THE ROLE OF INTERNATIONAL SOYBEAN TRADE IN TELECOUPLED HUMAN AND NATURAL SYSTEMS

By

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ABSTRACT

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International food trade and globalized agriculture production connects humans and the environment around the world. As consumption demands are increasingly met abroad by importing food products, environmental and socioeconomic effects of production are left in the producing region, while the effects on the importing countries' domestic production remain understudied due to the complexity and low visibility of the impacts. As population growth increases the caloric demand and rising affluence drives changes in consumption patterns, connections via food trade will continue to increase. Therefore, to identify local impacts of global phenomena, this dissertation analyses the environmental and socioeconomic impacts of international soybean trade within Brazil (e.g., largest producer), China (e.g., largest consumer) and the U.S. (e.g., the former largest producer). Drawing from both natural and social science disciplines, global trade data, satellite-imagery, farmer interviews and soil samples were combined for an interdisciplinary assessment of how international soybean trade couples distant human and the environment systems, the true extent of land-use change driven by soybean trade and the resulting impacts within each respective country. Chapter 1 provides a review of the published literature and background on international soybean trade and production. In chapter 2, the influence of China's soybean demand was measured on Brazil's production and trade. The results suggest that export-oriented soybean expansion in Brazil displaced the production of other crops and increased imports from nearby countries. For chapter 3, the impact of imported soybeans on production in China's main agricultural region was explored. Competition from imported soybeans has resulted in many

farmers switching cultivation to corn or to abandon farming in search of more lucrative options. This cultivation shift requires changes in management that involve increased nitrogen inputs and residual crop biomass – both of which have resulted in environmental spillovers. Chapter 4 furthered the analysis by considering the impacts of farmer cultivation and management decisions on soil properties. Soil texture, pH, total organic carbon and 16S rRNA gene sequence were used in combination with detailed farmer management surveys to understand how changes in residue management effect efficiency, productivity, profitability and sustainability of the system. The results indicated that the accumulation of residual corn biomass has increased the use of residue fires and decreased the amount of crop residue being returned to the soil. The culminating chapter used an agent-based modeling (ABM) to integrate the above chapters into a TeleABM. The teleABM models land use change in Brazil and China based on global soybean demand. Land-use change decisions are made by farmer agents which have parametrized using the farmer interviews. Next, the farmer agent cultivation and management decisions have environmental impacts that were determined by analyzing the soil samples under the context of management decisions. Finally, production and the impact of farmer agent decisions on the soil properties feedback to the farmer's future cultivation and management decisions. Because of the economic, environmental and political importance of international soybean trade, the results of this dissertation are of great interest for future soybean production and trade between the specified countries as well as food security and environmental sustainability across the world.

To my parents and my husband.

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To my major advisor, Dr. Jack Liu, thank you for believing in me even before I believed in myself. To my husband, Dr. Sheng Chen, thank you for being my morning coffee and evening whiskey, my daily motivation and my nightly resolve and available anytime for comic relief. To Mom and Dad, thanks for buying me books and letting me dig holes in the yard. To my brothers, thanks for being proud of me. I will never stop trying to impress you. To Sue Nichols, thanks for always being around to remind me who I am, what my story is and why that is valuable. To Dr. Scott & Missy Meiners, thank you for showing me a way off the farm and the way back. To my high school science teacher, Dr. Jason Vicich, thank you for being so annoying and pushing me to finish this work. To my childhood best friends, thank you for teaching me that even if you don’t score a lot of points (or publications), there is real value in being on the team.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION AND LITERATURE REVIEW

1.1. Overview

International food trade and globalized agriculture production connects humans and the environment around the world [*1, 2*]. The rate and scale of food trade has significantly increased in the past several decades, even though similar food types exist in both importing and exporting countries [*1, 3-5*]. As consumption demands are increasingly met abroad by importing food products, environmental and socioeconomic effects of production are left in the producing region [*6-8*]. However, the effects of food trade beyond the immediate trade partners, known as spillover effects, are often understudied due to the complexity and low visibility of the socioeconomic and environmental impacts. Connections via food trade and the associated spillover effects are expected to continue to increase as population growth increases the caloric demand increased affluence drives changes in consumption patterns. The highly interconnected and complex trade networks that society has come to rely pose threats that are difficult to foresee, understand and control. One of the world's greatest challenges is how to balance growing human demands for food and sustainability[*9-11*].

International soybean trade is representative of how distant people and places are connected. Soybean production and trade are dominated by a small number of countries; 97% of the area planted to soybeans, globally resides in Brazil, the United States, China, Argentina and India[*12*]. China first domesticated the soybean nearly 3,000 years ago and was the world's largest producer and exporter during much of the 19^{th} and early 20^{th} centuries[*13*]. However, due to domestic population growth and rising affluence, China enacted a series of polices which encouraged importing 80% of its total soybean supply, importing 88 million tonnes in 2018[*14-16*]. Much of this demand has been supplemented by Brazil and the United States, the world's top two soybean producers and exporters[*1*, *14*].

Much research has been conducted on either the socioeconomic or environmental impacts of international soybean trade at international and national scales[*6*, *17-19*]. That is, we know broadly soybean production is increasing in Brazil as well as several other countries (Argentina, Canada, Uruguay, Paraguay, etc. and several African countries such as Mozambique, South Africa and Zimbabwe [*12, 15, 20, 21*]) to meet China's rising demand.

Several studies have focused on the environmental and socioeconomic consequences of soybean expansion in the sending system, Brazil. Briefly, land use change associated with soybean expansion has led to unfavorable environmental impacts including deforestation, displacement of cattle production, biodiversity loss and increased greenhouse gas emissions [*3*, *12*, *22*, *23*]. While the socioeconomic effects include economic growth of the agricultural sector including the agribusiness sector (production, processing, transportation, trade, etc.), increased farmer incomes, creation of on-farm employment as well as jobs within the supply chain (inputs, processing, transportation, etc.). Less research has been within the receiving system, China, but the literature does highlight low domestic soybean prices, land use change [*24-26*], increased nitrogen pollution [*27*], improved levels of soil carbon [*28*] and access to livestock feed for the pork sector as results of international imported soybeans.

However, little is known of the impacts of international soybean trade beyond the trading partners of Brazil and China. Specifically, how has land use change in the main production regions of Brazil and China has affected neighboring countries. Further, the internal mechanisms behind production and farmer cultivation decisions within Heilonjiang are not clear, the environmental and socioeconomic impacts of soybean decline are not well quantified and farmer response and ability to adapt is largely unknown. Soybean cultivation trends in Brazil and China's major production region are of great importance as they may influence future soybean production and trade as well as food security and environmental sustainability across the world. The information gained from this research will be relevant to Brazil, China and the US as they may inform agricultural and environmental policy across local to international scales.

1.2. Conceptual Framework

The telecoupling framework is an ideal tool for understanding the complex interactions within global soybean trade [*1*], offering a novel integration of natural and social systems across distances that historically would have been studied in their respective disciplines. The telecoupling framework consists of five interrelated components: *systems*, *flows*, *agents*, *causes*, and *effects*[*1*](Figure 1). *Systems* are coupled human and natural systems that exchange information, material, and energy with other systems, which may be located relatively close or far away [*1*]. *Systems* can be further classified as sending (origins, exporting country), receiving (destinations, importing countries), and spillover systems. Global soybean trade is a perfect example of this, where the importing country is the receiving system and the exporting country is the sending system. Movement of soybeans represents the *flows*, which could also be forms of information, materials, or energy responsible for connecting the two systems. Spillover systems are a byproduct of the coupled relationship between the sending and receiving systems. They may be connected to the sending and receiving systems in multiple ways: as a stopover between the two systems (e.g., port, truck stop), as the pathway between the two systems (e.g., transportation route), as an outside entity that is connected to the telecoupling (e.g., third party in trade negotiations), or the recipient of externalities produced by the telecoupling[*1*] (e.g., GHG emissions, food price fluctuations). *Agents* are decision-making entities involved in the telecoupling, which facilitate or hinder flows between the systems; *agents* may take the form of domestic and international farmers, governments and agribusiness companies. *Causes* are drivers or factors originating from any system (sending, receiving, and spillover) and generate a telecoupling between a minimum of two coupled human and natural systems. Telecouplings often have multiple *causes* (e.g., economic, political, technological, cultural, and ecological), which are responsible for altering the dynamics (e.g., emergence, patterns, changes) of the telecoupling. *Effects* are the resulting socioeconomic and environmental impacts of a telecoupling, which can appear in the sending, receiving, and/or spillover system. *Effects* may result in feedbacks loops (to the cause), time lags (showing up years to decades later), and legacy effects (persisting for years or decades)[*1*].

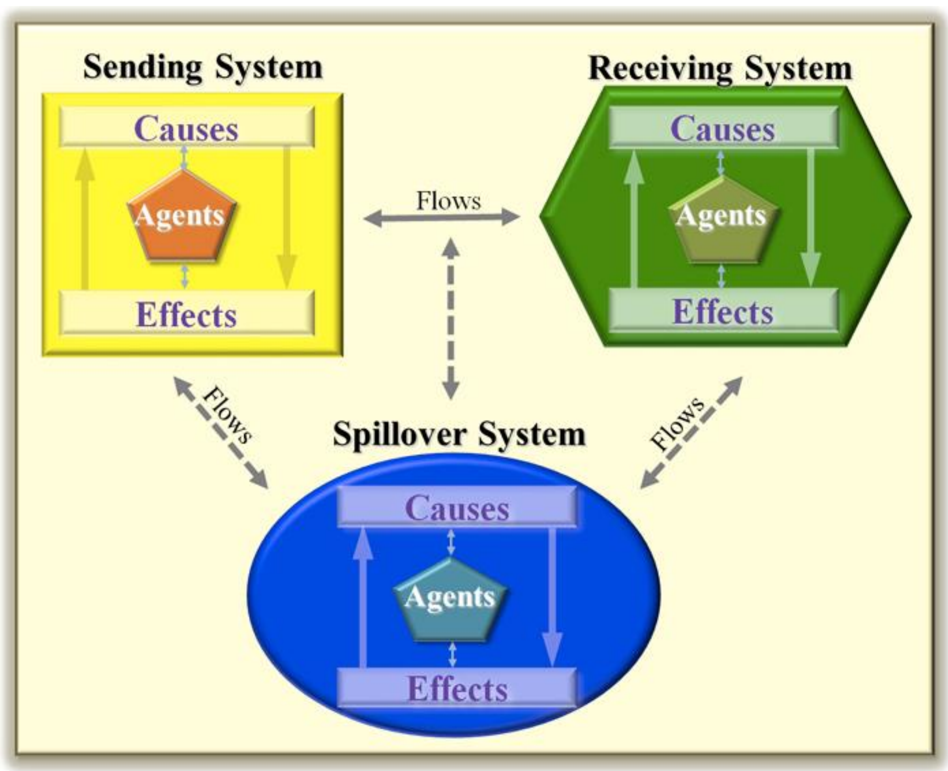

Figure 1. Adapted from Liu et al.[1]) Summary of the 5 interrelated components of the telecoupling framework.

1.3. Study Areas

In order to put this research in its' global context, the second and third chapters of this dissertation analyzes spillover effects of international soybean trade between Brazil and China. In chapter 2, the trade relationships between Brazil (shown in yellow, Figure 1) and other South American soybean sending systems (e.g., Argentina, Paraguay and Uruguay shown in grey, Figure 1) were analyzed for changes prior to, and after China's large soybean demand. In Chapter 3 we move from the sending system to the receiving system to analyzes how land use change patterns in Heilongjiang, China (shown in lime green, Figure 1) resulted in air pollution spilling across the border to Russian Provinces (shown in grey, Figure 1). Next, chapter 4 considers the effects of land use change in Heilongjiang on the soil conditions (shown in lime green, Figure 1). Finally, chapter 5 integrates the research done in previous chapters by simulating international trade and land use dynamics using an agent-based model (tele-ABM).

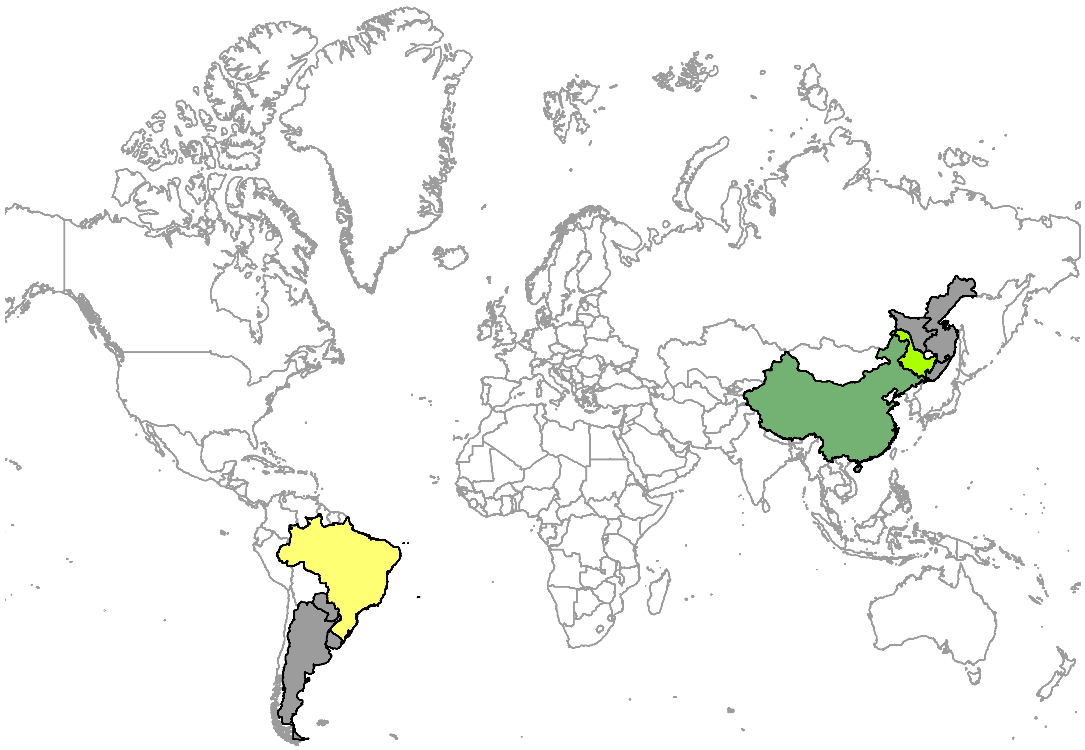

Figure 2. World map highlighting the study locations for this dissertation. Brazil, the sending system is shown in yellow while China, the receiving system is shown in green. Heilongjiang China, was the site of field work and the core study area is highlighted in lime green. Additionally, the spillover systems are shown in grey and include Argentina, Paraguay and Uruguay as well as the Russian Provinces that border Heilongjiang.

1.4. Objectives of this dissertation

Chapter 2 Analyzes the tele- and peri-coupled flows between South American soybean sending systems before and after China joined the World Trade Organization.

Chapter 3 Explores air pollution spillovers in Russia that are a result of land use conversion in Heilongjiang, China.

Chapter 4 Assesses the impact of farmer cultivation and management decisions in Heilongjiang on the soil microbial community.

Chapter 5 Evaluates to what degree land-use changes contributes to greenhouse gas emissions and soil carbon in Heilongjiang using the TeleABM.

1.5. Significance

This project will fill research gaps by providing insight on regional and local cultivation patterns, their relationship to microbial community composition and function and the environmental effects of international soybean trade in the receiving country. The telecoupling framework will serve as the conceptual framework for this work and will be used to better understand and identify the complex and interrelated *causes* and *effects* of international soybean trade[*1*]. Starting Chapter 2, the international soybean trade network will be organized conceptually using the telecoupling framework. The *systems* are countries that send *flows* of soybeans between them, the *causes* are the factors influencing soybean export or import behavior and the *effects* are soybean flows under future scenarios. This chapter will fill research gaps on how to apply quantitative methods to components of the telecoupling framework and how to integrate cross-scale data. Chapter 3 sees the continuation of the telecoupling concept by exploring how regional crop cultivation patterns, influenced by soybean imports, vary across Heilongjiang. This chapter will address the land use *effects* of soybean imports on the receiving countries' production at the regional scale. In addition to a regional comparison, Chapter 4 will consider the effects of management decisions (influenced by soybean imports) on microbial community composition and function at the local level. Lastly, Chapter 5 culminates this research project by integrating the previous chapters in an agent-based model. The model, created from information gathered during the household survey and soil sampling, builds upon empirical data to forecast future crop cultivation patterns and soil dynamics under different scenarios. By considering micro-scale effects of a macro-scale process we will integrate cross-scale data to address a major research challenge.

2. TELECOUPLED FOOD TRADE AFFECTS PERICOUPLED TRADE AND INTRACOUPLED PRODUCTION

Herzberger, A.; Chung, M.G.; Kapsar, K.; Frank, K.A.; Liu, J. Telecoupled Food Trade Affects Pericoupled Trade and Intracoupled Production. *Sustainability* **2019**, *11*, 2908.

2.1. Abstract

Technology, transportation and global appetites have transformed trade relationships between nearby and distant countries. The impact of distant food demand has had on local agricultural production and trade has attracted considerable scientific scrutiny, yet still little is known about how distant trade affects trade relationships between and production in adjacent countries. In this paper, we explore this important issue by examining international food trade and agriculture production, which represent how distant places are connected through trade networks. By analyzing patterns of soybean, corn and wheat trade from 1991-2016 under the framework of metacoupling (human-nature interactions within as well as between adjacent and distant systems), this study provides new insights on the spatio-temporal dynamics of trade flows. Results reveal that telecoupled (between distant countries) trade interacts with the geo-political landscape to enhance or offset intracoupled production (within country) and pericoupled (between neighboring countries) trade. Evidence from the literature and the results of autoregressive integrated moving average models indicate that when restrictions are placed on direct export routes, pericoupled trade increased. The extent to which telecoupled food trade affected pericoupled trade and intracoupled processes holds implications for the true extent of production driven by distant demands.

Keywords: soybeans; international trade; metacoupling; telecoupling

2.2. Introduction

International food trade and globalized agricultural production connect humans and the environment around the world [*37-41*]. The rate and scale of food trade have significantly increased in the past several decades, even though both importing and exporting countries produce and consume similar food types [*42*]. These interconnections may continue increasing as population growth increases caloric demand and greater affluence drives changes in consumption patterns [*43-46*]. Because these phenomena have been implicated as the main drivers of increased crop production and trade as well as their associated environmental and socioeconomic impacts, the conceptual framework of telecoupling has emerged to help disentangle distant human-environment interactions [*47*].

Soybean trade is representative of the ways distant people and places are connected through telecouplings. In the context of global food trade, much research has been conducted on the large flow of soybeans from the Americas to China [*12, 27, 48-50*]. For example, many studies have documented production increases in Brazil and the United States (U.S.) as well as several other countries (e.g., Argentina, Canada, Uruguay, Paraguay [*51, 52*]) to meet the rising demand from China. China's soybean demand is primarily driven by meat consumption of their burgeoning middle class [*53*], however, the catalyst that initiated the flow of soybeans from west to east was China lowering the soybean import tariff from 130% to 3% in 1995 [*48, 51*]. This reduction quickly increased China's imports of soybeans and sent a signal through the global market that increased demand for, and therefore production of, soybeans around the world. At the time, the U.S. was the world's largest producer and exporter of soybeans, accounting for 68% of China's soybean imports in 1995, but has since declined to 40% in 2016 [*54*]. Brazil first surpassed the U.S. in terms of Chinese market share in 2006 and then again in terms of total soybean production in 2013 [*54*]. Between 1995 (when China lowered their soybean import tariff) and 2016, total soybean exports from Brazil to China increased by over 750,000% [*54*]. Numerous previous studies have highlighted a highly concentrated trade network where Brazil and the U.S. account for 80% of global soybean exports and China makes up 64% of global soybean imports [*42, 46, 50, 54*]. Given the economic [*24, 53*], environmental [*12, 55*] and political [*56, 57*] importance of soybean trade, the dynamics among Brazil, China and the U.S. have been widely studied by academics [*49, 58, 59*], governments [*60-62*], industry [*63*] and NGOs [*64*].

While the literature documents production increases in South American countries in response to China's soybean demand [*52, 56*], little is known about how China's soybean demand has altered trade relationships among South American countries. Few studies have looked beyond soybean flows between the world's top producing and consuming countries to determine the structure of trade between medium-size producers or the effects that high volume soybean trade has had on them. To address this research gap, this study uses the metacoupling framework [*65*], which is an extension of the telecoupling framework [*47*], to explore how telecoupled (e.g., distant) soybean trade between Brazil and China has influenced pericoupled (e.g., trade between neighboring countries) and intracoupled (e.g., production within a country) processes within South America.

To study the interaction between telecouplings and pericouplings, we identified soybean exports from Brazil to China as our focal telecoupling, because it is the largest bilateral exchange of soybeans [*54*]. To explore the influence of telecouplings on pericouplings, Argentina, Paraguay and Uruguay were identified for several reasons. First, they share a border and joint membership in the Mercosur trade agreement with Brazil allowing feasible pericoupled trade both, geographically and politically [*66, 67*]. Second, Argentina, Paraguay and Uruguay are net soybean exporters to Brazil, while Bolivia, Chile, Colombia, Ecuador, Peru and Venezuela are net importers from Brazil and do not send soybeans to China. Because of their lack of participation in the Chinese soybean trade, these countries were excluded from further analysis. Third, Argentina, Paraguay and Uruguay have ideal climatic and environmental conditions for soybean production and were the respective 3rd, 4th, and 7th largest soybean exporters in 2016 [*54*]. Last, the literature has suggested that there are spillover effects of Brazil's large-scale soybean production on regional cropping patterns [*55, 68, 69*]. Corn and wheat trade were identified as possible relationships to be affected by soybean expansion based on production-substitute suitability, status as globally important food crops, literature review, preliminary analyses as well as data availability. After analyzing production and trade data to identify patterns in bilateral trade relationships of soybeans, corn and wheat, literature review and autoregressive integrated moving average models (ARIMA) were used to identify changes in trade patterns before and after China lowered their soybean tariff.

