UNVEILING SPATIAL DYNAMICS, DRIVERS, AND COMPLEMENTARITIES OF METACOUPLED MANGROVE HUMAN-NATURAL SYSTEMS

By

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ABSTRACT

The mangrove socio-ecological system is invaluable and has provided multiple ecosystem services to human beings, such as livelihood support, wildlife conservation, coastal resilience, and high carbon storage[1,2]. They have been globally converted for commodities such as palm oil, farmed fish, and agricultural cultivation in the past two decades[3–6] driven by international trade. However, the mechanisms and dynamics have not been explored much, with only sporadic discussions in deforestation studies. These studies found that consumers and laborers from neighboring and distant nations have exerted profound pressure on local forest loss[7–9], including mangrove forests. A growing body of literature has explored how global forces can be understood using integrated frameworks and models. For example, metacoupling framework can systematically address interactions across geographic borders, which categorize the human-nature interactions into different coupling types based on their geographic relationships to a specific system[10–12]; the IPAT/STIRPAT model statistically considers socio-economic factors such as population, affluence, technology, and other variables to examine their influences on environmental outcomes; and Sustainable Development Goals(SDGs) framework from the United Nations blueprints comprehensive sustainable goals for nations to fulfill by 2023.

My dissertation is to apply these tools to understand the spatial dynamics (chapter 2), drivers (chapter 3), and complementarities (chapter 4) of the mangrove human-environment system through its metacoupled interactions (chapter 1). Chapter 1 expands the metacoupling framework from a global market perspective to understand how international trade interacts with focal mangrove human-natural systems across space. Chapters 2 & 3 quantitatively explore the relationship between international trade and mangrove loss at the national scale. In particular, chapter 2 measures mangrove loss footprint, defined as the mangrove loss consumed to meet a

country's final demand, and provides a fine-scale representation of spatial patterns of mangrove loss footprint. Chapter 3 comprehensively examines the driving forces behind anthropogenic mangrove loss embedded within global supply chains. Chapter 4 takes Indonesia as an example to understand the policy pathways to achieve mangrove conservation success and sustainable development by understanding their complementarities. Lastly, Chapter 5 synthesizes the main conclusions in the dissertation and emphasizes the critical role of metacoupling interactions in mangrove conservation and governance.

As a result, Chapter 2 finds Japan, the USA, and China are the top 3 mangrove loss importers who outsourced their consumption to other countries' mangrove forests, while Indonesia, Myanmar, and Vietnam are the top 3 mangrove loss exporters whose mangrove losses are outsourced to other countries' consumption. Chapter 3 demonstrates the robustness of the IPAT/STIRPAT theory by investigating the driving forces behind mangrove loss embedded in international trade, showing that a 1% increase in population and GDP per capita results in a 0.925% and 0.629% rise in the mangrove loss footprint, respectively. Moreover, GDP per capita exhibits a significant positive elastic relationship with distant mangrove loss footprints, where a 1% increase in GDP per capita growth leads to more than a 1% rise in distant mangrove deforestation. Chapter 4 conducts a comprehensive network analysis by following the 'product space' method in economics and creates the 'Mangrove-SDG space' to explore the intricate interactions.

The research is the first to comprehensively evaluate the relationship between mangrove loss and global supply chains and pioneering work to decompose the drivers of mangrove loss from consumer perspectives and accounting for the geographical context. The metacoupling framework provides new integrated perspectives on the socio-economic drivers of mangrove ecosystems, which can help proactive strategies for mangrove conservation and global sustainability.

To Ashley and Erin

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CHAPTER 1: INTRODUCTION

1.1 Background

Mangrove forests can provide multiple ecosystem services to human beings, including economic benefits, coastal resilience, and high carbon storage[1,2,13,14]. However, during the past two decades, remote sensing studies have identified the extensive loss of mangroves in tropical forests. Mangroves have been negatively affected by activities for commodities such as palm oil, farmed fish, and agriculture cultivation[3–6,15,16]. However, these studies only demonstrate where land-use change has occurred but there is a strong need to address how land-use decisions are increasingly affected by the supply chain and how to explain the conversion driven by international trade activities.

Local land-use decisions are increasingly caused by and moderated by external actors[12,15,17]. Further, as regions become more interconnected, effective strategies for balancing the local challenge of resource use and conservation are increasingly linked to external causes. Metacoupling Framework (MCF) provides a holistic understanding of the interdependencies between local coupled human-nature system and their external actors across space qualitatively. It has explored the dynamics, impacts, mechanisms, and structure of external interactions to explain many environmental challenges such as biodiversity loss[18–21], climate change[22], food security[23,23–27], and deforestation[28–30]. However, our understanding of how these external interactions influence the mangrove ecosystem is limited. For example, how do global interactive forces impact local land-use decisions in mangrove exploitation? Are distal forces the root causes of mangrove habitat change? Answering these questions requires both a conceptual framework and an empirical assessment of the causes of mangrove ecosystem loss.

This chapter applies the metacoupling framework to systematically understand the complexity of the human-nature mangrove system and provide a qualitative foundation for future chapters to empirically understand its dynamic flows and unveil the drivers and mechanisms for explaining global mangrove loss.

1.2 Conceptual Framework

Mangrove human-nature system

A mangrove coupled human-nature system (M-CHANS) is an integrated and complex local socio-ecological ecosystem (SES) in which humans and nature interact within mangrove forests [31]. It brings together the theoretical and analytical techniques from both ecological and social sciences to understand the nuances of the complex mangrove system[32]. It consists of two main subsystems: the natural environment and the human subsystem. The natural environment, in our case, would be the biophysical conditions of the mangrove ecosystem, while the human subsystems are comprised of stakeholders with decision-making rights that can influence mangrove exploitation and conservation, including conservation organizations, local governments, and corporations with mangrove properties[33]. The characteristics of these two subsystems are closely interrelated and influenced by each other. For example, a positive interaction would be local communities encouraging mangrove restoration projects that would bring income to residents. In contrast, when residents convert mangrove habitats, local mangrove ecosystems are degraded; this will decrease household incomes because it affects wildlife, such as fish, utilized as food resources.

The concept of a market and its invisible and visible hands.

Since our study investigates the driving forces of international trade in the mangrove ecosystem, we use the market concept to understand the human subsystem in the M-CHANS and its interactions. Markets exist when groups exchange transactions, which means a group of people desire to obtain certain things while other groups can provide supplies depending on their needs.

The functional definition of a market is to allocate resources and meet a balance between supply and demand with a determination of relative prices[34]. However, demand and supply can be amended or replaced by institutions, production technology, and income effects. These indicators are affected by the local biophysical conditions and the decisions of the human communities they rely on. Therefore, the market's role is constrained by geographic locations and factors mentioned above, which interact with each other in the form of specific prices and quantities[34]. Table 1.1 lists the fundamental institutions in the market and their driving forces and actions related to the mangrove ecosystem.

Table 1.1: Components of a market and its driving forces, actions, and agents related to the mangrove human-nature system.

