	0.2	0.012	0.20	0.012

Table A3.5. Bootstrapped logistic regressions and marginal effects of deforestation (1992-2015) of Corruption Perception Index and Government Effectiveness index with a boot(15% sample)

Dependent Variable: Deforestation	(1) Logistic (CPI)	Marginal Effects	(2) Logistic (GE)	Marginal Effects
Constant	-2.0973*** (0.0048)		0.843*** (0.0285)	
Suitability	-0.1128*** (0.0074)	-0.0041*** (0.00003)	-0.103*** (0.000772)	-0.00367*** (0.00003)
Accessibility	-0.0003*** (2.46e-06)	-0.00001*** (0.000001)	-0.000317*** (2.46e-06)	-0.00001*** (0.000001)
CPI	-0.0240*** (0.0006)	-0.0008*** (0.00003)		
GE			-15.25*** (0.141)	-0.54531*** (0.00499)
# of Observations	8,758,260		8,675,758	

Notes: Bootstrapped results of 1000 replications with the 15% sample.
Model (1) Wald chi2(3)=53536.33; Pseudo R2=0.0249;Pearson chi2(356511)=660220; Prob>chi2=0.0000.
Model (2) Wald chi2(3)=55668.7; Pseudo R2=0.0286; Pearson chi2(274492) =544353 Prob > chi2=0.0000

Table A3.6. Bootstrapped logistic regressions and marginal effects of deforestation (1992-2015) of Corruption Perception Index and Government Effectiveness index with a boot(5% sample)

Dependent Variable: Deforestation	(1) Logistic (CPI)	Marginal Effects	(2) Logistic (GE)	Marginal Effects
Constant	-2.0987***		0.8518***	
	(0.0087)		(0.0493)	
Suitability	-0.1128***	-0.0041***	-0.1025***	-0.00368***
	(0.0013)	(0.00005)	(0.00012)	(0.00005)
Accessibility	-0.0003***	-0.00001***	-0.0003***	-0.00001***
	(0.000004)	(0.000001)	(0.000004)	(0.000001)
CPI	-0.0240***	-0.0008***		
	(0.0011)	(0.00004)		
GE			-15.296***	-0.550***
			(0.2454)	(0.0087)
# of Observations	2,919,284		2,891,945	

Notes: Bootstrapped results of 1000 replications with the 5% sample. Model (1) Wald chi2(3)=17289.01; Pseudo R2=0.0245; Pearson chi2(260458)=4399990.05; Prob>chi2=0.0000.

Model (2) Wald chi2(3)=19814.9; Pseudo R2=0.0282; Pearson chi2(198847)=283306.93; Prob>chi2=0.0000. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

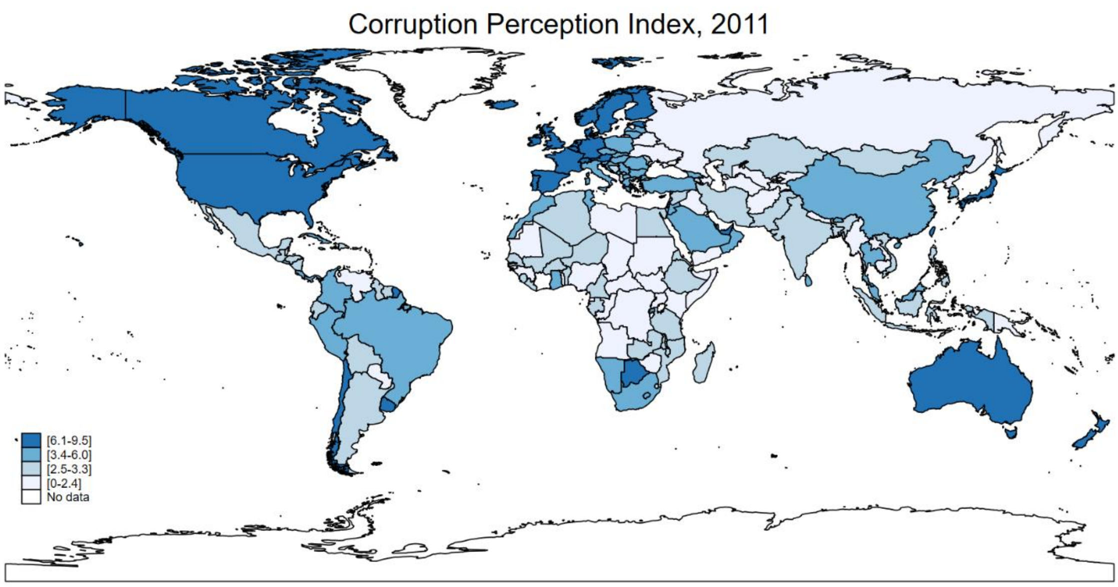

Figure A3.1. Corruption Perception Index, 2011 world map (0 highly corrupt to 10 very clean)

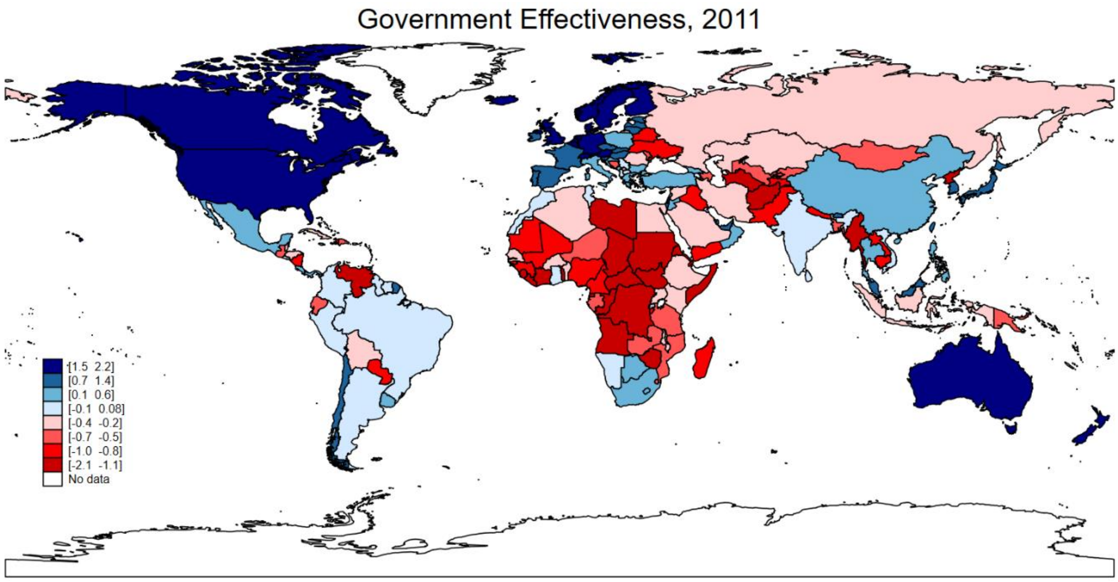

Figure A3.2. Government Effectiveness index, 2011 world map (-2.5 highly inefficient +2.5 highly efficient)

Chapter 4

Spatial effects of rural credit for family farming in Brazil: evidence from the Amazon

Authors: Ianna Dantas & Christian Henning

Abstract

Family farmers are important actors in food security and job generation in Brazilian rural areas. The National Program for Strengthening Family Farming (PRONAF) is the main public program granting credits to family farmers to foster sustainable production and market integration to reduce the poverty gap. Nevertheless, rural credit allocation is very uneven across Brazil, with the Legal Amazon having very few investments. Credit rationing is argued to target wealthier farmers engaged in livestock production while neglecting those producing under agricultural systems. This paper aims to investigate the presence of spatial spillovers as providing beneficial opportunities for PRONAF allocation in the region. For that, we employ a Spatial Durbin Error Model of PRONAF acquisition for husbandry and agricultural systems in 103 microregions of the Brazilian Legal Amazon. Credit data are available from 2012 to 2019 in the Central Bank of Brazil's database, and production data are based on the 2017 national agricultural census. Additionally, to enhance the paper's discussion, we conducted 35 semi-structured interviews with key informants from banks, technical assistance, and research. Results suggest that credits are not independently distributed, and they are rather influenced by spatial characteristics of neighboring microregions. Positive spillover effects are observed for credit history for husbandry and agriculture. This implies that microregions with steady credit acquisition enable social capital, knowledge transfer, and reduce the transaction costs for credits. Negative spillovers are observed for commercial banks, which we argue to be a sign of competitiveness across regions, given a limited amount of credit. Such competition is a plausible argument holding also for production value in neighboring regions. These results can potentially signalize inefficient credit allocation, where wealthier farmers have better opportunities to access markers, information, and credits. Thus, political efforts have to focus on targeting vulnerable farmers unable to benefit from social networks, stable markets, and financial investments.

Keywords: Rural Credit, Legal Amazon, Family Farming, PRONAF, Microfinance, Spatial Regression, Spillovers, Spatial Durbin Error Model

1. Introduction

In recent decades, Brazil has become an important player in international agri-food markets, being placed among the ten leading global economies and food exporters (FAO & OECD, 2015). This performance is a result of increasing investments in large extensive production systems that account for 11% of the total Brazilian farms (Alves et al., 2013). Despite the economic success of commodity enterprises, poverty and high-income inequality prevail in rural areas (Neves et al., 2020), where small family farmers have insufficient inputs, low market access, and production remains stagnant.

Family farmers account for 82% of productive units in the Legal Amazon (IBGE, 2017), supply 36% of the national food production (Guanziroli and di Sabbato, 2014), and spur job generation and economic activities in rural areas (Guanziroli et al., 2013). Nevertheless, they face considerable difficulties in integrating markets and accessing land and inputs (Alves et al., 2012; Medina et al., 2015). In this context, rural credits represent an essential tool to reduce the inequality gap, promoting market integration and living standards for rural populations (Zhu et al., 2021).

In Brazil, the creation of the National Program for Strengthening Family Farming (PRONAF) in 1995 was the core strategy to provide income transfer and improve credit distribution for economically vulnerable family farmers (de Castro and Teixeira, 2012; Zeller and Schiesari, 2020). Moreover, PRONAF was a milestone in recognizing family farmers as political agents, including the land reform rhetoric in political agendas (Guanziroli et al., 2013), and has a strong political slant for consolidating rural families as promoters of sustainability (Resende and Martins Mafra, 2016). PRONAF grants credit with low interest rates (Kumar, 2005) to enable investments, input acquisition, technology, information and income transfer, and job generation while fostering sustainable development and production in marginalized rural areas (Medina et al., 2015).

Despite strong aspirations, studies suggest an underperformance of PRONAF. In particular, it failed to reduce the inequality gap (Helfrand et al., 2009), and credit acquisition and contracts have been unevenly distributed across Brazil (Zeller and Schiesari, 2020). For instance, states in the Legal Amazon[20] showed the lowest concentration of credit contracts over the years (Grisa et al., 2014). In parallel, credit rationing has been observed for prioritizing farmers specialized in monocultures with technology, financial resources, and market access (Grisa et al., 2014; Resende and Martins Mafra, 2016).

It is argued that PRONAF investments did not integrate vulnerable producers and have instead supported monoculture expansion in the Amazon (Maia et al., 2020; Mattei, 2011). Yet, there are very few studies investigating PRONAF's performance in the Amazon (Madeira de Souza et al., 2021; Pokorny et al., 2010). Moreover, there is a need for empirical-based assessments of credit opportunities while addressing the conditions of Amazonian family farmers.

Spatial analysis is especially relevant given that credit loans vary among local banks, financial institutions, and networks (Zeller, 2006). PRONAF's credit lines are managed by several banks with distinct characteristics., in which microregions have contrasting market and

[20] The Law 1.806 from 06.01.1953 politically recognized nine Brazilian states (Acre, Amapá, Amazonas, Pará, Rondônia, Roraima, Tocantins and Mato Grosso, and parts of Maranhão) as the Legal Amazon. The area represents 59% of the national territory and is under the responsibility of the Superintendence of the Amazon Development (SUDAM) as a way to promote the economic development of the region (Brasil, 2021; IBGE, 2021).

production structures and technical assistance provisions. The term microregion[21] is an official and representative aggregation of neighboring municipalities presenting similar natural characteristics and socioeconomic organizations (SNIRH, 2021).

To the best of our knowledge, despite the growing spatial microfinance literature in developing countries (Assunção et al., 2020; Ayalew et al., 2012; Koç et al., 2019; Yeung et al., 2017), gauging spatial spillovers influencing PRONAF credit provision in the Legal Amazon is still inexistent.

While considering that credit rationing is inherent to loan markets (Bester and Hellwig, 1987) and public subsidies generally have a rationing character, this paper aims to assess the existence of beneficial spatial correlations that offer opportunities for credit allocation across microregions.

We fill these gaps in the extant literature by applying a spatial Durbin error model to assess the spillover effects of PRONAF for husbandry and agricultural systems in 103 microregions composing the Brazilian Legal Amazon. Credit data are available from 2012 to 2019 in the Central Bank of Brazil's database, and production data are based on the 2017 national agricultural census. Production variables are highly aggregated, which limits their inclusion and assessments in econometric models. Alternatively, to uphold and enhance the paper's discussion and explanation of the findings, we conducted 35 semi-structured interviews with key informants from banks, technical assistants, and researchers specialized in family farming in the Legal Amazon.

The remainder of the paper is organized as follows: Section 2 contextualizes PRONAF in the Legal Amazon and the characteristics of credit for husbandry and agricultural production systems. Section 3 displays the spatial estimation model and describes the data employed in the paper and semi-structured interviews. Estimation results are presented in section 4, followed by the discussion of findings in section 5. Lastly, the conclusion of the research and political recommendations are drawn in Section 6.

2. Contextualizing PRONAF in Brazil and the Legal Amazon

Rural finance in Brazil is historically characterized by a strong dualism between allocating public investments to spur agricultural productivity and subsequently increase exports or to support family systems that are of core importance to domestic food production (Ghinoi et al., 2018). Since the 1960s, export-oriented large-scale farms, especially in southern Brazil, have been prioritized for rural public funds (Helfand, 2001). Family farmers, in turn, mainly remained excluded and weakly represented in political spheres and unable to access credit (Guanziroli et al., 2013; Resende and Martins Mafra, 2016).