2.3. Methods

2.3.1. Conceptual Framework

This study treats the South American food trade network as a metacoupled system. The metacoupling framework is an umbrella framework that examines three types of human-nature interactions. Human-nature interactions occurring within a coupled human and natural system are called intracouplings. Pericouplings occur when human-nature interactions cross boundaries between adjacent systems, while telecouplings examine human-nature interactions across distance. By providing a typology that categorizes processes as intracouplings, pericouplings, and telecouplings (Figure 3), the metacoupling framework provides a structure for developing a more complete understanding of the complexity within trade networks. In relation to telecoupled trade between South American soybean-sending systems (e.g., Brazil, Argentina, Paraguay and Uruguay) and China, trade relationships among the neighboring countries in South America are classified as pericouplings and production within a country is considered as intracoupling. Because 30% of all global soybean trade flows in 2016 occurred between Brazil and China [*54*], this relationship is considered the main soybean telecoupling and a driver of structural change in the metacoupled soybean trade network.

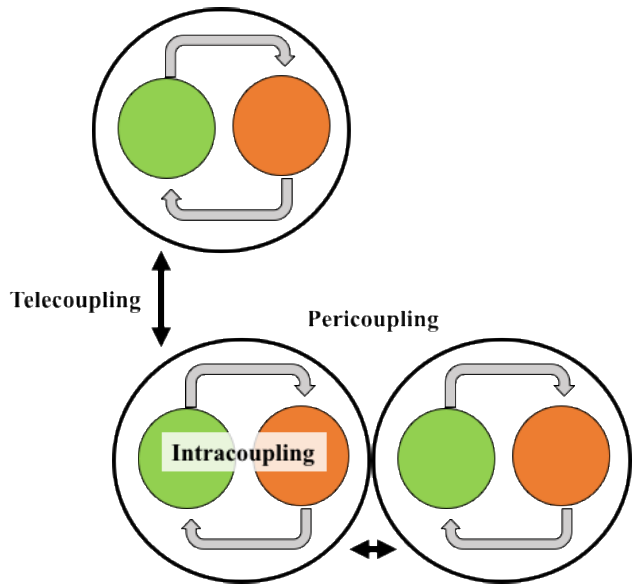

Figure 3. Conceptual overview of the metacoupling framework adapted from Liu (2017). The green circles represent natural components while the orange circles represent human components of the system. Grey arrows are interactions within systems (i.e., intracoupling) and black arrows are interactions between systems (i.e., peri- and telecouplings).

2.3.2. Relevant Theories

Originating in the interdisciplinary field of land system science, the metacoupling framework aims to capture various socioeconomic and environmental interactions as well as their impacts, at multiple distances. The metacoupling concept and framework [*65*] is an extension of the telecoupling concept and framework [*47*] which was derived from the integration of the concepts such as teleconnections (e.g., distant climatic connections [*70*]) and globalization (e.g., distant connections among human systems [*71*]). The metacoupling concept and framework are also supported through the integration of a variety of interdisciplinary concepts and theories [*72*]. For example, metacoupled systems can be treated as complex adaptive systems [*73*, *74*] with interacting feedbacks and spillovers at multiple scales.

The metacoupling framework can also be integrated with traditional theories of international trade. International trade theory suggests that every country has a comparative advantage in terms of a good or service that could be produced at a relatively lower cost than other countries. Countries producing similar goods and services still trade with one another, because comparative advantages stem from not only differences in climate as well as natural and human resources but also from differences in technology, economies of scale, preference for variety, and other factors [*75*]. By framing this study under the metacoupling framework and incorporating interdisciplinary concepts, such as theories of international trade, we were able to identify multiple drivers that influence tele- and pericoupled trade relationships.

2.3.3. Data Collection

Soybean, corn and wheat production data were collected from FAOstat for the years 1991 to 2016 [*15*]. Total imports, total exports, and bilateral crop trade data were collected from UNComTrade [*54*] under HS code 1201 (soybeans), 1005 (corn), and 1001 (wheat) for the same time period. The study period 1991-2016 was chosen to capture change in the soybean trade network since the Chinese soybean tariff was lowered from 130% to 3% in 1995 [*27, 51*]. While China did not join to the World Trade Organization (WTO) until 2001, the study period was chosen to reflect the time before and after China's soybean demand entered the global market. Data were thus split into two periods, before (1991-1995) and after (1996-2016) China's soybean demand entered the global market. Due to limited trade during the pre-period values are reported as average to avoid comparing trade values in 2016 to a trade value of 0. Trade values below 25,000 MT, which is 0.0007% of the soybeans exported from Brazil to China in 2016, were excluded from the analysis. Furthermore, many countries did not report bilateral trade data prior to 1991 which limited further historical analysis. While this study discusses four countries (i.e., Brazil, Argentina, Paraguay and Uruguay) in detail, data were collected and analyzed for all countries that were available during the study period (~75 countries).

2.3.4. Data Analysis

To identify trends in the production and trade of soybeans, corn, and wheat both within and between country pairs from 1991 to 2016, descriptive statistics, data visualization and trend analyses were performed. To understand the drivers behind these trade trends, literature was collected from academic, government and NGO sources. Finally, to capture the interaction between tele- and pericouplings and to estimate the impact of China's soybean demand on trade between South America sending systems, time series autoregressive integrated moving average (ARIMA) models [*76-78*] were specified for each commodity (i.e., soybeans, corn and wheat) and bilateral country pair (e.g., China, Brazil, Argentina, Uruguay and Paraguay). When the dependent variable was telecoupling (e.g., soybean export to China), pericoupling (e.g., cross-border trade) was added as an independent variable and vice versa, to test for significance. Several country pairs had very little or no trade for certain commodities during the study period and are not discussed in the manuscript, full ARIMA results can be found in the appendix (Figures 9-12, Table 2).

Following the protocol specified in [*77*], outliers were smoothed and missing values were linearly interpolated before diagnostic tests were used to determine parameters and the best model fit using R packages *tseries* [*79*], *forecast* [*77*] and *ggplot2* [*80*]. The ARIMA models capture time series trends and predict future values of trade ($\boldsymbol{Y}$) at time $\boldsymbol{t}$ by including autoregressive (AR(p)), integrated (I(d)) and moving average (MA(q)) model terms. The AR model term assumes the current value of trade between two countries is a linear function of the previous trade values and therefore includes p time lags to predict future values of $\boldsymbol{Y}$(1).

$$\boldsymbol{Y_t = c + \emptyset_1 y_{t-1} + \emptyset_p y_{t-p} + \varepsilon_t} \qquad \text{(1) AR}$$

where $\boldsymbol{c}$ is a constant, $\boldsymbol{\emptyset_1 + \cdots + \emptyset_p}$ are parameters and $\boldsymbol{p}$ is AR polynomial order. The integrated model term I refers to the differencing degree which is calculated by subtracting the current of trade between two countries and previous values of trade $\boldsymbol{d}$ times to stabilize the time series, where $\boldsymbol{yd_t}$ is $\boldsymbol{y_t}$ differenced $\boldsymbol{d}$ times (2a-b).

$$\boldsymbol{yd_t = Y_t - Y_{t-1}} \qquad \text{(2a) I}$$

$$\boldsymbol{Y_t = c + \emptyset_1 yd_{t-1} + \emptyset_p yd_{t-p} + \varepsilon_t} \qquad \text{(2b) AR+I}$$

The MA model term calculates future error terms, $\boldsymbol{e}$ at time $\boldsymbol{t}$, by combining previous errors terms, $\boldsymbol{e_{t-1}}$, where $\boldsymbol{q}$ indicates the number of error terms included (3).

$$\boldsymbol{Y_t = c + \theta_1 e_{t-1} + \theta_q e_{t-q} + \varepsilon_t} \qquad \text{(3) MA}$$

where $\boldsymbol{c}$ is a constant, $\boldsymbol{\theta_1 + \cdots + \theta_q}$ are parameters and $\boldsymbol{q}$ is the MA polynomial order. Through the combination of model terms, ARIMA models (4) are commonly used to recreate a time series trend and then project into the future for predictive purposes.

$$\boldsymbol{Y_t = c + \emptyset_1 yd_{t-1} + \emptyset_p yd_{t-p} + \theta 1 e_{t-1} + \theta_q e_{t-q} + \varepsilon_t} \qquad \text{(4) AR+I+MA}$$

Last, the ARIMA models were modified to test the influence of pericoupling processes ($\boldsymbol{x}$) on telecoupling processes ($\boldsymbol{Y}$) (5).

$$\boldsymbol{Y_t = \beta x_t + \emptyset_1 yd_{t-1} + \emptyset_p yd_{t-p} + \theta 1 e_{t-1} + \theta_q e_{t-q} + \varepsilon_t} \qquad \text{(5) AR+I+MA+X}$$

Where $\boldsymbol{x}$ is a covariate at time $\boldsymbol{t}$ and $\boldsymbol{\beta}$ is its coefficient.

While ARIMA models are traditionally used for the purpose of forecasting, in the present case it is more informative to hindcast the predicted values in order to examine the influence of China's tariff reduction on soybean trade. Therefore, the ARIMA models were trained on trade data in the post period (e.g., 1996-2016) and then hindcast for the pre period (e.g., 1991-1995). This method allowed for comparison between the observed and hindcast trade data among South American sending systems before China lowered the soybean import tariff. Because the hindcast values were calculated from the trend in the post period, differences between the observed and hindcasted data approximate the effect that China's soybean demand (e.g., telecoupling) had on trade between Brazil and nearby countries (e.g., pericoupling).

2.4. Results

2.4.1. Trend Analysis

Overview

While several countries in South America, as well as around the world, increased intracoupled soybean production and telecoupled export in response to China's increased demand after entering the global market [*59*], Brazil emerged as the most competitive. Brazil's success as a soybean sending system may be due to strategies used by the Brazilian government to liberalize trade and increase imports of and farmer access to fertilizers, pesticides, and seeds [*81*]. Since the pre-period average (1991-1995), Brazil steadily increased their market share from 0% to 46% of China's soybean imports in 2016. The remaining 2016 market shares belonged to the U.S. (40%), Argentina (9%) followed by Uruguay and then Canada, who each accounted for less than 2% of China's soybean imports [*54*]. While, Argentina, Paraguay and Uruguay share a border with Brazil as well as suitable land for soybean cultivation, their varying shares of the Chinese soybean market are largely reflective of the unique geo-political strategies taken by each country's respective government.

Argentina

Exports of soybeans from Argentina to China started in 1995 and experienced rapid growth during the first decade of the study period. However, in 2006, the Argentine government placed a domestic tariff on exports of soybean of 23.5% which resulted in slower growth in soybean exports to China [82] (Figure 4). Soybean exports to other South American countries were exempt from the tariff through joint membership in the Mercosur trade agreement [66]. Between the pre-period average and 2005, Argentina's soybean exports to China increased more than 35,000%, corresponding with a cessation of soybean exports from Argentina to Brazil in 1995 that did not start again consistently until 2005, just before Argentina's domestic tariff went into effect. In contrast, since 2006 soybean exports from Argentina to Brazil, Paraguay and Uruguay have increased by 128,766%, 128% and 88%, respectively, while exports to China increased by 23% (Figure 5, Table 1) [54, 83]. Furthermore, the rate of soybean expansion by area planted in Argentina was much higher before the domestic tariff started in 2006 (e.g., 215% increase between 1995-2005 vs. 45% increase between 2006-2016). In contrast, the rate of corn expansion by area planted was much higher after 2006 (e.g., 80% increase between 1995-2005 vs. 175% increase between 2006-2016), while the rate of wheat expansion by area planted occurred at approximately the same rate before and after Argentina's domestic tariff started in 2006 (e.g., 41% increase between 1995-2005 vs. 46% increase between 2006-2016) (Figure 5, Table 1). Along with literature support, these results suggest that Argentina's domestic tariff on soybean exports slowed soybean expansion and drove corn expansion while wheat intracoupling has remained relatively stable during the study period *[*24, 84-88*]*.

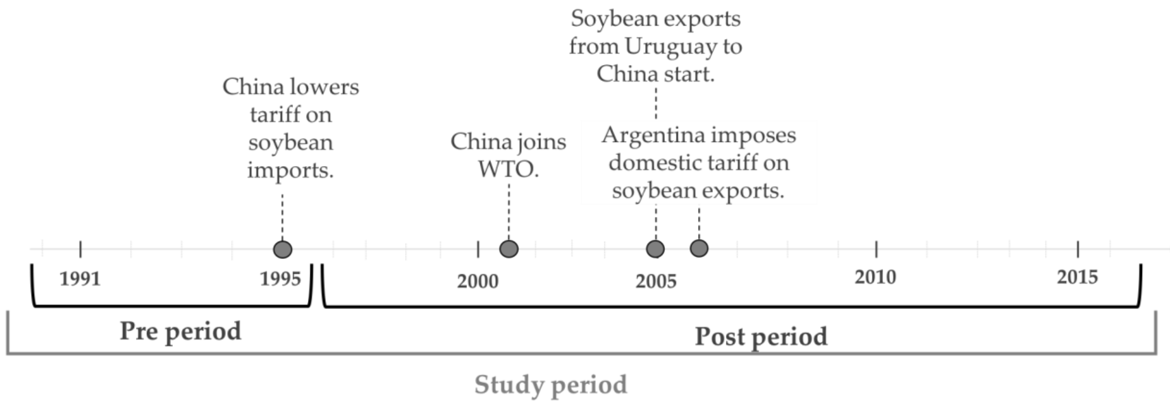

Figure 4. Timeline that defines the pre period (1991-1995) and post period (1996-2016) and highlights important events.

Uruguay

Differing from Argentina, Uruguay has tariff-free access to the Chinese soybean market as well as land prices that are about 50% cheaper than soybean land in Argentina. These factors, in combination with the financial crisis during the early 2000s, promoted investment in Uruguayan agriculture from nearby producers. In addition to investments from multinational companies, soybean expansion in Uruguay was driven primarily by investments from Argentina [63]. The flows of investment capital rapidly expanded Uruguay's soybean production and exports, increasing exports to China by 1,250% between 2005 and 2016 [54]. In 2007, two years after Uruguay began exporting soybeans to China, its soybean imports from Argentina, Brazil and Paraguay were equal to 60% of the amount Uruguay exported to China. As Uruguay increased soybean intracoupling, the contribution from nearby countries had become consistent but small. However, the rapid establishment of soybean production and foreign land ownership limited the development of soybean processing industry. Therefore, Uruguay is a net importer of both soybean oil and meal to support its a booming livestock industry, 100% of which comes from Argentina, Brazil and Paraguay [54].

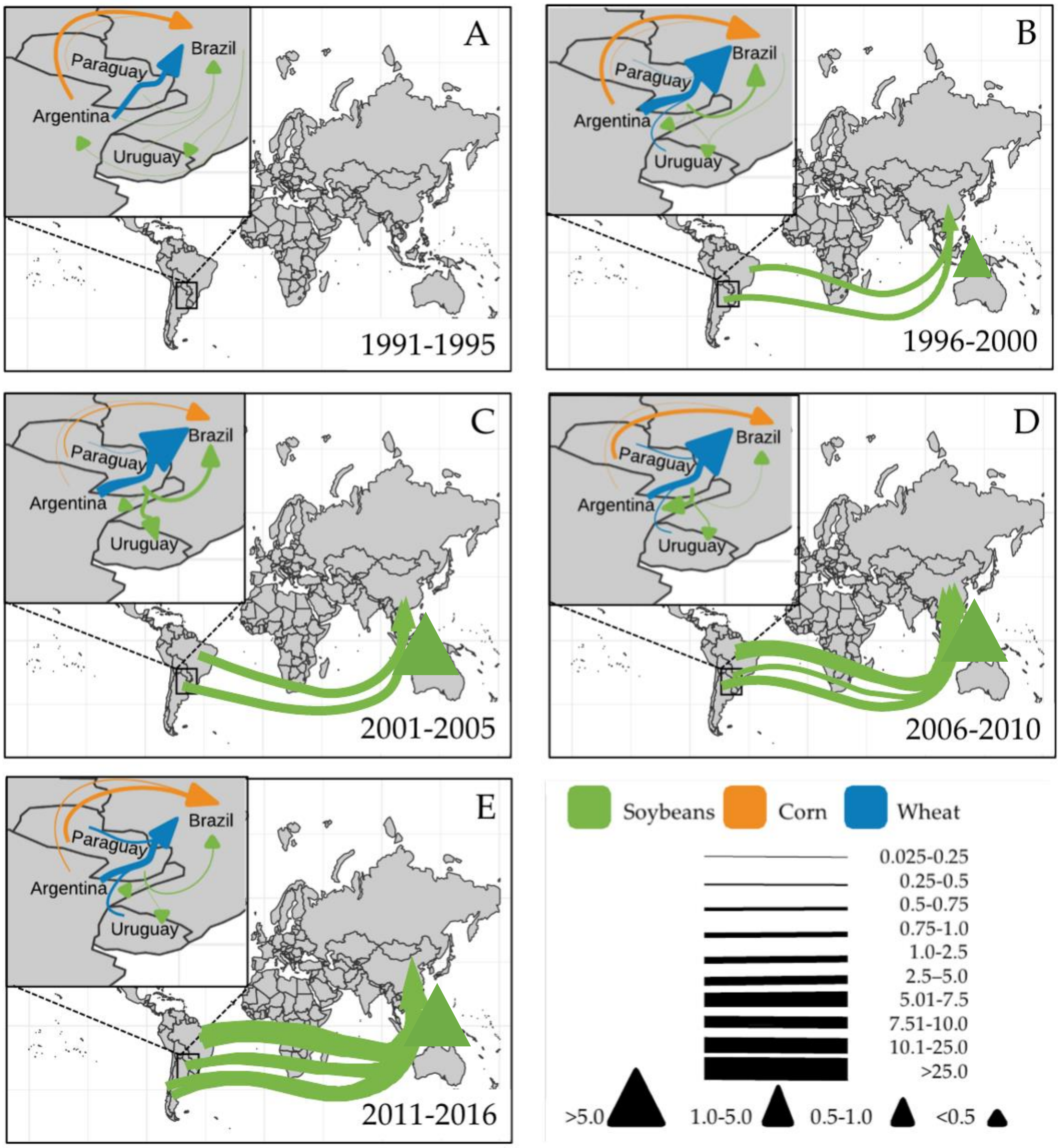

Figure 5. Flow maps depicting telecoupled soybean trade and pericoupled trade of soybeans (green arrow), corn (orange arrow) and wheat (blue arrow) from 1991-2016. Panels are split into 5-year time periods: 1991-1995 (A), 1996-2000 (B), 2001-2005 (C), 2006-2010 (D) and 2011-2016 (E). The width of the line represents average commodity flow from a single trade partner during the respective time period and the arrows are weighted according to total import from all trade partners. All values are presented in millions of metric tonnes. Trade amounts averaging below 25,000 MT per year were excluded.

Paraguay

Unlike Argentina and Uruguay, Paraguay chose to forgo diplomatic ties with China and market access due to ties with Taiwan [*89*]. Despite having restricted access to the largest soybean market, Paraguay's soybean production increased by more than 400% between 1995 and 2016, more than half of which were exported [*15, 64, 90*]. Due to the geographic and political landscape, Paraguayan soybeans were sent via barge to river ports in Argentina and Uruguay [*89, 91*]. Prior to 2009, exports to Argentina, Brazil and Uruguay accounted for between 40% and 70% of Paraguay's total soybean exports. Since 2009, Paraguay has increased soybean exports to Russia and Turkey. Russia and Turkey are net exporters of processed soybean products and export soybean oil to China [*54*]. In 2016 29% of Paraguay's soybean exports went to Argentina, Brazil, and Uruguay, while 15% went to Russia and 13% to Turkey [*54*]. While re-export analysis was not performed in the present study, the literature confirms that even though Paraguay does not directly engage in soybean trade with China, intracoupled soybean production, and pericoupled and telecoupled soybean exports have been increasingly driven by China's soybean demand [*89, 91, 92*].

Table 1. Brazil's soybean (HS 1201), corn (HS 1005) and wheat (HS 1001) imports in metric tonnes (MT) from Argentina, Paraguay, Uruguay and the U.S. The table includes the trade value for the pre period (the average trade value between 1991 and 1995), 2016 and the percent change between the pre period and 2016.

Brazil's Soybean Imports				
	Argentina	Paraguay	Uruguay	USA
Pre Period	129,079	177,765	33,016	187,397
2016	670	381,448	0	0
Percent Change	-99.5%	114.6%	-100%	-100%
Brazil's Corn Imports				
	Argentina	Paraguay	Uruguay	USA
Pre Period	811,167	80,831	5,188	123,894
2016	1,436,245	1,465,053	0	532
Percent Change	77%	1712%	-100%	-99.5%
Brazil's Wheat Imports				
	Argentina	Paraguay	Uruguay	USA
Pre Period	1,074,906	14,544	47,287	173,355
2016	3,950,036	956,125	577,415	1,226,210
Percent Change	268	6474%	1121%	607%

2.4.2. Differences in Trade Between the Pre- and Post-Period Trends

Overview

To explore differences in trade between the pre-period trend (e.g., 1991-1995, prior to China's soybean tariff reduction) and the post-period trend (e.g., 1996-2016, after China's soybean tariff reduction), autoregressive integrated moving average (e.g., ARIMA) models were constructed. For illustrative purposes, Figure 6 shows the ARIMA results for soybean exports from Argentina, Brazil and Uruguay to China. In all three cases, the hindcast values (e.g., dashed line) for the pre period were higher than the observed values (e.g., solid black line), indicating that based on the trend during the post period, more trade was expected during the pre period. Differences in the hindcast values and observed trade values during the pre period indicate that the trade trends before and after China's market entry were different but cannot be used to directly infer the influence of China's market demand. The relationships between telecoupled exports and pericoupled imports are shown in Table 2. Brazil and Uruguay's soybean exports to China had a statistically significant relationship with their pericoupled soybean imports. Many other factors could drive bilateral trade relationships, such as population and economic growth, however because the models were constructed from the observed data the impact of major factors is endogenized in the ARIMA trend. The varying degrees of access to the Chinese soybean market by Argentina (somewhat restricted access), Uruguay (unrestricted access) and Paraguay (completely restricted) allow for a unique analysis of how telecoupled, pericoupled and intracoupled processes interact.