	Driving factors	Actions	Agents
Visible hand	Biophysical conditions; Economic security; Political stability	Policy objective and responses	Governments
	Values	Public awareness and Ecosystem services evaluation	Communities
Invisible hand	Population; affluence; Globalization	Agricultural expansion; Urbanization; Shrimp farming	Industries

The market is an essential component in the human subsystem of mangrove coupled human-nature system. Local agents' decisions to maintain or utilize their lands depend on the local markets' prices and quantities of certain commodities from local ecosystems. Meanwhile, their decisions on commodities in the local ecosystem, in return, will change the market's supply and demand, which will restructure the market and affect buyers and sellers who set competitive prices and exchange products. This allocation mechanism metaphorically denotes an "invisible hand."[35,36] The invisible hand mediates the increasing demand of the growing population and global markets in fierce land competition with mangrove forests. The competition attracts local opportunists to keep converting existing mangroves into shrimp, agriculture and other commodity plantations, and other coastal developments from the urbanization processes for financial gain.

Unfortunately, the unsustainability of invisible hands among interconnections between supply and demand of the market has never been more evident. Institutions across geographic scales play an irreplaceable role in protecting the common-pool resources such as mangrove forests, otherwise known as a “visible hand”[37–39]. Institutions such as government and communities, which have the power to integrate societal norms and rules, can equitably or sustainably manage their resources by setting tangible objectives in maintaining political stability, environmental sustainability, or economic security. These goals will arrange the demand and supply of the global market. Further, non-governmental organizations, communities without formal social structures, and companies rethink their working styles and life practices and reshape their interactions with others and nature.

Global market and metacoupled human-nature systems

Nowadays, more and more local markets are involved in a global market, with social institutions deciding the quantity of commodities exchanged. Prices fluctuate due to supply and demand, as shown in Fig. 1.1 These social institutions facilitate and structure the market at global and local divisions through prices and policies, and local decisions from stakeholders will affect the demand and supply. In contrast, global market prices will hugely reframe local decision-makers strategies to distribute their natural resources. Taking the mangrove ecosystem as an example, the global market, in response to the increasing demand of growing populations, increases the price of commodities[16]. The high economic value of commodities attracts local land users to convert mangrove forests into shrimp farms, agriculture, and other commodity plantations to meet global needs. As a result, the loss and degradation of mangrove ecosystems result in the rearrangement of the local supply of goods and services, affecting not only the local mangrove CHANS but also the supply and demand of the global market. These processes include different coupling interactions across space. Fig. 1 shows how local market-based Mangrove-CHANS is associated with the global market and the different coupling interactions across space in incorporating Liu's metacoupling framework[10].

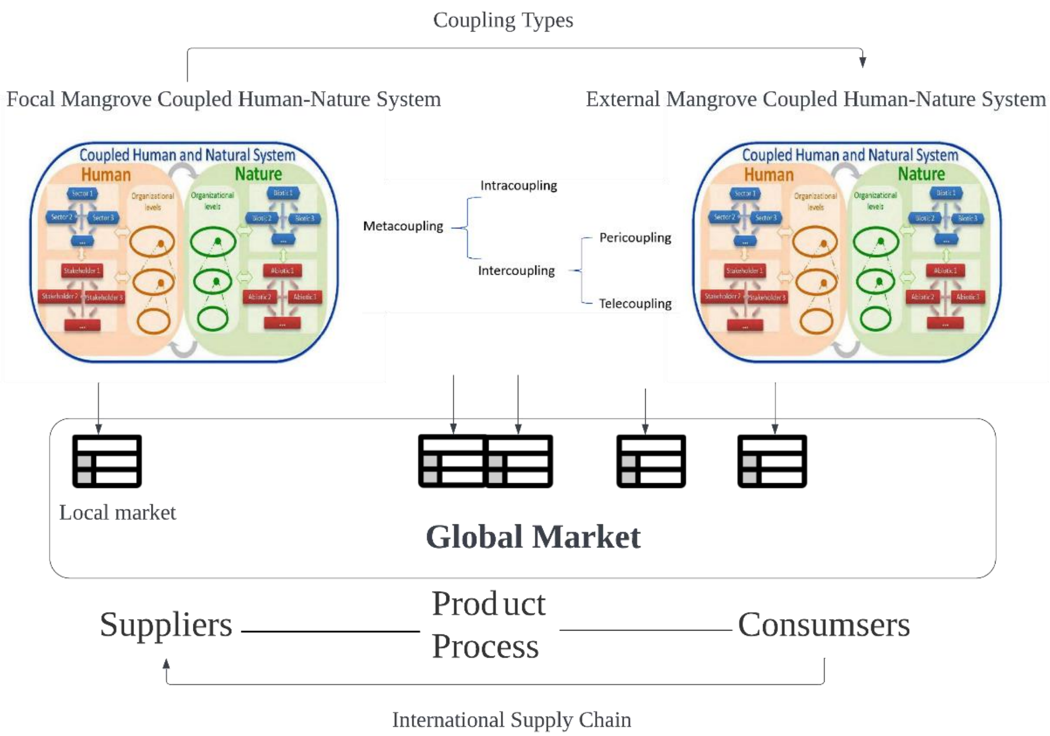


Figure 1.1 (Fig. 1.1): Global market and mangrove metacoupled interactions adopted of Liu's CHANS and metacoupling frameworks[10,31,32].

Examples of intracoupling include local road construction, consumption by local households, fish harvesting, and the collection of mangrove branches for charcoal. These are all human-nature interactions within a local coupled human and natural system, albeit with connections to the larger world.

The pericoupling framework refers to interactions between adjacent systems, such as trade to nearby countries for products hard to transport or with low per unit value, consumption from institutions for exploitation or conservation expenditures in adjacent countries, etc. The nearby places may share similar political, geomorphic, and cultural settings, but their impacts on the environment are separate. They are not influenced by the socio-economic settings of the focal system. Therefore, their human-nature interactions need to be examined distinctly from local ones. In the mangrove case, which has dense roots and is sensitive to intertidal changes, its natural habitats are hard to be separated by political boundaries while the ecosystem services mangrove forests can increase or degrade are shared among mangrove-holding countries. Mangrove forests' pericouplings are distinctive to telecouplings and must be discussed separately. For example, mangroves will be affected directly by local land conversion(intracoupling) and indirectly degraded by nearby countries' plantations, which emit nitrogen and phosphorus into the water and lead to eutrophication and damage the living conditions of its nearby mangrove forests (pericoupling)[4,40]. Further, dam construction in upstream areas will affect the salt-fresh water exchange[41], which, in consequence, can degrade the mangrove ecosystem downstream. Another example could be conservation institutions in the focal country raising funding to stop their nearby country's mangrove exploitation, which can benefit the condition of their domestic mangrove forests and the related ecosystems[5,42]. These are examples of pericoupling interactions.

Telecoupling is the most discussed type of external forces, which act across distances and can shape the residents' local land-use decisions. International trade activities between countries that are not geographically close to one another, usually for products with high per-unit values relative to their transaction cost over distance, are the main drivers examined in telecoupling research[43,44]. Several studies have illustrated the potential mangrove threat from commodities such as shrimp, rice, and especially emerging palm oil plantations driven by distal market demand with high profits compared to their transport and production costs[39,45] regardless of the economic values mangroves can provide through ecosystem services. Other examples of telecoupling include the labor demands by urban centers that generate rural-urban migration and reduce the local population [33] and the conservation spending from distal countries that brings conservation efforts and restoration projects to mangrove-deforested areas[42,46].