Only in the mid-1980s, with the end of the military dictatorship, Brazil experienced the upswing of political groups reclaiming rights to land and demanding governmental support for rural workers and family farmers (Guanziroli et al., 2013). As a result, the government created a program funded by the National Development Bank (BNDS) exclusively targeting family farmers. The program underwent several modifications and was officially established as the so-called PRONAF[22] in 1996.

[21] For further details about regional aggregation see https://biblioteca.ibge.gov.br/visualizacao/livros/liv2269_1.pdf
[22] law 1.946/1996.

Over the decades, PRONAF has developed subprograms to widen the program's portfolio and target groups (e.g., PRONAF woman, agroecology, forestry, integrated systems) (Maia et al., 2020). The main PRONAF objectives are i) Offering credits to cover costs or investments in agricultural and non-agricultural activities, ii) promoting infrastructural development and providing essential services in poor rural areas, iii) training family farmers and technicians towards sustainable production, and iv) supporting and promoting research and rural extension, and information transfer among farmers (Petrini et al., 2016; Schneider et al., 2021).

According to Medina et al. (2015), Brazilian family farmers are a highly diverse category with their own historical and political construction, ranging from European descendants, indigenous groups, the so-called *quilombola* African descendant groups, and the traditional communities in the Amazon, among others. These actors engage in local and context-specific production systems highly diversified across Brazil but commonly experience social and political disadvantages compared to market-oriented large farmers (Godar et al., 2012). Notwithstanding the diversity of family farmers, this paper follows the family farming definition enacted by law[23] in 2006 and endorsed by the (FAO, 2014).

Studying PRONAF in the Legal Amazon is important since it covers 59% of the national territory and 67% of the global tropical forest (IMAZON, 2009) (Figure 4.1). Moreover, rural Amazonian populations remain in acute economic vulnerability (Verner, 2004) and are the most relevant public microfinance program amounting to about 30% of national costs from the agricultural sector (de Castro and Teixeira, 2012).

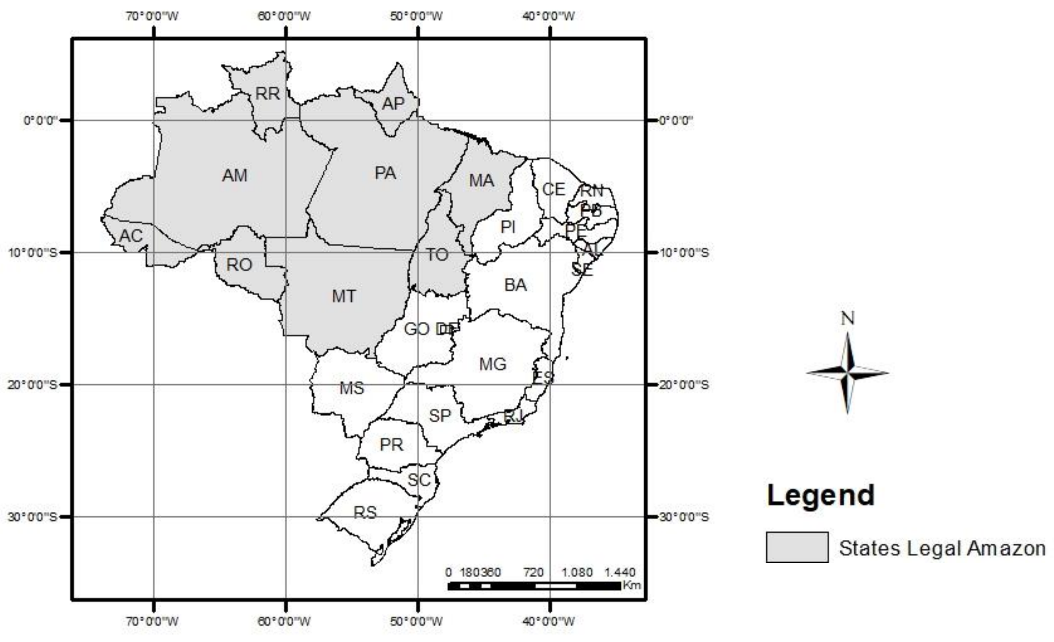

Figure 4.1. The Brazilian Legal Amazon Note: The Legal Amazon, located in the North of Brazil, also embraces the State of Mato Grosso (Center-west), Tocantins (Center), and parts of Maranhão (Northeast)

[23] Law 11.326/2006. Family farmers are defined as: i) owning no more than four fiscal modules (measurement varying across municipalities following the law 6746/1979), ii) work force predominantly from family members, iii) income generated mostly by farm activities, and iv) farm managed by the family.

Comparing the allocation of rural credits to family farmers in Brazil, the Legal Amazon shows the lowest credit provision. Only nearly 9% of family farmers access credits in the Amazon, while in the south and southeast, about 30% and 15%, respectively (IBGE, 2017). Disparities in credit allocation become even more pronounced given that over 65% of the total national PRONAF recourses are absorbed in southern Brazilian states, while only 6% are granted in the Legal Amazon (Zeller and Schiesari, 2020).

The main PRONAF's credit lines in the Amazon are to support husbandry and agricultural production systems (BNDES, 2021). Nevertheless, family farmers have increasingly diversified systems toward milk and meat production (Martins and Pereira, 2012). These commodities are highly tradable and add value to production activities, leading to the continuous intensification of farming systems (Carpentier et al., 2000). Meanwhile, farmers producing agricultural crops do not have the economic means to access credits and food markets.

Godar (2009) points out, for instance, that over 65% of credits managed by the Bank of the Amazon (Banco da Amazônia or BASA) were granted to cattle ranchers along the Transamazon Highway (state of Pará). Similarly, Pacheco and Poccard-Chapuis, (2012) found that rural credits and market integration are economic structures spurring the adoption of and strengthening already existing smallholder cattle ranching systems. Moreover, family farmers engaged in husbandry systems that highly depend on credit to maintain production and acquire production inputs (Martins and Pereira, 2012).

Despite higher investments in husbandry systems, family farming units engaged in crop production are predominantly higher in all states in the Legal Amazon (Table 4.1). This fact brings forward the claims of PRONAF overlooking the majority of smallholders to prioritize animal production.

Table 4.1. Shares of husbandry and agricultural family farming units across Legal Amazon states

State	Share of family farm units (%)	
	Husbandry	*Agriculture*
RO	23	77
AC	32	68
AM	39	61
RR	35	65
PA	39	61
AP	29	71
TO	27	73
MA	36	64
MT	21	79

Source: Authors' calculations adapted from the 2017 agriculture census (IBGE, 2017).

In this context, de Paula Filho et al. (2016) analyzed credit and technical assistance for family farmers in the Transamazon region and observed that public funds for husbandry projects lead to a shift in the local economy from vegetal extraction to marketed commodities.

Conversely, according to Mertens et al. (2015) and Godar et al. (2012), family smallholders producing essential food crops for local markers and food security experience barriers to accessing public credits. This fact is seen as a priority target failing to deliver economic and political integration of a diverse category of vulnerable farmers (Neves et al., 2020).

Family farming plays a vital role in maintaining both husbandry and agricultural systems in the Amazon. The husbandry system refers to milk and small and big-size livestock production, while agricultural systems constitute the production of temporary and permanent crops. Over the years, PRONAF data from the Central Bank of Brazil[24] (BCB, 2021) point out that credits granted in the region have been predominantly higher to husbandry production systems (Figure 4.2). Moreover, agricultural credits have gradually decreased over the years. This fact not only endorses the aforementioned advantages of husbandry systems in Brazil since it also raises discussions about forest preservation in the Amazon. Such debates are timely relevant, given that deforestation prevails with more than 20% of the natural vegetation cleared (Nobre et al., 2016). Moreover, it emphasizes the need to evaluate the existing disparities between both production systems.

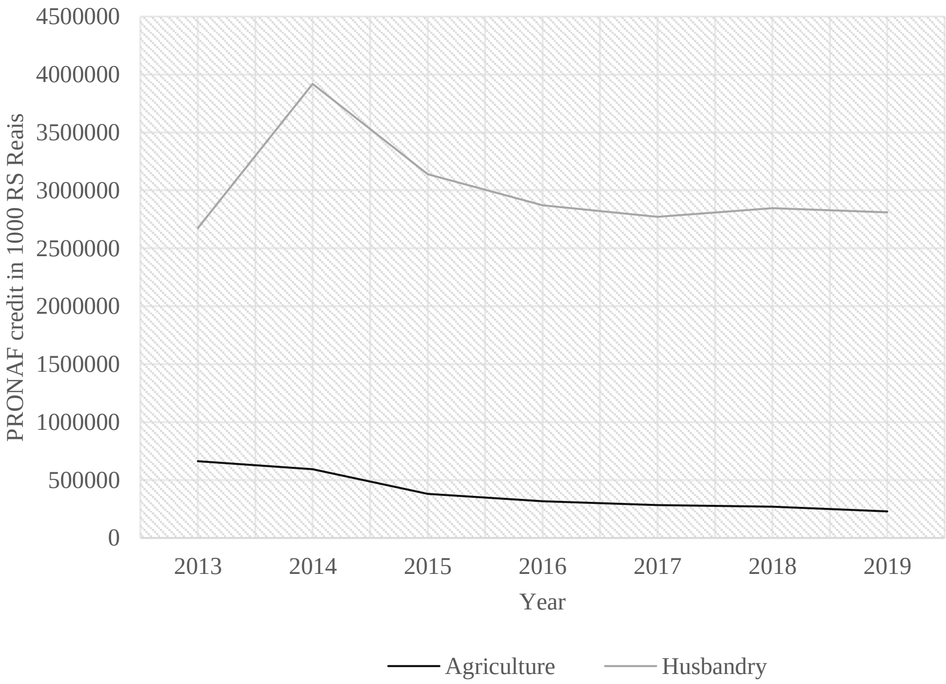

Figure 4.2. PRONAF values granted to husbandry and agricultural systems in the Legal Amazon from 2013 to 2019. Source: Authors' elaboration adapted from (BCB, 2021).

3. Spatial Estimation Model, Data, and Interviews

In this section, we first present the estimation strategy (3.1), then describe the data and variables used in the empirical model (3.2), and finally present the design of the questionnaires used for the interviews (3.3).

[24] The values were corrected for inflation using the 2019 IGP-DI index provided from The Institute for Applied Economic Research (IPEA, 2021)

3.1. Spatial modeling approach

The spatial econometrics literature follows Tobler's First Law of Geography, stating that neighboring regions are more related to one another than those located far away (Tobler, 1970). This premise suggests that the values of its neighbors influence observed variables in a certain region. In the case of rural credits, capital might flow over neighboring markets, generating local interactions, also called spillovers (Zhu et al., 2021). Thus, ignoring spatial autocorrelation would lead to misleading estimators, which might be the case with commonly applied models in the field of rural finance (Anselin et al., 1996).

Following that, there are several modeling approaches for assessing possible spatial interactions among dependent and independent variables. Popular models are the spatial lag model of X (SLX), the spatial error model (SEM), the spatial lag model (SAR), the spatial Durbin model (SDM), and the spatial Durbin error model (SDEM) (Wang et al., 2019; Zhu et al., 2021; Zubek and Henning, 2016). The model specification follows Elhorst (2014) and LeSage and Pace (2009).

In our setting, the dependent variables refer to the average value of PRONAF loans for husbandry (agriculture) in 2018 and 2019 per hectare of cultivated area. Adjusting the values according to the production area in every microregion is important; otherwise, absolute values of larger microregions would underestimate the overall effects.

We perform a spatial regression analysis for two distinct production systems, namely husbandry and agriculture. Family farmers engaged in husbandry activities have different characteristics from those farmers producing crops. These production activities likewise have different costs and advantages to accessing credits and markets (Helfand, 2001). These factors support the choice of conducting separate analyses.

The SLX model is expressed as:

$$C_i = \alpha_i + X\beta + WX\gamma + \varepsilon, \qquad \varepsilon \sim N(0, \sigma^2 I_n) \tag{1}$$

where C_i is the n x 1 vector of dependent variables in microregion i; α_i is the intercept for each microregion; X is the n x p matrix of explanatory variables; β is the regression slope coefficients in the n x 1 vector; ε is the noise error; the σ^2 is the parameter for scalar noise variance; W is then a n x n matrix containing information about the spatial relationship of observations. This model considers the effects of exogenous interactions when control variables of neighboring microregions influence the outcome variable.

Subsequently, the SEM is specified in equation (2), as shown by Golgher and Voss (2016):

$$\begin{gathered} C_i = \alpha_i + X\beta + u \\ u = \lambda W u + \varepsilon, \qquad \varepsilon \sim N(0, \sigma^2 I_n) \end{gathered} \tag{2}$$

where λ represents the average strength of the spatial correlation among error terms that are conditional to a W weight matrix. The latter defines the structure of spatial neighbors' influences among residuals.

The SAR model (equation 3) considers the effects of endogenous interactions when dependent variables of neighboring microregions influence the dependent variable in one microregion. Here ρ is a coefficient of the endogenous variable Wy.

$$C_i = \alpha_i + X\beta + \rho Wy + \varepsilon, \qquad \varepsilon \sim N(0, \sigma^2 I_n) \tag{3}$$

As explained by LeSage and Fischer (2008), the aforementioned models, SAR and SLX, could be combined in a way to account for spatial lags of dependent ($\rho \neq 0$) and independent variables ($\gamma \neq 0$). Considering these specifications result in the so-called SDM as in equation (4). Alternatively, the combination of both SEM and SLX generates the Spatial Durbin Error Model (SDEM) as expressed in equation (5).

$$C_i = \alpha_i + X\beta + \rho Wy + WX\gamma + \varepsilon, \qquad \varepsilon \sim N(0, \sigma^2 I_n) \tag{4}$$

$$C_i = \alpha_i + X\beta + WX\gamma + u, \tag{5}$$

$$u = \lambda Wu + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2 I_n)$$

The model specification follows two strategies: standard statistical tests such as the Wald test asymptotically equivalent to the Lagrange multiplier and the likelihood ratio (Juhl, 2020), and include both Akaike (AIC) and Bayesian (BIC) criteria; additionally, model selection is based on theoretical arguments, as suggested by (Ward & Gleditsch, 2008).

In this paper, we apply an SDEM because it offers several advantages for controlling spatial effects of dependent and independent variables and generates unbiased estimates and coefficients' t-values (Zubek and Henning, 2016). Additionally, the model is suited when spillovers are given only in neighboring regions (Lesage, 2014), which is the case of PRONAF in Amazonian microregions. In other words, it is unlikely that a change in credit in one microregion will result in global other than local spillovers. It is also argued that ignoring spatial dependent and independent effects generates higher unreliability when disregarding the spatial error (Patton and Mcerlean, 2003).