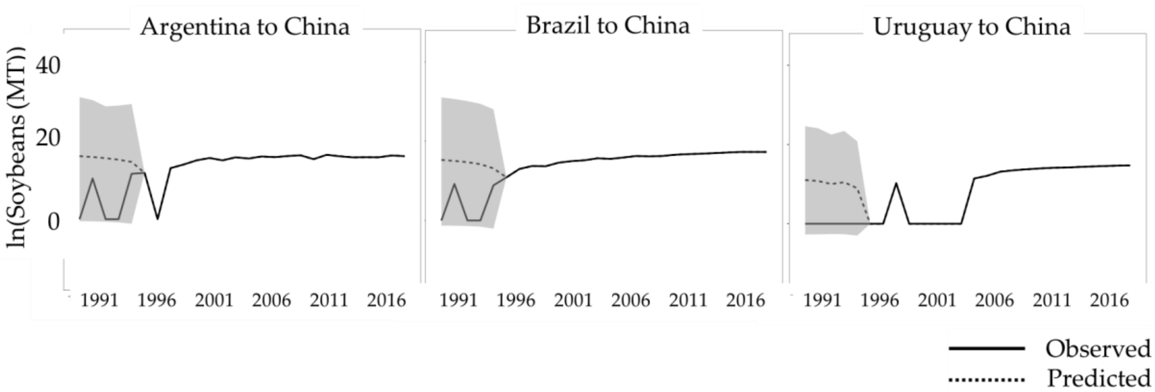

Figure 6. ARIMA for Argentina, Brazil and Uruguay's soybean exports to China. See SF1 for full country and commodity results. The solid line represents the natural log of imports in metric tons and the dashed line represents the natural log of the trend derived from the ARIMA models. The shaded grey area is the 95% CI. P-values, NRMSE (normalized by standard deviation) and MASE can be found in Table S1.

Argentina

The observed trade data show that soybean exports from Argentina to Brazil have declined by 99% between the pre period (average of 1991-1995) and 2016 while exports of corn and wheat have increased 77% and 267%, respectively (Table 1) [*54*]. Using the trend from post period to hindcast the values for the pre period, the ARIMA results indicate that the observed soybean and corn exports from Argentina to Brazil during the pre period were higher than the hindcast values while the observed wheat exports were lower than the ARIMA values (Figure 7 A1). With respect to soybean trade, the lower hindcast values reflect when the observed soybean exports from Argentina to Brazil dropped to zero in 1995 and did not start again consecutively until 2005, which respectively correspond with the reduction of the Chinese import tariff and the start of the Argentine export tariff.

The ARIMA results suggest that fewer soybean exports from Argentina to Brazil reflect the observed trend during the first half of the study period. However, between 2006 and 2016 soybean exports from Argentina to Brazil increased by over 400% [*54*]. The opposite trend observed during the second half of the study period may have masked the and contributed to the relatively small difference between the observed and hindcast values (Table 2). These results suggest that pericoupled soybean trade between Argentina and Brazil was reduced between 1995 and 2005 and then enhanced between 2006 and 2016. Similarly, the hindcast values for corn exports from Argentina to Brazil are slightly lower than the observed data (Figure 7 B1) which supports the literature finding that corn expansion in Argentina was driven by biofuel mandates in Europe and the U.S. during the mid-2000's [*88*]. Competition from biofuel mandates, as well as other drivers, may have offset pericoupled corn trade between Argentina and Brazil during the post period. Differing from soybeans and corn, the observed wheat imports from Argentina to Brazil were much lower than the hindcast values (Figure 7 C1), indicating that while pericoupled corn and soybean trade were offset during the post period, pericoupled wheat trade was enhanced.

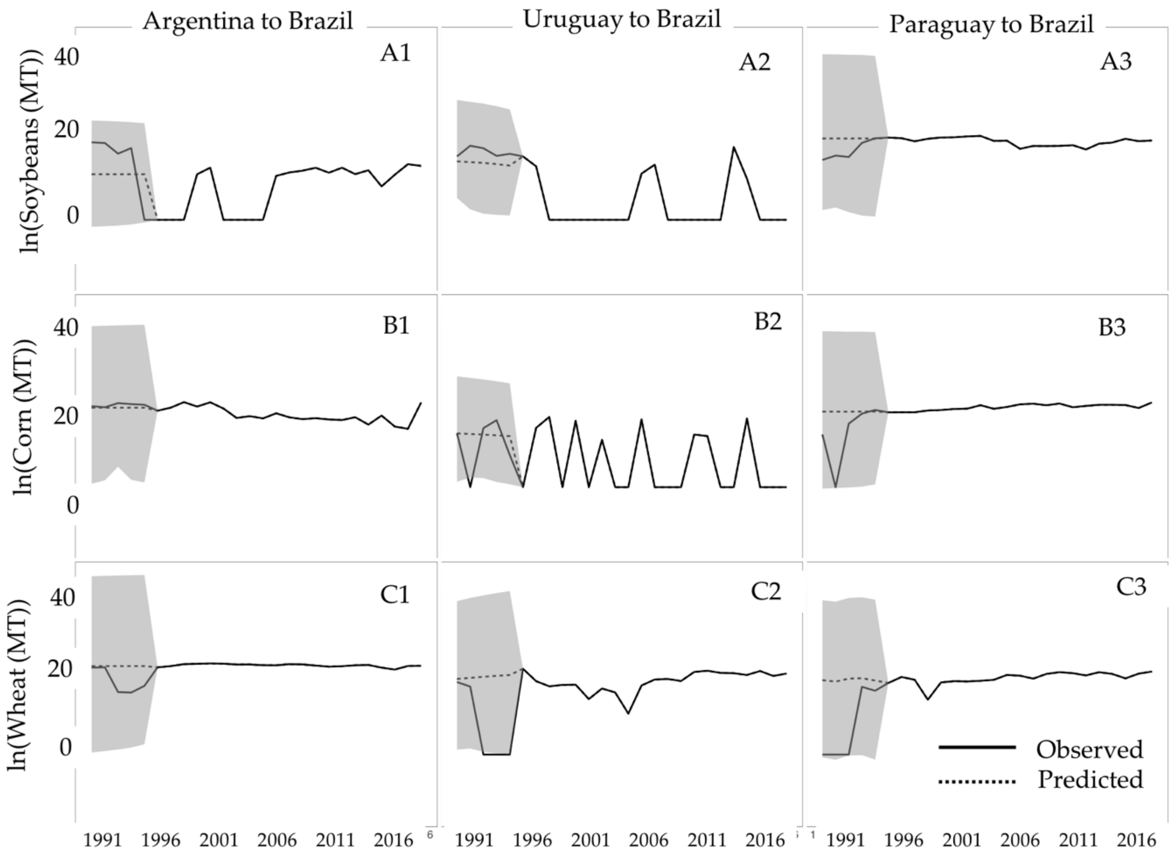

Figure 7. ARIMA for Brazil's soybean (A), corn (B) and wheat (C) imports from Argentina (1), Uruguay (2) and Paraguay (3). The solid line represents the natural log of imports in metric tons and the dashed line represents the natural log of the trend derived from the ARIMA models. The shaded grey area is the 95% CI.

Uruguay

Based on hindcasting the post-period trend, the ARIMA values for soybean and corn exports from Uruguay to Brazil were lower than the observed values during the pre period (Figure 7 & Table 2). This is because observed soybean and corn exports from Uruguay to Brazil during the post period decline to zero (Table 1). In 1997, three years after China's tariff was lowered, soybean exports from Uruguay to Brazil decline to zero and do not start again consistently. Further, corn exports from Uruguay to Brazil both increase and decrease but trade only occurred intermittently during the post period. The highly variable pattern and lower hindcast values indicate that exports of corn and soybean from Uruguay to Brazil were reduced in the post period. In contrast, the observed values for wheat exports from Uruguay to Brazil were substantially lower than the hindcast values (Figure 7 C2). The observed exports from Uruguay to Brazil increased by 1121% since the pre period (Table 1), indicating that pericoupled wheat trade was enhanced during the post period. Additionally, there was a significant relationship between Uruguay's soybean exports to China and their soybean imports from Argentina, Brazil and Uruguay. Further, the hindcast values were higher than the observed trade for exports of corn and wheat from Argentina to Uruguay and exports of corn and wheat from Paraguay to Uruguay (Figure 11), suggesting Uruguay's pericoupled imports were enhanced during the post period.

Paraguay

In contrast to Argentina and Uruguay, Paraguay showed a consistent pattern across soybean, corn and wheat exports to Brazil. Paraguay is the only country that is completely restricted from accessing the Chinese market and experienced increases in exports to Brazil of all three crops. Specifically, since the pre-period (average of 1991-1995) exports of soybeans, corn and wheat to Brazil have increased by 114%, 1,712% and 6,474% , respectively (Table 1). The observed values for soybean, corn and wheat exports from Paraguay to Brazil, during the pre period were all lower than the ARIMA hindcast values (Figure 7, C1, C2 & C3). The consistent pattern across crops indicates that pericoupled trade between Paraguay and Brazil was enhanced during the post period. Paraguay's wheat exports to Brazil had a statistically significant relationship with Brazil's soybean exports to China (Table 2). Further, in supplemental Figures 10 and 11, the hindcast values are higher than the observed soybean exports from Paraguay to Argentina and soybean and corn exports from Paraguay to Uruguay.

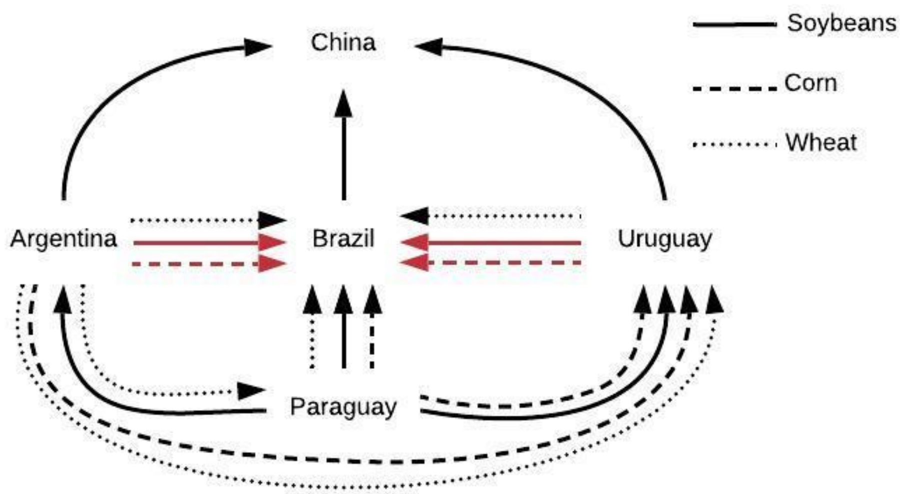

Figure 8. Summary of ARIMA results for all bilateral trade relationships. Black lines are cases where trade flows were enhanced (hindcast values were higher than the observed trade) and red lines indicate situations where trade was offset (hindcast values were lower than the observed trade) during the pre period. Solid lines are soybean flows, dashed are corn flows and dotted are wheat flows.

2.5. Discussion

This study highlights a complex web of interactions that have been shaped by China's soybean demand, domestic policies and international geo-political relationships (Figure 8). First, Brazil's imports of wheat substantially increased from Argentina, Uruguay and Paraguay during the study period. The ARIMA models confirm that wheat trade during the post period was enhanced compared to the pre period. Interestingly, Argentina's exports of wheat to Uruguay and Paraguay were also enhanced. Second, while there was a significant relationship between Brazil's soybean exports to China and Brazil's pericoupled soybean imports, the pattern across Argentina, Uruguay and Paraguay varied and may be related to the respective government strategies used to facilitate or inhibit trade. Soybean exports from Argentina to Brazil decreased in the first half of the study period (e.g., 1995-2005) and increased in the second half (e.g., 2006-2016), corresponding with the reduction of China's soybean tariff and the start of a domestic export tariff. Further, while corn exports from Argentina to Brazil increased during the study period, differences between the observed and hindcast values suggest that pericoupled corn trade was offset in the post period. Direct and indirect competition from European and U.S. ethanol mandates and China's soybean demand may have interacted to offset and enhance pericoupled soybean and corn trade between Argentina and Brazil during the post period. Uruguay did not start exporting soybeans to China until 2005, but since then has increased exports. Both soybean and corn exports from Uruguay to Brazil declined after the pre period and only occur intermittently. Additionally, Uruguay increased imports of corn from Argentina and Paraguay. The ARIMA models indicate differences in the trend between the pre and post period which supports the observation that pericoupled trade was offset in the post period. Third, soybean and corn exports from Paraguay to Brazil increased throughout the study period and Paraguay's wheat exports to Brazil had a significant relationship with Brazil's soybean exports to China. The ARIMA models confirm differences between the pre and post period trends and suggest pericoupled trade was enhanced during the post period. The inability to access the Chinese market directly may have contributed to increased pericoupled trade with Brazil as well as Argentina and Uruguay, which offer convenient export routes [*89, 93*]. Paraguay's strengthening trade relationships with Russia and Turkey, top exporters of soybeans and soybean products, may compete with pericoupled exports and provide further evidence that Paraguay is indirectly influenced by the Chinese market.

In the meta- and telecoupling literature there are no studies that specifically address the synergy between telecoupling and pericoupling processes. However, a number of studies document spillover effects of Brazilian soybean expansion. For example, Bicudo da Silva et al. found that as a result of increased soybean production in Brazil, farmers increased operations from growing 1 to 2 crops each year which increases risk of precipitation anomalies. Soybeans are planted first, followed by corn, most of which is for domestic consumption rather than export [*24*]. Further, Dou et al. found that conservation efforts (i.e., Soy Moratorium and zero-deforestation beef agreement) meant to contain deforestation in the Amazon biome displaced deforestation to the Cerrado region [*55*]. In the respective cases, soybean expansion temporally displaced corn production and spatially displaced deforestation within Brazil's system boundary. The results of the present study indicate that similar interactions may occur across system boundaries where telecouplings interact with pericouplings to enhance or offset one another. On the other hand, a network analysis of global soybean trade [*50*] identified Brazil, China and the USA as the key players but did not find regional or continental geography to be predictor of trade patterns. The present findings suggest that pericoupled relationships are important in global trade patterns and may be dwarfed, contextually and computationally, by the massive flows among Brazil, China and the USA. Therefore, analyses that only consider direct trade routes or bilateral exchanges could mask the true value of the flow and therefore underrepresent the land-use impact of production. Because soybean expansion has already threatened ecosystems and displaced land-use in Brazil [*24*], Argentina [*56*] and Uruguay [*69*], stakeholders should consider pericoupled trade when designing policy interventions.

This study explored the impact of China's tariff reduction and subsequent increases in soybean demand on pericoupled trade relationships between Brazil, the largest soybean exporter, and the adjacent soybean-sending systems of Paraguay, Uruguay and Argentina. We note that this analysis lacks systematic consideration of other factors that could have driven differences between the pre and post period. For example, population growth and income level have been shown to be significant factors for food trade [*43*] and were not explicitly considered in this analysis. While the lack of other consideration is valid, ARIMA models accurately capture time-series trends by endogenizing the impact of major drivers through accounting for non-stationarity, seasonality and auto-correlation. ARIMA models use lags of the dependent variable or lags of errors as independent variables to capture the underlying systematic patterns in the data [*76, 94*]. Additional independent variables can be added to ARIMA-X models, however those factors should not have been affected by the intervention in question, i.e. China acceding to the WTO, and can result in over-specification. Further, ARIMA models have been shown to capture the same trend with only slight differences from ARIMA-X models [*76*]. Therefore, the ARIMA models can determine if the trends between the pre and post periods differ, however, those differences cannot be casually attributed to China's soybean demand. Rather, the multitude of academic and government literature support this hypothesis [*95*]. One possible future research direction is to consider the impact of telecouplings on pericoupled trade among receiving systems.

2.6. Conclusions

The present research highlights the importance of pericoupled relationships in global trade and provides insights on how commodities flow in a metacoupled world. Despite government (e.g., Argentina and Paraguay) policies that inhibited soybean exports and expansion, China's distant demand affected intracoupling and trade both directly, via telecouplings, and indirectly through pericouplings. This suggests that in a metacoupled world commodities flow from areas of supply to areas of demand using the most cost-effective route [*96*]. If that route is restricted, the commodity will likely still flow to the area of demand, but via a different route. These results should be considered by and may stimulate future studies on metacoupled systems (e.g., beyond soybean trade, such as migration, tourism, species invasion) and provide insights for governing metacoupling systems.

APPENDIX

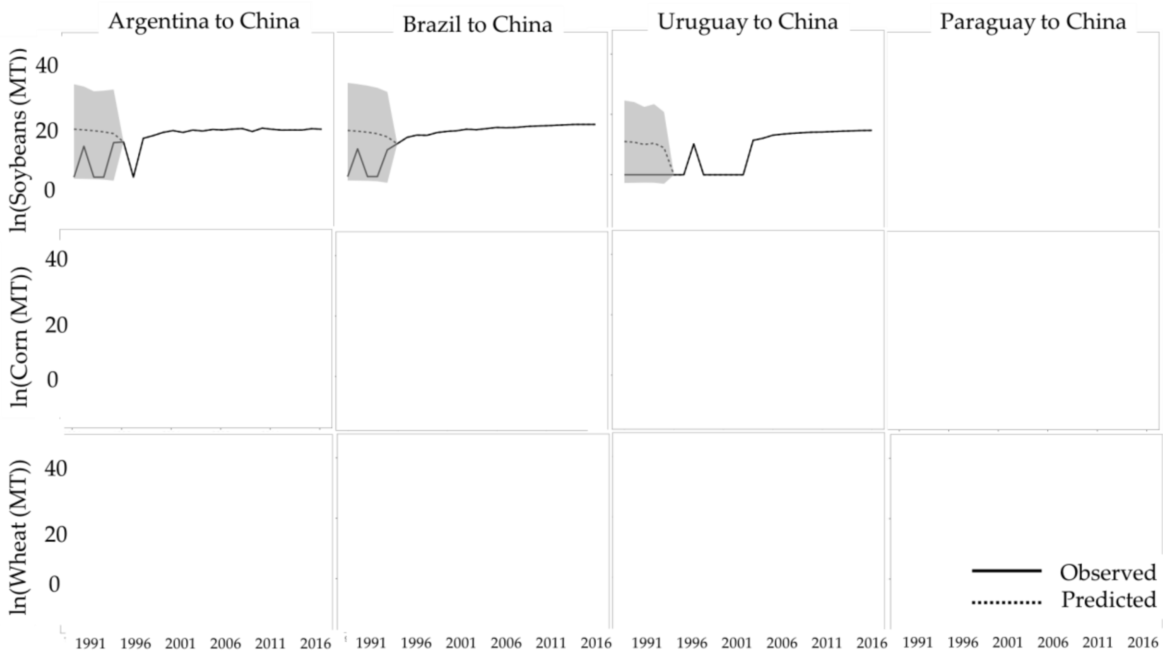

Figure 9. Full ARIMA results for China's soybean, corn and wheat imports from Argentina, Brazil, Uruguay and Paraguay. The solid line represents the natural log of imports in metric tons and the dashed line represents the natural log of the trend derived from the ARIMA models. The shaded grey area is the 95% CI. Trade values below 25,000 MT per year were excluded. Blank graphs indicate no or very little trade occurred.

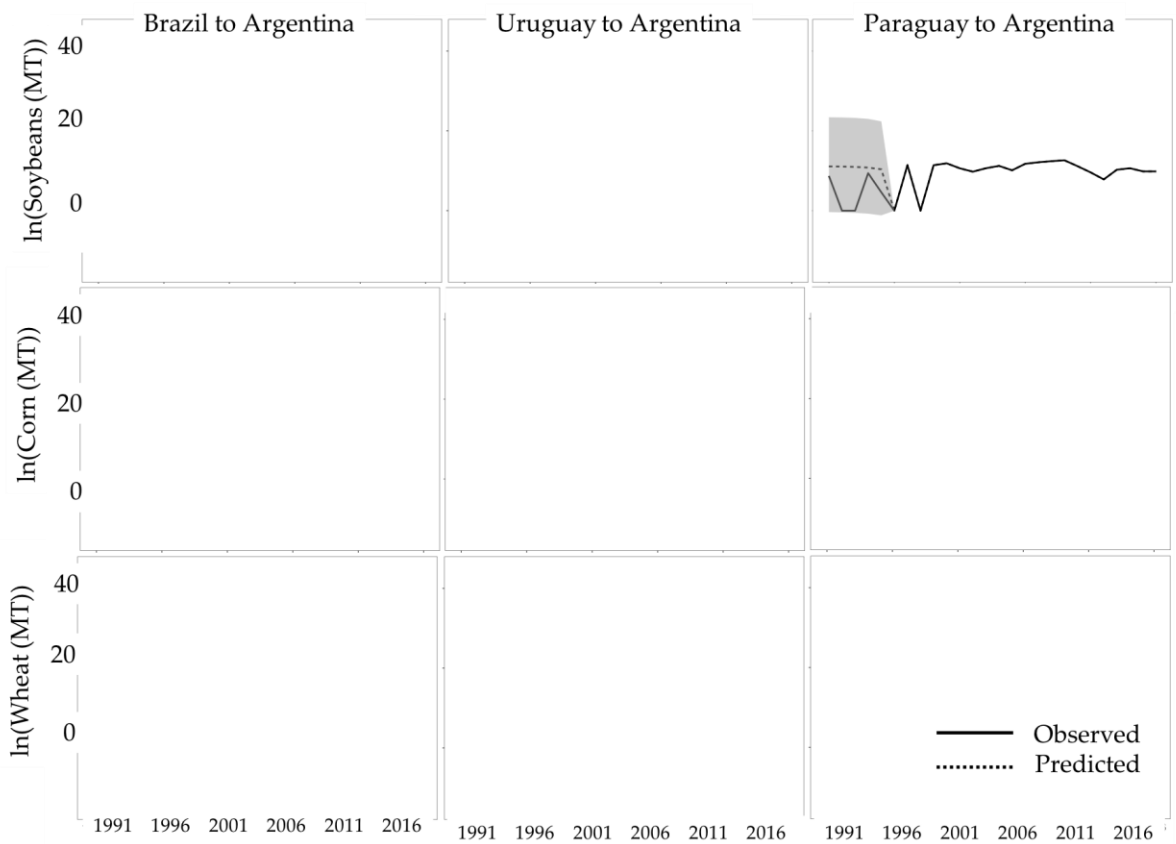

Figure 10. Full ARIMA results for Argentina's soybean, corn and wheat imports from Brazil, Uruguay and Paraguay. The solid line represents the natural log of imports in metric tons and the dashed line represents the natural log of the trend derived from the ARIMA models. The shaded grey area is the 95% CI. Trade values below 25,000 MT per year were excluded. Blank graphs indicate no or very little trade occurred.