In summary, to comprehensively examine the role of international trade on mangrove human-nature systems, we first understand international trade from a market perspective by decomposing the market's driving forces, actions, and agents. We then incorporate a metacoupling framework to offer a systematic view of the mangrove human-nature system. By recognizing that human and natural systems are interconnected and mutually form complex interactions across multiple geographic scales, the framework can holistically understand the potential drivers and their mechanisms in explaining the global mangrove forest loss[47].

CHAPTER 2: MANGROVE LOSS FOOTPRINT MAPPINGS

Abstract

Declines in mangrove forest cover have raised global concern for decades, given the numerous ecosystem services these forests provide. However, the root causes of this loss still need to be explored, particularly through the lenses of globalization and international trade. Although past research has used case studies to link mangrove deforestation to the production of distant commodities as drivers, there has yet to be a comprehensive evaluation of the relationship between mangrove loss and global supply chains. This study provides a fine-scale representation of spatial patterns of mangrove loss associated with international trade by linking 30m*30m remote sensing data with a multi-region input-output model and quantifying their spatiotemporal changes in three periods from 2000 to 2016. Moreover, the study adopts a metacoupling framework, which provides a holistic understanding of the interdependencies between the local coupled human-nature systems and their external actors (adjacent and distant) to understand how global consumption across space drives mangrove forest changes. Results indicate that mangrove loss in each country is largely driven by domestic consumption; however, consumption by developed economies has influenced mangrove losses beyond their own borders. Japan, the USA, and China are the top 3 mangrove loss importers who outsourced their consumptions to other countries' mangrove forests. These countries mainly outsourced to distant countries, with a decreasing trend in outsourced loss from 2000 to 2016. China has the slowest declining rate and became the largest importer of mangrove loss in 2011-2016, with its mangrove loss footprint expanded from nearby Southeast Asian countries in 2000-2005 to distant countries such as Guinea and Madagascar in 2011-2016. In comparison, Indonesia, Myanmar, and Vietnam are the top 3 mangrove loss exporters whose mangrove losses are outsourced for other countries' consumption. These countries are hotspots of mangrove loss embodied in international trade and biodiversity hotspots. Our results emphasize the need to use mangrove loss footprint mapping approaches to monitor, evaluate, and implement mangrove regulatory policies and provide science-based interventions for mangrove conservation with better supply chain transparency and stronger transnational efforts.

Keywords: mangrove loss footprint, global supply chains, spatially explicit,

2.1 Introduction

Mangrove ecosystems thrive within intertidal zones of tropical and subtropical coastlines. They nurture marine life, bolster local economies, mitigate poverty, sequester carbon, and participate in global climate regulation[1]. These vital services are threatened by mangrove deforestation, which has been as high as 35% during the 1980s-1990s and continues to raise the alarm at an annual rate of 1% to 8% between 1980 and 2012[4,48,49]. Global mangrove ecosystems are further threatened by escalating population growth, particularly in coastal regions, exacerbating recent net deforestation trends.[5,6,16,50–53] However, identifying the underlying drivers of mangrove forests has been challenging, particularly given the variation caused by the dynamic flux of landforms, climate change, and the erosive dynamism of extreme events[54–56]. Moreover, mangrove ecosystems display substantial heterogeneity driven by abiotic contexts, forest configurations, species richness, and regional disparities[54]. Hence, while numerous case studies delve into the intricacies of localized mangrove loss drivers and their interplay[57,58], a conspicuous research gap persists concerning a comprehensive global exploration of these drivers and their interactions.

Land change science has quantified mangrove forest dynamics across spatial scales, with analytical improvements propelled by the availability of high-resolution satellite imagery. Illustratively, Hamilton and Casey (2016)[53] mapped the planetary ebb and flow of mangrove extents, leveraging pre-existing datasets, such as the comprehensive mangrove map crafted by Giri et al.[56], the global forest change atlases devised by Hansen et al.[59], and the terrestrial ecosystems database enveloping the world's biomes[60]. Hamilton and Casey converged these datasets into an intersected mangrove map, enabling the quantification of global mangrove cover change from 2000 to 2014 at the granularity of 30 meters. Thomas et al. (2017)[16] created an alternative dataset, harnessing radar datasets systematically collected across the planet, with particular emphasis on data from the

Japanese L-land sensors. Their comprehensive dataset, hosted on the Global Mangrove Watch platform, encompasses mangrove coverage during two distinct epochs: 1995-1997 and 2007-2010. By amalgamating resources from multiple time-series radar composite imagery, this dataset provides a nuanced depiction of mangrove dynamics. Notably, this dataset has undergone updates, with the latest iteration, as of 2022, attributed to Bunting et al.[6,52]. This update extends the dataset's reach, documenting global mangrove forest changes and gains from 1996 to 2020, enriching our understanding of long-term trends. The most recent insights into mangrove loss and its underlying drivers have been expounded upon by Goldberg et al. (2022). Their seminal work underscores the significant human-induced mangrove losses, with a staggering 62% of global losses between 2000 and 2016 attributable to land-use changes, primarily stemming from conversions to aquaculture and agriculture. These insights provide a critical foundation for comprehending the complex dynamics of global mangrove ecosystems and their vulnerability to anthropogenic influences.

The global transition of mangrove forests is typically studied through the synthesis of localized case studies, and the discourse surrounding this topic has unearthed an array of drivers influencing mangrove losses across diverse spatial scales[58,61–63]. Interestingly, these independent inquiries have a common finding: trade plays a pivotal role in the degradation and deforestation of mangrove ecosystems. Friess et al.[4] traced this relationship over millennia to its nascent origins in the Middle East approximately 6500 years ago and found that the evolutionary trajectory of mangrove resource usage witnessed a transformative phase with industrial practices; that is, the voracious demand for mangrove timber, driven by the imperatives of shipbuilding, was discernible under the auspices of Spanish and German colonial administrations in the 1750s. Furthermore, the comprehensive synthesis conducted by Bhowmik et al. (2022)[57], which scrutinized two hundred published papers from 1980 to 2021, aimed to unravel the intricate tapestry of social-ecological drivers underpinning the global deforestation of mangroves. These studies employ divergent methodological approaches but converge on recognizing commodities, notably aquaculture and agriculture, as the predominant catalysts driving global mangrove deforestation, impacting regions worldwide[64].

In response to the far-reaching influence of economic globalization over the last two decades, a growing body of research has underscored the harmful ramifications of international trade on local environments. A compelling instance lies in studies identifying a symbiotic relationship between China's economic surge and shifting dietary preferences toward meat products. This dietary transformation, primarily to satiate the appetite for pork, has triggered a rise in soybean imports from Brazil, resulting in Amazon deforestation, including mangrove ecosystems[7,8,65,66]. Another study has explored the economic beneficiaries of the commercialized products of large agribusiness enterprises in Thailand. It underscored that a mere 17% of the workforce employed in mangrove concessions hails from residents of mangrove forests, and the other beneficiaries are outsiders[9]. These studies have pointed out that examining deforestation at only the domestic level can lead to misleading interpretations of its drivers. Notably, consumer demand in other countries may instigate the drivers of forest loss in one region. Moreover, to compensate for the environmental pressures caused by international trade, countries such as the USA, Japan, France, China, and India have embarked on mangrove restoration initiatives, resulting in forest cover gains. Nonetheless, the complex entanglement between these gains and the continued imports that entail 'embodied' mangrove loss in distant regions remains an enigmatic problem, underscoring the need for a nuanced scientific exploration of the intricate dynamics of international trade vis-à-vis global-scale mangrove deforestation.

