Uncovering the spatially distant feedback loops of global trade: a network and input-output approach

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ABSTRACT

Land-use change is increasingly driven by global trade. The term “telecoupling” has been gaining ground as a means to describe how human actions in one part of the world can have spatially distant impacts on land and land-use in another. These interactions can, over time, create both direct and spatially distant feedback loops, in which human activity and land use mutually impact one another over great expanses. In this paper, we develop an analytical framework to clarify spatially distant feedbacks in the case of land use and global trade. We use an innovative mix of Multi-regional Input-output (MRIO) analysis and stochastic, actor-oriented models (SAOMs) for analyzing the co-evolution of changes in trade network patterns with those of land use, as embodied in trade. Our results indicate that the formation of trade ties and changes in embodied land use mutually impact one another, and further, that these changes are linked to disparities in countries’ wealth. Through identifying this feedback loop, our results support ongoing discussions about the unequal trade patterns between rich and poor countries that result in uneven distributions of negative environmental impacts. Finally, evidence for this feedback loop is present even when controlling for a number of underlying mechanisms, such as countries’ land endowments, their geographical distance from one another, and a number of endogenous network tendencies.

Key words: global trade, land use, feedback loops, telecoupling, trade networks, embodied land

1 Introduction

Land-use change is increasingly caused by global drivers. The interdependencies between countries implies that human actions in one part of the world have impacts in another. In efforts to better understand the distant influence of human activities on land use, the concept of 'telecoupling' has been proposed as a new analytical perspective to address the increasing importance of distant connections and the growing complexity of the factors driving land use change. Telecoupling, first introduced by Liu et al. (Liu et al. 2007), describes how natural and socioeconomic processes are linked within and across distant regions. In a telecoupled system, agents (e.g. individuals or corporations) in one location interact with aspects of the natural environment (in our case, various kinds of land) in either the same and/or different location. These interactions, over time, create both direct and spatially distant feedback loops in which both human activity and the natural environment mutually impact one another.

In the case of land, a growing body of research illustrates the ways in which land becomes embodied in international trade relations (EF and P 2011; Eric F. Lambin 2001; Hubacek and Feng 2016; Lambin et al. 2001; Schaffartzik et al. 2015; Seto et al. 2012; Weinzettel et al. 2013; Yu, Feng and Hubacek 2013; Yu, Feng and Hubacek 2014). Here, analysts demonstrate how land-intensive goods produced in one country get consumed in another, drawing attention to the spatially-distant relationships between consumption and production, and their associated environmental impacts. In doing so, this research often emphasizes that it is wealthy, developed countries that tend to be net importers of land-intensive goods, and hence, fulfilling their land requirements elsewhere, while poorer, less-developed countries are net exporters of such goods (Moran et al. 2013; Yu, Feng and Hubacek 2013).

Classic and critical economic perspectives regarding global trade offer potential explanations for such environmental disparities between rich and poor countries. The 'comparative advantage' perspective (Porter, 1990; Ricardo, 1821) argues that economic agents in given countries strive to produce goods at lower costs in order to become competitive globally. Thus, in relation to embodied land, countries striving for a competitive advantage in the production of land-intensive goods can be assumed to tend towards becoming net exporters of land. Yet a more critical perspective would extend this argument by noting that, via a variety of historical events, wealthy, developed countries have accumulated a strategic position in the global economy, and are hence able to dictate the rules of global trade. Thus, these more wealthy, developed countries extract under-valued, natural resources (such as land-intensive commodities) from poorer countries, and/or externalize resource-intensive activities to these more peripheral areas (Arrighi and Drangel 1986; Chase-Dunn and Hall 1993; Chase-Dunn 1998; Jorgenson 2006; Rice 2007). Given this more critical perspective, it is not just that poorer countries may seek to develop a competitive advantage in certain kinds of exports, targeting wealthier markets in efforts to grow their economies (Jain 2006; Pao and Tsai 2010), but also, this process tends to place increased stress on poorer countries' environments, for example, through increased domestic land use (Moran et al. 2013; Yu, Feng and Hubacek 2013; Yu, Feng and Hubacek 2014), deforestation (Jorgenson 2006), land and/or water grabs (Rullia, Savioria and D'Odorico 2013), and emissions (Jorgenson 2012; Jorgenson 2011; Kagawa et al. 2015; Moran et al. 2013; Prell and Feng 2016).

Collectively, the above discussion on international trade and embodied land highlights how human activities and environmental impacts can span large spatial distances, where environmental impacts resulting from these activities become unevenly distributed among poor and rich countries. In addition, the above discussion suggests a feedback loop, in which land can both prompt new trade relationships and be impacted by these trade relations and/or their structural patterns. To make this more explicit, we note how past research indicates a positive relationship between being a net importer of land and wealth (Moran et al. 2013; Yu, Feng and Hubacek 2013); research on global trade networks indicates that structural features of global trade and trade networks, e.g. level of centrality or position in the overall network, are good predictors of countries' wealth (Clark 2010; Mahutga and Smith 2011) and/or for environmental outcomes such as environmental pollution, either territorial or consumption based (Burns, Davis and Kick 1997; Prell et al. 2014; Prell 2016; Prell and Sun 2015; Prell et al. 2015; Prew 2010); and finally, research on trade tie formation has shown how features such as countries' level of wealth, proximity to other countries, and/or embodied carbon can prompt the formation of trade ties (Koskinen and Lomi 2013; Prell and Feng 2016), as well as even be considered to 'co-evolve' alongside environmental accounts such as carbon (Prell and Feng 2016), Collectively, this research suggests that features of trade networks can predict changes in countries' environmental accounts (e.g. embodied carbon or land), and similarity, that the formation of these trade networks can be conditioned by these same environmental accounts, as well as other country characteristics, such as wealth.