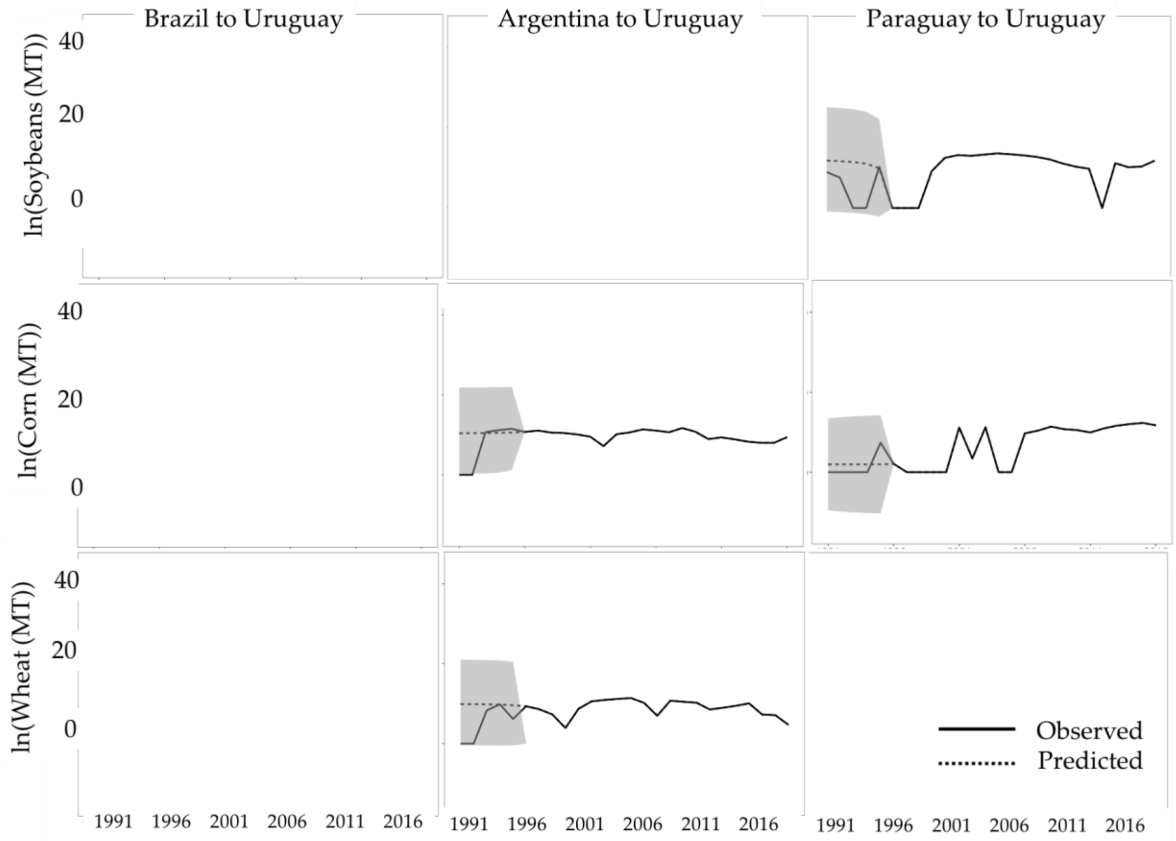

Figure 11. Full ARIMA results for Uruguay's soybean, corn and wheat imports from Argentina, Brazil and Paraguay. The solid line represents the natural log of imports in metric tons and the dashed line represents the natural log of the trend derived from the ARIMA models. The shaded grey area is the 95% CI. Trade values below 25,000 MT per year were excluded. Blank graphs indicate no or very little trade occurred.

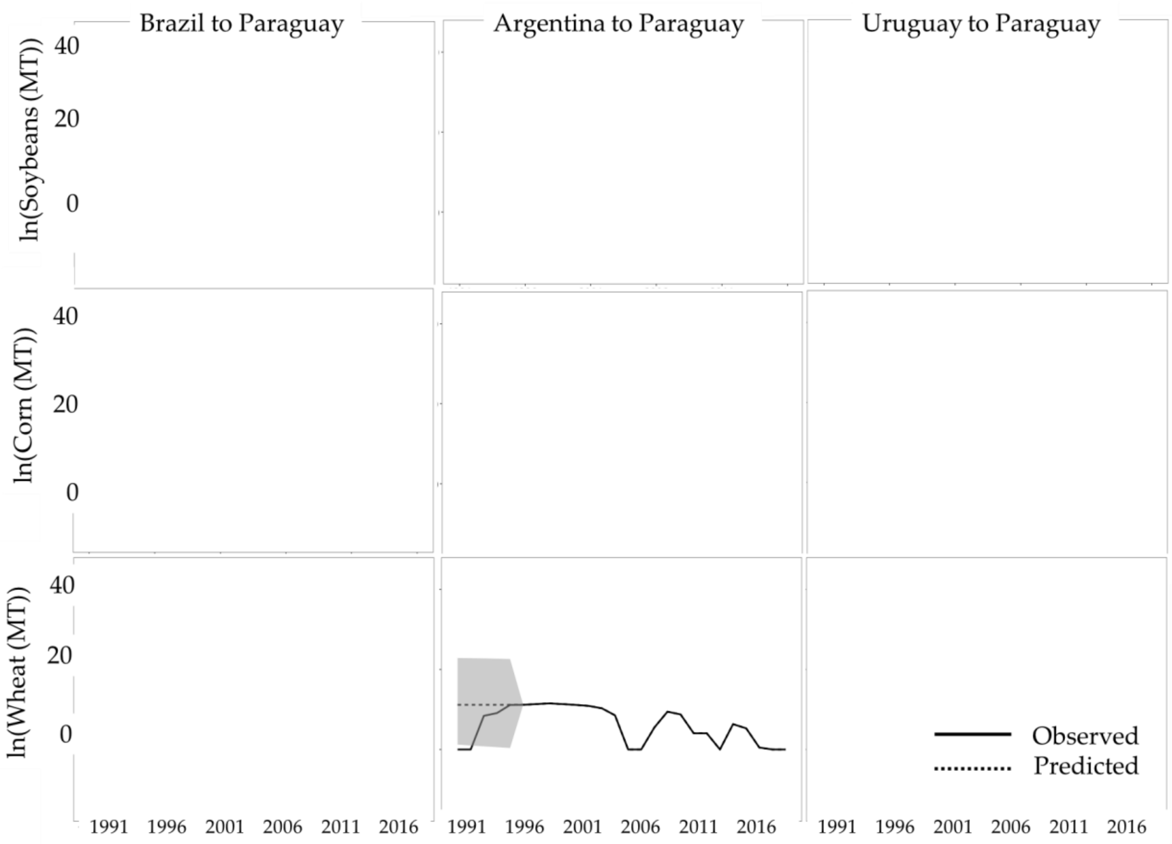

Figure 12. Full ARIMA results for Paraguay's soybean, corn and wheat imports from Argentina, Brazil and Uruguay. The solid line represents the natural log of imports in metric tons and the dashed line represents the natural log of the trend derived from the ARIMA models. The shaded grey area is the 95% CI. Trade values below 25,000 MT per year were excluded. Blank graphs indicate no or very little trade occurred.

Table 2. Description of final ARIMA models including p (# of lags), d (# of differences), q (# of error terms). Followed by parameter descriptions and p-values, (***p < 0.001, **p< 0.05 and *p < 0.01). AR and MA parameters refer to the autoregressive and moving average model terms. The pericoupled parameters are relative to the country in the dependent variable and are the aggregated imports from the adjacent countries. For example, if Y = Soybean exports from Argentina to China, then pericoupled soybean imports are equal to Argentina's soybean imports from Brazil, Uruguay and Paraguay. The fourth column includes the sum of the differences between the observed and predicted values for 1991-1995 in MT. Positive numbers can be interpreted as a predicted increase in trade during the pre period of X MT compared to the observed values; negative numbers indicate a predicted decrease of X MT during the pre period relative to the observed values. Finally, normalized root mean squared error (NRMSE) and mean absolute scaled error (MASE) were included as measures of model validity. NRMSE was normalized by dividing the RMSE by the standard deviations of the dependent variable. In both cases, values close to zero indicate a high performing model that captures the variation in the data. Values around 1 indicate the model is explaining some of the variation in the data, while values beyond 1 indicated noise and a low-performing model.

ARIMA Model (p, d, q)	**Parameter**	**p-value**	**Σ(Observed-Predicted values)**	**NRMSE**	**MASE**
Soybean exports from Argentina to China (0, 1, 1)	MA1	0.00***	21,065,499	0.55	0.82
	Pericoupled soybean imports	0.27			
	Pericoupled corn imports	0.63			
	Pericoupled wheat imports	0.69			
Soybean exports from Brazil to China (0, 2, 1)	MA1	0.00***	12,115,029	0.11	0.71
	Pericoupled soybean imports	0.05*			
	Pericoupled corn imports	0.7			
	Pericoupled wheat imports	0.1			
Soybean exports from Uruguay to China (1, 1, 0)	AR1	0.00***	174,735	0.06	0.4
	Pericoupled soybean imports	0.05*			
	Pericoupled corn imports	0.9			
	Pericoupled wheat imports	0.69			
Soybean exports from Argentina to Brazil (0, 1, 1)	MA1	0.00***	-515,895	0.78	0.7
	Telecouping (e.g., Brazil's soybean exports to China)	0.8			
Soybean exports from Uruguay to Brazil (0, 2, 1)	MA1	0.00***	-180,406	0.37	1.1
	Telecouping (e.g., Brazil's soybean exports to China)	0.8			
Soybean exports from Paraguay to Brazil (0, 2, 1)	MA1	0.00***	2,217,646	0.71	0.92
	Telecouping (e.g., Brazil's soybean exports to China)	0.3			
Corn exports from Argentina to Brazil (0, 1, 0)	Telecouping (e.g., Brazil's soybean exports to China)	0.38	-2,054,664	0.63	0.9
Corn exports from Uruguay to Brazil (0, 1, 0)	Telecouping (e.g., Brazil's soybean exports to China)	0.9	-18,305	0.4	0.97
Corn exports from Paraguay to Brazil (0, 1, 1)	MA1	0.05*	423,823	0.51	1
	Telecouping (e.g., Brazil's soybean exports to China)	0.34			
Wheat exports from Argentina to Brazil (0, 1, 0)	Telecouping (e.g., Brazil's soybean exports to China)	0.58	12,012,323	0.6	0.94

Table 2 (cont'd)					
Wheat exports from Uruguay to Brazil (1, 2, 1)	AR1	0.00***	911,268	0.3	0.7
	MA1	0.00***			
	Telecouping (e.g., Brazil's soybean exports to China)	0.46			
Wheat exports from Paraguay to Brazil (3, 1, 1)	AR1	0.00***	505,229	0.45	0.63
	AR2	0.00***			
	AR3	0.00***			
	MA1	0.00***			
	Telecouping (e.g., Brazil's soybean exports to China)	0.00***			
Soybean exports from Paraguay to Argentina (1, 1, 0)	AR1	0.00***	248,227	0.12	0.8
Soybean exports from Paraguay to Uruguay (2, 0, 1)	AR1	0.00***	417,083	0.23	0.79
	AR2	0.06			
	MA1	0.00***			
Corn exports from Argentina to Uruguay (1, 0, 0)	AR1	0.00***	37,552	0.48	0.89
Corn exports from Paraguay to Uruguay (0, 1, 0)			1,565	0.47	0.9
Wheat exports from Argentina to Uruguay (1, 0, 0)	AR1	0.00***	65,416	0.37	0.9
Wheat exports from Argentina to Paraguay (0, 1, 0)			271,462	0.45	0.96

Author Contributions:

All authors were involved in the conceptualization, writing, reviewing and editing of the manuscript; A.H. and M.C. curated the data, developed the methodology and performed the analysis.; A.H. and K.K. created the visualizations in the manuscript; K.F. and J.L. provided supervision; J.L. is responsible for project administration and funding acquisition.

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3. INTERNATIONAL FOOD TRADE LED TO AIR POLLUTION IN NON-TRADING COUNTRY

3.1. Overview

Almost all places around the world are interconnected via food trade [*1*]. Over the past three decades, global food production has doubled [*2*], with producing countries increasingly cultivating for exports rather than domestic consumption, resulting in a rise in food exports by an order of magnitude [*3*]. The increased global trade of agriculture products have numerous, well-documented socioeconomic and environmental impacts affecting both exporting and importing regions [*4*]. However, little is known about the spillover effects that influence other regions outside the trading partners [*5*-*7*].

To explore spillover effects of international trade, we choose international soybean trade as an example because it has been rapidly growing in recent decades. Several studies have analyzed the impact of soybean trade with China, the top soybean consumer, on Brazil, the top soybean producer. In addition to prosperous economic growth, soybean expansion in Brazil competes with production of other crops and land for conservation efforts[*8, 9*]. Further, changes in crop production and trade relationships with countries bordering Brazil indicate soybean expansion has displaced other crops production to neighboring countries[*10*]. On the other side of the world, increased soybean imports have prompted many farmers in China, particularly in Heilongjiang province (the most important soybean producing region in the country), to switch soybeans to alternative crops such as maize.

In this study, we explore the underlying regional cultivation and management shifts that resulted in air pollution locally and across the China-Russia border. We quantified the spatial and temporal patterns of PM 2.5 in Heilongjiang and in the nearby Russia Provinces. To confirm air pollutant transport, we used NASA Worldview images to capture smoke from the fires. Finally, we analyzed the spatiotemporal patterns of agricultural fires and crop conversion patterns and evaluated the household mechanisms behind the patterns.

3.2. Results

In this study, through a combination of remotely sensed data and household surveys, we found that air quality in Russia is unexpectedly affected by soybean trade between China and major soybean exporters such as Brazil and the USA. Specifically, the concentration of atmospheric fine particulate matter smaller than 2.5 microns in diameter (PM 2.5) [*11*] in several provinces of Russia next to China's Heilongjiang Province are particularly elevated during spring (i.e., February-May), and with a conspicuous peak in late autumn (i.e., November; Fig. 13). During spring the PM 2.5 concentrations are mostly associated with household heating (with coal) over the winter months[*12*, *13*]. The effects of pre-planting crop residue burning (Fig. 14) on PM 2.5 concentration in neighboring Russian provinces during spring seem to be lower than in November because they increased PM 2.5 concentration in Heilongjiang province but not in neighboring Russian provinces (Fig. 13). In contrast, the conspicuous increase in PM 2.5 in November across the entire region (including areas in Russia) is mostly associated with post-harvest residue burning in Heilongjiang (Figs. 13 and 14). This seasonal difference in the effects of crop residue burning may be explained by thermal inversions characteristic of autumn months, impeding the vertical movement of air (convection) thus reducing the dilution of PM 2.5 pollutants [*11*]. Using images from NASA Worldview [*14*](Fig. 15), we observed that smoke from agricultural fires in Heilongjiang was blowing into neighboring Russian provinces.

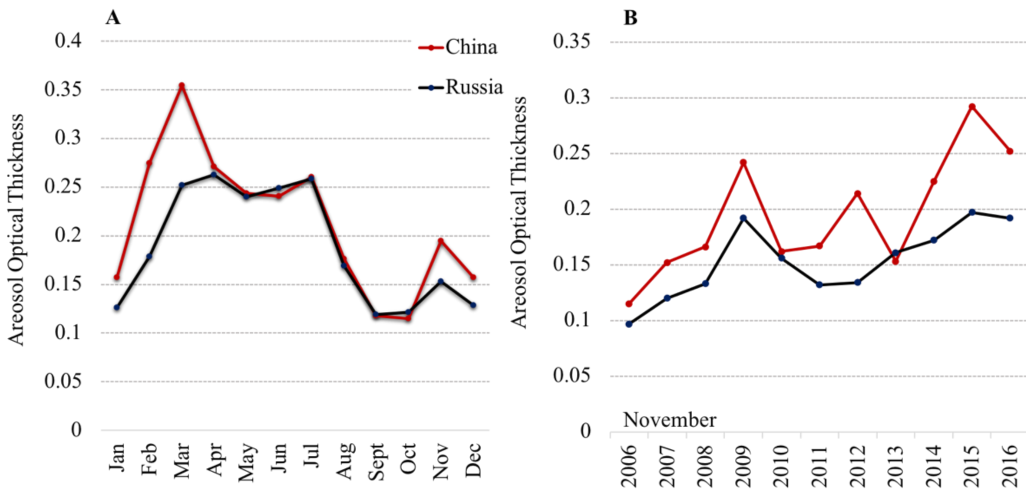

Figure 13. Temporal dynamics of AOT aggregated across Heilongjiang province, China and across neighboring provinces in Russia (Amur, Khabarovsk, Primorsky and Yevrey). Panel A shows multi-annual (2006-2016) monthly average AOT values and Panel B shows the average AOT values for the month of November of each year from 2006 to 2016.

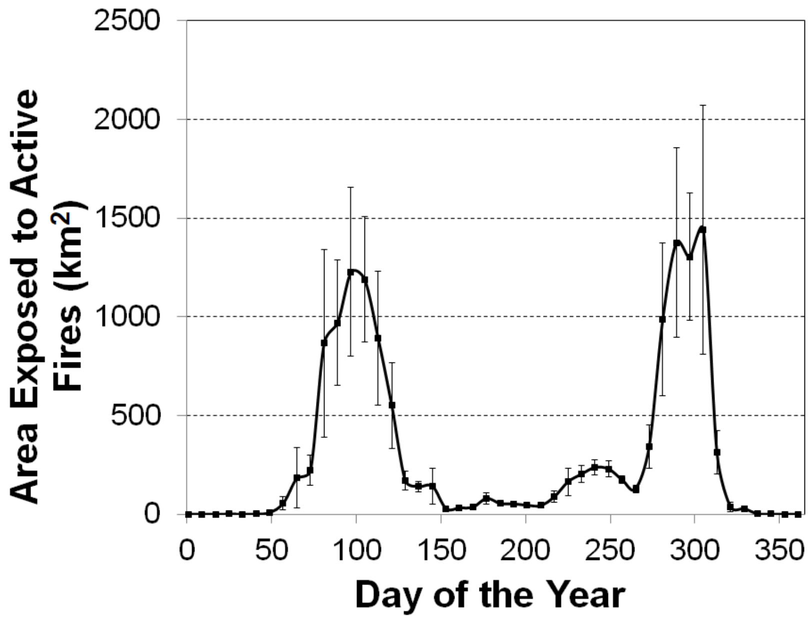

Figure 14. Average seasonal dynamics of the areas where fires were detected in Heilongjiang province, Northeast China during the 2006-2016 period. Error bars correspond to 1 SEM.

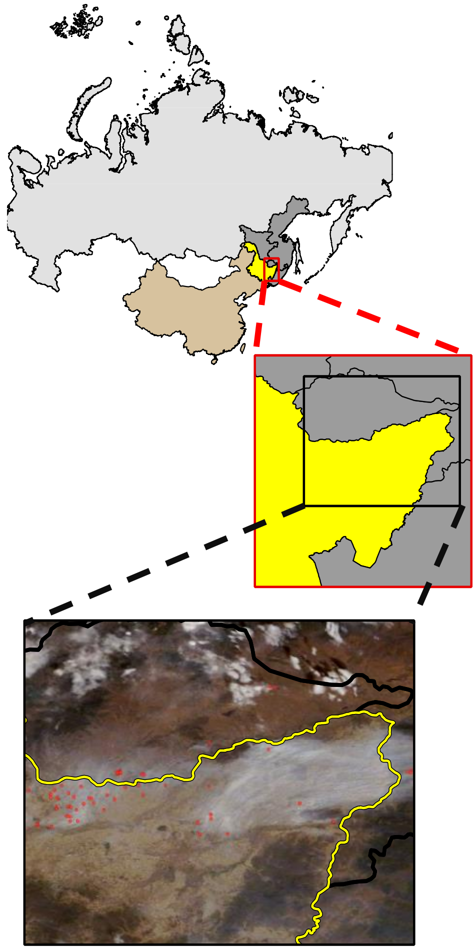

Figure 15. Location of the study site, Heilongjiang, China (in yellow) and neighboring Russia Provinces (in grey) with inset snapshots of the China-Russia border from NASA worldview[14]. The inset image snapshot is from 10/14/16 and captures smoke from agricultural fires blowing across the international border. Panel A shows 1:5000, Panel B shows 1:2500 and Panel C shows 1:1500. The red dots on the inset image map are satellite detections of fires, derived from MODIS and VIIRS instruments, in the area. https://go.nasa.gov/30UQllB.

The liberalization of soybean importation in China has pushed farmers, particularly in Heilongjiang province (Fig. 15; the most important soybean producing area in the country), to switch soybeans to alternative crops such as maize [*15*]. During the household surveys, nearly 50% of the farmers reported that international soybean imports affect their decisions compared to the 24% which reported no impact (Table 3). The majority of farmers were against international soybean trade often citing price competition as support while 31% supported soybean trade due to the availability of cheaper soy-based animal feed. In follow-up questions regarding the decision to abandon soybean production, 50% of the farmers mentioned decreasing soybean price as a reason.

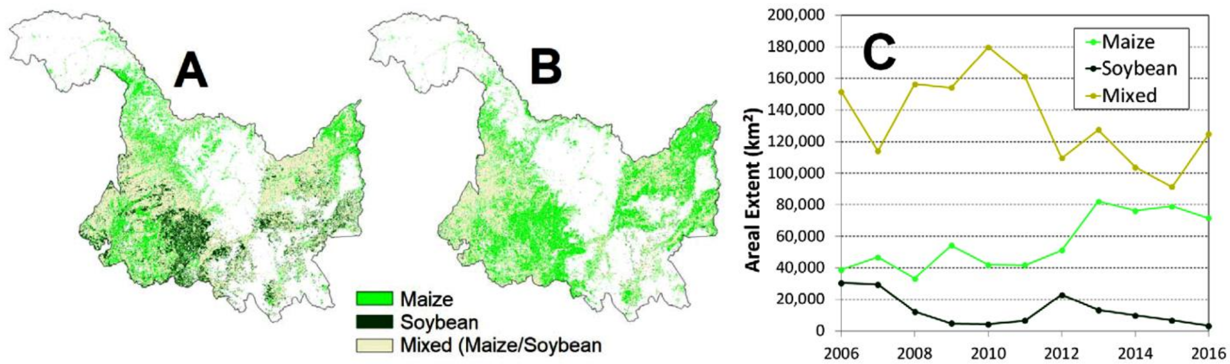

Figure 16. Spatio-temporal dynamics of agricultural land use (maize, soybean and mixed maize/soybean in Heilongjiang province, Northeast China. (A) Spatial distribution of agricultural land use classes during 2006. (B) Spatial distribution of agricultural land use classes during 2016. (C) Temporal dynamics of agricultural land use classes between 2006 and 2016.