The metacoupling framework (MCF) provides a holistic understanding of the interdependencies between locally coupled human-nature systems and their external actors (adjacent and distant) across space qualitatively[10,22,47]. It has explored the dynamics, impacts, mechanisms, and structure of external interactions to explain many environmental challenges such as biodiversity loss[18–21], climate change[22], food securit[y23–27], and deforestation[28–30]. However, our understanding of how these external interactions influence the mangrove ecosystem is limited. This chapter is the first investigation to understand global mangrove loss embodied in international trade. It also provides the first spatially explicit map that traces the spatial patterns of the mangrove loss footprint to better understand mangrove dynamics. Using high-resolution mangrove loss data at 30m*30m, a spatial classification of mangrove loss drivers, and a detailed global supply chain model, we visualize the map-based comprehensive synthesis of how international trade drove the spatiotemporal changes in global mangrove loss from 2000 to 2016. Our research answers three questions: (1) How can spatially explicit mangrove loss footprint maps be calculated and visualized? (2) Which mangrove loss hotspots are driven by which consumer countries? (3) How do geographic factors (adjacent vs distant) of international trade affect mangrove deforestation?

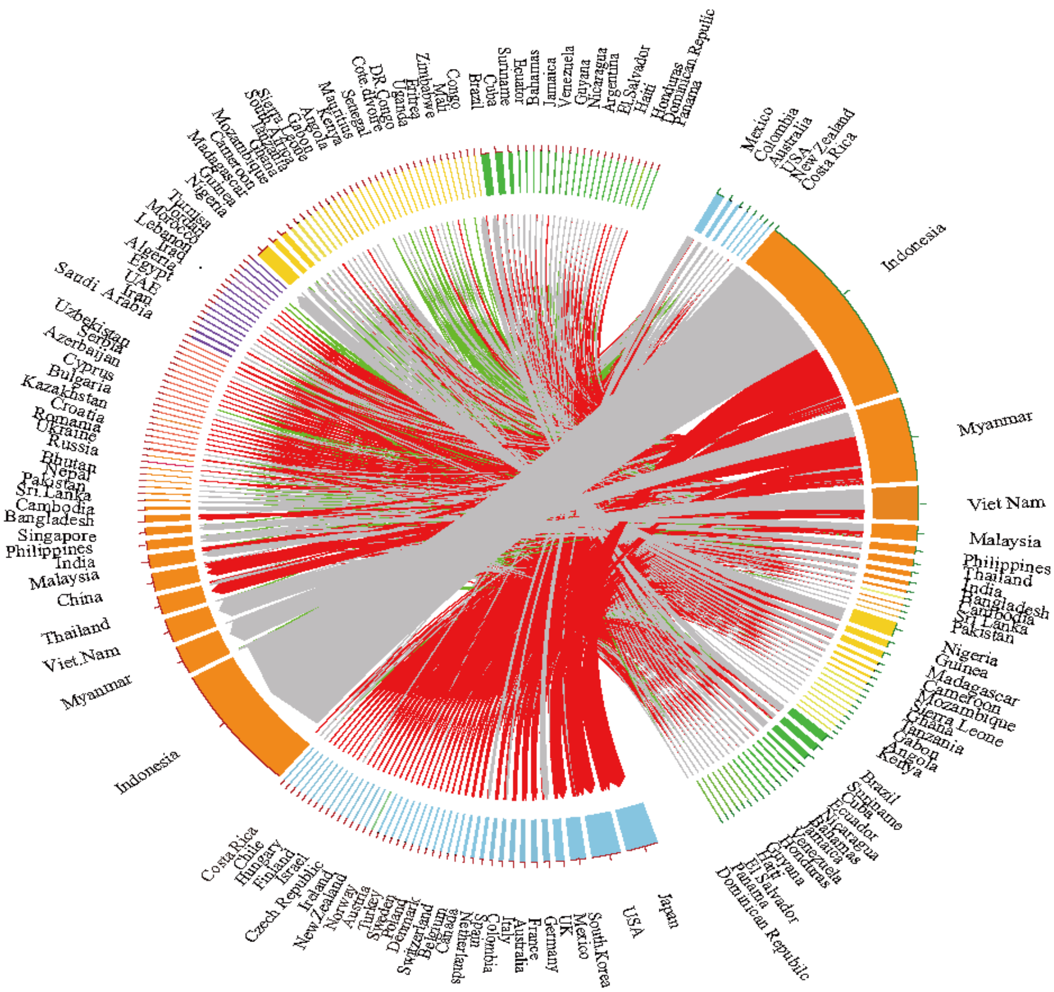
Table 2.1: Concept clarification.

Concepts	Definitions	Description	Method	References
Mangrove loss	Direct mangrove loss from the ground through remote sensing data. It is measured as the complete removal of tree cover exceeding a height threshold of 5 meters within the mangrove habitat.	The final products include spatial-explicit raster data with 30m*30m resolution per mangrove driver per epoch in 39 countries and aggregated mangrove loss dataset per country per driver per epoch in 72 countries in three periods: 2000-2005, 2005-2010, and 2010-2016	Remote Sensing	Goldberg et al. (2022)
Human-induced mangrove loss	Mangrove loss from the ground due to direct human-related conversion: commodities, human settlement, and non-productive conversion	same as above.	Remote Sensing	Goldberg et al. (2022)
Mangrove loss footprint (Trade-adjusted mangrove loss)	Mangrove loss that is consumed to meet a country's final demand, such as local mangrove conversion to commodities exported and consumed abroad. It is the loss caused by final demand through the global supply chain.	Mangrove loss footprint is measured for 189 countries in the Eora database for three periods: 2000-2005, 2005-2010, and 2010-2016. The Eora sectors are aggregated to link with mangrove loss's anthropogenic drivers and then connected to spatially explicit human-induced loss to calculate the mangrove loss footprint.	MRIO+ Remote sensing+ GIS mapping	Goldberg et al. (2022); Hoang et al. (2021)

2.2 Results

Our analysis establishes a nuanced linkage between global mangrove loss data from 2000 to 2016 and the intricate worldwide supply chain model[5,51,67]. We create detailed, high-resolution global mangrove loss footprint maps and pinpoint potential deforestation footprints at a granular pixel level. This enables the dynamic tracking of spatiotemporal changes and facilitates a comprehensive understanding of global-scale mangrove forest dynamics from 2000 to 2016 embedded in international trade.