A consistent trend across this research pertaining to trade networks is the focus on the *structural patterns* arising from the presence (or absence) of between-country trade ties (as opposed to the volume of capital flowing between countries, for example). In doing so, analysts tend to focus on the presence of *strong* trade ties, e.g. ties existing over and beyond a given cut-off value, in order to draw attention to the main structural features of the trade network (Kagawa et al. 2013; Kagawa et al. 2015). Doing so enables analysts to reduce the complexity of the network in question, allowing analysts to reveal the global structural features of the most important ties characterizing global trade, and in doing so, revealing important features implicit to ideas of economic globalization, namely, ideas of interconnectivity and/or regionalization (Kali and Reyes 2010; Kali and Reyes 2007; Kim and Shin 2002; Koskinen and Lomi 2013; Prell and Feng 2016; Reyes, Schiavo and Fagiolo 2010).

Given this past research, we propose two hypotheses, that combined, explore how trade tie patterns and land trade imbalance(s) change in response to one another, forming a positive feedback loop:

H1 A net exporter of embodied land is more likely to form a (strong) export tie with a relatively wealthier country.

H2: Having a strong export tie with a relatively wealthier partner makes the country more likely to become a net exporter of embodied land.

In stating the two hypotheses above, we would like to clarify that a *strong export tie* refers to an export link that represents the upper 5th percentile of total trade between countries, and that a *net exporter of embodied land* refers to a country whose land-intensive exports exceeds its land-intensive imports. If support for H1 and H2 were found, we argue that such support would imply a positive, reinforcing feedback loop between displaced land-use and the formation (or maintenance) of strong trade ties, in which the embodied land of given countries are prompted by (but also drive) the presence and/or formation of strong export ties with wealthier countries. Thus, H1 conceptualizes the first half of the loop, testing how LTI levels drive trade tie formation. In contrast, H2 tests the second half of the loop, testing the impacts of trade ties on LTI levels.

Empirical confirmation of H1 and H2 helps clarify some of the complexities of global social ecological systems (Kissinger 2010; Lenschow, Newig and Challies 2016; Young et al. 2006), and demonstrate how consumers and producers are linked together in furthering environmental degradation through land use and land stress (Lenzen et al. 2007).

2 Material and Methods

Our data consists of 3 waves of input-output trade flows data, representing the time span of 2000-2010. These data were extracted from the EORA database (http://www.worldmrio.com/), an MRIO database that provides time series input-output (IO) tables, consisting of 26 economic sectors, with matching land accounts, i.e. cropland, forestland, grazing land, build up land and land used by fisheries (Lenzen et al. 2012). While the disaggregated form of these MRIO will be indispensable for computing our Land Trade Imbalance (LTI) measure as we will present in detail later, for obtaining our trade network data, we first aggregated the 26 sectors into a single, value matrix with its elements representing all sectorial trade flows between countries. With this matrix, we then computed binary trade matrices based on the upper 5th percentile of our trade-value matrix, to represent strong trade flows between countries (for similar cut-off value and justification, see Prell and Feng 2016)[1]. This procedure is in line with the standard guidelines of network analysts (Prell 2012; Wasserman and Faust 1994) and previous trade network studies (eg. Clark 2010; Prew 2010).

Countries' GDP per capita, a proxy of wealth, were downloaded from the World Bank database (http://www.worldbank.org). As geographic proximity is often found to influence trade tie formation between countries (Anderson 2011; Dueñas and Fagiolo 2011), we also included data on the distances between countries, based on the great circle distances between capital cities

[1] Additional analyses were done on matrices using cut-off values of the upper 10th and upper 2.5th percentile of trade flows, i.e. 'moderately strong' and 'very strong' flows, respectively. Results for these additional network models were similar to the ones presented here, and thus, we do not discuss the results further.

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of the world (Gleditsch 2008). Finally, to control for countries' land endowments, we included each country's total land per capita, where total land includes cropland, forestland, grazing land, build up land and land used by fisheries. In total, our sample consists of 172 countries.

To calculate countries' embodied land in trade, we used multi-regional input-output (MRIO) analysis on the three waves of disaggregated EORA data. MRIO analysis is a well-established approach (Miller and Blair 2009; Murray and Wood 2010) and provides an accounting framework that enables analysts to track the environmental implications of consumption, by quantifying, in a single measure, the total land displacement arising from the consumption of goods (Moran et al. 2013; Weinzettel et al. 2013; Yu, Feng and Hubacek 2013). At its core, MRIO analysis uses an accounting procedure on regional economic input-output (I-O) tables and inter-regional trade matrices, depicting the flows of money to and from each sector within and between the interlinked economies, thus revealing each sector's role in the entire and multiple global supply chains (for a recent discussion and comparison of datasets see Inomata and Owen 2014).