Table 3. Farmer Survey Responses

1. Are you aware that most of the soybeans in China are imported?	**57% Yes**	**43% No**		
2. If yes, do you know which countries soybeans are imported from?	43% U.S.	>1% Brazil	56% Don't Know	
3. Do imported soybeans affect your decisions?	24% No	49% Yes	27% Don't Know	
4. If it affects your decision, does it make you anxious?	15% No	22%A little	31% A lot	32% Don't Know
5. What is your attitude towards soybean trade?	60% Against	9% Don't Know	31% Support	

Concurrent with the reduction in areas under soybean and increases in areas under maize, there is a concomitant increase in the areal extent of fires in Heilongjiang (Fig. 16). While fires are not restricted to agricultural areas, the proportion of fires occurring in agricultural areas increased from 60% in 2006 to 77% in 2016 (Fig. 17). Further, the area exposed to fire and the area under maize cultivation between 2006 and 2016 are significantly positively correlated (r =

0.68, $p = 0.02$) and the area exposed to fire and the area under soybean cultivation are significantly negatively correlated ($r = -0.59$, $p = 0.05$). The increase in agricultural fires is explained by not only the increase in residual crop biomass, which is more than 4 times higher for maize than for soybeans [*16*] but also, the greater tendency to burn maize residue compared to soybean residue. For example, based on the average crop yields obtained during the farm interviews, soybeans produce 2,401 kg/ha of residual straw biomass, while maize produces 11,164 kg/ha of residual straw biomass[*17*]. Further, during the household surveys farmers revealed that they most often use soybean residue for household fuel, animal fodder or returning it to the soil (i.e., 92%) than burning it (i.e., 8%) (Table 4). Whereas over one-third of the farmers burned maize residue in the field which explains why the fires in Heilongjiang are concentrated seasonally in two periods corresponding to pre-planting (around day of the year 100) and post-harvesting (around day of the year 300) (Fig. 2). Due to a residue burn ban and monitoring agricultural fires by the local government [*18*], the percent of farmers burning their maize residue declined from 44% to 38% between 2005 and 2015 (Table 4). Despite this reduction, the area planted with maize increased by 83% (more than 30,000 km^2) between 2006 and 2016 resulting in an increase in residual crop biomass. Cultivating maize (instead of soybeans) was found to be the most significant and influential factor affecting a farmer's decision to burn crop residue (Table 5 & 6).

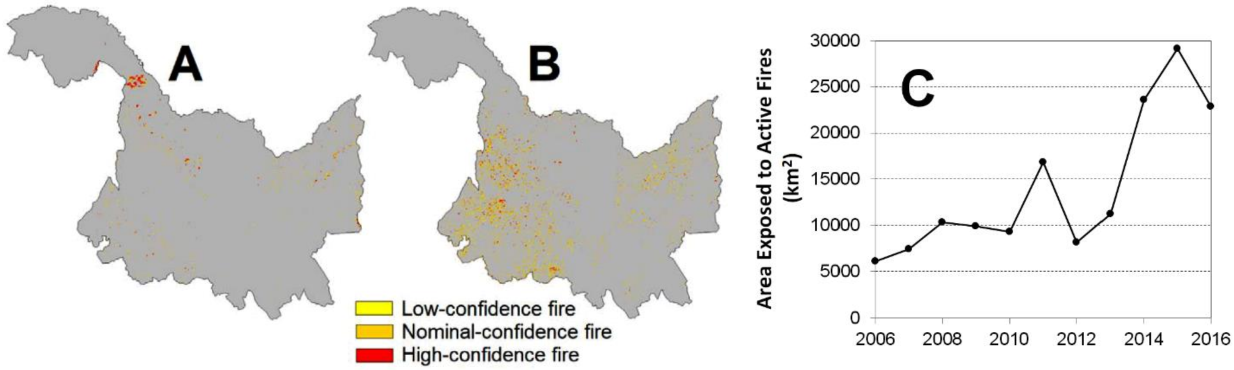

Figure 17. Spatio-temporal dynamics of fires in Heilongjiang province, Northeast China. (A) Spatial distribution of fires during 2006. (B) Spatial distribution of fires during 2016. (C) Temporal dynamics of the area exposed to fire (combining low, nominal and high confidence fires) between 2006 and 2016.

Table 4. Crop residue management in Heilongjiang, China.

	Return	***Burn***	***Household Fuel***	***Livestock Fodder***
		Maize		
2015	31%	38%	27%	4%
2005	12%	44%	37%	7%
Soybeans				
2015	28%	8%	62%	2%
2005	26%	8%	67%	0%

3.3. Discussion

Managing crop residue with fire is an emerging issue of concern, posing environmental and human health hazards not only locally, but also at regionally and international scales[*19*]. The particles released during the inefficient combustion of crop biomass can travel from the area of production to regions unassociated with the offending activity [*20, 21*], which makes identifying the underlying land-use drivers of air pollution is difficult [*22*]. In the present study, we combine remotely sensed data and farmer interviews to understand how international soybean trade increased crop residue fires in Heilongjiang and negatively affected air quality across the Russian border.

First, levels of PM 2.5 were elevated over Heilongjiang, China and the neighboring Russian provinces, seasonally, corresponding to pre-plant and post-harvest activities. Seasonal spikes were also observed in the area exposed to active fires over Heilongjiang and both the levels of PM 2.5 and area exposed to active fires have increased over the past decade. Similar findings have been reported in the literature, where Northeastern China in general and Heilongjiang in particular, have been identified as one of the top contributing-regions to air pollution due to residue fires [*23, 24*]. Many studies have found patterns in emissions associated with crop residue fires in this region [*23-26*] and have documented an exponential increase in residue burning compared to other provinces [*27-29*]. Additionally, studies have documented air pollution spillovers from crop residue fires that reduce air quality and visibility in nearby urban areas. These fires and subsequent air pollution are seasonal, in the fall, after harvest, and the spring, before planting [*21, 30, 31*].

Second, the pattern of active fires in Heilongjiang is significantly and positively correlated with the spatial and temporal increase in maize cultivation and significantly and negatively correlated with the decline of soybean production. Farmers in Heilongjiang more often use fire to management maize residue than soybean residue and are increasing the area planted to maize and reducing the area planted to soybeans. From the household survey, we also know that many farmers are choosing to covert rice production, the residue of which is most often burned. The increase in rice cultivation in the region, while not analyzed in this study, is likely also contributing to the levels of PM 2.5. Additionally, beyond the pollutants linked residue fires, emissions of ammonia from nitrogen fertilizer contribute to PM 2.5 levels[*32*]. Both maize and rice require nitrogen application whereas soybeans do not and previous studies have documented the increase used of nitrogen alongside the land-use change in Heilongjiang [*33, 34*]. In fact, the nutritional value of legume residue is a driver for leaving soybean residue on the field compared to the more common practice of removing maize and rice residue[*35, 36*]. To manage the accumulating maize residue sustainable, farmer need access to crushing or mulching technology to ensure the straw breaks down on the field overwinter. Other uses for the residue include biochar or biomass gasification, however, this maybe limited by transportation costs to the nearest plant.

Last, interviews with farmers confirmed that the reduction in soybean production is in response to low prices driven by international trade competition. The decline of soybean production in China is the result of several domestic policies that promoted the import of soybeans to support the domestic pork industry[*37*]. The dynamics observed in this study are illustrative of unexpected spillover effects that can arise from the international trade of an agricultural commodity. Because international trade will continue connecting producers and consumers around the globe, it is crucial that future studies consider the impact beyond trade partners[*7, 38*]. Similarly, in order to develop effective policy for a more sustainable future, the impact of international trade on the domestic environment as well as the impacts that spillover to other countries must be considered[*39, 40*].

3.4. Materials and Methods

3.4.1. Study Site

To explore the patterns and mechanisms behind crop residue fires we chose Heilongjiang Province in Northeast China as our study area (Fig. 1). Heilongjiang is the top grain producing-area in China, producing one-quarter to one-third of the nation’s grain over the past decade [*41, 42*]. The farms in Heilongjiang average around 3.5 ha and typically lack mechanization. The growing season lasts from early May to mid-August [*42*]. While winters are harsh, the area has a humid continental climate with high temperatures and rainfall in the summer months. Previous analyses conducted by members of our research team suggested the total amount of cropland planted to soybeans decreased by 24% from 43,722 km^2 in 2005 to 35,384 km^2 in 2010 [*42*] and indicated that soy-planting proportion is decreasing while maize planting proportion in increasing as a response to competition from international soybean imports [*17, 33, 34, 42*].

3.4.2. Land use change analysis

To classify agricultural land use dynamics in Heilongjiang Province we used a bi-weekly composite image time series (250 m/pixel) of the Normalized Difference Vegetation Index derived from surface reflectance data acquired by the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the National Aeronautics and Space Administration (NASA) Terra satellite, between January 2006 and December 2016 (MOD13Q1 product). The time series imagery for the year 2016, together with the geographic location of 76 soybean and 99 maize fields obtained during the summer of 2016, were input into MaxENT, a general-purpose algorithm that generates fuzzy inferences from an incomplete set of information. The field data were split into calibration (2/3) and validation (1/3) datasets, but to reduce the dependence on a single partition into calibration and validation datasets, we performed five different partitions. Through this algorithm we obtained continuous maps of the probability distribution of agricultural fields under soybean, maize and mixed soybean/maize (with an average area under the receiver operating characteristics (ROC) curve of 0.91). To change from continuous maps to a single choropleth output map, we used threshold values of 0.48 for maize and 0.43 for soybean. Values above these thresholds indicate that these crops are present, while below them, absent. Under a "mixed" pixel both maize and soybean are present. Model coefficients were then applied to the MODIS-NDVI image time series of 2006 through 2015 to obtain annual maps of agricultural land use.

3.4.3. Household surveys

To gain insight on the mechanism behind crop residue fires, household surveys were conducted during the summer of 2016 in Heilongjiang Province, China. The questionnaire was designed to acquire information on farmer demographics, land use decisions and the influence of international soybean trade on cultivation and management practices (See Tables 3 and 4). The surveys were conducted face-to-face with 1,190 household heads in 42 villages. Farming in Heilongjiang is dominated by households, so the household survey is the main method to collect relevant management information, such as residue management practices across the province.

3.4.4. Fire

To assess spatio-temporal fire dynamics over the 2006-2016 period, we used the Terra-MODIS eight-day summary fire product (MOD14A2). This product is a 1 km/pixel composite of fire pixels detected in each grid cell over each 8-day compositing period, including measures of confidence (i.e., low, nominal, high). Fire occurrence was integrated annually, to obtain estimates of the areas showing evidence of fire along each year. Images of smoke from fires in Heilongjiang on 10/29/16 were captured using NASA worldview snapshot [*14*]. These photos provide evidence that smoke from the fires reject injection heights that allowed particulate transfer across the international border.

3.4.5. Aerosol Optical Thickness

To assess spatial-temporal dynamics in aerosol optical thickness (AOT, a surrogate of atmospheric fine particulate matter, $PM_{2.5}$ [*43*]) in Heilongjiang Province and in neighboring provinces in Russia, we used the Terra-MODIS aerosol product (MOD04L2). This product provides information on the atmospheric aerosol loading in 1-km pixels, composited over a month. A value of 0.01 corresponds to a clean atmosphere, while values larger than 0.4 correspond to hazy atmospheric conditions.

3.4.6. Statistical Analysis

Data processing and analysis was done in the R environment using packages lme4[44], ggplot2[45], reshape2[46]. To determine the factors that significantly influenced residue management, an ordinary least squares regression model was constructed and standards errors were clustered (1) to account for autocorrelation and heteroskedasticity that exists at the individual level [47]. Data processing and analysis were done in the R environment using packages plm[48], lmtest[49], car[50], reshape[46], ggplot2[45] and MASS[51]. We considered the decision to burn crop residue as a dichotomous dependent variable (Y) with '1' indicating the residue was burned in field and '0' indicting the residue was not burned in the field. During the household interview farmers reported what percent of their residue was returned to the soil, used on the farm for fuel or fodder and burned. In trying to determine the factors that led to increased residue burning, the data were simplified by combining the farmers that returned their residue to the soil with the farmers who used their residue on the farm for fuel or fodder. The regression analysis was conducted with 251 farmers (i) in 38 villages (v).

$$\mathrm{Y}_{\mathrm{i,v}} = \ln \frac{\mathrm{P}_{\mathrm{i,v}}}{1-\mathrm{P}_{\mathrm{i,v}}} = \beta_0 + \beta_1 X_{1,i,v} \ldots \beta_n X_{n,i,v} + U_i \quad (1)$$

Where, P is the probability that $Y = 1$ for farmer i in village v and Y = residue burning (1=yes, 0=no); $X_1 \ldots X_n$ are explanatory variables; and U is the error term.

APPENDIX

In addition to cultivating soybeans, larger planted areas and family size had a significant, suppressing impact on burning crop residue while increases in nitrogen use and time spent off the farm had a significant positive relationship with crop residue burning. Farmers with larger planted areas are likely more financially established which may have allowed them allocate more time, access to additional rented land and invest in labor saving-machinery. Further, having larger families would provide additional labor capital that is needed to use or return their crop residue. This is in contrast with farmers who spend much of their time in urban areas and supplement their income with off-farm employment. Needing to migrate for work after planting crops in the spring and harvesting them in the fall competes for a farmer's time and incentives the quickest residue management strategy. Further, farmers in Heilongjiang are constrained by a lack of mechanization. Some villages communally owned a single tractor to be shared amongst the farmers, in other cases farmers would hire someone else for planting, spraying and harvest activities, but often the farmer would perform these tasks by hand. The lack of mechanization consumes time and results in crop residue that is intact (i.e., whole maize stalks). The large pieces of crop residue do not break down during the harsh winters and it is more feasible for the farmer to collect and burn the maize stalks rather than chop them fine enough to be returned to the soil.

Table 5. Logistic regression analysis with clustered SE at the village level. Includes factor names, coefficients, p values and VIF

Variable	Estimate	SE	*p*-value	VIF
(Intercept)	5.39	20.33	0.79	
Crop (Soybean)	-0.31	0.06	0.00***	1.4
Planted Area	-0.01	0.00	0.00**	1
Nitrogen Use	0.00	0.00	0.00***	1.3
Family Size	-0.08	0.02	0.00***	1
Time off-farm	0.02	0.01	0.05*	1
Farmer Edu.	-0.02	0.02	0.34	1
Farmer Age	0.00	0.00	0.08	1
Electricity Use	0.00	0.00	0.62	1
Coal Use	0.01	0.02	0.82	1
Maize Cob Use	0.00	0.00	0.63	1
Gas Use	0.00	0.01	0.79	1
Year	0.00	0.01	0.82	1

R2 = 0.35 and adjusted R2 = 0.31. Coefficient and p value (***p < 0.001 and *p < 0.01) indicated that crop type, planted area, nitrogen use, family size and time spent off the farm are significant and exhibited strong influences on residue management, further farmer age had a p-value of 0.08 and was still considered to be an influential factor.

To determine the factors that significantly influenced residue management, an ordinary least squares regression model was constructed and standards errors were clustered (1) to account for autocorrelation and heteroskedasticity that exists at the individual level [*47*]. Data processing and analysis were done in the R environment using packages plm[*48*], lmtest[*49*], car[*50*], reshape[*46*], ggplot2[*45*] and MASS[*51*]. We considered the decision to burn crop residue as a dichotomous dependent variable (Y) with ‘1’ indicating the residue was burned in field and ‘0’ indicting the residue was not burned in the field. During the household interview farmers reported what percent of their residue was returned to the soil, used on the farm for fuel or fodder and burned. In trying to determine the factors that led to increased residue burning, the data were simplified by combining the farmers that returned their residue to the soil with the farmers who used their residue on the farm for fuel or fodder. The regression analysis was conducted with 251 farmers (i) in 38 villages (v).

$$Y_{i,v} = \ln\frac{P_{i,v}}{1-P_{i,v}} = \beta_0 + \beta_1 X_{1,i,v} \ldots \beta_n X_{n,i,v} + U_i \ (1)$$

Where, P is the probability that Y = 1 for farmer i in village v and Y = residue burning (1=yes, 0=no); $X_1 \ldots X_n$ are explanatory variables; and U is the error term.

Table 6. Factor description.

Variable	Description	Mean	SD
Y	Residue (Burn = 1, Use = 0)	0.26	0.44
X1	Crop Type (Soybean = 112, Maize = 138)		
X2	Planted Area (ha)	6.4	8.4
X3	Nitrogen Use (kg/ha)	160	120
X4	Family Size	3.4	1
X5	Off-farm employment (months)	0.96	2.6
X6	Farmer Education (1=illiterate, 2=elementary, 3=junior high, 4=high school)	2.3	1.1
X7	Farmer Age	49.5	10.7
X8	Electricity (degrees)	1692	1525
X9	Coal Use (MT)	2	1
X10	Maize Cob Use (truckloads)	14	28.4
X11	Gas Use (tanks)	1	3.6
X12	Year (2010=80, 2015=170)		

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4. TELECOUPLED MANAGEMENT DECSIONS DRIVE MICROBIAL COMMUNITY COMPOSITION

4.1. Overview

Soil microbes are both economically and environmentally important in agriculture systems and many feedbacks exist between agriculture land management and microbial community composition[1-4]. Starting with crop choice, essentially every management decision has a cascading effect on the soil community that feedbacks to crop production via nutrient cycling processes and sometimes soil borne diseases. Understanding the factors impacting these decisions, as well as the potential synergies or trade-offs between different decision-making scenarios and their cascading impacts on microbial communities, can help researchers to better understand and promote environmentally sustainable and economically profitable practices.

Farm cultivation and management decisions are shaped by endogenous socioeconomic and environmental factors as well as the exogenous market conditions (Figure S1). The literature identifies a variety of farmer demographics used to help inform cultivation decisions, such as age, education, phase in the family farm lifecycle, off-farm employment, crop diversification, and farm size[5-10]. Beyond household attributes, environmental conditions and variability heavily influence cultivation decisions. Climate, rainfall, soil type and quality all must be taken into consideration prior to cultivation. Decisions are also influenced by farmers' beliefs, values, experience, and goals, which is another component of the strategic decision-making process[11]. Farmers also use the crop cultivation and management practices of their peers to inform their own decision-making, adding elements of cooperation and competition to the decision process. Further, farmers must decide on their cultivation strategy for the year months before actual crop prices are available, necessitating the use of current market information (e.g., crop prices, subsidy amounts) while considering both domestic and international markets to estimate future prices at harvest. This complex decision-making process plays out on the individual farm-scale, aggregates to regional cultivation patterns[12,13] and is affected by national and international policies and markets, resulting in both bottom-up and top-down processes.

The soil microbial community is a crucial component of agricultural systems that is affected by and feedbacks to farmer decision-making. Soil microbes play a substantial role in both carbon and nitrogen cycling, which are major determinants in crop productivity as well as nutrient losses[1,4,14,15]. The aboveground plant community supplies the belowground community with carbon and nitrogen inputs via root exudates and residual root and crop biomass which influences the microbial community by increasing the relative abundance of microbes that prefer nutrient rich environments (e.g., copiotrophs) and decreasing the relative abundance of microbes that prefer nutrient depleted environments (e.g., oligotrophs)[16]. The microbial community decomposes residual organic matter and mineralizes organic nitrogen and phosphorous into forms usable for plant and microbe uptake[4], which improves nutrient cycling and reduces farmers dependences on nitrogen fertilizer[16]. Decomposition rates depend on the quality of the residual crop straw (e.g., C:N ratio, nitrogen concentration, cellulose and lignin content)[16] as well as the existing edaphic and nutrient conditions[17]. Crop choice[17,18], crop rotation[3,19,20], residue management[2,21], fertilizer inputs[22] and tillage disturbance[3,21] all affect the concentration of nutrients in the soil and therefore the microbial community. Furthermore, excess nutrients associated with agricultural management select for microbes that accelerate the production of greenhouse gases such as N_2O [2,23-25].

Many experimental studies[2,3,15,18,19,21,26,27] have reduced the complexity in the relationships between agricultural land management and the soil microbial community by using long-term test plots to limit variation and isolate the relationships in question. Often located on research farms, under University management, these test plots offer a semi-controlled environment for measuring the impact of different management strategies on the microbial community. These studies commonly use “recommended best practices” as a conventional agriculture baseline to compare the impact that alternative practices would have on the microbial community. While these studies provide a wealth of knowledge, in reality, only a fraction of farmers report using best management practices[4,28], which limits the real world applicability of their findings. Given that over 80% of anthropogenic N_2O comes from agriculture fields[29] and the overwhelming majority of agriculture land is managed by farmers, there is a crucial need to understand the realized impact cultivation and management decisions have on the microbial community.

To address this research gap and investigate the relationships between on-farm cultivation and management decisions and the soil microbial community, we assessed the results of 135 paired in-person farm surveys and soil samples across China’s most important grain production region, Heilongjiang Province. Historically, the province was dominated by continuous soybean production, however starting in the early 2000s low soybean prices, driven by competition from international imports, lead to regional declines in soybean production and corn cultivation increased[30-32]. We ask: 1) How did changes in crop rotation practices shift regional cultivation patterns? 2) What were there cascading changes in management associated with the crop rotation practices? and 3) Did changes in crop rotation and management practices influence the soil microbial community’s structure, diversity and abundance?

4.2. Results

4.2.1. Changes in crop rotation practices shift regional cultivation patterns

The most pronounced response to competition from imported soybeans was a change in crop rotation practices among farmers that resulted in a regional cultivation shift away from a soybean-dominated and toward a corn-dominate agricultural system in Heilongjiang (Figure 18). Using the past five years of cultivation history reported by the farmer, we grouped farmers and soil samples by rotation strategy (Table 7). Among respondents, continuous cultivation (5 or more years of cultivating the same crop) was 4 times more common than rotating annually between crops. Continuous corn (C) cultivation was the most frequent strategy, followed by continuous soybean (S) cultivation. Continuous corn farmers were found across Heilongjiang while continuous soybean farmers were found mainly in the northern part of province. Existing between the two continuous crop rotations, a fifth of the farmers had diversified by including both corn and soybeans in their crop rotation. The most common mixed rotations (M) were simple annual corn-soybean rotation (e.g., C-S-C-S-C) and bi-annual rotations (e.g., C-C-S-C-C; S-S-C-S-S) with a total of 10 unique rotation patterns recorded.