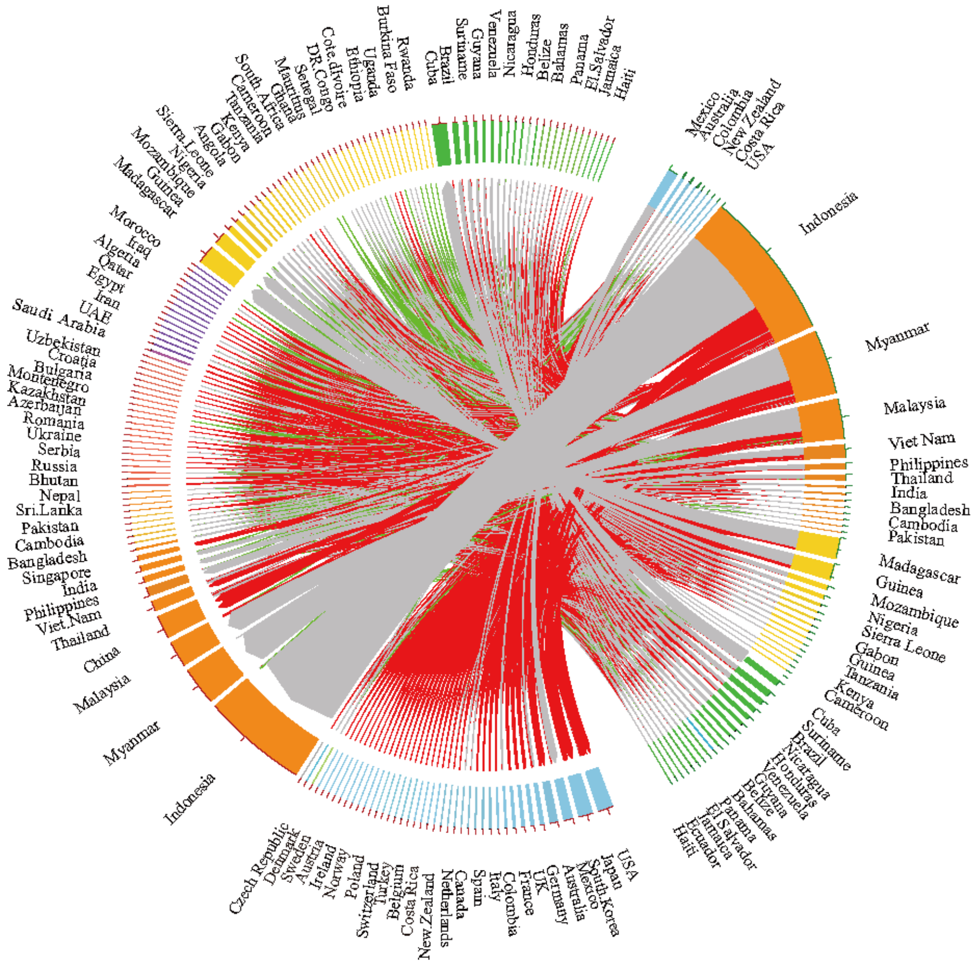
2.2.1. Mangrove-holding countries' consumption drives the most domestic mangrove loss, while mangrove losses driven by distant high-income and OECD countries are second.



(a)

Figure 2.1 (Fig. 2.1): Mangrove loss footprint flows (km2) between mangrove-holding countries and consumer countries in (a) 2000-2005

Figure 2.1 (cont'd)



(b)

Mangrove loss footprint flows (km2) between mangrove-holding countries and consumer countries in (b) 2011-2016. Mangrove-holding countries are marked by green outer circle bars, and consumer countries are marked by red. The arc length of the circle indicates the sum of consumption exported and imported between the mangrove-holding and consumer countries. The arc color of the circle indicates the region of countries, which is ordered by their geographic location. The red color of mangrove loss flows suggests that the consumption of higher-income countries drives lower-income countries' mangrove loss, and the green color is the opposite.

As shown in Fig.2.1, by comparing the flows between consumption and sourcing patterns in 2000-2005 (a) and 2011-2016 (b), the main trading partners in mangrove deforestation include many Southeast Asian countries and some Latin and African countries, such as Indonesia, Myanmar, Vietnam, Malaysia, Nigeria, Guinea, Madagascar, Cuba, and Brazil. These mangrove-holding countries export mangrove-risk commodities (such as shrimp, rice paddy, coffee, palm oil, and timber) to satisfy their consumption and consumptions in OECD countries (for example, Japan, USA, South Korea, Mexico, Germany), China, and India. Indonesia is the largest mangrove loss exporter, with 34% of its loss driven by consumption from high-income or OECD countries such as USA, Japan, South Korea, China, and India. Moreover, Indonesia's mangrove loss is identified to be driven by geographically distant consumer countries (Fig. 2.2c). Similarly, the top 20 mangrove-holding countries' mangrove loss is also significantly driven by distant consumption (Fig. 2.2c).

Of the top 20 consumer countries that drive mangrove loss, fifteen are mangrove-holding countries (Fig. 2.2d). Most of these countries are low—and lower-middle-income countries, whose mangrove loss is driven by domestic consumption. Exceptions include China, Thailand, and India, which have much mangrove loss driven by adjacent consumption. Countries such as Japan, the United States, Korea, Singapore, the United Kingdom, and Germany have driven mangrove loss in distant countries. These high-income countries transfer their consumption through international trade to mangrove-holding countries.

2.2.2 Although consumer countries imported distant mangrove forests rather than consuming their forests, their import percentage decreased from 2000 to 2016.

As shown in Fig. 2.1, high-income and OECD countries such as Japan, the USA, South Korea, China, India, and Singapore mainly imported mangrove loss from other countries rather than consuming their mangrove forests. This phenomenon is reflected in the red flow lines in the graph, which show that countries with higher-income consumption drive lower-income countries' mangrove loss. For example, the USA imported 72 and 11.76 (km2) mangroves globally, while its own country's mangrove loss was 1.89 and 0.018 (km2) in 2000-2005 and 2011-2016, respectively. Moreover, the relationship between local mangrove loss in mangrove hotspots and external consumers varies in countries and needs case-by-case discussions.

In addition, the total amount and percentage of mangrove loss exported to consumer countries decreased between both epochs. In Fig. 2.1, we notice that the domestic consumption percentage increased in 2011-2016 compared to 2000-2005 in representative mangrove-loss countries such as Indonesia, Myanmar, Vietnam, Malaysia, Madagascar, Guinea, and Cuba. For example, domestic consumption in Myanmar took 13 % in 2000-2005 and 41.3% in 2011-2016. This indicates a decreasing trend of mangrove forest consumption in external countries from 2000 to 2016. Moreover, in Fig. 2.2-a and b, the top 10 countries that either outsource their consumption to external mangrove-holding countries or countries whose losses are attributed to external consumption have a decreasing trend in their losses from 2000 to 2016.

2.2.3 The top 10 countries that outsourced their consumptions are from OECD and high-income countries except Thailand, and they outsourced mainly from distant countries.