To estimate embodied land, we began with the MRIO technical coefficients matrix $\boldsymbol{A}$, which contains all input-output relationships of the economy, and took the inverse of ($\boldsymbol{I} - \boldsymbol{A}$), where $\boldsymbol{I}$ is a unit matrix ($\boldsymbol{I} - \boldsymbol{A}$ is commonly known as the Leontief matrix). Next, we calculated the total input requirements to satisfy final demand (y) by multiplying the inverse matrix by final demand of a particular consumption item in a given country. Next, to calculate the land embodied in import of region s, we use the following calculation:

$$Land^{imp} = k^{\sim s}(I - A)^{-1} y^{\cdot s}$$

(1)

where $Land^{imp}$ is the total embodied land in import region s; $k^{\sim s}$ is a vector of sectoral land use coefficients of different regions with zeros for the sectoral land use coefficients of region s; $y^{\cdot s}$ is the final demand vector with the true sectoral demand values for region s but zero for all other regions We used the following equation to estimate the land embodied in export of region s:

$$Land^{exp} = k^{s}(I - A)^{-1} y^{s\cdot} \quad ..$$

(2)

where $Land^{exp}$ is the total embodied land in export of region s; k^{s} is a vector of sectoral land coefficients with the sectoral land use coefficients for region s but zeros for all other regions ; $y^{s\cdot}$ is the vector of sectoral final demand of different regions with zeros for region s.

To create the LTI ratio, we combined $Land^{exp}$ with $Land^{imp}$ to create a ratio, which we refer to as our **Land Trade Imbalance** (LTI) measure such that ${Land^{exp}}/{Land^{imp}}$, and then took the natural log of this calculation, such that ln(*LTI*) = ln(${Land^{exp}}/{Land^{imp}}$). Here, a value of ln(*LTI*) being greater than 0 indicates the country concerned being a net exporter of embodied land, and a value less than 0 indicating the country being a net importer of embodied land (for similar measures, see Moran et al. 2013; Weinzettel et al. 2013). Finally, we transformed these data to even, ranked ordinal values ranging from 1-10 in order to accommodate data restrictions of our stochastic modeling framework (see paragraph below).

The LTI measure calculated using MRIO analysis was then brought into a dynamic modeling framework, along with the trade matrix composed of strong ties, the geographical proximity matrix, and data on countries' GDP per capita. This dynamic modeling framework is known as the stochastic actor-oriented models (SAOMs), which were developed by Snijders and colleagues (2010). This framework estimates parameters for tie formation tendencies alongside those for changes in country characteristics through the use of two multinomial logistic functions. The first such function we refer to as our "TRADE Change Function", which models changes in networks, and hence, positions trade ties as the dependent variable. A second, similar function, which we call the "LTI Change Function", handles changes in countries' LTI in response to network features. As these two models were estimated simultaneously in SAOMs, changes in one set of processes (i.e. the TRADE Change) affect processes modeled by the second function (i.e. the LTI Change).

We specified a number of network effects for testing our two hypotheses. H1 requires specifications in the TRADE Change model, to model processes impacting the formation of trade ties. Specifications in the TRADE Change model take the form of endogenous and exogenous effects. *Endogenous effects* control for underlying tendencies across the network, for example, the general tendency to form outgoing ties (outdegree effect) or the general tendency for actors to form a reciprocal tie (reciprocity effect). *Exogenous covariate effects* involve attributes (covariates) of actors, in particular the attributes of focal actors (referred to as 'egos') and/or the attributes of actors to whom egos are tied (referred to as 'alters'). These exogenous effects, moreover, take three forms: e*go effects* pertain to the attributes of focal actors (egos), and measure the tendency of focal actors (egos) with higher values for a given attribute to have higher numbers of outgoing ties. *Alter effects* pertain to the attributes of those to whom an ego is tied (alters), and measure the tendency of egos to be drawn to form ties to those alters with higher values for a given attribute. Finally, *similarity effects* measure the tendency of more ties to form between actors with similar values for a given attribute. For H1, we created an interaction term from two exogenous, covariate effects, i.e. the *LTI ego × GDPpc alter effect*, where a resulting positive coefficient indicates the tendency for net land exporting countries to form export ties with wealthier others.

In contrast, H2 requires specifications in the LTI Change model, to model how network features impact changes in LTI. Here, we specified the *total alters' GDP per capital effect,* where a resulting positive coefficient implies that the wealth levels of alters to whom a focal country exports positively impacts that focal country's LTI level, in such a way that the total influence of the alters' wealth is proportional to the number of alters.

In addition to the hypothesized interaction terms for testing H1 and H2, we specified additional effects to control for underlying, endogenous configurations (e.g. the general tendency to reciprocate ties) and to control for competing exogenous influences (e.g. Land per capita and Geographical Distance). First, as testing H1 and H2 involve interaction effects, we also included the primary terms for these interaction effects. More specifically, in the TRADE Change model, we included the *GDP pc alter* effect, where positive parameters indicate a tendency of countries to form export ties with wealthy others, and the LTI ego effect, where a positive parameter indicates countries with high LTIs (net exporters of land) tending to form more export ties, relative to others. Similarly, in the LTI Change model, we included the *outdegree effect*, which measures the tendency for countries' LTIs to change in response to the number of export ties they hold, and the effect of *ego's GDP per capita* on ego's LTI, which measures the extent to which countries' wealth impacts their LTI levels.