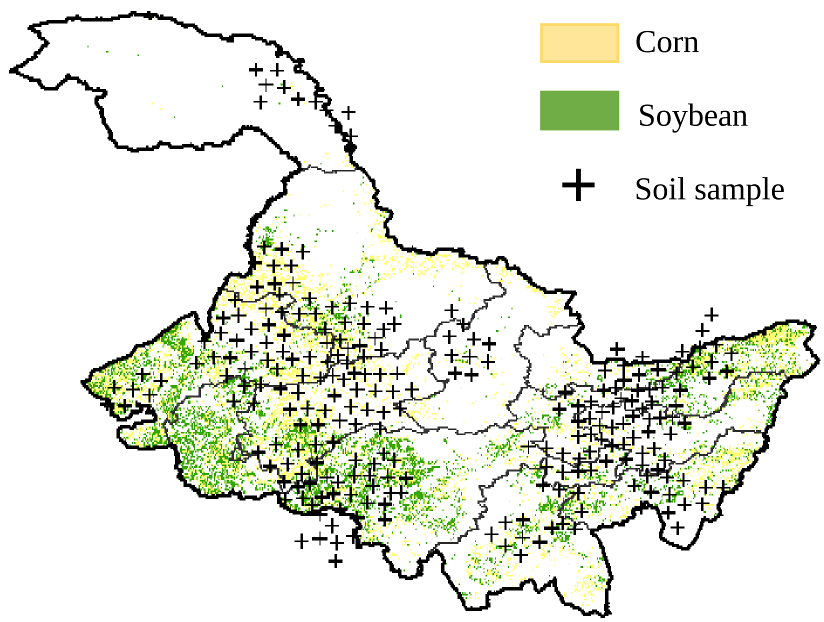

Figure 18. Underlying cropscape map from 2010 showing farm survey and soil sample locations in Heilongjiang for 2016. Green is soybean and yellows is corn. Point shape corresponds to crop rotation practice.

Table 7. Mean and (standard deviation) of influential variables grouped by crop rotation practice. The influential factors determined by PCA include: pH, Total organic carbon, silt, Nitrogen use, crop residue weight returned and yield. The lower case letters designated significant groups differences (p>0.05).

			Farm Interviews				Soil Samples		
Group	Label	N	Definition	N-Use kg/ha	Yield kg/ha	Residue kg/ha	pH	TOC	Silt
Continuous Corn	C	60	5+ years of corn cultivation	234 (119)a	9930 (2091)a	42 (27)a	5.66 (0.86)a	2.15 (0.79)	0.28 (0.5)
Mixed Rotation	M	27	Any corn-soybean rotation	134 (129)b	5958 (5415)b	38 (26)a	5.43 (0.53)a,b	2.36 (0.68)	0.21 (0.4)
Continuous Soybean	S	48	5+ years of soybean cultivation	64 (27)c	1971 (363)c	56 (26)b	5.29 (0.50)b	2.46 (0.70)	0.09 (0.08)

4.2.2. Changes in crop rotation practices have cascading impacts on management

Crop type and rotation practice significantly affected nitrogen inputs, yield, the amount of residue returned and soil pH (Table 7). Total organic carbon and the silt content did not differ significantly between rotation practices. Farmers cultivating C reported higher nitrogen use and higher yields, followed M and S cultivation. Despite soybeans having only $1/10^{th}$ the residual biomass of corn, the amount of residue returned to the field was highest with S cultivation (> C > M). This is because farmers reported removing corn residue twice as often as soybean residue. The average soil pH significantly differed between C and S samples, but neither differed from M samples. Regardless of rotation practice, most samples were slightly acidic compared to the optimal pH range of 5.8-6.2. In addition, to the absence of lime application in the region, low soil pH can result from removing crop residue (and the nutrients that control acidity) and heavy application of nitrogen fertilizer[18,33].

4.2.3. Changes in crop rotation practices influence microbial community structure, diversity, species abundance

Microbial community structure differed significantly between the three crop rotation practices (Figure 19, Table 8). The influential factors from the farmer interviews and the abiotic soil analysis explained 25.1% (dim 1) and 12.2% (dim 2) of the variation in community structure for a total of 37.3%. Nitrogen use loads the highest on dimension 1 and is the most significant variable, likely capturing C, M, S management gradient. Additionally, the residue management factor loads on dimension 1 with removing residue on the negative side and returning residue on the positive side, which supports the C, M, S management gradient. The remaining variables load on dimension 2, pH is the most significant and loads opposite of silt, as well as residue weight returned and TOC, which likely represent soil conditions along the C, M, S gradient. Temperature zone and sampling month were significant factors that explained regional variation within the soil community that may exist due to samples being collected across a large geographic extent.

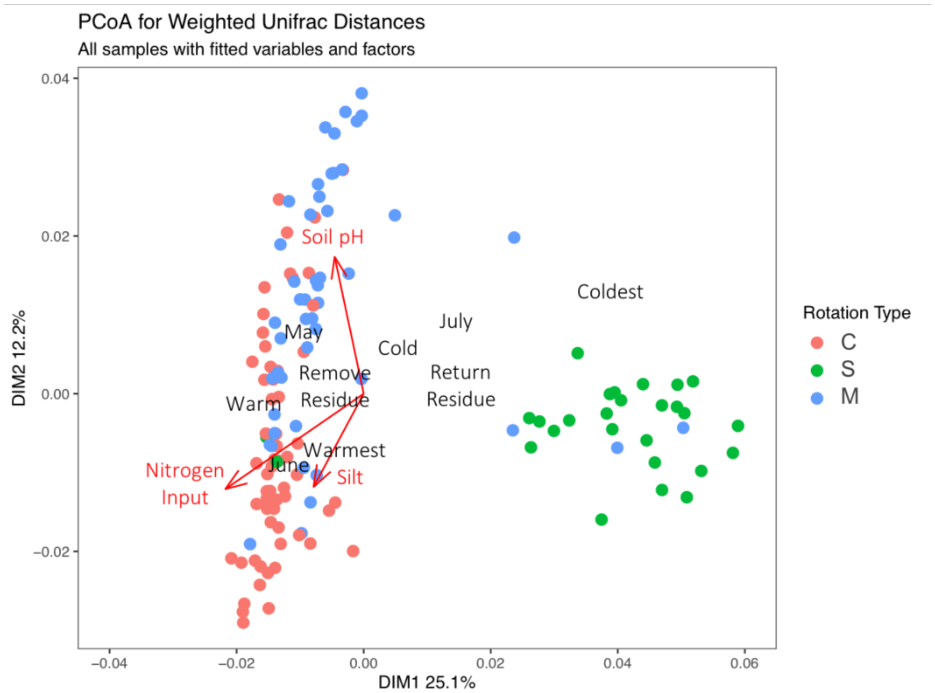

Figure 19. Principle coordinates analysis based on Unifrac distances for soil microbial communities sampled from farm fields in Heilongjiang China. The samples are colored by rotation method - which include C, S and M. The distance of 3% was used to define operational taxonomic units. Significant variables are in red and significant factors are in black. The vector points toward the direction of increase for a given variable and the arrow length indicates the correlation between the variable and the ordination scores.

Table 8. The extracted PCoA components (e.g., Dim1 and 2) represent the major sources of variation in the data and determine the most influential variables and factors.

Vector	Dim 1	Dim 2	p-value	Factors	Dim 1	Dim 2	p-value
pH	-0.08	0.28	0.003**	Temp Zone 1 (warmest)	-0.007	-0.007	0.001***
TOC	0.08	-0.13	0.2	Temp Zone 2 (warmer)	-0.01	-0.001	
Silt	-0.13	-0.20	0.03*	Temp Zone 3 (colder)	0.002	0.001	
Nitrogen use	-0.36	-0.2	0.001***	Temp Zone 4 (coldest)	0.017	0.007	
Residue Weight	0.13	-0.15	0.07	May sample collection	-0.009	0.003	0.001***
				June sample collection	-0.008	-0.007	
				July sample collection	0.009	0.005	
				Removing Residue	-0.003	0.000	0.005**
				Returning Residue	0.012	-0.000	

Across all indices of alpha diversity, soil communities from continuous soybean rotations were the most diverse (Figure 20, Table 9), followed by samples from mixed rotations and continuous corn rotations.

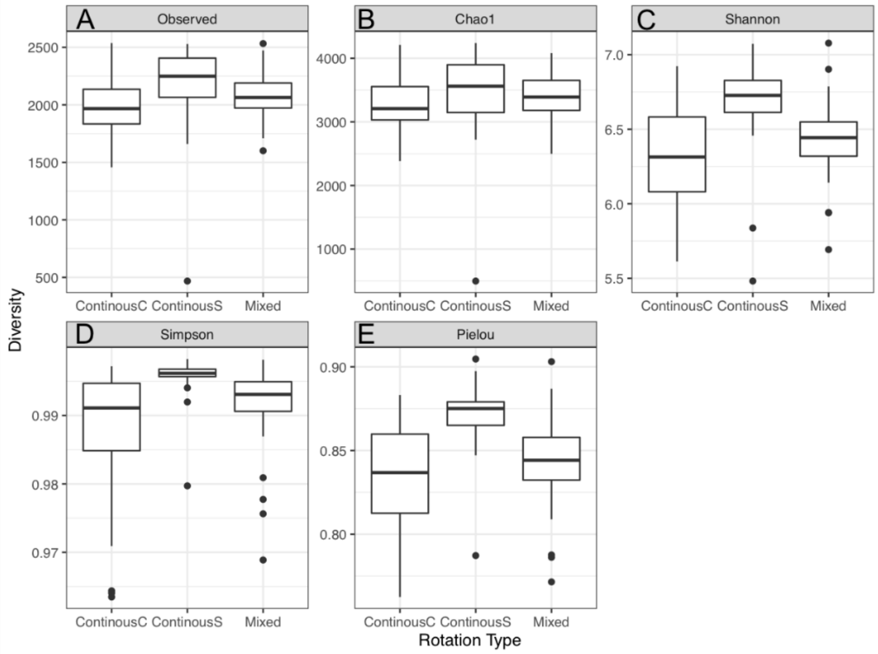

Figure 20. Box plots for alpha diversity analysis: (A) observed species, (B) Chao 1, (C) Shannon, (D) Simpson and (E) Pielou indexes of samples grouped by rotation type.

Table 9. Mean and (standard deviation) for the alpha diversity analysis.

Group	Observed	Chao 1	Shannon	Simpson	Pielou
C	1996 (229)	3314 (405)	6.3 (0.32)	0.988 (0)	0.83 (0.03)
S	2167 (405)	3433 (725)	6.7 (0.33)	0.995 (0)	0.87 (0.02)
M	2078 (194)	3382 (368)	6.4 (0.24)	0.991 (0)	0.84 (0.02)

We recovered 23,315 operational taxonomic units (OTUs) from soil samples taken along a C, M and S management gradient. Across all rotation types 92% of the taxa were assigned to eight Phyla: Proteobacteria (36.3%), Acidobacteria (16.9 %), Bacteroidetes (12.4%), Actinobacteria (8.1%), Verrucomicrobia (8%), Chloroflexi (4.2%), Firmicutes (2.8%) and Gemmatimonadetes (2.6%). With the exception of Chloroflexi and Verrucomicrobia, which were the most abundant in S and M rotations respectively, the remaining phyla decreased in relative abundance from C > M > S rotations (Figure 21). The relative abundance of 9% of the sequences, representing 40 taxa or 0.5% of the total taxa identified, differed between rotations practices. Notably, more than 20 families were significantly associated with C and M rotations, while 2 families were significantly associated with S and M rotations and 3 families were found to significantly associated with only S rotations ($p < 0.01$) (Table 10).

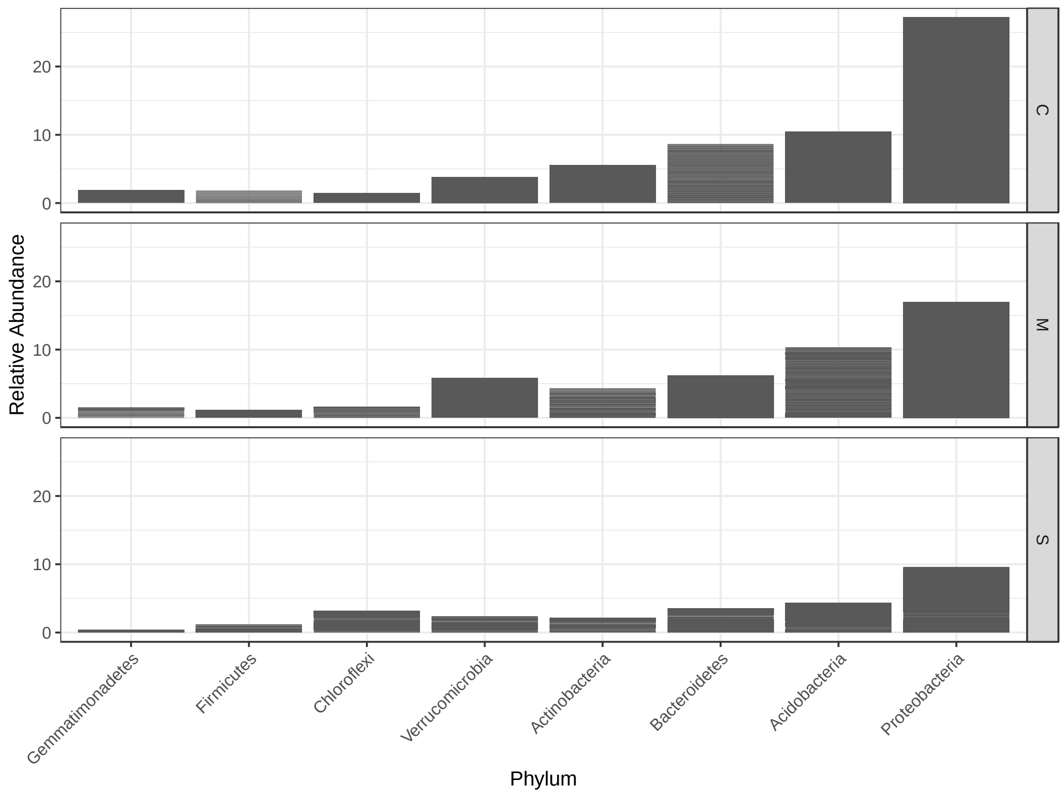

Figure 21. Relative abundance for the top 8 most abundant phyla, representing 92% of the taxa across 3 rotation practices: continuous corn, mixed rotations and continuous soybean.

Table 10. Bacterial groups whose abundance differed significantly (p<0.001) between crop rotation practices.

Bacterial groups that significantly (p<0.001) associated with:					
Phyla/ (Family)	C & M Rotations	S & M Rotations	S Rotations	Type	indicators/ associations
Acidobacteria				Oligotrophs	Nutrient limited environments, negative correlation with C amendments[18,34]
	Gp1, Gp3, Gp4, Gp6	*Gp 16*			
Actinobacteria				Oligotrophs	Nutrient limited environments, negative correlation with C amendments[35,36]
Micromonosporaceae					High pH & N inputs[14,37]
Nocardioidaceae					Pesticide degrader, Polluted soils[38]
Streptomycetaceae					Residue degrader[39]
			Micrococcaceae		Residue degrader
Armatimonadetes					
Chthonomonadaceae					
Bacteroidetes					Degradation of OM, pesticides, soil fatigue[33,40,41,42]
Chitinophagaceae					
Gemmatimonadetes					
Gemmatimonadaceae					Low moisture conditions[43], high pH[44]
Proteobacteria					
	Coxiellaceae				
Oxalobacteraceae					Pesticide degrader[40]
Sphingomonadaceae					Degradation of OM[41], pesticides[40,42],Corn cultivation[20], Polluted soils[44]
Rhizobiaceae					Corn cultivation[20]
Sinobacteraceae					Polluted soils[45]
Xanthomonadaceae					Pesticide degrader[40],
Xanthobacteraceae					Polluted soils[44]

Table 10 (cont'd)

Caulobacteraceae				
	Nitrosomonadaceae		Nitrifying bacteria[46]	High N inputs, Nitrification, polluted soil[44]
Chloroflexi				
		Anaerolineaceae		Intensified agriculture, High N inputs, root worm infestation, burned residues, soil fatigue[30,47]
		Caldilineaceae		Intensified agriculture
Thaumarchaeota			Ammonia oxidizing bacteria	High N inputs,[42] Nitrification
Nitrososphaeraceae				Polluted soils[44]
Verrucomicrobia			Oligotrophs	Nutrient limited environments, negative correlation with C amendments[18,34]
c_Spartobacteria				
c_Subdivision3				
Verrucomicrobiaceae				

4.3. Discussion

Conventional wisdom dictates that soil under continuous corn management should receive higher inputs of carbon and nitrogen than the soil under a continuous soybean managment[31]. This is because corn produces 10 times more residual crop biomass than soybeans, which is theoretically returned to the soil post-harvest[31]. Crop residues provides labile sources of carbon and nitrogen to the microbial community and are drivers of microbial community structure. Additionally, corn relies on external nitrogen inputs, whereas soybeans form associations with nitrogen fixing bacteria and do not require additional nitrogen fertilizer. However, the management practices in the present study differ from previous research[2,3,15,17-19,21,26,27,48] and result in unexpected impacts on the microbial community. In response to competition from international soybean imports[31,32,49], farmers in the region decreased soybean production and shifted towards continuous corn cultivation. The shift towards continuous corn was accompanied by changes in residue management, where farmers commonly remove and burn corn residue after harvest. Additionally, farmers reported using the highest amount of nitrogen fertilizer with C cultivation, on average 30 kg/ha more than recommended by best management practices[50]. Farmers also reported using nitrogen fertilizer in S production, on average 64 kg/ha. Because soybeans do not require nitrogen inputs, nitrogen overuse was more than double in S cultivation than C cultivation. The crop rotation and management strategies observed in the field resulted in different abundances of bacteria that are frequently associated with sources of carbon and nitrogen in soil.

Due to a lack of mechanization in the region, crop residue is often left whole which prevents the biomass from breaking down over the winter. Therefore, the farmer often collected and remove the crop stalks/straw from the field. This practice was twice as likely to occur when farmers cultivated corn compared to soybeans and may explain why, contrary to previous research in the study region[31], TOC did not significantly differ between C and S samples. Further, the levels of TOC measured in the sampled soils were relatively high and may make changes, especially increases, in soil carbon hard to detect. The tendency for farmers to remove crop residue and overuse nitrogen may explain the acidic soil pH values and abundance of oligotrophic bacteria, which favor nutrient depleted environments[16], in the soil community. Several of the most abundant phyla are found in intensified agricultural systems[33,40]. Within the most abundant phyla (Proteobacteria), several families were significantly associated with C & M (Table 10). Notably, the presence of *Sphingomonadaceae*, *Oxalobacteraceae*, *Xanthomonadaceae* (Proteobacteria), as well as *Chitinophagaceae* (Bacteroidetes) has been associated with the degradation of organic matter[15,41] as well as pesticides[40], and have been used as indicators of soil fatigue (caused by continuous monocultures and inputs[33]). The phyla's Acidobacteria, Actinobacteria and Verrucomicrobia are commonly regarded as oligotrophs and have frequently been shown to prefer nutrient limited environments and to be negatively correlated with carbon amendments[34,36,37]. In the present study, acidobacterial subgroups 1, 3, 4 and 6 significantly associated with C and M while acidobacterial subgroup 16 was significantly associated with S and M. Additionally, Verrucomicrobia and Actinobacteria (*Micromonosporaceae)* were also significantly associated with C and M rotations (Table 10). Further, previous research suggests that additions of legume residue would increase the relative abundance of groups belonging to Actinobacteria while suppressing groups belonging to Proteobacteria, which may explain the significant associations between Micrococcaceae (Actinobacteria), a known residue degrader[15,16], and S cultivation.

Nitrogen inputs and pollution were found to increase in Heilongjiang when farmers across the province shifted from soybean to corn cultivation[31,49]. This pattern held true in a meta-analysis that measured nitrogen balance in areas that had undergone soybean-corn conversions[49]. The obvious explanation for increase nitrogen use is that corn requires additional inputs of nitrogen while soybeans fix nitrogen through microbial associations. Among the sampled farms, nitrogen application rates were highest in continuous corn rotations, however, many of the farmers unnecessarily apply nitrogen to soybeans as well. The presence of several groups of bacteria found in soils of all rotations may indicate that there is more nitrogen present than can be used by the crops. For example, groups within the phylum Actinobacteria are known to associate with high soil pH and nitrogen inputs[26,37]. *Nocardioidaceae* and *Streptomycetaceae* significantly associated with soil from C and M while *Micrococcaceae* significantly associated with samples from S.

Additionally, two subphyla of Chloroflexi, *(Anaerolineaceae* and *Caldilineaceae)* significantly associated with soil from S. This phylum is generally associated with intensified agriculture and can be associated with corn or soybean cultivation [20,47]. High abundance of *Anaerolineaceae* has been found by the literature in association with excess N inputs[26], root worm infestation[20], burned crop residues[26] and as an indicators for arable land fatigue[26]. Additionally ammonia oxidizing bacteria, which are key actors in the nitrogen cycle and indicate high levels of ammonia[46], were found in soils from all rotations. In agricultural systems these bacteria are essential for nutrient uptake by crops but can also lead to losses of ammonia-based fertilizer as N_2O and NO3- nitrate pollution[23,26,46,51]. *Nitrososphaeraceae* (Thaumarchaeota) significantly associated with C and M rotations while *Nitrosomonadaceae* (Proteobacteria) significantly associated with S and M rotations (Table 10). The nitrification process is generally associated with continuous corn cultivation which requires high nitrogen inputs to maintain yields. Considering soybeans do not need external nitrogen inputs, the association of *Nitrosomonadaceae* with S rotations may indicate that there is more nitrogen present than can be used by the plant community[52].

4.4. Conclusion

Overtime, agriculture management could impact the microbial community to such an extent that the changes feedback to the management decision. Depriving the soil community of the valuable nutrients in crop residues, regardless of crop type, can lead to a nutrient depleted environment. It is possible that removing crop residue from the field could lower yields over time and that would feedback to management decisions. Some farmers may invest the time, labor and capital required to return the crop residue to the field. However, it is more likely that farmers may compensate for yield loss by increasing nitrogen fertilizer use [16,53]. Increased input cost could affect profitability, but given that nitrogen fertilizer is relatively cheap, widely available and easy to apply, farmers may find it worth the cost[14,17,19]. Excess fertilizer that cannot be utilized by plants is lost as N_2O and NO_3^- pollution and can even result in a microbial community that is more likely to release nitrogen rather than convert it into a form useable by plants[25,54]. Overtime, agriculture management could impact the microbial community to such an extent that the changes feedback to the management decision.