An essential element of spatial econometric models is spatial weight matrices N x N, using the geographical arrangements of regional units to summarize the relationship among them. A spatial weight matrix defines neighboring units by different means. Neighbors can be assigned within a certain distance or by sharing a common border. Because we are testing separate models for two independent production structures, in our analysis, we define two different symmetric spatial weight matrices: The first matrix was built by means of the first order contiguity matrix (W), which is automatically normalized by spectral normalization. Microregions sharing a common vertex are considered neighbors and assume the value of 1, while non-neighboring regions assume the value of zero.

The second weight matrix (M) refers to the inverse distance between microregions normalized by spectral normalization. This criterion is based on polygons' centroids obtained by latitude and longitude, considering neighbors those microregions located within the inverse distance ratio. In other words, the farther the distance, the smaller the relation between variables (Waller and Gotway, 2004).

Prior to the spatial regressions, testing the regional spatial dependence is of core importance. The Moran's I test suits this purpose very well and is generally applied as in equation (6).

$$\text{Moran's I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n}\sum_{j}^{n} \omega_{ij}} \tag{6}$$

The Moran's I test ranges from -1 to 1, where negative values purport negative autocorrelation among regions, whereas positive outcomes represent positive autocorrelation. When the test outcome is zero, it is interpreted as data not showing any spatial correlation. Values closer to 1 indicate a higher degree of aggregation. In equation (6), x_i are observed values, $\bar{x}$ is the sample mean, S^2 is the sample variance, and ω_{ij} is the weight matrix of microregions i to j.

Subsequently, to interpret the model coherently, the direct, indirect, and total effects of explanatory variables over the outcome variable are calculated. In other words, if an explanatory variable in a specific microregion changes, this could result in a change in the dependent variable of the microregion (direct effect) and the dependent variable of neighboring microregions (indirect effect) (Elhorst, 2010). Thus, total effects account for both direct and indirect effects altogether. The calculation of such effects based on the SDEM, as elaborated by Zhu et al. (2021), re as follows:

$$C_i = (I_n - W\rho)^{-1}(X\alpha + WX\gamma) + (I_n - W\rho)^{-1}\varepsilon \qquad (7)$$

In equation (7), I_n is an identity matrix. Afterwards, we obtain equation (8) when X comprises k independent variables.

$$C_i = \sum_{r=1}^{k} S_r(W)x_r + (I_n - \rho W)^{-1}WX\gamma + (I_n - \rho W)^{-1}\varepsilon \qquad (8)$$

where x_r is the r^{th} control variable and S_r(W) is equivalent to $\alpha_r(I - \lambda W)^{-1}$. Subsequently, rewriting equation (8) in terms of a matrix, it is given as follows:

$$\begin{pmatrix} C_1 \\ C_2 \\ \vdots \\ C_n \end{pmatrix} = \begin{pmatrix} S_r(W)_{11} & S_r(W)_{12} & \cdots & S_r(W)_{1n} \\ S_r(W)_{21} & S_r(W)_{22} & \cdots & S_r(W)_{2n} \\ \vdots & \vdots & & \vdots \\ S_r(W)_{n1} & S_r(W)_{n2} & \cdots & S_r(W)_{nn} \end{pmatrix} \begin{pmatrix} x_{1r} \\ x_{2r} \\ \vdots \\ x_{nr} \end{pmatrix} \qquad (9)$$

$$+(I_n - \rho W)^{-1}WX\gamma + (I_n - \rho W)^{-1}\varepsilon$$

Lastly, the equations for average direct, average total, and average indirect effects, given a change in the model variable X_r, are represented in equations (10), (11), and (12), respectively.

$$\bar{M}(r)_{direct} = n^{-1}tr(S_r(W)) \qquad (10)$$

$$\bar{M}(r)_{total} = n^{-1}l'_n S_r(W)l_n \qquad (11)$$

$$\bar{M}(r)_{indirect} = \bar{M}(r)_{total} - \bar{M}(r)_{direct} \qquad (12)$$

3.2. Data and variables

The data are based on microregion level PRONAF loans and production variables for husbandry and agricultural production for the Brazilian Legal Amazon. Microregion level

PRONAF data are provided by the Central Bank of Brazil (BCB, 2021) from 2012 to 2019, differentiating loans intended for husbandry and agricultural activities.

Moreover, we employ production statistics from the 2017 agricultural census (IBGE, 2017), which is reported every ten years and is the only official database with representative agricultural statistics at various geographical levels.

Although family farming data are available in the 2006 agricultural census, our analysis comprises data solely from the 2017 agriculture statistics. It is due to the fact that the 2017 census presents a more complete family farming data set in a further disaggregated manner. Thus, it is not possible to fully control for variable specifications between the two censuses and to allow for a robust comparison.

Concerning the variables used in the empirical analysis, the dependent variable is defined as the average credit amount (in thousand R$ Reais) for the years 2018 and 2019 over the production area (hectares) in 103 Amazonian microregions. The analysis assesses variables affecting credit acquisition (for husbandry and agricultural systems) following the production year 2017.

As shown in Figure 4.3, the PRONAF values for husbandry production are unevenly distributed across the region, also leading to the presence of regional clusters. For instance, a microregion with high credit acquisition is not geographically isolated since its neighbors tend to present similar credit levels. Similarly, credits for agricultural production are unevenly distributed in the Legal Amazon, also indicating the presence of cluster microregions (Figure 4.4). Furthermore, considering that agricultural credits are assumed to be absorbed in the productive land, the average credit values are divided by the total production area (hectare) in the microregion. The latter comprise the total area under agricultural cultivation or used for husbandry systems in all family farming units at the microregion level.

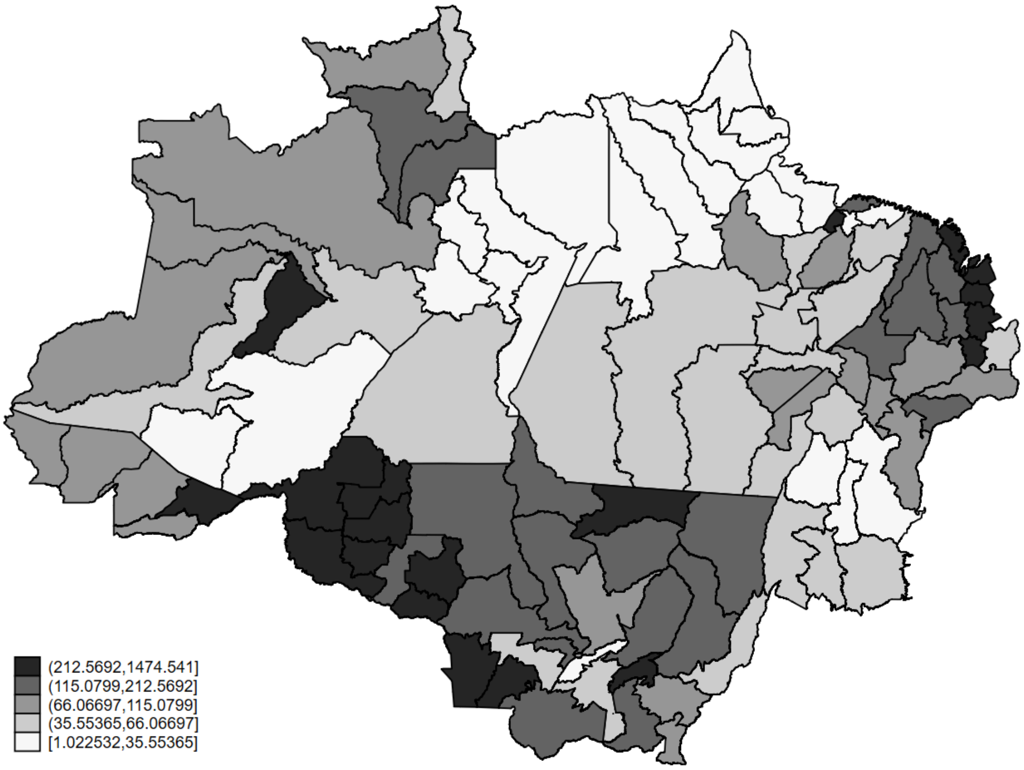

Figure 4.3. Spatial distribution of PRONAF credits (average 2018-2019 in thousand R$ Reais per hectare of production area) for husbandry systems across 103 Amazonian microregions

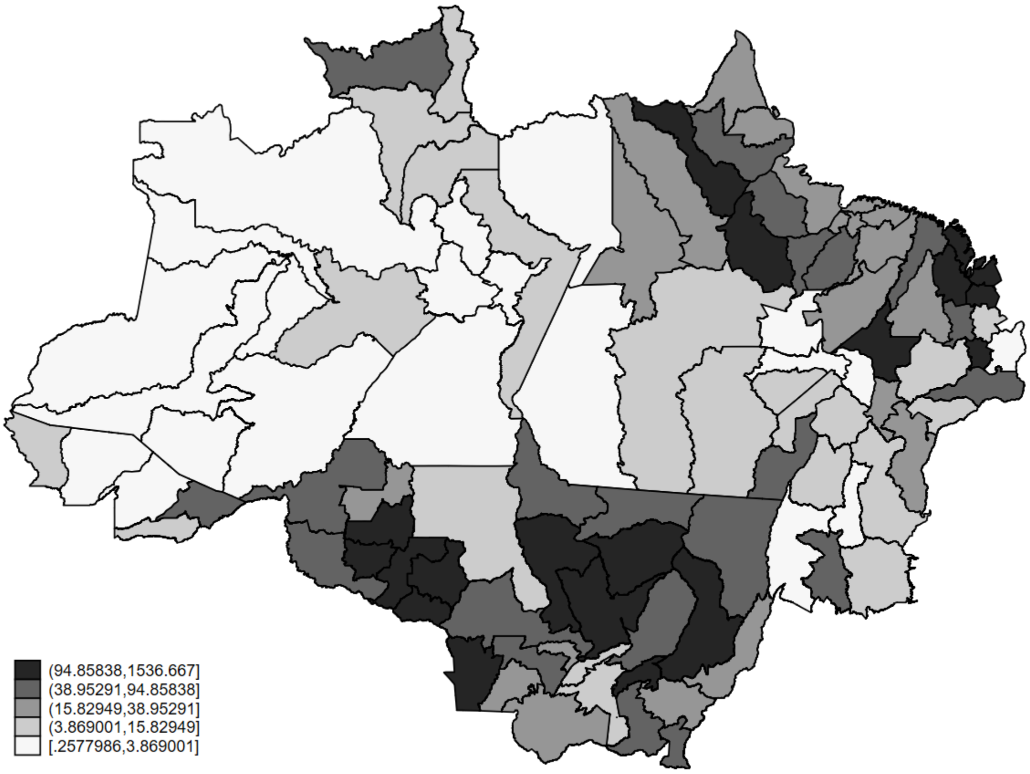

Figure 4.4. Spatial distribution of PRONAF credits (average 2018-2019 in thousand R$ Reais per hectare of production area) for agriculture systems across 103 Amazonian microregions

Regarding the control variables, we computed the credit history referring to an average credit value from 2013 to 2017 per hectare. This variable suggests that microregions with predominantly high credit acquisition might present advantageous characteristics enabling continuous credit access. By contrast, microregions with low credit acquisition might face structural difficulties in receiving financial investments.

Additionally, we include the production value of agriculture and husbandry (thousand R$ Reais) per hectare in 2017. We assume that the amount produced influences the ability to receive PRONAF loans in the following years. This assumption is supported by Helfand (2001), who found that high production values lead to lower barriers to access credits since banks have a lower likelihood of defaults.

Next, a bank dummy captures the regional influences of banks managing PRONAF credits in the Legal Amazon. The variable takes the value of one when the Bank of Brazil is responsible for managing PRONAF in the microregion and zero for the Bank of the Amazon. Three main banks are managing PRONAF credit lines in the region, namely, the Bank of the Amazon, the Bank of Brazil (Banco do Brasil), and the Northeast Bank (Banco do Nordeste). The latter is active only in the state of Maranhão; however, there has been a strong performance of the Bank of Brazil in the state. Thus, the bank dummy variable accounts only for the Bank of the Amazon and the Brazilian Bank.

Including a bank variable is vital because, in rural credit programs, financial agents managing credit lines are seen as key determinants of credit distribution (de Castro & Teixeira, 2012; Zeller, 2006). Furthermore, Carrer et al. (2020) explain that bank bureaucracy, lengthy negotiations, and information asymmetry increase transaction costs, a fact that might discourage farmers when applying for PRONAF credits. For instance, bank bureaucracy was observed as a key obstacle to credit provision by livestock farmers in the state of Mato Grosso (Gil et al., 2015). Thus, we find sufficient argument to believe there might be spatial influences of different banks over PRONAF allocation in the Amazon.

Lastly, we include a variable comprising the share of family farming units accessing technical assistance services in the microregion. A large literature perceives technical assistance as core to supporting agriculture production (Masresha et al., 2017; Ouma and de Groote, 2011; Wainaina et al., 2016). Likewise, technical assistance and financial training are assumed to improve credit access by promoting production efficiency and enhancing managerial skills and human capital in general (Biosca et al., 2014; Garcia et al., 2022). However, only 8% of family farms in the Amazon region receive technical assistance.

Similarly to Zubek and Henning (2016), we could not find appropriate economic and political variables to explain the differences in market access, price fluctuations, lobbying, and political influences on credit provision. However, the SDEM employed in this paper is a suitable econometric approach to control for variables not included in the analysis (LeSage and Pace, 2010).

The summary statistics of 103 Amazonian microregions for husbandry and agricultural systems are displayed separately[25] in Table 4.2. In the whole region, the amount of credit invested per hectare of productive area (hectare) is higher for husbandry systems, receiving almost double the amount of the average credit for agricultural production. Similarly, the average credit history for both production systems shows the same pattern of credit provision.

[25] Detailed descriptive statistics at the state level are available in the supplementary material of this paper.