Other attribute-based controls we included were *GDP per capita* ego effect, the *LTI alter effect*, and *similarity effects* for countries' LTI, and GDP per capita. To control for land endowments, we included the *Land per capita -ego, -alter,* and *-similarity* effects. Thus, for each attribute (GDP per capita, LTI, and Land per capita), three effects were included, and this was done as research suggests that they can spuriously create hypothesized patterns (e.g. Koskinen and Lomi 2013; Schaefer 2013). In addition to attribute-based effects, we controlled for a number of endogenous network tendencies that affect tie formation in general, and which may also result in biased estimates of other specified effects if not included in the model (e.g. Mouw and Entwisle 2006; Snijders, van de Bunt and Steglich 2010). Our selection of these endogenous effects was aided by the use of goodness of fit tests (Lospinoso 2012) found in the Siena package, and explained in its manual (Ripley et al. 2016). These tests compare the average values of simulated, auxiliary statistics with values in the observed data, and if the distribution of these average scores corresponds closely to observed values, then the fit of the model is deemed good. Thus, through a process of trial and error using these GOF tests, we developed model specifications for endogenous network effects with the best fit (see Appendix for GOF test results). The endogenous effects we specified include i) *outdegree*, i.e. the general tendency to form outgoing ties, ii) *reciprocity,* which is the tendency for ties to be mutual, iii) in- and outdegree *popularity,* where a positive parameter indicates the likelihood of country *i* to form a new import or export tie with some country *j*, as the number of ties held by *j* increases, and iv) the gwespFF and gwespBB effects, two effects, that combined, test the likelihood for transitivity, which refers to the tendency whereby a tie from actor *i* to *j*, and from *j* to *h*, leads to a strong likelihood of a tie also forming from *i* to *h.* In every day parlance, transitivity refers to the scenario where 'friends of my friends are my friends too.' In the context of international trade, firms might be introduced to new partners through existing ones, or firms with common trade partners may be interested in the same markets (Matous and Yasuyuki 2015). In addition, past research on international ties (be they trade-based or other) have shown support for the presence of triadic closure, more generally, and transitive closure in particular (Manger et al. 2012; Kinne 2014; Koskinen and Lomi 2013).

Additional, default controls built into SAOMs include the *rate effect* for both tie formation and changes to LTIs. For tie formation, the rate effect indicates the extent to which actors have opportunities to change their ties, and for LTIs, the *LTI rate effect* controls for the opportunities to change LTI values from one time wave to the next. The *linear shape effect* measures the overall tendency toward high or low LTI values; here, a negative parameter indicates that the majority of countries scored below the LTI mean, and a positive parameter indicates the opposite. The *quadratic shape effect* controls the effect of *a country's LTI value* on itself, e.g. when the parameter is negative, this implies the tendency of the LTI value to decrease overtime, when the value was originally high. Conversely, when the coefficient is positive, this reflects the tendency for countries to score at the extreme ends of the scale for LTI values (Snijders et al., 2010).

A full listing of these network effects can be found in Table 1. The descriptive statistics of the basic variables underpinning our dynamic modeling effort is presented in the Appendix.

Table 1: All network effects specified for SAOMs

Endogenous network effects impacting trade tie formation		
Outdegree effect :	$\sum_j x_{ij}.$	[redacted]
Reciprocity	$\sum_j x_{ij}x_{ji}.$	[redacted]
GWESP forward	$\sum_{j=1}^{n} x_{ij}e^{\alpha}\left\{1-(1-e^{-\alpha})^{\sum_{h=1}^{n} x_{ih}x_{hj}}\right\}$	[redacted]
GWESP backward	$\sum_{j=1}^{n} x_{ij}e^{\alpha}\left\{1-(1-e^{-\alpha})^{\sum_{h=1}^{n} x_{hi}x_{jh}}\right\}$	[redacted]
Number of actors at distance 2	$\#\{j \mid x_{ij}=0, max_{\mathrm{h}}(x_{i\mathrm{h}}x_{\mathrm{h}j})>0\}$	[redacted]
Indegree popularity and square root	$\sum_j x_{ij}\ x_{+j}$ and $\sum_j x_{ij}\sqrt{x_{+j}}$	[redacted]
Outdegree popularity and square root	$\sum_j x_{ij}\ x_{j+}$ and $\sum_j x_{ij}\sqrt{x_{j+}}$	[redacted]
Indegree activity (sqrt)	$x_{i+}\sqrt{x_{+i}}$	[redacted]
Outdegree activity and square root	x_{i+}^2 and $x_{i+}\sqrt{x_{i+}}$	[redacted]
Covariate network effects impacting trade tie formation		
Covariate similarity	$\sum_j x_{ij}(sim_{ij}^{v_n}-\widehat{sim}^{v_n})$	[redacted]
Covariate-alter	$\sum_j x_{ij}v_{nj}.$	[redacted]
Covariate-ego	$v_{ni}x_{i+}$	[redacted]
Geographical Distance	$\sum_j x_{ij}(w_{ij}-\overline{w})$	[redacted]

Effects impacting LTI changes			
LTI linear and quadratic shape	$(z_i - \bar{z})$ and $(z_i - \bar{z})^2$	[redacted]	
Alter's total GDP pc effect on LTI	$z_i x_{i+} \breve{v}_i$	[redacted]	
Outdegree effect on LTI	$z_i \sum_j x_{ij}$	[redacted]	
GDPpc effect on LTI	$z_i v_{ni}$	[redacted]	