4.5. Materials & Methods

4.5.1. Site Description

The study area is Heilongjiang Province located in northeastern China, between 44° and 53° north and 121° to 135° east, and is bordered by Russia on the north and east sides. Heilongjiang has an area of 454,800 km^2 and is comprised of thirteen prefectures. While winters are harsh, the region has a humid continental climate with high temperatures and rainfall in the summer months. July temperatures reach 20° C [9], falling just short of the ideal temperature, 25° C [10], for soybean cultivation (e.g., Koppen's classifications Dwa Dwb and Dwc). The growing season lasts from early May to mid-August which, in addition to a relatively low population and large contiguous land parcels, contributes to Heilongjiang producing one-third to one-quarter of the nation's soybeans over the past decade. However, since 2009 the area planted to soybeans has continuously declined. Previous analyses indicate that on-farm soy-planting proportion is decreasing while corn planting proportion is increasing in response to competition from international soybean imports and fertilizer subsidies [30-32,55].

4.5.2. Sampling Design

Farm surveys and soil samples were collected in Heilongjiang Province, China between May and July of 2016. Interview questions covered farmer demographics such as education, age, income, off-farm employment, land-ownership status and questions on the influence of policy and price fluctuations that may be used to help explain management decisions. Management decisions included in the survey were land level, crop type, inputs (fertilizers, herbicides and pesticides types and application rates), growth period, planting and harvest date, production costs, farm gate price, yield, mechanization, subsides, residue management, crop-rotation and planting history. At the conclusion of the survey, the interviewer would ask the farmer for permission to take a soil sample and the farmer would then identify their field boundaries. The boundary was marked with field flags before 6 (10 cm deep cores, 1 cm wide) samples were collected from the root-influenced soil (layer where the majority of crop roots are located, 0-10 cm from soil surface) and mixed to generate one composite sample per field. One hundred and thirty-five unique soil samples were collected and the field composite was used to measure abiotic attributes of the soil including soil pH, total organic carbon and soil texture. Samples were processed with a 3 mm soil sieve and soil texture was determined each night, so that the soil was field moist. Soil texture classifications were checked against published values for the region[56,57]. The samples were then dried at ambient temperatures and stored in marked plastic bags[58]. Soil pH was measured using pH meter at the Chinese Academy of Sciences, Institute of Soil Sciences in Nanjing. Soil organic carbon was determined by Yingtan Red Soil Ecological Experimental Station.

4.5.3. DNA extraction, PCR, and DNA sequencing

From the processed samples, 5 grams of soil was separated into small plastic tubes, labeled and stored at -40 C upon returning to the research institute and prior to DNA extraction.

DNA was extracted from 0.25 grams portions of the frozen soil samples at the Chinese Academy of Sciences, Institute of Soil Sciences in Nanjing, using an adapted protocol from PowerSoil™ DNA Isolation kit (MO BIO Laboratories, Inc.) [13]. A NanoDrop was used to make sure all samples had A260/280 readings between 1.8 and 2.0. Aliquots of the extracted DNA were freeze-dried and transported to Michigan State University's Center for Microbial Ecology for further analysis. The samples were rehydrated with PCR-grade water to reach the original concentration, vortexed and allowed time to re-suspend. Rehydrating dry samples improves the quantity and quality of extracted DNA [12]. The aliquots were used for amplification of a portion of the 16S rRNA genes (~250 nucleotides) using the Schloss primers F515 and R806 (respectively, 5'-GTGCCAGCMGCCGCGGTAA-3' and 5'-GGACTACVSGGGTATCTAAT-3'). Sequencing of the amplicons was done on Illumina's MiSeq instrument at MSU's Research and Technology Support Facility. Raw sequences were initially processed by pair-end assembled, chimeras removed and filtered for quality before being clustered into operational taxonomic units (OTUs) at 97% similarity. Raw paired-end sequences were merged and chimeras removed using UCHIME's *de novo* mode. The quality of the merged reads for all samples was then checked using FastQC [59]. A value above 30 indicates good quality and a value below 20 indicates poor quality. The average quality per read was 37, the minimum and maximum observed were 32 and 38, respectively for all samples. Furthermore, with almost 100% expected overlap, the merged reads have a high rate of accuracy identifying a nucleotide. Furthermore, with almost 100% expected overlap, the reads have a high rate of accuracy identifying a nucleotide. Processing was done via the UPARSE pipeline (i.e., usearch, cluster_otus), chimeras were automatically removed. Taxonomy was assigned using RDP's Bayesian Classifier and Taxonomy.

Merged reads were clustered using USEARCH version 8.1 with the usearch_global command and an id of 0.985 so that reads within a cluster differed by no more than 3%. Representative sequences were classified using RDP's Bayesian classifier[60] with training set No.16. A phylogenetic tree was constructed with FASTTREE [61] from the representative sequences aligned with INFERNAL[62].

4.5.4. Microbial Data Analysis

A principle coordinates analysis (PCoA) based on Unifrac distances was used to depict distances (β-diversity) among samples from farm fields in Heilongjiang China. Environmental variables were fit to the ordination plot using vegan's envfit function[63]. Additionally, Chao, Shannon, Simpson and Pielou diversity indices were calculated. Last, species relative abundance was calculated and compared between crop rotation types. Bacterial groups that differed significantly between rotation groups were identified and interpreted. All statistical analysis were performed in the R environment[64], using packages phyloseq[65], RDPutils[66], ade4[67], ggplot2[68], ggrepel[69], ggordiplots[70], QsRutils[71], RVAideMemoire[72], tidyverse[73], indicspecies[74], vegan[63], data.table[75] and nlme[76].

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5. USING AGENT-BASED MODELLING TO MEASURE THE IMPACT OF LAND MANAGEMENT ON EVIRONMNETAL HEALTH IN TELECOUPLED HUMAN AND NATURAL SYSTEMS

5.1. Overview

One challenge of conducting interdisciplinary research is how to integrate the natural and social components of a system. Much of this complexity lies in how to characterize the environment and its relationship to human actions, which vary at different temporal and spatial scales[1]. One approach is to employ a systems dynamics model using the impact of human action as an aggregated effect. However, agricultural land-use patterns are formed from cultivation decisions made by individual actors. Aggregating the impact of human action on a landscape may overlook the importance of variations between actors and cause the researcher to miss key insights. This omission may result in a loss of predictive and explanatory power as well as a generalization of the underlying processes[1]. Agent-based models provide a key advantage for modeling an individual actor's decisions based on specific social, economic, and environmental influences[2]. This allows for the integration and analysis of human action into the causes, effects, and processes of landscape use and cover change while incorporating individual actor variation[2].

5.2. Model Description

5.2.1. Purpose

The present ABM is an adaption of TeleABM[3,4], which simulates soybean trade and land-use change in the sending (e.g., Brazil) and receiving (e.g., China) systems. The TeleABM was written in Java using the Repast platform and designed to be easily adapted to other land systems. The model was calibrated with empirical land use data and farmer interviews for decision rules. Land use and production patterns in each system are aggregated to the regional level to influence crop price in the trade model and, ultimately, land use is the telecoupled system.

5.2.2. Study System

The sending system, Mato Grosso, Brazil, was not modified from the original TeleABM[3]. The receiving system, Heilongjiang a, is the top grain producing region in China. Driven by competition from international imports, farmers in Heilongjiang are converting to rice and corn at the expense of soybean production[3,5-7]. The data that was used to calibrate the receiving system was collected during the summers of 2016 and 2017, which included ground-truth points, farmer surveys and soil samples.

5.2.3. Agents

There are 3 types of agents within the receiving system, *farmer agents, government agent* and *trader agents.* Each *farmer agent* is given a list of properties (e.g., labor, capital, property) and actions (e.g., land use decision; calculate profit). Information gathered from the farmer interviews was used for agent attributes. *Government agents* set domestic production quotas and subsidies in the receiving system and tariffs on imported soybeans from the sending system in the trade model. Local *trade agents* aggregate soybean production to the international *trade agent* where soybean price is determined from production in both systems. Soybean price is then passed from the international *trade agent* to the local *trade agents* and then to *farmer agents* for the next time step. *Government* and *trader agents* were not modified from the original[3] in this model adaption and are used for scenario analysis.

5.2.4. Environment

The environment is based on a grid of *cells*, representing 900 m^2 or 0.0625 km^2 based on 250m X 250m map resolution. Each cell is assigned biophysical properties (e.g., soil texture, pH, SOM, temperature, precipitation, elevation) based empirical data. Cells are assigned to a farmer agent, who determines cultivation and management decisions. Crop yield is a function of crop type, crop rotation, fertilizer inputs and residue management. Table 11 provides a details on the household and farm characteristics in the TeleABM.

Table 11. Household and farm characteristics of the TeleABM receiving system. Including variable names, variable description, variable distribution, parameters and independence. *denotes variables selected for Uncertainty and Sensitivity Analysis.

Household Characteristics					
Var_Name	**Var_Description (units)**	**Var_Distribution**	**Parameters**	**Independent (yes/no)**	**SA/UA**
familyPopulation	Number of family members	Normal	M (sd) = 3.46 (1.15)	Yes	*
hhdHeadMale	Gender Dummy for head of household (0 = M; 1 = F)	Discrete	0=0.073; 1=0.027	Yes	
age	Head of Household Age	Normal	M (sd) = 28.5 (10.8)	Yes	
dependentRatio	((kids + elders)/ total family num)	Normal	M (sd) = 0.21 (0.1)	No	*
genderRatio	ratio of male to female (0 = M; 1 = F)	Normal	M (sd) = 0.1597 (0.18)	No	*
hhdHeadunHealth	Health Dummy for head of household (0=healthy; 1=not healthy)	Discrete	0=0.716; 1=0.284	Yes	
occupation	1 full time farmer; 2 part-time farmers; 3 non farmer	Discrete	1=0.82;2=0.14; 3=0.04	Yes	
knowInternationalTrade	0=don't know; 1=know of soybean trade	Discrete	0=0.46; 1=0.54	Yes	
whetherknow_soybean_ixYes	0=don't know; 1=know of imported soybean competition	Discrete	0=0.28; 1=0.72	Yes	*
whetherknow_pericoupledperi	0=don't know; 1=know	Discrete	0=0.978; 1=0.022	Yes	
whetherknow_transgeneYes	0=don't know; 1=know of GM	Discrete	0=0.3; 1=0.7	Yes	
whether_know_import_gmoYes	0=don't know; 1=know that imported soybeans are GM	Discrete	0=0.69; 1=0.31	Yes	

Table 11 (cont’d)

noOffFarmIncome	Scale 1-5 (1 = no off farm income)	Disrete	0=0.664; 1=0.23; 2=0.08; 3=0.007; 4=0.007; 5=0.002	Yes	*
noBigMachine	Number of machines (1-8)	Discrete	0=0.165; 1=0.153; 2=0.158; 3=0.150; 4=0.148; 5=0.092; 6=0.056; 7=0.032; 8=0.032	Yes	*

Farm Characteristics

Var_Name	**Var_Description (units)**	**Var_Distribution**	**Parameters**	**Independent (yes/no)**
cellSize	Farm size	Normal		
totalFertilizerInput	Fertilizer input for all crops	Normal		No
totalWaterInput	Water input for all crops	Normal		No
totalExtraN	Fertilizer input that exceeds crop requirements for all crops	Normal		No
totalExtraNsoy	Fertilizer input that exceeds soybean requirements	Normal		No
totalExtraNcorn	Fertilizer input that exceeds corn requirements	Normal		No
totalExtraNrice	Fertilizer input that exceeds rice requirements	Normal		No
farmPM25	PM 2.5 emissions	Normal		No
farmNOX	NOx emissions	Normal		No
farmCO2	CO2 emissions	Normal		No
cornProportion	Corn cells/ total cells	Normal		No
riceProportion	rice cells/ total cells	Normal		No
soyProportion	soybean cells/ total cells	Normal		No
meanTemp	Soil temperature	Uniform	2.6	Yes
meanSoila	Soil texture	Uniform	22.02	Yes

Table 11 (cont'd)

meanSoilb	Soil texture	Uniform	57.14	Yes
meanSoilc	Soil texture	Uniform	20.83	Yes
farmpH	Average farm soil pH	Uniform		No
farmSOC	Average farm soil organic carbon	Uniform		No
elevation	cell elevation	from a map		Yes
soc	farm soil organic carbon	from a map		Yes
toc	farm soill organic carbon/ cellSize	Normal		No
soilpH	cell soil pH	Normal		No
soyYield	Farm soybean yield	Uniform	2000 + (0.141* Soc - 0.703) + planting area	No
cornYield	Farm corn yield	Uniform	9597 + (0.141* Soc - 0.703) + (1.195* Fertilizer) + planting area	No
riceYield	Farm corn yield	Uniform	8112 + (0.141* Soc - 0.703) + (1.1* Fertilizer) + planting area	No
burnRatecorn	0=nothing; 1=burn	Discrete	0=0.45; 1=0.55	Yes
returnRatecorn	0=nothing; 1 = return	Discrete	0=0.55; 1=0.45	Yes
burnRatesoy	0=nothing; 1=burn	Discrete	0=0.94; 1=0.06	Yes
returnRatesoy	0=nothing; 1 = return	Discrete	0=0.06; 1=0.94	Yes
burnRaterice	0=nothing; 1=burn	Discrete	0=0.26; 1=0.74	Yes
returnRaterice	0=nothing; 1 = return	Discrete	0=0.74; 1=0.26	Yes

5.2.5. Process Overview

To *initialization* the TeleABM the user must first set the global parameters by determining which systems to simulate (e.g., sending, receiving or both) and setting crop price as either static, empirical or trade scenario. When only one system is initialized, crop price is either set as a static price or read in as a dynamic price from file.

Next, land use and suitability maps must be read in before initializing the agents, allocating land cells and setting up agent properties (Table 11). *Farmer agent*s determine their land use decision by deciding how much land to allocate to rice production and then by deciding the proportion of corn and soybeans from what land is left. This is because rice price is the highest but also requires suitable land (e.g., next to existing water) and investment capital to convert from dry to paddy land production. *Farmer agents* then pass their land use decision (e.g., corn, soybeans, rice) and inputs (e.g., fertilizer, crop residue) to the land cell and update land use in the current step. The previous land uses are recorded to the land cell property and undergo ecological processes to generate new crop yield, soil pH and SOM – in response to management decisions. When all agents and land cells have been updated the model moves to the annual accounting step, where profit and environmental impacts are stored (e.g., crop production, GHG emissions and nutrient runoff) (Figure 22). Information on crop production is passed to the trade agent then to the trade model which returns the next year's crop price. Soil pH and SOM are used to measure soil degradation, soil quality feedback to cultivation and management decisions through the yield and profit functions. After the annual accounting step, the model moves to the next time step.

5.2.6. Design Concepts

To extend this model, management decisions were added after cultivation decisions.

Residue Management & GHG Emissions. Residue management starts by setting each farmer agents decision to burn or return the residual crop biomass post-harvest. The decision to burn/return is set randomly, per crop type, in proportion to the values observed by farmers in the field (Table 11). If the residue management decision is to burn, then *GHG emissions* i,t are calculated, which include g/kg of CO2, NOx and PM 2.5 released from burning straw biomass for crop type *c* by farmer agent *i* at time *t* (equation 1)[8-12]. Alternatively, if the residue management decision is to return, the residual biomass is added to the soil as carbon(equation 4)[6].

$$GHG\ Emmisions_{i,t} = Emmisons\ Factor_c \times Straw\ Biomass_{i,t}$$

Nitrogen Fertilizer Use & Overuse. For each crop nitrogen fertilizer input for farmer agent *i* at *t* is set as the average input observed in the field for crop type *c* random deviation for crop type *c* (equation 2). Excess nitrogen fertilizer use for farmer agent *i* at time *t* is then calculated by subtracting the recommended fertilizer rate for crop type c from the fertilizer input for farmer agent *i* at time *t* (equation 3).

$$Fertilizer\ Input_{i,t} = Observed\ Input_c + u_c$$

$$Excess\ Nitrogen_{i.t} = Fertilizer\ Input_{i,t} - Recommended\ Input_c$$

SOC. SOC is the model component that connects agent management decision to the quality of the cell which in turn feeds back to cultivations decisions. SOC for land cell *l* at time *t* is equal to *SOC* for land cell *l* at time *t-1* plus the residual biomass, root biomass and seed carbon of crop type *c* for farmer agent *I* at time *t*, plus fertilizer use at land cell *l*, plus rhizodeposition, temperature and perception in region *r* (equation 4).

$$SOC_{l,t} = SOC_{l,t-1} + ((Constant_c \times Straw\ Biomass_{i,t}) + Root\ Biomass_c + Seed\ Carbon_c + Fertilizer\ Input_l + Rhizodepisition_r) \times Temperature_r \times Percipitation_r$$

Yield. Yield is the cumulating model step and is used to feedback to cultivation decisions between model ticks. Yield for farmer agent *i* at time *t*, is based off the observed yield for crop type c plus the nitrogen fertilizer input for farmer agent *i*at time *t* response for crop type *c* plus SOC for land cell *l* at time *t* (equation 5).

$$Yield_{i,t} = Observed\ Yield_c + (Yield\ Response_c \times Fertilizer\ Input_{i,c,t})$$
$$+ \left(0.414 \times SOC_{i,l,t} - 0.703\right) + u_c$$

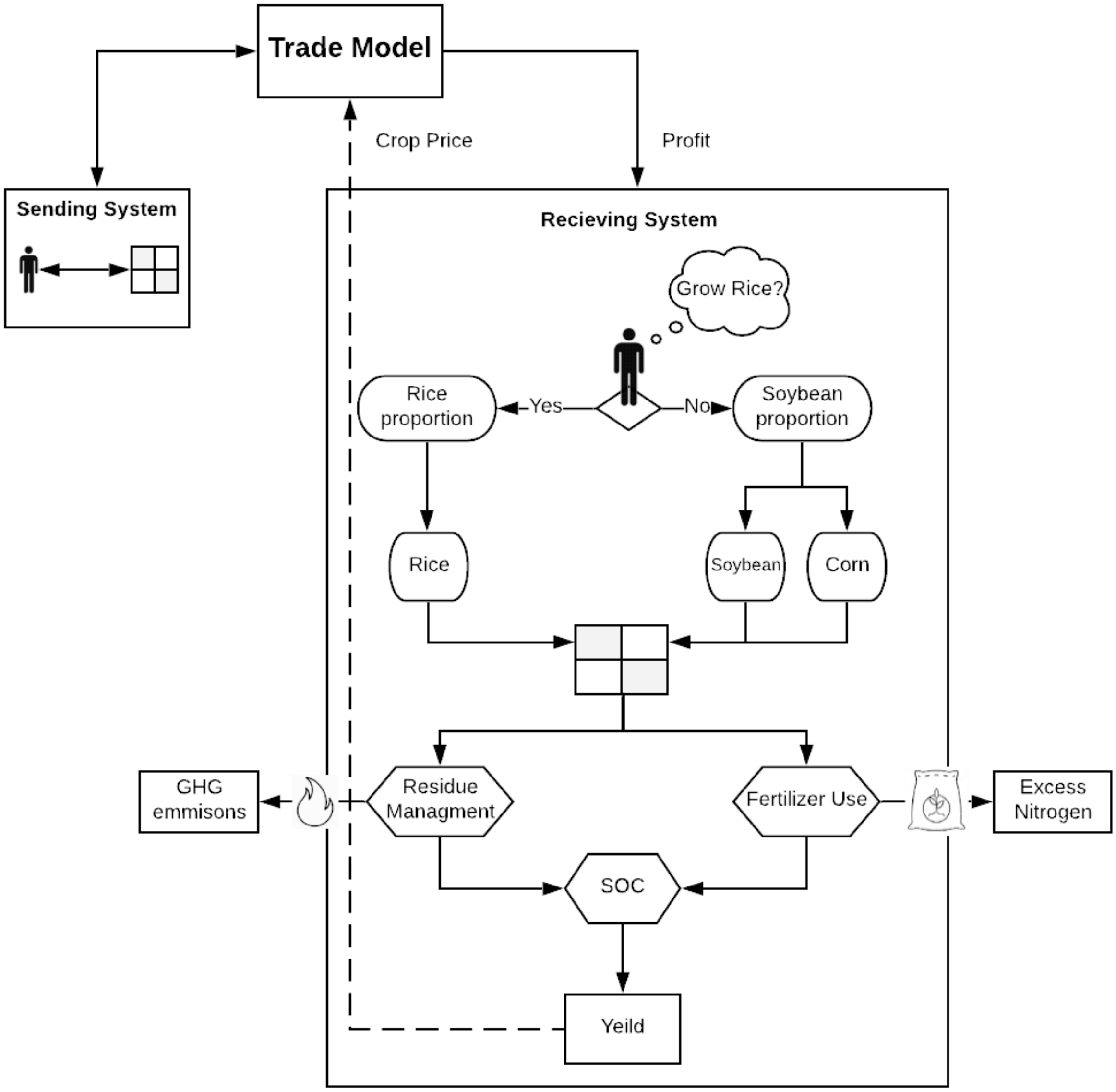

Figure 22. Adapted from Dou et al. Figure 63, the decision-making process making process in the receiving system of teleABM. The dotted lines represent linkages to the sending system which can be turned on or off to simulate different trade scenarios. The present version of the model extends beyond the cultivation decisions and adds management decision which decisions affect soil properties that then feedback to the cultivation decisions via a profit function (i.e., yield * price).

5.2.7. Validation

The land use decision has been validated by Dou et al.[3,4] Validation of the Management Decisions sub model was done by ensuring that simulated soil carbon values fell between the maximum and minimum value measured from the field (Figure 27).

5.3. Results

Based on the empirical data, model initialization starts with 50% of the simulated area in Heilongjiang planted to corn, 35% to soybeans and 15% planted to rice (Figure 23 & 24). The area planted to corn increases at the expense of soybeans rice until model tick 7. Then Rice begins to increase the expense of corn and soybeans. From Figure 24 we can see the spatial hot spots of soybean decline on the east and west sides of Heilongjiang. Rice and corn expansion are somewhat clustered. Rice can only expand near water and when adjacent to other rice cells which creates the blocks of white (Figure 24).

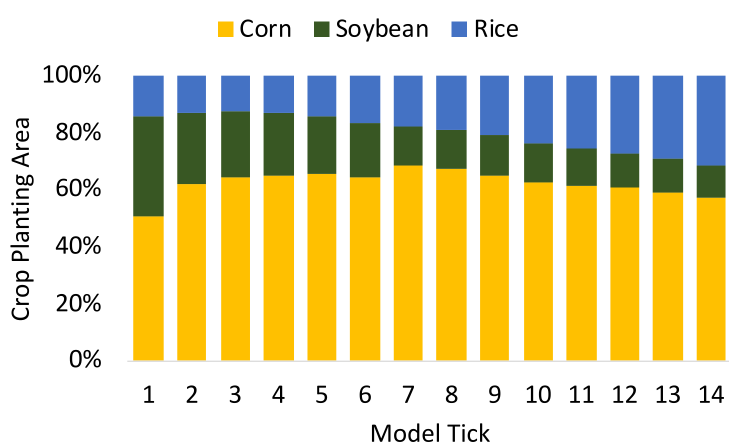

Figure 23. The area planted to corn, soybean and rice overtime.