In Fig. 2.2a and b, we compare the differences between actual and trade-adjusted mangrove loss and select the top 10 countries' insourced and outsourced mangrove loss in three periods. Southeast

Asia countries, such as Indonesia, Myanmar, and Vietnam, are the central mangrove resource-providing countries, i.e., the top insourcing countries. The differences between countries varied in different epochs. For example, Indonesia and Myanmar alternate as the countries with the most insourced mangrove loss. Some emerging countries, such as Malaysia, could potentially take more losses from international trade because the difference in mangrove loss increased as the years passed. Moreover, small countries in Latin America and Africa, such as Guinea, Suriname, Nigeria, and Madagascar, should be prioritized for international conservation policies because they are within the top 10 countries that have mangrove loss driven by external consumer countries and have relatively small total areas to effectively manage.

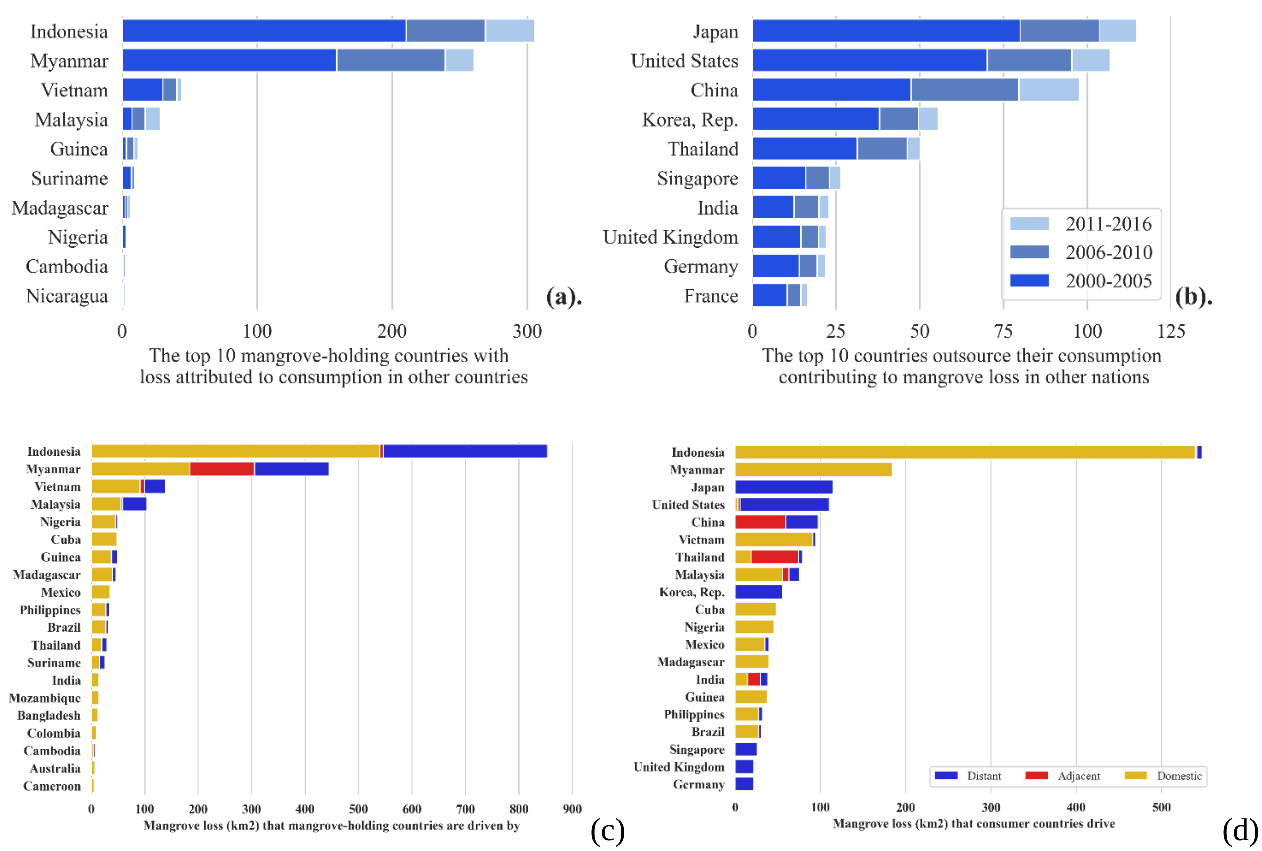


Figure 2.2 (Fig. 2.2): a-b: Top 10 countries (a) insourced and (b) outsourced mangrove loss (km2) in three periods: 2000-2005, 2006-2010, and 2011-2016.

These are calculated by measuring the difference between the in-situ loss and mangrove loss footprint. The in-situ mangrove loss was derived from Goldberg's mangrove loss per country in 65 mangrove-holding countries. The mangrove loss footprint is equivalent to the mangrove loss minus the mangrove loss embodied in exports plus the mangrove loss embodied in imports. Mangrove restoration efforts, shown as mangrove gain, are not considered due to data discrepancy. (c) The consumption's geographic distribution of the top 20 mangrove-holding countries (d) The geographic distribution of mangrove loss in the top 20 consumer countries. Adjacent countries are defined by whether two countries have overlapping political boundaries.

Japan, the USA, and China are the main contributors that transfer their mangrove loss to other countries through international trade. Their differences decreased as the years passed, indicating the total loss embodied in these countries' trade consumptions decreased. However, China's contribution increased to the top in 2010-2016, becoming the country with the most extensive mangrove loss difference between its actual loss and trade-adjusted loss. These countries that outsourced their consumption related to mangrove loss are high-income and OCED countries, except for Thailand. Moreover, these consumer countries outsourced their consumption mainly to distant countries (Fig. 2.2d). The exception lies in China, Thailand, and India. China and Thailand mainly drove the loss of mangroves in adjacent countries, while India relied on its own mangrove forests as well as adjacent countries' resources.

2.2.4 Spatial explicit mapping indicates that US consumption has a more intense impact on closer areas, such as Latin America, due to commodity production, and a smaller effect on distant regions, such as Southeast Asia, through non-productive conversion and human settlement.

As the world's largest economy, the United States substantially influenced global mangrove loss from 2000 to 2016. The intensity of its impact diminishes with increasing geographic distance (Fig. 2.3b, c, and d), such that the region closer to the United States has more intense pixel-level mangrove loss footprints driven by US consumption embodied in international trade. Regions with larger amounts of mangrove loss footprints (depicted in red) are primarily situated in Latin America—encompassing nations like Belize, Nicaragua, El Salvador, and Honduras—and sporadically extend to African countries such as Nigeria and Gabon. The larger footprints in these countries stem from commodities imported by the USA from mangrove-rich nations. Conversely, Southeast Asian countries predominantly exhibit low footprint values (pixels in blue and yellow), mainly driven by non-productive conversion and human settlement consumption patterns originating from the USA.