Table 4.2. Summary statistics

Variable	Variable Description	Mean	St. Dev
Dependent variables			
PRONAF credit husbandry	Average (2018-2019) PRONAF husbandry credit thousand Reais (R$) per hectare	151.27	203.2
PRONAF credit agriculture	Average (2018-2019) PRONAF agriculture credit thousand Reais (R$) per hectare	85.65	217.6
Independent variables			
Credit History husbandry	Average (2013-2017) husbandry credit in thousand Reais (R$) per hectare	227.68	530.3
Credit History agriculture	Average (2013-2017) agriculture credit in thousand Reais (R$) per hectare	110.46	212.4
Production value husbandry	Production value husbandry in thousand Reais (R$) per hectare	0.892	1.53
Production value agriculture	Production value agriculture in thousand Reais (R$) per hectare	1.21	1.03
Bunk dummy	1=Bank of Brazil, 0= Bank of Amazon	0.37	0.48
Technical Assistance	Share of family farms accessing technical assistance (2017)	0.09	0.06
Production area			
Husbandry area	Area under husbandry production systems (hectare) in 2017	191693.3	194509.3
Agriculture area	Area under agriculture production systems (hectare) in 2017	65607.0	81589

Note: N=103.

The production values per hectare are slightly higher for agricultural production since husbandry systems occupy larger areas when compared to the crop production areas. As for the bank dummy, it shows that in 37% of Amazonian microregions, PRONAF credit is managed by the Bank of Brazil. Lastly, the share of households accessing technical services shows low outreach, where only 9% of households in the Amazon reported receiving any type of technical assistance.

3.3. Qualitative methods: Semi-structured interviews with key informants

Key informant semi-structured interviews were conducted mainly to provide some context of credit for family farming. The information provided covers aspects of credit processing and management, limitations to support food production, technical assistance practices, and potential policy recommendations

35 key informants were selected for interviews through snowball-sampling techniques. The selection method used is important to identify the so-called "hard-to-reach" informants (Shoenberger, 2018). As a result of the selection process, three informant groups were interviewed: Field expert extensionists and managers of EMATER (Technical Assistance and Rural Extension Company), bank managers specializing in PRONAF contracts from the Bank of the Amazon and Bank of Brazil, and researchers specialized in family farming in the Amazon.

EMATER is the official public agency providing technical assistance and extension services in the entire Legal Amazon territory. Public technical agencies respond to different names[26]; thus, we refer to these agencies as public technical assistance (PTA).

The Bank of the Amazon is a regional development bank responsible for managing the contracts and transferring PRONAF funds to beneficiaries in most Amazonian states. As previously mentioned, in this paper, we consider that the Bank of Brazil is the leading financial agency managing PRONAF in Maranhão and Mato Grosso. The qualitative process of interviews was done from October 2021 to April 2022 online and in presence[27].

4. Main Results

4.1. Spatial regression analysis

Before the spatial regression analysis, it is crucial to test for spatial autocorrelation among regional units. Moran's I tests the hypothesis for the errors that are independently and identically distributed. The was done for PRONAF credits per hectare for husbandry and agriculture production separately.

For husbandry systems, we obtained significant positive results (z value = 5,36; P=0,000) while using the contiguity weight matrix (W), leading to the existence of spatial correlation in PRONAF allocation. Similarly, Moran's I test for PRONAF credits per hectare for agriculture shows significant positive spatial autocorrelation (z value= 6,98; P=0,008) while using the inverse distance weight matrix (M). Following these test results, assessing the influences of credit allocation in the Legal Amazon requires econometric approaches controlling for spatial dependence among microregions.

The spatial regression model results are first presented for husbandry systems, followed by the outcome for the agricultural system. Firstly, we estimate the maximum likelihood regression with the PRONAF credit for husbandry production per hectare as the dependent variable. After testing the aforementioned spatial models, the SDEM presented better results in the statistical tests[28].

Estimation results for PRONAF husbandry (Table 4.3) and agriculture (Table 4.4) credits show a positive effect of credit history per hectare, purporting that regions with yearly steady credit acquisition can more easily access credits in the following years. The spatial lag coefficient ρ indicates the correlation of the dependent variable among neighboring microregions. The SDEM adds independent and error lags to the analysis, and in the presence of spatial lag of the dependent variable, the covariate coefficients change (LeSage and Pace, 2010).

Hence, interpreting regression coefficients is not straightforward. For instance, in a certain microregion, a change in technical assistance (p>0.000) modifies the conditional mean of the dependent variable in the microregion, and this change will subsequently modify the conditional mean of the dependent variable in neighboring microregions. This triggers a

[26]EMATER (Pará, Acre, Rondônia, Roraima); IDAM (Amazonas); RURAP (Amapá); AGERP (Maranhão); RURALTINS (Tocantins); EMPAER (Mato Grosso).

[27] Detailed description of the semi-structured interviews are available in the suplplementary material of this paper.

[28] The maximum likelihood and SAR results are presented in the supplementary material. While the SDEM had better performance for the AIC test, the SAR model was preferred for the BIC test.

cascade effect since the change in the dependent variable results in changes in the outcome variables over other neighboring microregions.

Table 4.3. Spatial Durbin error model for average PRONAF credit per hectare (2018-2019) for husbandry systems

	Spatial Durbin Error Model (SDEM)	
	coef.	SE
Credit History husbandry	0.215***	0.03
Production value husbandry	1.08	10.66
Bank dummy	100.2	62.03
Technical Assistance	431.39**	219.3
Constant	18.13	32.26
ρ	0.33	0.229
Wx		
Credit History husbandry	0.313**	0.125
Production value husbandry	-18.2	21.22
Bank dummy	-93.8	83.94
Technical Assistance	-516.19*	299.59
error lag	-0.304	0.329
Number of observations	103	

Notes: *** P < 0.01; ** P < 0.05; *P < 0.1; SDEM: Log likelihood = -643.45754; chi2(6) = 25.90; Prob > chi2= 0,0000; Pseudo R2= 0.6220; Wald test of spatial terms: chi2(6) = 25.90; Prob > chi2 = 0.0002

Table 4.4. Spatial Durbin error model for average PRONAF credit per hectare (2018-2019) for agricultural systems

	Spatial Durbin Error Model (SDEM)	
	coef.	SE
Credit History Agriculture	0.852***	0.03
Production value Agriculture	20.95***	7.214
Bank dummy	46.907**	20.848
Technical Assistance	-46.042	85.620
Constant	-99.115	63.43
ρ	-4.097***	0.357
Wx		
Credit History Agriculture	5.865***	0.307
Production value Agriculture	-151.73**	76.879
Bank dummy	-275.66**	129.16
Technical Assistance	-4.0973	0.3576
error lag	4.82***	0.257
Number of observations	103	

Notes: *** $P < 0.01$; ** $P < 0.05$; *$P < 0.1$; SEDM model: Log likelihood = -553.703; chi2(6) = 894.91; Prob > chi2 = 0.0000; Wald chi2(5) = 1183.85; Pseudo R2 = 0.9308

Table 4.5. Post estimation covariate effects. SEDM direct, indirect, and total spillover effects for average PRONAF credit per hectare (2018-2019) for husbandry systems

	Direct			Indirect			Total		
	dy/dy	SE	P>z	dy/dy	SE	P>z	dy/dy	SE	P>z
Credit History husbandry	0.23***	0.031	0.000	0.458***	0.152	0.003	0.695***	0.158	0.000
Production value husbandry	0.075	10.6	0.994	-21.14	23.43	0.36	-21.06	22.761	0.355
Bank dummy	96.86*	58.78	0.09	-71.06	75.88	0.349	25.79	41.08	0.530
Technical Assistance	410.40**	211.43	0.05	-438.93	311.6	0.159	-28.52	307.6	0.926

Notes: *** P < 0.01; ** P < 0.05; *P < 0.1; N= 103; SDEM: Log likelihood= -643.45754; chi2(6)= 25.90; Prob > chi2= 0.0000; Pseudo R2= 0.6220; Wald test of spatial terms: chi2(6) = 25.90; Prob > chi2 = 0.0002

Table 4.6. Post estimation covariate effects. SEDM direct, indirect, and total spillover effects for average PRONAF credit per hectare (2018-2019) for agricultural systems

	Direct			Indirect			Total		
	dy/dy	SE	P>z	dy/dy	SE	P>z	dy/dy	SE	P>z
Credit History agriculture	0.76***	0.037	0.000	0.543***	0.103	0.000	1.303***	0.101	0.000
Production value agriculture	30.184***	7.68	0.000	-54.428***	16.538	0.001	-24.244	16.094	0.132
Bank dummy	65.08**	26.46	0.014	-107.178***	41.454	0.010	-42.094*	24.624	0.087
Technical Assistance	-70.35	105.05	0.503	143.35	193.68	0.459	72.999	144.58	0.614

Notes: *** P < 0.01; ** P < 0.05; *P < 0.1; N=103; SEDM model: Log likelihood = -553.703; chi2(6) = 894.91; Prob > chi2 = 0.0000; Wald chi2(5)= 1183.85; Pseudo R2 = 0.9308

The SDEM post estimation results (Table 4.5) show that husbandry credit history, technical assistance, and the presence of a commercial bank are significant determinants of credit absorption in the Legal Amazon. Additionally, high amounts of credit over the years have led to a positive effect on credit acquisition in neighboring microregions (spillover).

In agricultural systems, the spatial lag coefficient ρ indicates a positive correlation between the dependent variable in one microregion and its neighbors (Table 4.4). The SEDM model provides sufficient robust results to explain spatial effects. From that, we observe that credit history, production value, and the bank are significant determinants of agricultural PRONAF credit absorption in the Legal Amazon. These variables confer a significant direct effect in the same region since they are significant spillovers (Table 4.6).

Furthermore, an increase in agricultural production value (per hectare) in one Amazonian microregion leads to a significant negative spillover effect of PRONAF acquisition in neighboring microregions. Interestingly, the bank dummy reports a negative spillover effect, indicating that when the Bank of Brazil is the financial manager of PRONAF loans in a microregion, its neighboring microregions are to absorb less PRONAF credit.

The different model specifications indicate robust coefficients regarding credit history, bank dummy, and production value. Thus, following theoretical grounds, we are confident that the SDEM model is the best specification to study the spatial correlation of PRONAF.

5. Discussion

Results suggest that PRONAF loans for both husbandry and agricultural production systems are not independently distributed and are affected by spatial characteristics in neighboring microregions in the Legal Amazon. Credit history is consistently significant in both production systems, where the amount of credit acquired over the years significantly affects credit provision in neighboring microregions. Additionally, microregions, where PRONAF is managed by the Bank of Brazil, have better credit access, and technical assistance is related to an increase in local credit acquisition.

Yearly credit acquisition leads to regional financial developments able to reduce transaction costs and enable continuous credit access (Carrer et al., 2020). The direct and spillover effects of credit history are explained in interviews with bank representatives and researchers. In the Amazon, especially for the husbandry system, farmers expand production and trading products over neighboring regions. For high-value commercial goods (e.g., livestock, milk), market structures are not isolated in one regional unit (Zhu et al., 2021). Hence, credit provision spurs local demand for agricultural inputs and enables farmers' networks to exchange information about credit and market opportunities. Farmers' social capital is a plausible representation of spillover effects from the SDEM for both husbandry and agricultural systems. This result is aligned with the growing evidence of social capital to spur technology adoption, credit, and information access (Heikkilä et al., 2016; Okten & Osili, 2004; van Bastelaer, 2001).

The bank variable leads to both direct and spillover spatial effects for both husbandry and agricultural systems. The literature argues that credit distribution depends on geographically sparse commercial banks' networks (Carrer et al., 2020) with autonomy to manage available credit lines with preferred systems (Westercamp et al., 2015). This fact might result in different credit integration systems in cities managed by different banks. Moreover, financial institutions determine the regional credit performance over distribution channels (Assunção et al., 2018).

The SDEM results indicate that where the Bank of Brazil manages PRONAF, family farmers have a positive advantage in accessing credits. The two banks considered in the analysis are distinct in terms of priority and structural characteristics. The Bank of Brazil is one of the most important national commercial banks, with wide outreach, a large number of agencies across municipalities, and technological means to improve bank transactions. In turn, the Bank of the Amazon is a regional development bank managing credit lines in most Amazonian microregions. Yet, with lower outreach and few agencies to attend the whole territory. For instance, in the state of Amapá, only two bank agencies attend to four microregions (sixteen municipalities).

In relation to this result, de Paula Filho et al. (2016) found that the absence of bank agencies in the Transamazon region discourages credit access because farmers have to travel long distances to receive credits which certainly hampers the integration of vulnerable farmers into microfinance programs and opportunities for social capital. Furthermore, Zeller and Schiesari (2020) found a significant positive association of amount of bank agencies and higher PRONAF grants because they facilitate service capacity to manage the regional financial transactions. The negative spillover effect might signal competition across microregions, given that public subsidies are naturally rationed. In other words, where commercial banks manage credit lines while foreseeing payments and higher production gain, investments are more likely to flow within profitable other than neighboring microregions.

The SDEM model for agriculture also shows negative spillover effects of production value. Our work explains this negative spillover as means of competition among neighboring microregions. It means that credit loans tend to be granted where production value is higher because it is more likely that credits will be repaid. Thus, while public subsidies are now abundant, the probability that neighboring regions will also access credit is low. The structural competitions arising from bank and production value exemplify spatial correlations resulting in inefficiencies for PRONAF allocation insofar as they do not offer beneficial opportunities for a higher PRONAF outreach.

Our results do not show significant spillover effects of technical assistance but rather a positive direct effect on husbandry systems. In most interviews, however, technical services were considered central to improving credit performance for family farmers. The combination of credit and technical assistance enables poor households to acquire production inputs, strategize toward soil productivity and food production, and improve the social status of more vulnerable smallholders (Binam et al., 2008; de Paula Filho et al., 2016).

Several elements restrict effective technical services. For instance, within PRONAF's regimentation, there is no mechanism to ensure technical services to credit takers. Bank informants explained that farmers could choose to invest 2% of their contract value in hiring public or private technical services. Farmers with low contract values (especially those covering crop and input costs) tend not to invest in technical assistance. Additionally, in regions where credit investments are low, the economic incentives are insufficient for hiring private services.

In this context, PTA is the public technical assistance agency managed by state governments and responsible for supporting family farmers in the Amazon. PTA alone has insufficient resources to assist all farmers because the distribution of technicians and their qualifications are very sparse in the whole territory. As a result, extension and technical assistance fall short in the rural Amazon (Bicalho and Hoefle, 2010).