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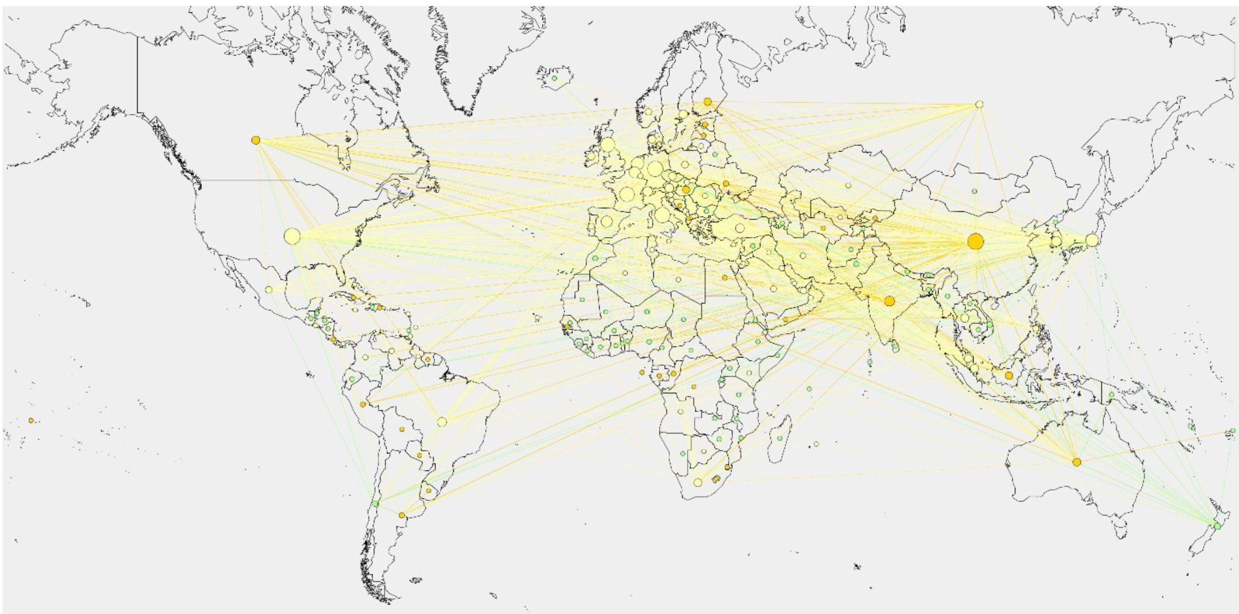
3. Results

We begin by discussing Figure 1, showing maps of global trade and countries' Land Trade Imbalances:

Figure 1: Digraphs of the trade network, countries' export centrality and ln(LTI) values

Year 2000

Year 2010

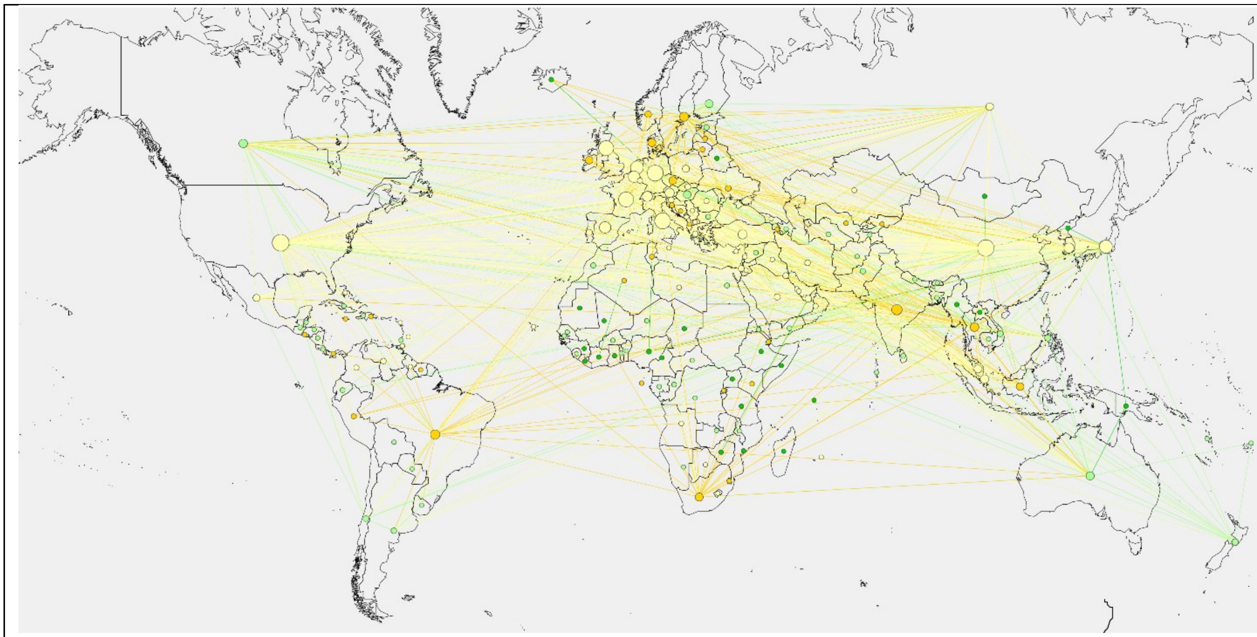


Figure 1 shows two snapshot views (years 2000 and 2010) of the countries' export centrality and their logged Land Trade Imbalance (ln(LTI)). The nodes in the digraphs represent countries, and the size of nodes indicates their quantity of strong export ties (i.e. their export centrality), with larger nodes indicating higher numbers of export ties (or higher export centrality). The color of nodes in Figure 1 reflect ln(LTI) levels. Orange nodes are net importers of land, light yellow are countries whose ln(LTI) levels hover around zero, and the remaining green nodes represent net exporters of land. Hence, Figure 1 suggests that 'developed' countries, e.g. France, Germany, Italy, Japan, the UK and the US tend to have a high number of export ties, and at the same time tend to be net importers of land. In contrast, less developed, or developing countries tend to be net exporters of land and have fewer (strong) export ties. Exceptions include certain emerging economies such as China and India, who are very central and who are net exporters of land.