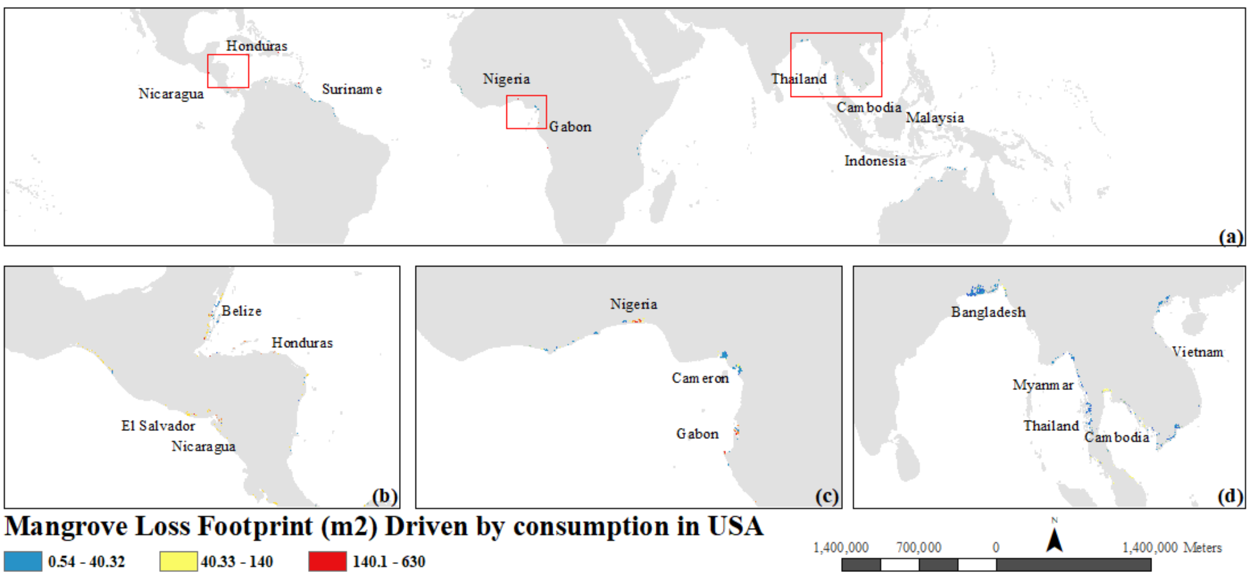


Figure 2.3 (Fig. 2.3): Global spatially explicit mangrove loss footprint map at 30*30m resolution driven by USA consumption from 2000 to 2016. Spatial explicit mangrove loss footprint mappings can depict the drivers and tensity of the USA's consumption.

Most countries with noticeable mangrove losses driven by US consumption in 2000-2005 experienced fewer impacts in 2011-2016 (Appendix S2-1). Exceptions include Indonesia and Madagascar, which maintained their mangrove loss trends in both periods and Honduras, which has an increased mangrove loss footprint. The escalating trend in Honduras is substantiated by remote sensing evidence, revealing extensive mangrove deforestation across the mangrove delta over the past three decades[68,69]. Appendix S2-2-a, c, and d compare the footprint expansion driven by US consumption in these three epochs by applying natural break classifications to categorize mangrove loss footprints in each epoch. US-driven consumption has a varied impact on other countries and needs case-by-case discussion, and no clear expansion patterns are identified across time. For example, US consumption's impact on Latin America and most African countries decreased although some African countries experience more mangrove loss driven by US consumption, such as Madagascar, whose mangrove loss footprint increased from 2000 to 2016. In contrast, Southeast Asian countries had a variety of responses to US consumption.

2.2.5 The overall mangrove loss driven by China has decreased, but its impact on mangrove forests has extended from adjacent to distant countries between 2000 and 2016.

We compare the mangrove loss footprints' changes and expansions in 65 mangrove-holding countries driven by China consumption in three epochs, shown in Fig. 2.4. In Fig. 2.4a and b, the total amount of mangrove loss driven by China has decreased over the years, with the mangrove loss footprint ranging from 0-25.7 in 2000-2005, decreasing to a range of 1-7.03 in 2011-2016. Moreover, China's consumption has expanded its impact from nearby to distant countries, as shown in Fig. 2.4a, c, and d. From 2000-2005, the countries with the worst mangrove loss footprint for China shared boundaries with China in Southeast Asia, such as Myanmar, Thailand, and Vietnam. Suriname is the only country that has a weak mangrove loss footprint that is not in Southeast Asia. The impacts expanded to distant countries in epochs 2 and 3 (2006-2016), where Indonesia's mangrove loss footprint from China increases the most, and more countries in Latin America, such as Cuba and Brazil, and Africa, such as Madagascar and Guinea, also received impacts from China's consumption.

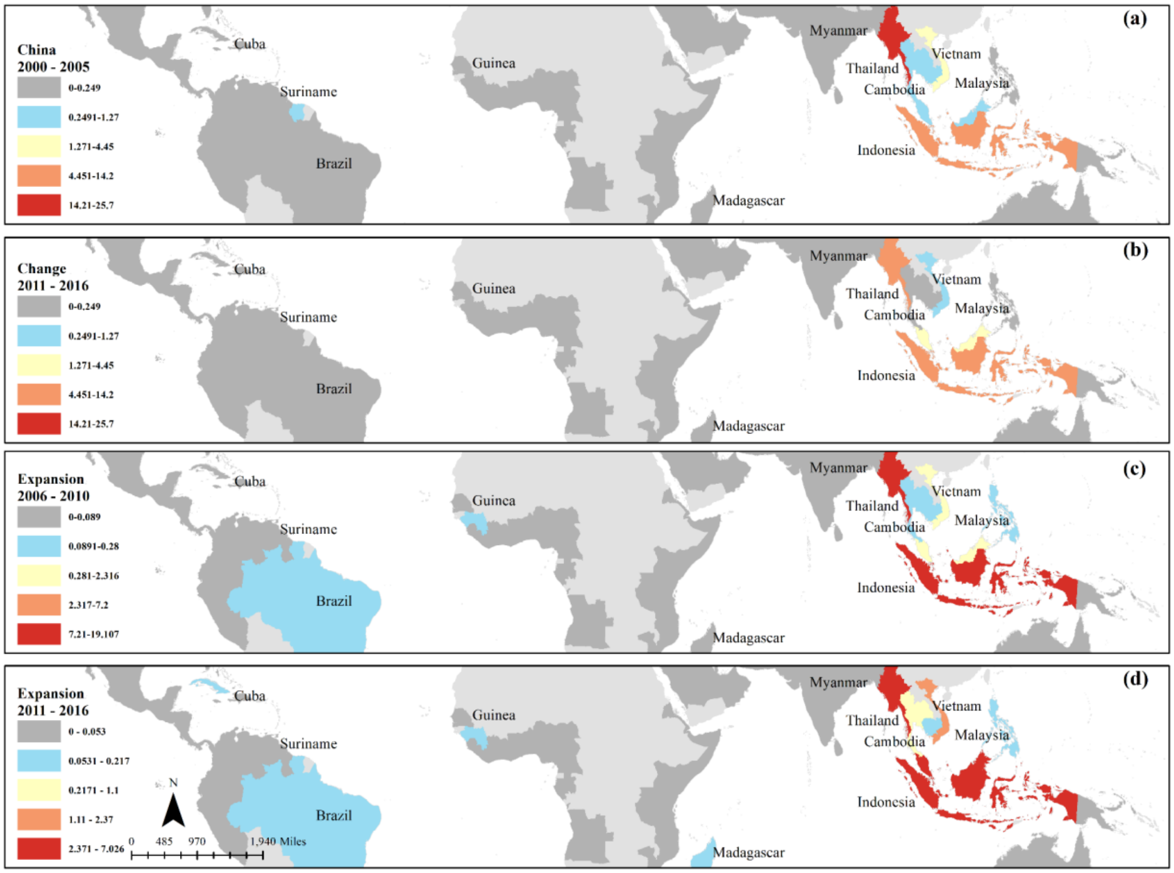


Figure 2.4 (Fig. 2.4): Maps of mangrove loss footprints (km2) driven by China in 65 mangrove-holding countries to compare the changes (a) and (b) and expansion (a), (c), and (d) in three epochs (2000-2005, 2006-2010, 2011-2016) at the country level.