Studying PRONAF and technical assistance in the State of Pará, de Paula Filho et al. (2016) found that few family farmers received technical visits in the region due to shot human capital.

Although PTA is entitled to assist all farmers technically, there is a tendency to prioritize non-family farmers and PRONAF beneficiaries only. Furthermore, there is no consolidated process to assist family farmers towards sustainable, productive systems, neither under PRONAF nor within PTA's framework.

Technical service informants mention that public investments to improve the condition for technical visits are scarce. The team of technicians is limited and does not have a logistic structure to access cities located in remote areas (Ludewigs et al., 2009). This issue was pointed out in most interviews and calls for public investments to improve technical assistance working conditions, hire technicians, and enhance PTA's outreach.

Alternatively, developing a framework to cooperate with various groups might result in better synergies with technical orientation and producers. For instance, a joint work of technical assistance and NGOs resulted in lowering risks and integration of vulnerable farmers in production systems in Malawi (Brummett & Jamu, 2011). The technical process shall be done by understanding production priorities and farmers' experiences to enable information transfer and stronger social capital (Ferreira et al., 2014).

Performances of technical assistance and credit access refer to an interrelated process with several synergies. In this context, the program "*Agroamigo*" is a bank mechanism offering microcredits in combination with technical services, able to accompany smallholders during the entire production process. The program resulted in a positive outcome for credit takes in the State of Maranhão (BNB, 2021). The "*Agroamigo*" framework could be replicated in the Legal Amazon as a whole, addressing sustainable production, forest conservation, and financial training targeting farmers and technicians. The latter is directly related to default rates in the sense that financial training could empower family farmers to allocate credits more efficiently (Dumer et al., 2017).

Available production and PRONAF data show a higher emphasis on husbandry over agricultural systems. The literature corroborates the fact that microfinance programs have a selecting character for targeting wealthier farmers in areas with stronger market structures (Binswanger et al., 1993; Zeller & Meyer, 2002).

Due to data limitations, our model cannot fully describe the range of spatial influences enabling PRONAF access over time. Despite that, we contribute to the understanding of spatial dependences and highlight possible spatial inefficiencies in PRONAF allocation due to competition arising from banks and production value. Furthermore, steady credit access spills over into neighboring microregions by developing financial structures, lowering transaction costs, and fostering social capital through farmers' networks. These developments enable continuous PRONAF acquisition across neighboring microregions. Such an arrangement might not, *per se*, contribute to the integration of vulnerable farmers.

While PRONAF is argued to prioritize livestock producers in regions with advanced market structures and steady credit provision, this paper highlights the potential competition for credit, where commercial banks and regions with higher production values are benefited. Therefore, there is a clear need for further research to gauge temporal influences and detailed economic structures in the region. Furthermore, there is an apparent demand for public investments to improve technical work, promoting financial training for both technicians and farmers. Additionally, implementing mechanisms combining credit and technical services for family farmers represent a headway in rural development.

6. Conclusion

This paper investigates the spatial direct and spillover effects over PRONAF credit granted for husbandry and agricultural systems in 103 microregions of the Brazilian Legal Amazon. Additionally, we performed 35 semi-structured interviews with key informants to have a deeper understanding of the results and identify PRONAF improvement potentials.

Our results indicate that PRONAF credits are not independently distributed across regions as they are influenced by spatial characteristics coming from neighbor microregions in the Legal Amazon. We found that being successful in credit acquisition in the past has a positive and significant influence on the current acquisition and that there are positive spillover effects across regions. This means that a steady credit acquisition leads to a positive influence to credit access locally and in neighboring microregions. In the Amazon, particularly for husbandry farmers, social networks and market integration are not isolated in a single microregion. Thus, credit takers benefit from social capital across microregions, acting to reduce transaction costs and enabling information transfer to credit access.

Another interesting result is that we obtained direct and indirect effects, especially in regions where a commercial bank manages PRONAF credit. Informants argue that bank outreach is a key limiting factor when reaching farmers located in remote areas. Aligned with the literature, improving bank outreach can potentially reduce transaction costs and enable the integration of farmers without information and financial means to production.

Although we do not find significant spillover effects of technical assistance, informants argue that there is a clear need for public investment to improve working conditions and technical visits in the Legal Amazon. There are few technicians with insufficient knowledge and structure to pursue the technical work. Interviews indicate that besides public investments intended to hire technicians and enhance working conditions, establishing cooperation with local NGOs would result in information transfer and social network. Moreover, replicating the "*Agroamigo*" program across Amazonian microregions could potentially result in benefits for credit takers.

The results show relevant insights into geographical interdependence. Credit history is possibly a result of consolidated structures, through which wealthier farmers have continued access to markers, information, and credits. Furthermore, spatial inefficiencies are potentially due to competition from banks and regions with high production value.

With that, there is still the need for stronger political efforts targeting the integration of poorer and vulnerable farmers unable to benefit from social networks, stable markets, and financial investments. For further research, we highlight the need to use refined models when addressing the role of social capital and market structures to target vulnerable family farmers. In particular, the models should capture spatial influences over time that affect credit acquisition.

References

Alves, E., Silva e Souza, G., & de Paula Rocha, D. (2013). Desigualdade nos campos na ótica do Censo Agropecuário 2006. *Revista de Política Agrícola*, *22*(2), 67–75.

Alves, E., Sousa, G. S., & Rocha, D. P. (2012). Lucratividade da agricultura. *Revista de Política Agrícola*, *21*(2), 45–63.

Anselin, L., Bera, A. K., Florax, R., & Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics*, *26*(1), 77–104.

Assunção, J., Gandour, C., Rocha, R., & Rocha, R. (2020). The Effect of Rural Credit on Deforestation: Evidence from the Brazilian Amazon. *Economic Journal*, *130*(626), 290–330. https://doi.org/10.1093/ej/uez060

Assunção, J., Souza, P., & Figueiredo, B. (2018). *Policy Brief: Distribution Channels for Rural Credit*.

Ayalew, D., Klaus, A., The, D., & Bank, W. (2012). *Causes and Implications of Credit Rationing in Rural Ethiopia The Importance of Spatial Variation* (No. 6096). http://econ.worldbank.org.

BCB. (2021). *Central Bank of Brazil*. Retrieved November 03, 2021 from https://www.bcb.gov.br/

Bester, H., & Hellwig, M. (1987). Moral Hazard and Equilibrium Credit Rationing: An Overview of the Issues. In G. Bamberg & K. Spreman (Eds.), *Agency Theory, Information, and Incentives* (pp. 135–166). Springer.

Bicalho, A. M. S. M., & Hoefle, S. W. (2010). Economic development, social identity and community empowerment in the central and Western Amazon. *Geographical Research*, *48*(3), 281–296. https://doi.org/10.1111/j.1745-5871.2009.00626.x

Binam, J. N., Gockowski, J., & Nkamleu, G. B. (2008). Technical efficiency and productivity potential of cocoa farmers in West African countries. *Developing Economies*, *46*(3), 242–263. https://doi.org/10.1111/j.1746-1049.2008.00065.x

Binswanger, H. P., Khandker, S. R., & Rosenzweig, M. R. (1993). How infrastructure and financial institutions affect agricultural output and investment in India. *Journal of Development Economics*, *41*(2), 337–366.

Biosca, O., Lenton, P., & Mosley, P. (2014). Where is the 'Plus' in 'Credit-Plus'? The Case of Chiapas, Mexico. *Journal of Development Studies*, *50*(12), 1700–1716. https://doi.org/10.1080/00220388.2014.957279

BNB. (2021). *Banco do Nordeste: Programa Agroamigo*. Retrieved November 03, 2021 from https://www.bnb.gov.br/agroamigo/sobre-o-agroamigo

BNDES. (2021). *PRONAF microcrédito- grupo B*. Banco Nacional de Desenvolvimento Econômico e Social. Retrieved November 03, 2021 from https://www.bndes.gov.br/wps/portal/site/home/financiamento/produto/pronaf-microcredito-grupo-b

Brasil. (2021). *Legislação da Amazônia*. Retrieved December 12, 2021 from https://www.gov.br/sudam/pt-br/acesso-a-informacoes/institucional/legislacao-da-amazonia

Brummett, R. E., & Jamu, D. M. (2011). From researcher to farmer: Partnerships in integrated aquaculture - agriculture systems in Malawi and Cameroon. *International Journal of Agricultural Sustainability*, *9*(1), 282–289. https://doi.org/10.3763/ijas.2010.0570

Carpentier, C. L., Vosti, S. A., & Witcover, J. (2000). Intensified production systems on western Brazilian Amazon settlement farms: Could they save the forest? *Agriculture, Ecosystems and Environment*, *82*(1–3), 73–88. https://doi.org/10.1016/S0167-8809(00)00217-6

Carrer, M. J., Maia, A. G., de Mello Brandão Vinholis, M., & de Souza Filho, H. M. (2020). Assessing the effectiveness of rural credit policy on the adoption of integrated crop-livestock systems in Brazil. *Land Use Policy*, *92*. https://doi.org/10.1016/j.landusepol.2020.104468

de Castro, E. R., & Teixeira, E. C. (2012). Rural credit and agricultural supply in Brazil. *Agricultural Economics*, *43*(3), 293–302. https://doi.org/10.1111/j.1574-0862.2012.00583.x

de Paula Filho, G. X., Calvi, M. F., & de Castro, R. R. A. (2016). Socioeconomic Analysis of Rural Credit and Technical Assistance for Family Farmers in the Transamazonian Territory, in the Brazilian Amazon. *Journal of Agricultural Science*, *8*(10), 177. https://doi.org/10.5539/jas.v8n10p177

Dumer, M. C. R., Carvalho, N., Souza, A. M., Ribeiro, A. L., & Costa, R. A. O. (2017). Inadimplência do PRONAF: Um estudo no município de Afonso Cláudio - ES. *Revista de Agonegócio2*, *6*(2), 36–48. https://link-springer-com.proxy.libraries.uc.edu/content/pdf/10.1007%2F978-3-642-19199-2.pdf

Elhorst, J. P. (2010). Applied spatial econometrics: Raising the bar. In *Spatial Economic Analysis* (Vol. 5, pp. 9–28).

Elhorst, J. P. (2014). Spatial econometrics from cross-sectional data to spatial panels. *Springer*.

FAO. (2014). *The state of food and agriculture 2014: Innovation in family farming*.

FAO, & OECD. (2015). *OECD-FAO Agricultural Outlook 2015-2024*. Retrieved May 14, 2022 from https://www.fao.org/3/i4738e/i4738e.pdf

Ferreira, W. C., Rebello, F. K., & Oliveira, C. M. (2014). Assistência técnica e extensão rural na Amazônia: histórico, desafios e proposições. *Amazônia (Banco Da Amazônia. 2005)*, *9*, 59–78.

Garcia, A., Cecchi, F., Eriksen, S., & Lensink, R. (2022). The Plus in Credit-Plus-Technical Assistance: Evidence from a Rural Microcredit Programme in Bolivia. *Journal of Development Studies*, *58*(2), 275–291. https://doi.org/10.1080/00220388.2021.1928639

Ghinoi, S., Wesz Junior, V., & Piras, V. J. (2018). Political debates and agricultural policies: discourse coalitions behind the creation of Brazil's Pronaf. *Land Use Policy*, *76*, 68–80.

Gil, J., Siebold, M., & Berger, T. (2015). Adoption and development of integrated crop-livestock-forestry systems in Mato Grosso, Brazil. *Agriculture, Ecosystems and Environment*, *199*, 394–406. https://doi.org/10.1016/j.agee.2014.10.008

Godar, J. (2009). *The environmental and human dimensions of frontier development in the Transamazon Highway colonization area*. University of León.

Godar, J., Tizado, E. J., Pokorny, B., & Johnson, J. (2012). Typology and characterization of Amazon colonists: A case study along the Transamazon highway. *Human Ecology*, *40*(2), 251–267. https://doi.org/10.1007/s10745-012-9457-8

Golgher, A. B., & Voss, P. R. (2016). How to Interpret the Coefficients of Spatial Models: Spillovers, Direct and Indirect Effects. *Spatial Demography*, *4*(3), 175–205. https://doi.org/10.1007/s40980-015-0016-y

Grisa, C., Wesz Junior, V. J., & Buchweitz, V. D. (2014). Revisitando o Pronaf: Velhos questionamentos, novas interpretações. *Revista de Economia e Sociologia Rural*, *52*(2), 323–346. https://doi.org/10.1590/s0103-20032014000200007

Guanziroli, C., Buainain, A., & Sabbato, A. (2013). Family farming in Brazil: Evolution between the 1996 and 2006 agricultural censuses. *Journal of Peasant Studies*, *40*(5), 817–843. https://doi.org/10.1080/03066150.2013.857179

Guanziroli, C. E., & di Sabbato, A. (2014). Existe na agricultura brasileira um setor que corresponde ao "Family Farming" Americano? *Revista de Economia e Sociologia Rural*, *52*, 85–104. https://doi.org/10.1590/s0103-20032014000600005

Heikkilä, A., Kalmi, P., & Ruuskanen, O. P. (2016). Social Capital and Access to Credit: Evidence from Uganda. *Journal of Development Studies*, *52*(9), 1273–1288. https://doi.org/10.1080/00220388.2016.1139695

Helfand, S. M. (2001). The Distribution of Subsidized Agricultural Credit in Brazil: Do Interest Groups Matter? *Development and Change*, *32*(3), 465–490. www.nemesis.org.br

Helfrand, S., Rocha, R., & Vinhais, H. (2009). Pobreza e desigualdade de renda no Brasil rural: uma análise da queda recente. *Pesquisa e Planejamento Econômico*, *39*(1), 59–80.