Dynamics of trade and ln(LTI) are shown in the model results displayed in Table 3. The two interaction terms for testing our two hypotheses are indicated in the columns led by H1 and H2.

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Table 3: All results for TRADE Change and LTI Change Functions

TRADE CHANGE FUNCTION		**Model 1**		**Model 2**		**Model 3**		**Model 4**	
	TRADE rate (period 1)	2.501***	(0.187)	2.487***	(0.210)	2.565***	(0.197)	2.555***	(0.194)
	TRADE rate (period 2)	2.120***	(0.192)	2.110***	(0.175)	2.095***	(0.181)	2.201***	(0.193)
	outdegree (density)	-4.849***	(0.253)	-4.931***	(0.259)	-6.580***	(0.630)	-7.770***	(0.676)
	reciprocity	0.708***	(0.167)	0.739***	(0.165)	1.351***	(0.195)	0.791***	(0.224)
	GWESP I -> K -> J (69)	1.748***	(0.160)	1.803***	(0.159)	2.323***	(0.421)	1.901***	(0.404)
	GWESP I <- K <- J (69)	0.683***	(0.175)	0.682***	(0.152)	0.668***	(0.233)	0.714***	(0.223)
	number of actors at distance 2					0.060***	(0.009)	0.041***	(0.010)
	indegree - popularity					0.121***	(0.042)	0.136***	(0.038)
	indegree - popularity (sqrt)					-0.431	(0.477)	-0.477	(0.464)
	outdegree - popularity					-0.036	(0.036)	-0.035	(0.032)
	outdegree - popularity (sqrt)					-0.278	(0.425)	-0.085	(0.395)
	outdegree - activity					0.029	(0.018)	0.022	(0.017)
	outdegree - activity (sqrt)					0.121	(0.237)	0.317	(0.228)
	Geographical Distance							-0.912***	(0.070)
	LTI alter	-0.147***	(0.043)	-0.073	(0.050)	-0.137*	(0.072)	-0.114*	(0.067)
	LTI ego	-0.066	(0.057)	-0.033	(0.064)	0.093	(0.078)	0.091	(0.081)
	LTI similarity	0.896**	(0.457)	0.698	(0.470)	1.480**	(0.631)	0.585	(0.547)
	GDPpc alter	-0.430***	(0.053)	-0.373***	(0.051)	-0.413***	(0.084)	-0.537***	(0.082)
	GDPpc ego	-0.218***	(0.072)	-0.190***	(0.071)	-0.465***	(0.103)	-0.546***	(0.106)
	GDPpc similarity	1.137**	(0.620)	1.184*	(0.688)	3.726***	(0.933)	3.742***	(0.943)
	Landpc alter			-0.247***	(0.074)	-0.216**	(0.084)	-0.112	(0.091)
	Landpc ego			-0.145	(0.109)	-0.481***	(0.130)	-0.403***	(0.136)
	Landpc similarity			0.063	(0.640)	-0.496	(0.713)	-0.735	(0.713)
H1	**LTI ego x GDPpc alter**	**0.056*****	**(0.021)**	**0.053****	**(0.023)**	**0.094*****	**(0.035)**	**0.075****	**(0.032)**

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LTI CHANGE FUNCTION									
	Rate LTI (period 1)	6.095***	(1.607)	6.609***	(1.738)	6.239***	(1.640)	6.447***	(1.896)
	Rate LTI (period 2)	0.362***	(0.069)	0.358***	(0.061)	0.362***	(0.066)	0.358***	(0.065)
	LTI linear shape	-1.264***	(0.338)	-1.332***	(0.400)	-1.266***	(0.349)	-1.315***	(0.377)
	LTI quadratic shape	-0.108***	(0.034)	-0.150***	(0.041)	-0.149***	(0.044)	-0.150***	(0.049)
	LTI: outdegree	-0.022	(0.016)	-0.029*	(0.016)	-0.029**	(0.015)	-0.028	(0.017)
	LTI: effect from GDPpc	-0.215**	(0.099)	-0.279***	(0.106)	-0.280**	(0.121)	-0.284*	(0.116)
H2	**LTI: total alter's GDPpc**	**0.034****	**(0.018)**	**0.039****	**(0.017)**	**0.039****	**(0.018)**	**0.039****	**(0.019)**
	LTI: effect from Landpc			0.281**	(0.130)	0.280**	(0.136)	0.285**	(0.131)

Note: Standard errors are in parentheses. ***, **, and * indicate the significant level at 1%, 5%, and 10%, respectively.