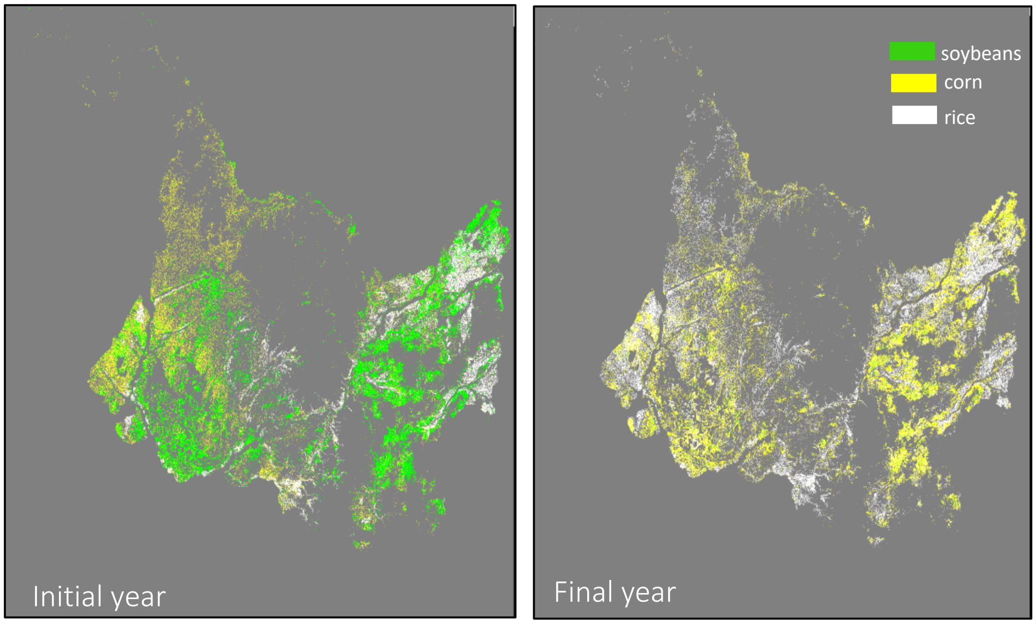

Figure 24. Simulated land use maps showing the initial and final model tick. Soybeans are green, corn is yellow and rice is white.

The pattern of greenhouse gas emissions as a result of crop residue burning is closely tied to the area planted to each crop (Figure 25). Emissions of CO_2, NO_x and $PM_{2.5}$ all increase over the model simulation. In the first few ticks the levels of CO_2 increase rapidly but slow around tick 7, following the increase in the area planted to corn (Figure 23). Emissions of $PM_{2.5}$ also increase quickly in the first 7 ticks but do not slow as much as the emissions of CO_2. At tick 13 the emission of $PM_{2.5}$surpasse the emissions of CO_2. This pattern is because burning rice residue produces more $PM_{2.5}$ while burning corn residue produces relatively more CO_2.

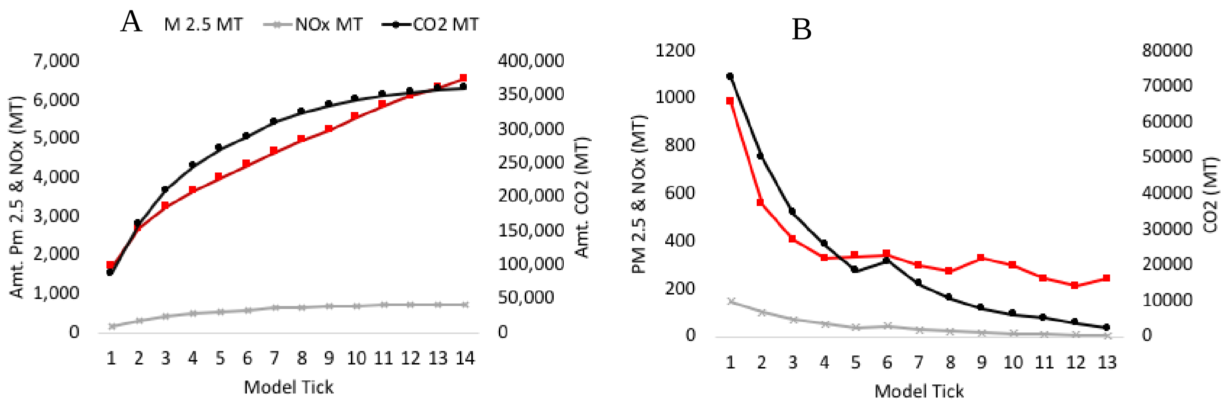

Figure 25. (A) total emissions from all farms over time (b) change in total emissions from all farms over time. PM2.5 is red, CO2 is black and NOx is grey.

Additionally, the emissions can be viewed based on the area planted to each crop (Figure 26). The emissions of $PM_{2.5}$ are highest from farms planting high proportions of rice. The $PM_{2.5}$ emissions factor for rice is 14.73 while the PM 2.5 emissions factor for corn is 11.7 and soybeans is 5.6. CO_2 and NO_x emissions were highest from farms planting high proportions of corn. Farms planting high proportion of soybeans had the lowest emissions because soybean residue is seldomly burnt.

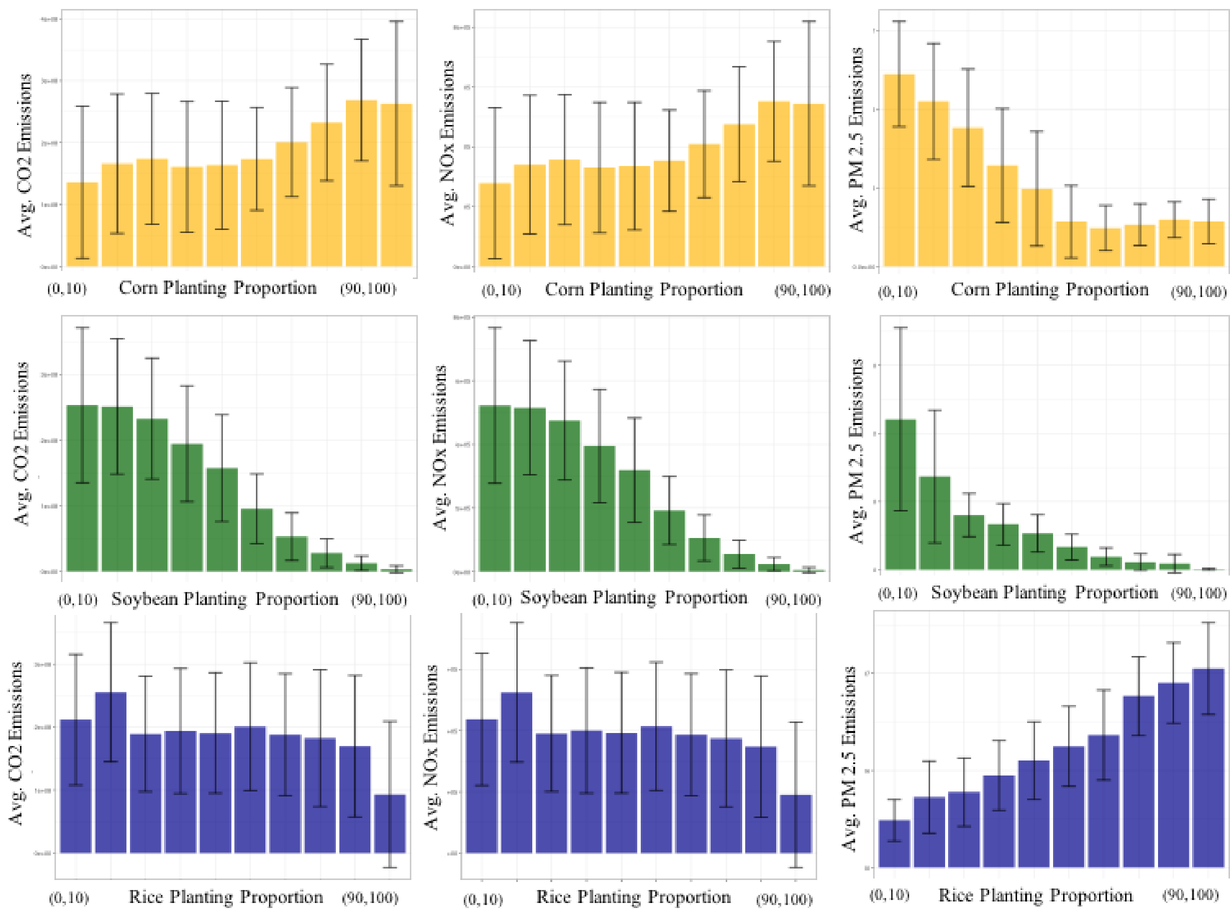

Figure 26. Average emissions of CO2 (left column), NOx (center column), and PM2.5 (right column) from farms shown by crop planting proportion. Corn is yellow, soybeans green and rice blue.

The level of toc was empirically measured using soil samples and input maps, toc was higher in samples from corn and rice than samples taken from soybean fields (Figure 26 & 27). When simulated using the residue return rates, the level of toc in corn and soybeans cells was higher than rice, however, the level of toc in rice cells increased over the simulation while the level of toc in corn and soybeans cells decreased. The spatial pattern of TOC is similar to the pattern of land use change (Figure 24). Areas planted to rice experienced the most rapid soil TOC decline followed by areas planted to corn (Figure 27).

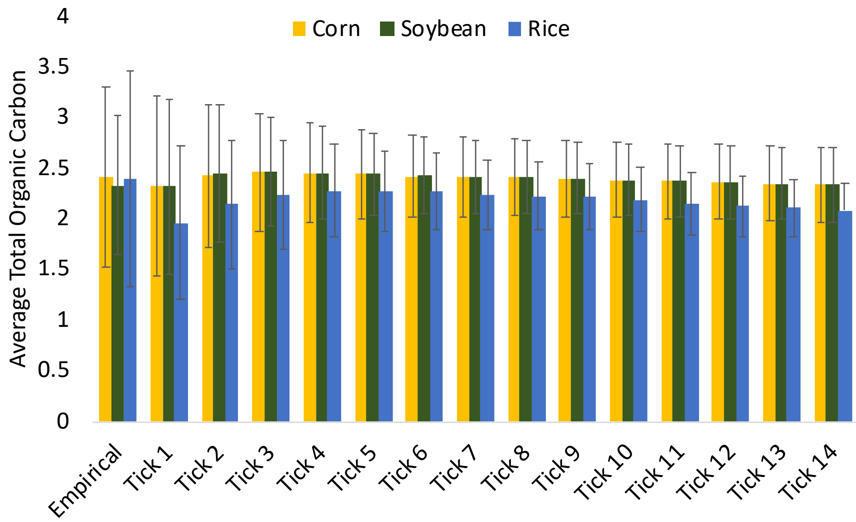

Figure 27. Average total organic carbon by crop type overtime. Corn is yellow, soybeans green and rice blue.

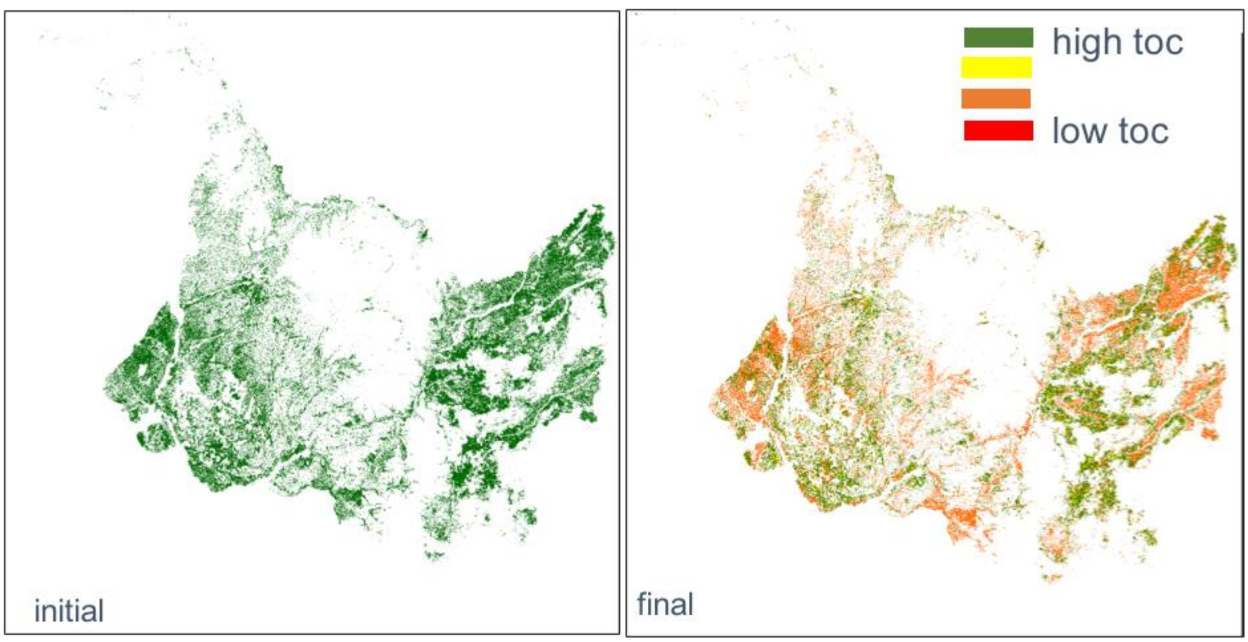

Figure 28. Simulated land use maps showing the initial and final model tick. Green indicates high levels of total organic carbon, followed by yellow, orange and finally red. Red indicates degraded soil.

On average, yield slightly decreased over the model simulation for all crops (Figure 29). This is likely due to the small decrease in toc overtime which was driven by the removal of crop residue from fields.

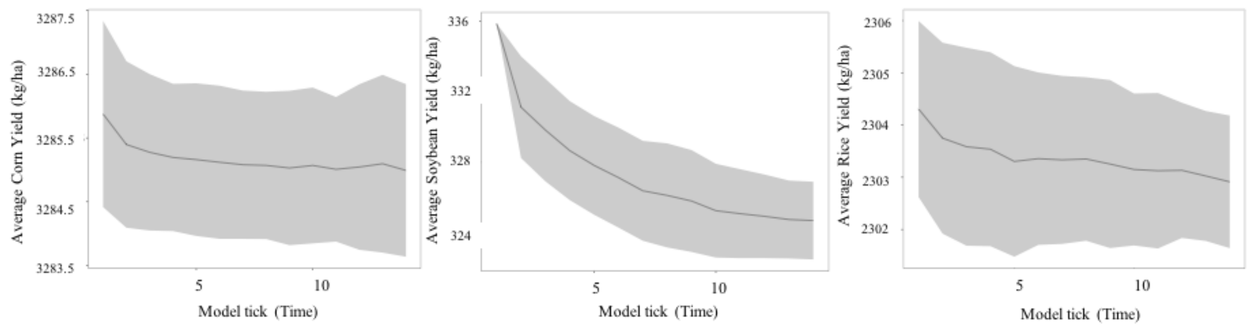

Figure 29. Yield by crop type over time. Corn is shown in the left panel followed by soybean and rice. The grey shaded area represents standard deviation.

Nitrogen overuse was highest from farms with high planting proportions of corn and lowest from farms with high planting proportions of soybeans (Figure 30). Excess nitrogen use contributes to the emissions of NO_x (Figure 25 & 26).

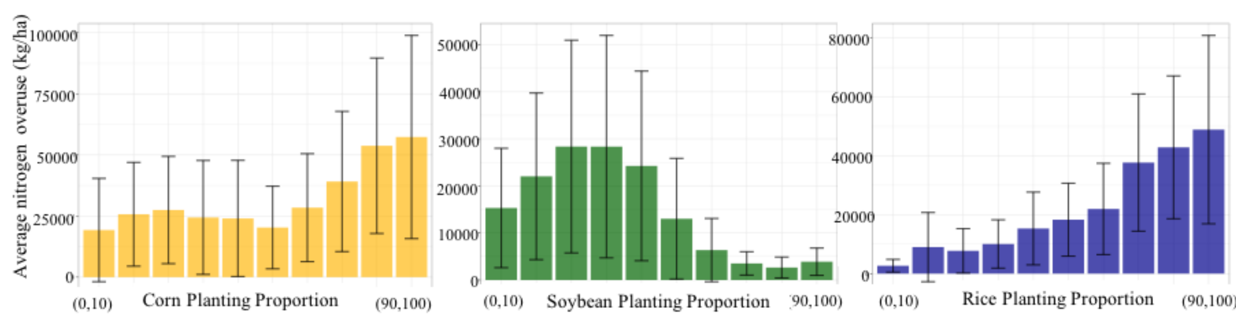

Figure 30. Average nitrogen overuse on farms shown by planting proportion. Corn is yellow, soybeans green and rice blue.

5.4. Discussion

The presented extension advances the TeleABM, which represents two different land systems that our connected through trade flows, by going beyond land use changes to assess the biophysical impact of international trade on soil properties and greenhouse gas emissions. The sub-model builds relationships between nitrogen use, residue management, soil TOC and greenhouse gas emissions. Notably, a surprising land use pattern emerged from the parametrized cultivation and management decisions. Initially, across all farms the area planted to corn increased before decreasing while the area planted to rice increased. This land use pattern indicates that a threshold of rice conversion must of first been reached before rice expansion became notable. This is likely because rice expansion can only occur near existing rice production based on access to water. Therefore, early rice expansion feedbacks through the TeleABM and facilitates further rice expansion clearly indicating a network effect. The shift from corn expansion early in the model to rice expansion in the second half of the model can be seen in the simulated greenhouse gas emissions. Where corn cultivation contributes more heavily to CO_2 emissions and rice production to $PM_{2.5}$ emission. Lastly, the area planted to soybeans and the average soybean yield experienced a consistent decline throughout the model run. Soybean production does not benefit from nitrogen fertilizer as do rice and corn cultivation but would be subject to the same level of soil carbon loss as the cells that grew corn and rice. Therefore, farmers could compensate for low soil carbon by adding nitrogen fertilizer to corn and rice but not soybeans. This mechanism lead to a negative feedback in farmer-decision making and may partially explain the decline in soybean production.

5.5. Future Work

Sensitivity analysis (SA) and uncertainty (UA) analysis are important steps to complete an ABM. SA is used to evaluate the variability of model outputs due to uncertainty in input variables. UA is done before SA to quantify the outcome variability of in model inputs[13]. These next steps will be used to determine which model inputs are most responsible for outcome results. To do so, seven potentially influential variables have been selected (Table 11). These variables will change through multiple model runs while the rest of the model parameters are held constant. This allows us to assess the influence of the potentially influential variables on model outcomes.

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6. SYNTHESIS

This dissertation is part of a Belmont Forum- and NSF-funded Telecoupling Consortium, which brings scholars from four continents (Brazil, China, UK and US) together to study the dynamics of international soybean production and trade using the telecoupling framework. This dissertation contributes to the larger NSF project by integrating network analysis, genomic sequencing and agent-based modeling to explore the environmental and socioeconomic impact of international trade in the receiving country. This dissertation was grounded in the telecoupling framework and quantitatively addresses all the components (e.g., systems, flows, causes, effects and agents). Furthermore, this is a cross-scale study addressing the impacts of international soybean trade at the macro, meso and micro-scale.

For chapter 2, the influence of China's large soybean demand on trade networks among soybean-producing countries was analyzed. Using 15 years of global trade data, autoregressive integrated moving average models (ARIMA) were developed to measure the impact of China's demand on production and bilateral trade of corn, soybeans and wheat. The results reveal that China's large soybean demand increased export-driven soybean production in Brazil and displaced production of corn and wheat to nearby countries (e.g., Argentina, Paraguay and Uruguay). Additionally, when restrictions were placed on the direct export of soybeans to China, Argentina and Paraguay increased soybean exports to Brazil as an indirect export route to China. The results were published in *Sustainability* and presented at the Global Land Programme meeting in Taiwan – where it also won the Best Paper award. The research results hold implications for the true extent of production driven by distant demands as well as the impact of the geo-politics on trade networks.

Chapter 3 analyzed how soybean imports to China compete with domestic production and have altered domestic cultivation and management practices. Satellite-imagery and farmer interviews were used to quantify the regional cultivation shift from soybean to corn production.

To determine if the change in cultivation was influenced by international soybean trade an interrupted comparative time-series (ICTS) model was used. Interestingly, farmers in the region are causing air pollution to spill across the China-Russia border by using fire to manage the residual biomass that is left after harvesting corn. This was confirmed by measuring the amount of carbon in the soils of farmers and level of particulate matter (PM 2.5) in the air. Last, a multivariate regression determined which factors significantly influenced residue management decisions. The results have been presented at the AAAS Annual Meeting and submitted to *Science Advances.* This research highlights the impact of distant trade on production in the often overlooked importing country.

Chapter 4 of my dissertation furthered the above analysis by considering the impacts of farmer cultivation and management decisions on soil properties. Soil texture, pH, total organic carbon and 16s rRNA sequencing were used in combination with detailed farmer management surveys to understand how changes in residue management effect efficiency, productivity, profitability and sustainability of the system. The results indicated that the accumulation of residual corn biomass has increased the use of residue fires and decreased the amount of crop residue being returned to the soil. However, crop choice, planting history and nitrogen use has more noticeable effects on the microbial community than the amount of residue returned. Samples from continuous soybeans fields were the most diverse followed by mixed rotations and then continuous corn samples. The results of chapter are under internal review at MSU and plan to be published due to the uniqueness of the dataset.

The culminating chapter of this dissertation uses agent-based modeling (ABM) to integrate the above chapters into a TeleABM. The teleABM models land use change in Brazil and China based on global soybean demand. Land-use change decisions are made by farmer agents which have parametrized using the farmer interviews. Next, the farmer agent cultivation and management decisions have environmental impacts that were determined by analyzing the soil samples under the context of management decisions. Finally, production and the impact of farmer agent decisions on the soil properties feedback to the farmer’s future cultivation and management decisions. The results of chapter 5 highlight both a positive and negative feedback. First, rice expansion started off slow but quickly increased once a threshold of rice production had been met and allowed for conversion on adjacent land. Second, soybean production decreased in response to soybean yield declines that feedback to a farmer’s cultivation decision. Future work is needed to determine which model inputs most effect the model outcome.