IBGE. (2017). *Censo agropecuário 2017: Agricultura Familiar. Instituto Brasileiro de Geografia e Estatística*. Retrieved October 10, 2021 from https://sidra.ibge.gov.br/pesquisa/censo-agropecuario/censo-agropecuario-2017#caracteristicas-produtores

IBGE. (2021). *Legal Amazon*. Retrieved October 10, 2021 from https://www.ibge.gov.br/en/geosciences/environmental-information/vegetation/17927-legal-amazon.html?=&t=o-que-e

IMAZON. (2009). *A amazônia em números*. Retrieved October 03, 2021 from https://imazon.org.br/imprensa/a-amazonia-em-numeros/

IPEA. (2021). *Índice geral de preços - disponibilidade interna (IGP-DI) - Geral.* Instituto de Pesquisas Econômicas Aplicadas. Retrieved November 10, 2021 from http://www.ipeadata.gov.br/Default.aspx

Koç, A. A., Yu, T. E., Kıymaz, T., & Sharma, B. P. (2019). Effects of government supports and credits on Turkish agriculture: A spatial panel analysis. *Journal of Agribusiness in Developing and Emerging Economies*, *9*(4), 391–401. https://doi.org/10.1108/JADEE-11-2018-0164

Kumar, A. (2005). Access to Financial Services in Brazil. In *Directions in Development. The World Bank*. https://doi.org/https://doi.org/10.1596/0-8213-5716-6

Lesage, J. P. (2014). The Review of Regional Studies What Regional Scientists Need to Know about Spatial Econometrics *. *The Official Journal of the Southern Regional Science Association*, *44*, 13–32. www.srsa.org/rrs

LeSage, J. P., & Fischer, M. M. (2008). Spatial growth regressions: Model specification, estimation and interpretation. *Spatial Economic Analysis*, *3*(3), 275–304. https://doi.org/10.1080/17421770802353758

LeSage, J., & Pace, R. (2010). An introduction to spatial econometrics. In M. M. Fischer & A. Getis (Eds.), *Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications* (pp. 355–376). Springer.

LeSage, J., & Pace, R. K. (2009). *Introduction to spatial econometrics*. Chapman and Hall/CRC.

Ludewigs, T., D'antona, A. de O., Brondízio, E. S., & Hetrick, S. (2009). Agrarian Structure and Land-cover Change Along the Lifespan of Three Colonization Areas in the Brazilian Amazon. *World Development*, *37*(8), 1348–1359. https://doi.org/10.1016/j.worlddev.2008.08.018

Maia, A. G., Eusébio, G. dos S., & da Silveira, R. L. F. (2020). Can credit help small family farming? Evidence from Brazil. *Agricultural Finance Review*, *80*(2), 212–230. https://doi.org/10.1108/AFR-10-2018-0087

Martins, P. F., & Pereira, T. Z. (2012). Cattle-raising and public credit in rural settlements in Eastern Amazon. *Ecological Indicators*, *20*, 316–323. https://doi.org/10.1016/j.ecolind.2012.02.031

Masresha, D., Legesse, B., Haji, J., & Zemedu, L. (2017). Determinants of the adoption of improved white haricot beans in East Shewa Zone, South-Eastern Ethiopia. *Journal of Development and Agricultural Economics*, *9*(12), 355–372. https://doi.org/10.5897/jdae2017.0860

Mattei, L. (2011). Evolução do crédito do PRONAF para as categorias de agricultores A e A/C entre 2000 e 2010. In SOBER (Ed.), *Congresso da Sociedade Brasileira de Economia, Administração e Sociologia Rural*.

Medina, G., Almeida, C., Novaes, E., Godar, J., & Pokorny, B. (2015). Development Conditions for Family Farming: Lessons From Brazil. *World Development*, *74*, 386–396. https://doi.org/10.1016/j.worlddev.2015.05.023

Mertens, F., Fillion, M., Saint-Charles, J., Mongeau, P., Távora, R., Passos, C. J. S., & Mergler, D. (2015). The role of strong-tie social networks in mediating food security of fish resources by a traditional riverine community in the Brazilian Amazon. *Ecology and Society*, *20*(3). https://doi.org/10.5751/ES-07483-200318

Neves, M. D. C. R., Freitas, C. O., Silva, F. D. F., Costa, D. R. D. M., & Braga, M. J. (2020). Does Access to Rural Credit Help Decrease Income Inequality in Brazil? *Journal of Agricultural and Applied Economics*, *52*(3), 440–460. https://doi.org/10.1017/aae.2020.11

Nobre, C. A., Sampaio, G., Borma, L. S., Castilla-Rubio, J. C., Silva, J. S., & Cardoso, M. (2016). Land-use and climate change risks in the amazon and the need of a novel sustainable development paradigm. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(39), 10759–10768. https://doi.org/10.1073/pnas.1605516113

Okten, C., & Osili, U. O. (2004). Social networks and credit access in Indonesia. *World Development, 32*(7), 1225–1246. https://doi.org/10.1016/j.worlddev.2004.01.012

Ouma, J. O., & de Groote, H. (2011). Determinants of improved maize seed and fertilizer adoption in Kenya. *Journal of Development and Agricultural Economics*, *3*(11), 529–536.

Pacheco, P., & Poccard-Chapuis, R. (2012). The Complex Evolution of Cattle Ranching Development Amid Market Integration and Policy Shifts in the Brazilian Amazon. *Annals of the Association of American Geographers*, *102*(6), 1366–1390. https://doi.org/10.1080/00045608.2012.678040

Patton, M., & Mcerlean, S. (2003). Spatial Effects within the Agricultural Land Market in Northern Ireland. *Journal of Agricultural Economics*, *54*, 35–54.

Petrini, M. A., Rocha, J. V., Brown, J. C., & Bispo, R. C. (2016). Using an analytic hierarchy process approach to prioritize public policies addressing family farming in Brazil. *Land Use Policy*, *51*, 85–94. https://doi.org/10.1016/j.landusepol.2015.10.029

Pokorny, B., Godar, J., Hoch, L., Johnson, J., de Koning, J., Medina, G., Steinbrenner, R., Vos, V., & Weigelt, J. (2010). A produção familiar como alternativa de um desenvolvimento sustentável para a Amazônia. In *Lições aprendidas de iniciativas de uso florestal por produtores familiares na Amazônia boliviana, brasileira, equatoriana e peruana.* Center for International Forestry Research (CIFOR).

Resende, C. M., & Martins Mafra, R. L. (2016). Desenvolvimento rural e reconhecimento: Tensões e dilemas envolvendo o pronaf. *Revista de Economia e Sociologia Rural*, *54*(2), 261–280. https://doi.org/10.1590/1234.56781806-947900540204

Schneider, S., Cazella, A. A., & Mattei, L. (2021). Histórico, Caracterização E Dinâmica Recente Do Pronaf – Programa Nacional De Fortalecimento Da Agricultura Familiar. *Revista Grifos*, *30*, 12–41.

Shoenberger, N. A. (2018). *The Use of Snowball Sampling to Examine the Differences Between First-and Second-Generation Ex-Cult Members' Disaffiliation Processes*. SAGE Publications Ltd. https://doi.org/https://dx.doi.org/10.4135/9781526439932

SNIRH. (2021). *Catálogo de metadados da ANA - Microrregiões*. Sistema Nacional de Informações Sobre Recursos Hídricos. Retrieved October 11, 2021 from https://metadados.snirh.gov.br/geonetwork/srv/api/records/e6dd026c-afa7-4a7c-8904-abbb86662da5

Tobler, w. R. (1970). A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography*, *46*(234).

van Bastelaer, T. (2001). Imperfect Information, Social Capital and the Poor's Access to Credit. *IRIS Center Working Paper No. 234*. https://doi.org/van Bastelaer, Thierry, Imperfect Information, Social Capital and the Poor's Access to Credit (October 1999). IRIS Center

Working Paper No. 234, Available at SSRN: https://ssrn.com/abstract=260058 or http://dx.doi.org/10.2139/ssrn.260058

Verner, D. (2004). *Poverty in the Brazilian Amazon: An Assessment of Poverty Focused on the State of Pará. Policy Research Working Paper Series No. 3357*.

Wainaina, P., Tongruksawattana, S., & Qaim, M. (2016). Tradeoffs and complementarities in the adoption of improved seeds, fertilizer, and natural resource management technologies in Kenya. *Agricultural Economics (United Kingdom)*, *47*(3), 351–362. https://doi.org/10.1111/agec.12235

Wang, C., Zhang, X., Ghadimi, P., Liu, Q., Lim, M. K., & Stanley, H. E. (2019). The impact of regional financial development on economic growth in Beijing–Tianjin–Hebei region: A spatial econometric analysis. *Physica A: Statistical Mechanics and Its Applications*, *521*, 635–648. https://doi.org/10.1016/j.physa.2019.01.103

Ward, M. D., & Gleditsch, K. S. (2008). *Spatial regression models* (V. Knight, Ed.; Sage, Vol. 155).

Westercamp, C., Nouri, M., & Oertel, A. (2015). *Agricultural credit, assessing the use of interest rate subsidies.* .

Yeung, G., He, C., & Zhang, P. (2017). Rural banking in China: geographically accessible but still financially excluded? *Regional Studies*, *51*(2), 297–312. https://doi.org/10.1080/00343404.2015.1100283

Zeller, M. (2006). A comparative review of major types of rural microfinance institutions in developing countries. *Agricultural Finance Review*, *66*(2), 195–213. https://doi.org/10.1108/00214660680001187

Zeller, M., & Meyer, R. L. (2002). *The triangle of microfinance: Financial sustainability, outreach, and impact*. Intl Food Policy Res Inst.

Zeller, M., & Schiesari, C. (2020). The unequal allocation of PRONAF resources: Which factors determine the intensity of the program across Brazil? *Revista de Economia e Sociologia Rural*, *58*(3). https://doi.org/10.1590/1806-9479.2020.207126

Zhu, X., Chen, X., Cai, J., Balezentis, A., Hu, R., & Streimikiene, D. (2021). Rural financial development, spatial spillover, and poverty reduction: evidence from China. *Economic Research-Ekonomska Istrazivanja* , *34*(1), 3421–3439. https://doi.org/10.1080/1331677X.2021.1875859

Zubek, N., & Henning, C. H. C. A. (2016). Local Government, Spatial Spillovers and the Absorption of EU Structural Funds. *Journal of Agricultural Economics*, *67*(2), 368–397. https://doi.org/10.1111/1477-9552.12146

Appendix

Table A4.1. Average (2018-2019) PRONAF credit thousand

State	*N*	*Husbandry*		*Agriculture*	
		Mean	St. Dev	Mean	St. Dev
RO	8	311.85	77.20	141.10	102.06
AC	5	114.95	66.18	14.55	25.08
AM	13	67.08	106.87	2.88	1.84
RR	4	94.32	41.38	26.37	36.12
PA	22	72.55	92.55	30.38	28.38
AP	4	3.45	2.17	82.00	94.73
TO	8	45.79	29.61	14.18	24.21
MA	17	325.43	386.81	261.15	485.42
MT	22	170.63	115.06	87.62	84.54

Table A4.2. Average (2013-2017) PRONAF credit in thousand

State	*N*	*Husbandry*		*Agriculture*	
		Mean	St. Dev	Mean	St. Dev
RO	8	295.84	64.09	208.24	143.68
AC	5	126.01	54.64	57.18	100.30
AM	13	201.24	253.44	33.18	31.04
RR	4	123.30	44.54	50.14	53.24
PA	22	84.23	90.66	58.75	57.59
AP	4	8.92	4.39	71.06	77.20
TO	8	108.03	73.60	43.20	37.42
MA	17	609.86	1225.05	267.23	459.05
MT	22	192.01	105.36	105.83	103.66

Table A4.3. Production value in thousand Reais (R$) per hectare

State	*N*	*Husbandry*		*Agriculture*	
		Mean	St. Dev	Mean	St. Dev
RO	8	0.59	0.14	1.35	0.55
AC	5	0.30	0.13	0.37	0.23
AM	13	1.55	2.51	1.24	1.03
RR	4	0.24	0.04	0.57	0.45
PA	22	1.36	2.01	1.02	0.77
AP	4	0.65	0.35	0.58	0.34
TO	8	0.29	0.10	0.81	0.34
MA	17	0.97	1.88	1.30	1.64
MT	22	0.58	0.38	1.85	0.93

Table A4.4. Area under production systems (hectare) in 2017

State	*N*	*Husbandry*		*Agriculture*	
		Mean	St. Dev	Mean	St. Dev
RO	8	387045.1	235994.2	33382.2	22912.2
AC	5	188166	123535.7	147795.2	88217.2
AM	13	50148.4	54494.5	69673.6	48665.2
RR	4	103444	34712.9	64430.2	41549.1
PA	22	223337.5	238546.8	127699.8	136159.8
AP	4	14069	10583.5	37494.25	31996.14
TO	8	313864.9	105091.9	39780	14040.1
MA	17	157770.3	151164.7	46380.9	33252.8
MT	22	203581.8	200401.1	23723.7	29777.8

Table A4.5. Bank dummy and share of family farms accessing technical assistance

State	*N*	*Bank Dummy*	*Technical Assistance*	
			Mean	St. Dev
RO	8	0	0.18	0.05
AC	5	0	0.09	0.03
AM	13	0	0.11	0.06
RR	4	0	0.10	0.03
PA	22	0	0.05	0.03
AP	4	0	0.12	0.05
TO	8	0	0.11	0.05
MA	17	1	0.03	0.01
MT	22	1	0.14	0.07

Table A4.6. Maximum likelihood model, Spatial lag model, and Spatial Durbin error model for average PRONAF credit per hectare (2018-2019) for husbandry systems

	Maximum Likelihood (ML)			**Spatial Lag Model (SAR)**			**Spatial Error Durbin Model (SEDM)**		
	coef.	SE	P>z	coef.	SE	P>z	coef.	SE	P>z
Credit History husbandry	0.25***	0.0313	0.000	0.25***	0.02	0.000	0.215***	0.03	0.000
Production value husbandry	-2.16	10.607	0.839	-0.45	10.06	0.96	1.08	10.66	0.91
Bank dummy	78.88***	29.304	0.007	49.22*	29.36	0.09	100.2	62.03	0.106
Technical Assistance	131.96	200.68	0.511	139.13	190.1	0.46	431.39**	219.3	0.049
Constant	51.1*	28.617	0.074	18.23	29.11	0.53	18.13	32.26	0.57
P				0.38***	0.12	0.002	0.33	0.229	0.14
Wx									
Credit History husbandry							0.313**	0.125	0.012
Production value husbandry							-18.2	21.22	0.39
Bank dummy							-93.8	83.94	0.26
Technical Assistance							-516.19*	299.59	0.08
error lag							-0.304	0.329	0.35
Number of observations	103			103			103		
	Log likelihood = -653.085; Wald chi2(4) = 120.76; Pseudo R2 = 0.53; Prob > chi2 = 0.000			Log likelihood = -648.772; Wald chi2(5) = 144.12; Pseudo R2 = 0.5639; chi2(1) = 9.62; Prob > chi2 = 0.0019			Log likelihood = -643.457; Wald chi2(9) 203.33; Pseudo R2 = 0.622; chi2(6) = 25.90; Prob > chi2 = 0.0000;		