Four separate Models are presented in Table 3. Model 1 is the most basic, parsimonious model, and the addition models (Models 2-4), introduce more control terms to test the robustness of Model 1 in confirming our two hypotheses. Starting with Model 1, we first note that the *TRADE rate* effects indicate slightly more tie changes occurring in the first period than the second. The negative, significant coefficient for the outdegree effect indicates that countries tend to avoid forming too many export ties overtime. The rate parameters in the LTI Change Function block show countries tending to change their LTI levels more in period one than in period two. In addition, both the linear and quadratic coefficient are negative and significant, implying that there is a downward drive for changing LTI levels. As these findings for the default controls remain largely the same across the remaining models (Models 2–4), we will not comment on them further here. Most relevant to this research, Model 1 shows strong support to both H1 and H2. The positive and significant coefficient for *alter's total GDP per capita effect on country i's LTI* suggests that countries with strong export ties to wealthier countries experience increases in their LTI overtime, i.e. they are more likely to become stronger net exporters of land, as we expect in H1. The positive and significant coefficients for the interaction term *LTI ego × GDPpc alter* suggests that countries characterized as stronger net exporters of land tend to increase their export ties to countries wealthier than themselves over time, as we expect in H2. Models 2-4 further show consistent support to both H1 and H2, with additional controls added.

There are some control effects, across the four models, which also warrant discussion. In the Trade Change Function block, both the *GDP per capita-alter* and *-ego effects* are negative and significant, and show a similar magnitude in the fuller-specified Models 3 and 4, indicating that poorer countries tend to attract new import ties, and form new export ties, during the time period of this study. This finding is in keeping with past research suggesting that developing economies tend to rely heavily on establishing new trade ties as a means to build their economies (Pao and Tsai 2010). In contrast, countries of similar wealth tend to form new ties overtime, as indicated by the positive, significant coefficient for *GDP per capita similarity effect*. Such a finding also makes sense given that developed, wealthy countries not only hold the majority of trade ties (as shown in Figure 1), but also tend to form an internally cohesive block composed of reciprocal links (Clark 2010; Mahutga and Smith 2011; Prell et al. 2014).

In the LTI Change Function block, we also see a negative, significant coefficient for GDP per capita in relation to LTI, suggesting that wealthier, more developed countries tend towards being net importers of land, a finding reflective of past research suggesting that wealthy countries essentially 'outgrow' degrading their home environments, even as their economies continue to grow overtime (Bhattarai and Hammig 2001; Dinda 2004; Stern 2004). Such a finding also offers further support for the idea that poorer, developing countries are characterized by relatively more land-intensive or environmentally-harmful economic activities.

The results for the Land per capita-based effects are also noteworthy: the negative, significant *Land per capita ego,* in the Trade Change Function block for Models 3-4, indicates that countries with larger land endowments form fewer export ties overtime. However, the positive, significant coefficient for the *effect of Land per capita on LTI*, in the LTI Function block, suggests that countries with larger land endowments are more likely to become net exporters of land. Taken together, these two results suggest that countries with larger land endowments are more likely to become net exporters of land (Moran et al. 2013), but they are not likely to increase, on the whole, their number of strong export ties overall.

4 Discussion

Altogether, Models 1-4 underscore the presence of a positive feedback between trade tie formation and changes in countries' land trade imbalances, or LTIs. Countries' tendencies to form strong export ties to wealthier countries are driven by their ability to specialize in land-intensive exports, and similarly, this pattern of exporting to wealthier countries also leads, overtime, to becoming or maintain being a net exporter of land. Identifying this feedback loop lends support to ongoing discussions about the unequal trade patterns between rich and poor countries that result in uneven distributions of negative environmental impacts. Further, evidence for this feedback loop is present even when controlling for a number of underlying mechanisms, such as countries' land endowments, their geographical distance from one another, and a number of underlying, endogenous network tendencies.

In the present context of a telecoupled 'land and trade' system, the export of land-intensive commodities is an indicator of countries' putting stress on their own stock of natural resources (in this case land and associated ecosystems and their services) to meet consumer demand elsewhere, i.e. mainly consumers in developed countries. When poorer countries increase their levels of land-intensive exports, above and beyond their level of land-intensive imports, they are potentially placing themselves in a situation where they are stressing their land/environment in order to satisfy the wants/demands of consumers elsewhere. Such a feedback loop will likely persist for the foreseeable future, moreover, as emerging economies such as China, India and Brazil continually seek opportunities to expand their markets via developing a comparative advantage in land-intensive (and other environmentally stressing) commodities (Roberts and Parks 2007).

With regards to potential future consequences: the feedback loop we have uncovered here that links human consumption to environmental stress, has accelerated over the last few decades through the annihilation of space and distance with global trade but also reflecting other drivers such as lifestyle change and economic growth. We do not see such an acceleration slowing down any time soon. Supply chains have become truly global -- linking virtually every person and place for purposes of production and consumption. This paper clearly models this (tele-)coupled interaction(s) over time. We also note that the time period of our study (2000 to 2010) was a period when China joined the WTO and became *the* global manufacturer.

In an increasingly globalized world, developing frameworks that clarify spatially distant feedbacks in social-ecological systems is necessary, not only for demonstrating how environmental consequences are a shared responsibility between consumers and producers of commodities (Lenzen et al. 2007), but also, in demonstrating that these environmental consequences are unevenly distributed among countries, and actually work to reify traditional forms of global inequality. Such a framework and empirical demonstration(s) is important as policy makers, and individual consumers, attempt to move forward to address global sustainability.

APPENDIX

Figure A1: GOF tests for trade ties.