Notes: *** P < 0.01; ** P < 0.05; *P < 0.1

Table A4.7. Post estimation covariate effects. SAR direct, indirect and total spillover effects for average PRONAF credit per hectare (2018-2019) for husbandry systems

	Direct			Indirect			Total		
	dy/dy	SE	P>z	dy/dy	SE	P>z	dy/dy	SE	P>z
Credit History husbandry	0.25***	0.030	0.000	0.122**	0.61	0.046	0.37***	0.075	0.000
Production value husbandry	-0.466	10.32	0.964	-0.22	4.9	0.964	-0.687	15.23	0.964
Bank dummy	50.49*	29.83	0.09	24.02	15.39	0.119	74.51*	42.06	0.076
Technical Assistance	142.72	195.12	0.46	67.91	99.18	0.49	210.64	190.62	0.46

Notes: *** P < 0.01; ** P < 0.05; *P < 0.1

Table A4.8. Post estimation covariate effects. SEDM direct, indirect and total spillover effects for average PRONAF credit per hectare (2018-2019) for husbandry systems

	Direct			Indirect			Total		
	dy/dy	SE	P>z	dy/dy	SE	P>z	dy/dy	SE	P>z
Credit History husbandry	0.23***	0.031	0.000	0.458***	0.152	0.003	0.695***	0.158	0.000
Production value husbandry	0.075	10.6	0.994	-21.14	23.43	0.36	-21.06	22.761	0.355
Bank dummy	96.86*	58.78	0.09	-71.06	75.88	0.349	25.79	41.08	0.530
Technical Assistance	410.40**	211.43	0.05	-438.93	311.6	0.159	-28.52	307.6	0.926

Notes: *** P < 0.01; ** P < 0.05; *P < 0.1

Table A4.9. Maximum likelihood model, Spatial lag model, and Spatial Durbin error model for average PRONAF credit per hectare (2018-2019) for agricultural systems

	Maximum Likelihood (ML)			**Spatial Lag Model (SAR)**			**Spatial Error Durbin Model (SEDM)**		
	coef.	SE	P>z	coef.	SE	P>z	coef.	SE	P>z
Credit History husbandry	0.74***	0.058	0.000	0.65***	0.062	0.000	0.852***	0.03	0.000
Production value husbandry	47.94***	12.63	0.000	45.97***	12.02	0.000	20.95***	7.214	0.004
Bank dummy	13.47	22.06	0.541	-10.43	22.11	0.637	46.907**	20.848	0.024
Technical Assistance	-354.84**	154.48	0.022	-154.12	158.16	0.33	-46.042	85.620	0.591
Constant	-24.83	20.93	0.235	-82.06***	26.01	0.002	-99.115	63.43	0.118
ρ				0.654***	0.191	0.001	-4.097***	0.357	0.000
Wx									
Credit History Agriculture							5.865***	0.307	0.000
Production value Agriculture							-151.73**	76.879	0.048
Bank dummy							-275.66**	129.16	0.033
Technical Assistance							-4.0973	0.3576	0.556
error lag							4.82***	0.257	0.000
Number of observations	103			103			103		
	Log likelihood = -618.48948; Wald chi2(4) = 356.48; Pseudo R2 = 0.77; Prob > chi2 = 0.000			Log likelihood = -618.489; Wald chi2(5) = 406.18; Pseudo R2 = 0.8061; Prob > chi2 = 0.0000			Log likelihood = -553.703; Wald chi2(5) = 1183.85; Pseudo R2 = 0.9308; Prob > chi2 = 0.0000		

Notes: *** P < 0.01; ** P < 0.05; *P < 0.1

Table A4.10. Post estimation covariate effects. SAR direct, indirect and total spillover effects for average PRONAF credit per hectare (2018-2019) for agricultural systems

	Direct			**Indirect**			**Total**		
	dy/dy	SE	P>z	dy/dy	SE	P>z	dy/dy	SE	P>z
Credit History agriculture	0.663***	0.059	0.000	1.11	0.894	0.211	1.78**	0.88	0.044
Production value agriculture	46.73***	12.21	0.000	78.74	68.01	0.247	125.48*	72.81	0.085
Bank dummy	-10.61	22.52	0.638	-17.88	44.9	0.690	-28.49	66.7	0.669
Technical Assistance	-156.69	159.85	0.327	-263.99	278.7	0.344	-420.69	405.72	0.3

Notes: *** P < 0.01; ** P < 0.05; *P < 0.1

Table A4.11. Post estimation covariate effects. SEDM direct, indirect and total spillover effects for average PRONAF credit per hectare (2018-2019) for agricultural systems

	Direct			**Indirect**			**Total**		
	dy/dy	SE	P>z	dy/dy	SE	P>z	dy/dy	SE	P>z
Credit History agriculture	0.76***	0.037	0.000	0.543***	0.103	0.000	1.303***	0.101	0.000
Production value agriculture	30.184***	7.68	0.000	-54.428***	16.538	0.001	-24.244	16.094	0.132
Bank dummy	65.08**	26.46	0.014	-107.178***	41.454	0.010	-42.094*	24.624	0.087
Technical Assistance	-70.35	105.05	0.503	143.35	193.68	0.459	72.999	144.58	0.614

Notes: *** P < 0.01; ** P < 0.05; *P < 0.1

Semi-structured interviews with Key Informants

Semi-structured interviews were developed according to a predefined list of questions, and additional details presented by interviewees. The interviews aimed to understand the structure, process and management of PRONAF credit lines under the lens of specialists. Especially in the case of technical assistance, interviews were essential to learn about how technicians work, support family farmers in the region, and what the main working limitations are. It is important to disclaim that, despite the interviewees' relevance and expertise, their judgments do not represent the opinions of banks, public technical agencies and research institutions. Additionally, the interviewees freely agreed to participate in the interviews without identity disclosure. Details of semi-structured interviews are presented as follows.

1. Semi-structured interviews with key informants from three specialist groups:

    - Bank representatives working especially with rural credit for family farmers - PRONAF in the Amazon region. Here two banks were considered: The Bank of Brazil (Banco do Brasil) active in the state of Mato Grosso and the state of Maranhão; Bank of the Amazon (Banco da Amazônia) active in all other Amazonian States. They are the only banks managing PRONAF credit lines in the Legal Amazon.
    - Technical assistants: Public technical agencies are at the forefront to provide technical assistance and extension services to family and non-family farmers in Brazil. The technical agency is managed by State governments, a fact that leads to differences in planning, organization, financing, research and development (R&D) and research and innovation (R&I) investments, and service outreach.
    - Researchers: Professors and scientists engaged in studying PRONAF credit lines in the Amazon were consulted with the aim to learn from local projects, political and research initiatives to support family farmers in the Amazon, as well as challenges for research.

2. Interview information:

Interviews were developed during the period October 2021 to April 2022 remotely or in presence.

Presence interviews were done in the State of Pará in the period of October 2021 to January 2022.

Online interviews were done in the period of October 2021 to April 2022. The average duration of interviews was 90-120 minutes.

11 interviews with bank representatives
11 interviews with technical assistants
13 interviews with researchers

3. Interviews sampling strategy

The first stage consisted of screening researchers specialized in rural credit for family farmers and rural development in the Brazilian Amazon region. For that, State and Federal Universities and Research centers in all Amazonian States were consulted. All researchers specialized in rural credit and family farmers in the Amazon were contacted via email or phone call.

Subsequently, researchers who positively responded to the request were invited for an interview and asked for further relevant contacts. During research and consultancy projects, researchers have high interaction with public institutions, banks and technical representatives. Thus, contacts of professionals working on strategic areas both at the bank and technical agencies were initially provided by scientists. They were contacted via email and phone call and invited for an interview. Those bank and technical assistants who kindly accepted the interview were asked for further contacts. This allowed for a higher number of interviews and wider outreach.

The process of contacting and inviting informants for interviews was repeated up to the point that at least 10 references from each informant group were interviewed.

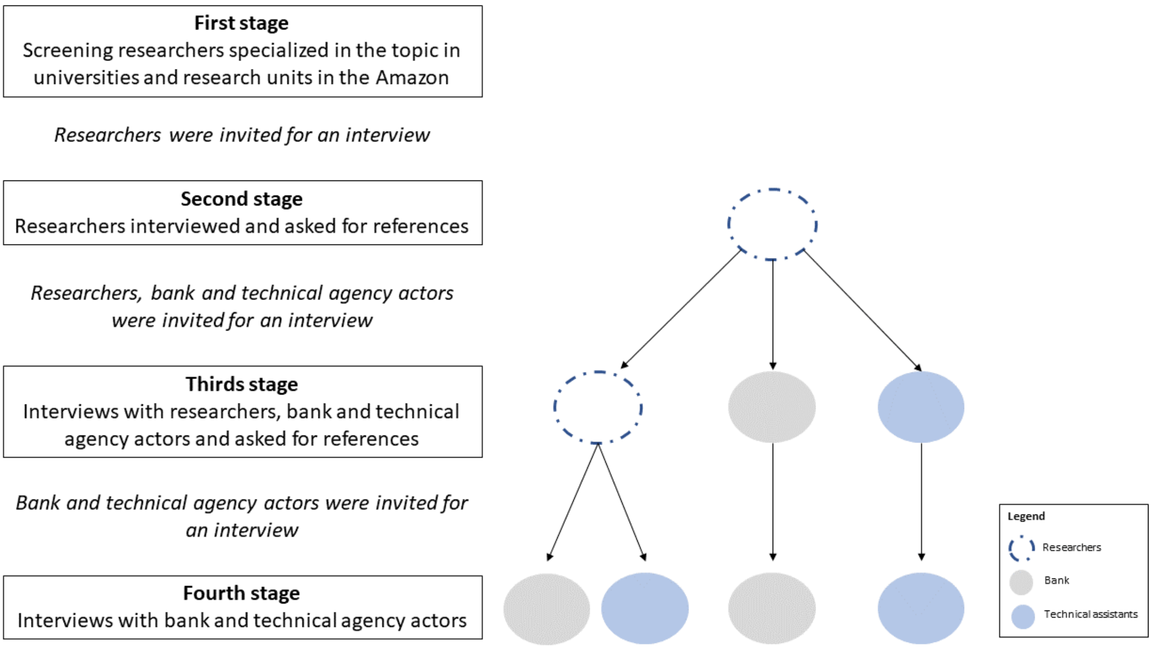

Figure A4.1. Schematic representation of snowball sampling developed to interview researchers, bank representatives and technical assistants in the nine states of the Brazilian Legal Amazon.

Figure A4.1 sets out the schematic representation of the sampling strategy. The first stage was initiated in September 2021 and in the same period researchers were invited for an interview. In the first stage, researchers were contacted by phone and email, where the research question was presented and the relevance of doing interviews. In general, positive responses were received after 4 weeks and researchers were subsequently invited for an interview. We obtained about 30% response rate in the first stage.

Subsequently, the second stage was initiated in October 2021, where the first informants were interviewed and asked for further suggestions of possible informants. Insofar as new references were obtained, invitations were forthwith sent. Ater the first round of interviews, researchers kindly provided contacts of potential bank representative and technical assistants and other researchers. The invitations were also facilitated in the second stage, because researchers had direct contact with potential informants. Interviews and invitations were likewise done in the third phase (also during October 2021 and January 2022), where new references asked were solely from bank representatives and technical assistants. Lastly, the fourth stage represents the interviews with bank representatives and technicians, which were held in the period of October 2021 until April 2022.

Interview question guide for key informants

Bank key informants

What is your role at the Bank?

How long do you work with rural credit?

Since when has the bank started managing PRONAF transfers?

Does the bank have any sort of autonomy in the granting process?

How many employees work with PRONAF transfers?

What is the structure to evaluate grant proposals across bank agencies?

Over the years, do you see a change in the amount of credit provision?

What are the main prerequisites to access credit?

What are the main activities receiving PRONAF grants?

What are the limitations to accessing credit?

Do you acknowledge credit rationing?

Does the bank have a mechanism to prevent defaults?

How does the bank manage defaults?

In case of defaults, who does bear the costs?

Are there guidelines from the government on how to process the credit lines?

Are there mechanisms to provide technical assistance?

How does the payment for technical assistance work?

What would contribute to improved performances of rural credit?

Is there any strategy to reach remote areas?

In practice, does the bank manage PRONAF credit lines as a traditional credit line or an income transfer program?

Are there regional differences in credit acquisition? If so, what could be possible causes?

Are there mechanisms to support credit takers during the production process (e.g. partnership with technical assistance)?

Why do you think that there is a notable difference between PRONAF grants and performance when comparing the Amazon region with other regions?

What is the distribution of credits for agriculture and husbandry activities?

Technical assistant key informants

What is your role at the technical agency?

How long do you work with technical assistance?

How many technicians work at your agency?

Do you follow a local planning or a general calendar?

How is the work divided?

Is there a limit or farmers per agency?

Do you assist family and non-family farmers?

Is the work allocated according to region or production activity?

How is the technical work done?

How frequent is the contact with farmers?

Does the agency you work for also engage in research?

In the case of research activities, how are they done?

How is research applied in farmers' reality?

How do you see the importance of PRONAF?

How do you evaluate the impact of PRONAF in the region?

What are the main limitations farmers face to production?

What are the difficulties to provide technical assistance?

Is there any type of synergies with other agencies?

Are there synergies with third-party initiatives to improve assistance to farmers?

Does the technical assistance support farmers' initiatives, and cooperatives?

How could activities be improved?

How are remote areas addressed in the work of the technical agency?

Is there any ongoing planning to reach remote areas?

Are there activities related to financial training?

Are there investments to support technicians?

What are the main limitations technicians face?

How could technicians working conditions be improved?

Researchers key informants

What is your main research area?

How long do you work with rural development and family farming in the Amazon?

Have you worked at other organizations related to local family farming before?

Do other professors/scientists work with PRONAF or family farming in your institution?

Do you have partnerships with other departments/institutions?

What is your main work with the topic?

Could you explain a bit more about projects you have developed related to PRONAF or family farming?

What are you currently working with?

How do you evaluate PRONAF's performance in the region?

What are the main limitations to supporting family farmers?

Why do you think PRONAF's performance is so different in the Amazon when compared to other Brazilian regions?

Could you elaborate on the way banks and technical assistance work in the region?

From your expertise, do you think PRONAF is delivering the goals of supporting family farming and environmental protection?

What could you say about credit rationing?

How do you evaluate the performance of technical assistance in the region?

How do you evaluate the performance of banks managing PRONAF credit lines?

What is the main limitation to developing research about family farming in the region?

What are PRONAF limiting factors?

How could PRONAF be improved?

How could research be improved?

Chapter 5

General conclusion

1. Conclusion

In times climate change is aggravating the natural dynamic of soil and water resources (Agrimonti et al., 2021), agriculture is certainly the most important sector to the sustainability agenda (FAO, 2021). Despite technological investments to double food production, current food systems are argued unable to meet food demand of the growing population (Ray et al., 2013). Currently, the world faces severe interrelated social and natural issues encompassing topics like acute food insecurity affecting all global regions (Pereira & Oliveira, 2020), poverty and hunger (Gassner et al., 2019), natural resources degradation (Warner et al., 2010), and natural resources management.

Meanwhile, international agreements have proposed guidelines setting the path to sustainable food production. Sustainable agriculture is the way to adapt and mitigate climate change while ensuring food security, natural resources management, and efficient policy enforcement toward food access and distribution (Maja & Ayano, 2021). This sustainable transformation calls for collective action where civil society is essential to inform and promote resources sustainability (Lambin & Thorlakson, 2018).

Following from that, research is fundamental to enhance the understanding about interrelated timely issues involving climate change, agriculture production, natural resources management, poverty, and hunger. In fact, scientific appraisals can potentially inform and support appropriate political measures to foster natural resources management while guaranteeing sustainable food production (Priyadarshini & Abhilash, 2020). Moreover, understanding current global issues is key when preventing the exacerbation of conflicts and resources degradation.

This dissertation investigates three distinct topics related to sustainable agriculture. The papers aimed at enhancing the understanding of water resources, the relation between deforestation and governance, and rural credits for family farmers. The three independent chapters offer in-depth discussions relevant to the scientific community and policy makers engaged in sustainability debates.

In this final chapter, the main findings and contributions of this dissertation are highlighted. Given that each chapter has individual objectives and research questions, section 2 describes main findings derived in every chapter. Section 3 discusses policy relevance, followed by caveats and future research in section 4.

2. Main findings

Chapter 2 investigates state of the arts of global, international, and national water databases. Following the acknowledged absence of well-documented water data (Floerke et al., 2013). The question that initially motivated this work is: “How could policies, regulations, economic and biophysical projections be designed without a consistent and robust water baseline?”. The study provides a list of global and national water databases, their reporting structure, definitions, and organizations responsible for data management. Furthermore, the paper distills important information regarding water data availability across regions, and presents the structure of databases, data compositions and definitions. The paper offers an approach to search for water data, followed by the analysis of data definitions and consistency. It informs the availability (or the absence) of water data and how comparable available data are. This is especially relevant when designing political and economic strategies for sustainable water resources management.

Chapter 2 found that there are considerable inconsistencies of available data, which hamper comparison across databases. Water statistics are well documented mainly in Europe, but every national water reporting system presents particular structures of data collection and reporting. Additionally, the absence of water data is a general issue and low-income nations are underrepresented. This implies that comparing country level water data is not straightforward. Moreover, the state of the arts of water databases suggests that there is little consistency in defining water categories, and various methods for data collection trigger uncertainty when comparing data.

Chapter 3 assesses the association between deforestation and institutional indices. Deforestation is a major agent of greenhouse gas emissions and results in a series of social and environmental issues. Despite growing empirical-based evidence about relations between political indicators and forest degradation (Kissinger et al., 2012), it remains unclear what the effects of corruption and weak institutions in forest management are (Obydenkova et al., 2016).

Employing a logistic model, chapter 3 explores the association of available international corruption and governance indicators in an analysis using global high-resolution cross-country deforestation data. The paper offers robust empirical-based evidence about the relationship between governmental performance and forest resources. Moreover, computer-intensive data management was employed to convert georeferenced raster data into a format compatible with economic statistical software and enable sample replications of a large original file.

Overall quantitative results show that higher government effectiveness, strong political enforcement, policy design, and lower corruption have a significant negative association with deforestation. Results remained robust across several robustness checks and endorse that weak government, inefficient regulations and facilitated corruption lead to a high probability of forest conversion.

Chapter 4 addresses spatial direct, and spillover effects on rural credit to family farmers engaged in husbandry and agricultural production in the Legal Brazilian Amazon rainforest. Family farmers are important actors in Brazilian agriculture but face considerable difficulties to integrate markets and access land and inputs. Rural credits represent an important tool to reduce the inequality gap, promoting market integration and living standards for rural populations. In this context, rural credits designed to economically integrate vulnerable family farmers are argued to target wealthier farmers engaged in livestock production, while neglecting those producing under agricultural systems.

Chapter 4 aims to investigate the presence of spatial spillovers as providing beneficial opportunities to credit allocation in the Amazon. The paper employs a spatial Durbin error

Model of credit acquisition for husbandry and agricultural systems in 103 microregions of the Brazilian Legal Amazon. Additionally, to enhance the paper's discussion we conducted 35 semi-structured interviews with key informants from banks, technical assistance and research.

Results indicate that credits are not independently distributed across regions as they are influenced by spatial characteristics coming from neighboring microregions. Being successful in credit acquisition in the past has a positive and significant influence in current acquisition and that there are positive spillover effects across regions. This means that a steady credit acquisition leads to positive influence to access credits in the future. This is possibly a result of consolidated structures, through which wealthier farmers have steady access to markers, information, and credits. Particularly for husbandry farmers, social networks and market integration are not isolated in a single microregion. Furthermore, spatial negative spillovers from commercial bank and production value are potential spatial inefficiencies explained by triggering competition among microregions.

3. Policy relevance

Every chapter highlights the relevance of political incentives and regulations towards water and land resources management, and to offer socioeconomic means for food security and reducing the poverty gap.

Chapter 2 has a direct link to political implications because systematic data collection enables benchmarking strategies. Water benchmark consist of instruments to compare the performance of water utilities and indicators at the local and country levels. Water issues are present in many political debates, so evaluating the global water resources and scarcity requires refined water models, which in turn rely on water data.

Implementing water data collection depends on political efforts particularly from sovereign nations. Thus, chapter 2 can be potentially used as a "starting point" to initiate water reporting in places where water statistic system is still missing. Moreover, the paper discusses essential aspects to bear in mind when communicating water data. When using and comparing the currently available water data, it is key to critically analyze what each number actually represents, understand to which level data are comparable, and think carefully about how they can be used to estimate reliable results.

In the long run, the headway of water research and assessments depend on political enforcements to refine the meaningfulness of water data and support water collection, reporting, and monitoring. Alternatively, in the short and medium run, water data challenges can be addressed by joint research efforts for water data harmonization.

Following from that, chapter 2 offers a data approach relevant for both policy makers and economists, especially because current policy decisions are based on existing water data. There is a timely need for collaborative research initiatives for model harmonization in combination with political incentives to improve water data.

Chapter 3 is a contribution grounded in political relevance. It investigates relations between deforestation and current cross-country political indicators of corruption and governmental effectiveness. It is challenging to draw specific political recommendations when results are based on several countries with distinct governmental structures, forestry sectors, and natural resources management. Nevertheless, further elaborating governance and corruption indicators with emphasis on natural resource management might be a plausible headway for local and cross-country quantitative. Furthermore, the findings can potentially contribute to international debates about deforestation, highlighting the importance of political enforcement to forest conservation and sustainable forest management.

In chapter 4, the case study of rural credits in Brazil is historically involved in political efforts to integrate vulnerable family farmers in local and national markets. The credit program for family farming consists of public investments to enable input acquisition, technology, income transfer, and job generation. Moreover, it aims at fostering sustainable development and production in rural marginalized areas. Despite strong aspirations, the literature indicates that the program has failed to meet its main objectives.

The few information available about family farmers in the Amazon certainly limits political assessments to improve the credit program while taking into account farmers priorities. With that in mind, the paper offers valuable information regarding spatial dependencies leading to opportunities for credit acquisition. Additionally, the paper proposes policy recommendations from robust empirical-based evidence and interviews.

In line with the literature, chapter 4 indicates the need for improving bank outreach as a way to reduce transaction costs and facilitate the integration of farmers located in remote areas. Additionally, public investment are needed to improve working conditions and technical visits in the Legal Amazon. The current technical assistance structures is insufficient to provide quality technical assistance to farmers. Besides public investments intended to hire technicians and enhance working conditions, establishing cooperation with local NGOs would result in information transfer, and stronger social capital. Furthermore, there is still the need for stronger political efforts targeting the integration of poorer and vulnerable farmers unable to benefit from social networks, stable markets, and financial investments.

4. Caveats and future research

The three papers comprising this dissertation have certainly limitations and potential for continuous research. Future research possibilities refer both to model refinement and the allocation of more robust data.

While chapter 2 offers an in-depth analysis of available water data, content and definition, the analysis is based on criteria dependent on research conditions. It suggest that data search could have resulted in additional references if looking into other languages. This shortcoming, however, does not affect the state of knowledge of global and international databases. Furthermore, it could be argued that the paper itself does not propose a data harmonization strategy. Indeed, future research on water harmonization could offer significant contribution to the scientific and political debates. It might be still unrealistic that data harmonization and water data reporting will be met in the short run. However, research collaboration would most definitely suit this aim.

Caveats in chapter 3 refer firstly to the potential for a time-series analysis and land transitions. In fact, land cover converts several times and transitions back to forest areas. In the model employed, it is not possible to assess the dynamics of deforestation. Thus, the model does not attain to when deforestation occurred, nor differentiates between natural and managed forests. Therefore, refining the model to assess temporal variation of forest cover with institutional variables would allow controlling for the spatiotemporal dynamics of forest transition.

Furthermore, chosing a cross-sectional specification was mainly due to modest variations in both CPI and GE indices, which could hinder the explanation of LUC and institutional variables over time. Additionally, it is not possible to control for missing country observations, and the model cannot control for that. Yet, institutional factors are available for more than 183 countries, especially those of high relevance to the deforestation discourse. In a time-series configuration, this study could be further enhanced by including additional variables such as the price for timber and agricultural products, type of political regime, and economic growth.

The main shortcoming of chapter 4 is data availability. The only family farming statistics available in Brazil is the agricultural census. Including family farming activities in national statistics, recognizing family farmers as legal beneficiaries of public policies, and legally securing their activities in governmental agendas was only possible from 2006 (Petrini et al., 2016). Hence, the first representative rural statistics to fully integrate family farming was the Brazilian agricultural census in 2006 (IBGE, 2006), however, most production data are not immediately comparable to the 2017 agricultural census. Therefore, addressing the overtime performance and drivers of rural credit in the region as well as to assess large set of potential regressors is still to be addressed in the future. There is further potential to refine the spatial model into a panel analysis when the next census data is available. With that, identifying spatial spillovers overtime stands for an opportunity to improve credit assessments, and spot regional interdependences influencing financial provision.

References

Agrimonti, C., Lauro, M., & Visioli, G. (2021). Smart agriculture for food quality: facing climate change in the 21st century. In *Critical Reviews in Food Science and Nutrition* (Vol. 61, Issue 6, pp. 971–981). Bellwether Publishing, Ltd. https://doi.org/10.1080/10408398.2020.1749555

FAO. (2021). *Sustainable Development Goals*. Retrieved July 08, 2021 from https://www.fao.org/sustainable-development-goals/indicators/241/en/

Floerke, M., Kynast, E., Baerlund, I., Eisner, S., Wimmer, F., & Alcamo, J. (2013). Domestic and industrial water uses of the past 60 years as a mirror of socio-economic development: A global simulation study. *Global Environmental Change*, *23*, 144–156.

Gassner, A., Harris, D., Mausch, K., Terheggen, A., Lopes, C., Finlayson, R. F., & Dobie, P. (2019). Poverty eradication and food security through agriculture in Africa: Rethinking objectives and entry points. *Outlook on Agriculture*, *48*(4), 309–315. https://doi.org/10.1177/0030727019888513

Kissinger, G., Herold, M., & Sy, V. de. (2012). Drivers of Deforestation and Forest Degradation: A Synthesis Report for REDD+ Policymakers. In *Lexeme Consulting* (Issue August). https://doi.org/10.1126/science.1239402

Lambin, E. F., & Thorlakson, T. (2018). Annual Review of Environment and Resources Sustainability Standards: Interactions Between Private Actors, Civil Society, and Governments. *Annual Review of Environment and Resources*, *43*. https://doi.org/10.1146/annurev-environ

Maja, M. M., & Ayano, S. F. (2021). The Impact of Population Growth on Natural Resources and Farmers' Capacity to Adapt to Climate Change in Low-Income Countries. In *Earth Systems and Environment* (Vol. 5, Issue 2, pp. 271–283). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1007/s41748-021-00209-6

Obydenkova, A., Nazarov, Z., & Salahodjaev, R. (2016). The process of deforestation in weak democracies and the role of intelligence. *Environmental Research*, *148*, 484–490.

Pereira, M., & Oliveira, A. M. (2020). Poverty and food insecurity may increase as the threat of COVID-19 spreads. In *Public Health Nutrition* (Vol. 23, Issue 17, pp. 3236–3240). Cambridge University Press. https://doi.org/10.1017/S1368980020003493

Petrini, M. A., Rocha, J. V., Brown, J. C., & Bispo, R. C. (2016). Using an analytic hierarchy process approach to prioritize public policies addressing family farming in Brazil. *Land Use Policy*, *51*, 85–94. https://doi.org/10.1016/j.landusepol.2015.10.029

Priyadarshini, P., & Abhilash, P. C. (2020). Policy recommendations for enabling transition towards sustainable agriculture in India. *Land Use Policy*, *96*. https://doi.org/10.1016/j.landusepol.2020.104718

Ray, D. K., Mueller, N. D., West, P. C., & Foley, J. A. (2013). Yield Trends Are Insufficient to Double Global Crop Production by 2050. *PLoS ONE*, *8*(6). https://doi.org/10.1371/journal.pone.0066428

Warner, K., Hamza, M., Oliver-Smith, A., Renaud, F., & Julca, A. (2010). Climate change, environmental degradation and migration. *Natural Hazards*, *55*(3), 689–715. https://doi.org/10.1007/s11069-009-9419-7