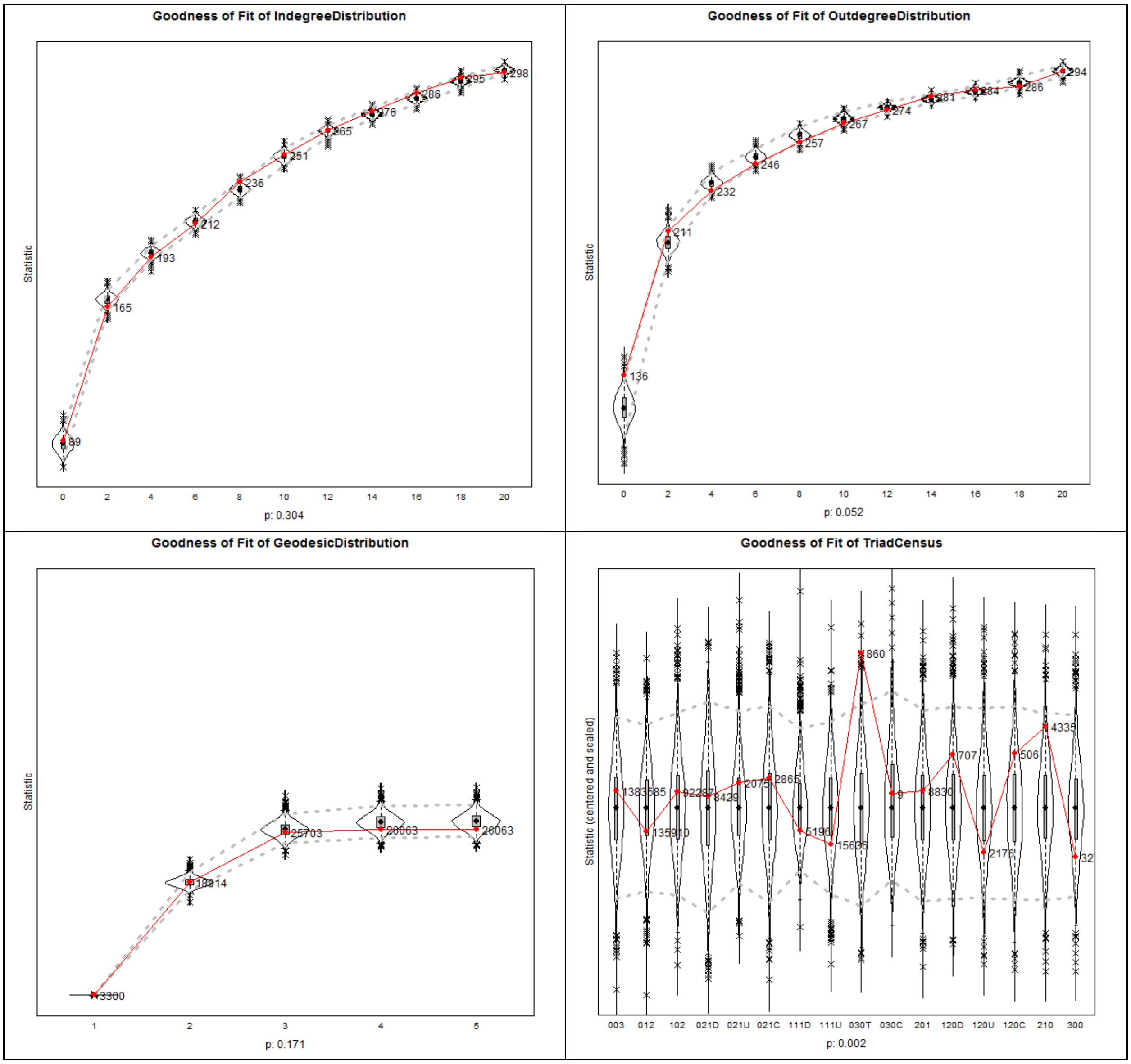

Table A1: Descriptive Statistics of the Basic Variables

	N	N missing	Mean	St.Dev.	Correlations between key variables		
					Ln(GDPpc)	Ln(Landpc)	Outdeg
Year 2000							
Ln(LTI)	166	6	6.6	2.28	-0.691	0.363	-0.438
Ln(GDPpc)	167	5	7.66	2.14	---	0.079	0.548
Ln(Land pc)	165	7	4.94	1.37		---	0.038
Outdegree	172	0	1141.99	323.47			---
Year 2005							
Ln(LTI)	168	4	7.87	2.25	-0.650	0.343	-0.408
Ln(GDPpc)	168	4	8.11	2.04	---	0.052	0.568
Ln(Land pc)	166	6	4.97	1.33		---	-0.009
Outdegree	172	0	1289.35	325.93			---
Year 2010							
Ln(LTI)	169	3	7.2	2.18	-0.622	0.359	-0.381
Ln(GDPpc)	165	7	8.51	2.25	---	0.022	0.593
Ln(Land pc)	168	4	4.85	1.27		---	-0.040
Outdegree	172		1403.75	331.06			---
All Years							
Ln(LTI)	503	13	6.87	(2.22)	-0.593	0.346	-0.335
Ln(GDPpc)	500	16	8.09	(1.63)	---	0.042	0.593
Ln(Land pc)	499	17	4.94	(1.01)		---	-0.015
Outdegree	516	0	1278.34	(343.38)			---

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