2.3 Discussion

This chapter is the first to calculate mangrove loss embodied in international trade (mangrove loss footprint) and provides fine-scale spatiotemporal maps of the mangrove loss footprint stemming from the demand of different nations. The global mangrove deforestation footprints can play an essential role in creating better regulatory policies and science-based interventions for mangrove conservation, especially in hotspot areas. We can use the maps to determine which consumer countries have driven mangrove loss in various producer countries. For consumer countries, we identify which sectors or commodities induce mangrove forest loss abroad. A similar method has been applied to understand the biodiversity loss and deforestation embodied in international trade, and these studies identified a noticeable amount of loss occurring outside the territorial boundaries of developed economies[44,67,70]. Our analysis has similar findings; distant nations, especially high-income and OECD countries, play a significant role in driving mangrove loss globally, but the trend has been decreasing.

Our results indicate that China, India, OECD and developed economies have expanded their external mangrove loss footprints to other countries where mangrove forests prevail. These consumers, such as Japan, the United States, Korea, Singapore, the United Kingdom, and Germany, mainly drive mangrove losses in distant countries. China and Thailand's consumption also significantly drives losses in adjacent mangrove forests. In contrast, mangrove-holding countries identified as mangrove loss hotspots embodied in international trade are also biodiversity hotspots, such as Indonesia, Myanmar, Vietnam, Malaysia, Cuba, Nigeria, and Madagascar, leading to significant conservation concerns. Although the international drivers of loss tended to decrease from 2000 to 2016, the mangrove deforestation activities remain. Domestic and distant consumptions accounted for the largest proportion of mangrove loss footprint from 2000 to 2016, illustrating their important roles. Because the ecosystem service values of mangrove forests are irreplaceable, a priority for mangrove conservation is to reduce the deforestation induced by domestic and distant consumption through international trade.

Despite these important findings, it should be noted that this analysis has limitations associated with the Eora database's classification and spatial resolution of mangrove deforestation drivers. Firstly, this analysis discusses mangrove loss embodied in the global supply chain, so only mangrove loss associated with anthropogenic drivers in Goldberg's dataset is addressed, and natural drivers such as erosion and climate change are excluded from the study because these two drivers have no visible direct human activity related to industry sectors in the Eora database. A similar exclusion was applied to the deforestation footprint measurement. Moreover, due to the resolution of Goldberg's mangrove loss driver maps, we cannot distinguish specific commodities' contribution, such as long-term/shifting agriculture and aquaculture on the ground; this driver merges various types of commodities in the Eora database with agriculture, aquaculture, wood, and paper, mining and energy infrastructure, and other commodity-related sector that drove loss. Accordingly, we may overestimate mangrove deforestation for the commodities sector when we link mangrove forest loss to the global supply chain. Second, because the Eora database is at the national level, we do not localize the magnitude of embodied mangrove loss for each driver at the subnational level. For instance, the mangrove loss footprint mapping cannot distinguish where farmed shrimp production contributes to exports because commodities are exported from various production areas in one country. Hence, the map pixels are the mean value of the mangrove loss area driven by each driver in the consumer country over the entire production country.

Although limitations exist, this study depicts the mangrove loss footprint at a global scale with high-resolution spatially explicit mappings for the first time. Understanding mangrove loss embodied in international trade can facilitate better regulatory policies for mangrove conservation, especially in those hotspots. For example, since mangrove forests can provide various ecosystem services, such as wildlife conservation, a spatially explicit mangrove loss footprint map can enhance existing deforestation footprint maps. Specific countries can prioritize mangrove conservation policies by incorporating mangrove loss footprint maps with other geospatial resources such as species hotspot maps. In particular, Guinea, Suriname, Madagascar, and Nigeria have been listed as the top 10 countries whose mangrove losses are outsourced for other countries' consumption. Yet, these countries are hotspots for many species and have relatively small areas to manage. These countries can be prioritized for mangrove forest management through international collaborations. By combining the spatial patterns of mangrove deforestation footprint with biodiversity footprints, global policies for reducing the impacts of international trade can be considered in the context of shared benefits for both forest and biodiversity conservation.

Moreover, spatially explicit mangrove loss footprint mappings can improve public awareness of mangrove forest loss embodied in the global supply chain. The global supply chain has traceability and transparency issues, which create the potential for laundering and leakage, and mangrove loss could be subjected to indirect suppliers, unexpected products, or unadopted areas. Moreover, adopting robust policies for private enterprises cannot solve the problem because the supply chain may leak losses to areas with illegal activities or poor forest governance related to public ownership. Therefore, the identification of mangrove loss drivers is challenging and complex. Mangrove loss footprint calculation and mapping provide a spatial and temporal overview of how mangrove loss is associated with producer and consumer countries through the supply chain and also offer policy-makers science-based knowledge in mangrove conservation. They provide a streamlined way to visualize the spatial and temporal mangrove losses driven by the global supply chain, which can be updated when the datasets associated with the drivers of mangrove loss and international supply chain data are improved with higher resolution. This approach can promote the transparency of the worldwide supply chain related to mangrove loss and elucidate the responsibilities of producers and consumers, which can help nations implement their mangrove-related pledges.

Future Improvements

This study is the first to conduct mangrove loss footprint and mapping, and the limitations are depicted in the discussion section. Several directions can be addressed in future analyses to improve these fomdomgs. Firstly, the commodities category in this chapter is coarse, and many new remote sensing techniques can be applied to enhance its resolution in the future. For example, the aquaculture land cover data from Clark Labs (https://clarklabs.org/aquaculture/landcover-data/) covers ten southeast countries in 1999-2014, 2014-2018, and 1999-2018 for 10km grid resolution and is developing a global aquaculture dataset[71]. This global dataset can be added to distinguish the aquaculture driver from the commodities driver in the future to enhance the accuracy of spatially explicit mangrove loss footprints with higher resolution of identified mangrove loss drivers. Moreover, this study used the Eora 26 to calculate the mangrove footprint by distinguishing the mangrove drivers in 26 sectors. In contrast, the full Eora dataset would offer a more precise calculation and can be applied to five countries: Vietnam, Thailand, Venezuela, Singapore, and Australia, by incorporating their drivers into more sophisticated categories of sectors. In addition, other multi-regional input-output table (MRIO) datasets with more comprehensive data on mangrove-holding countries and more sophisticated categories of commodities products can enhance the resolution of the current mangrove loss footprint analysis. For example, the Carbon Accounts & Datasets (CEADs) website just published a new MRIO table (EMERGING) for 2010, 2015, 2016,2017,2018, and 2019 with 246 countries and 135 sectors covered[72], which covers all mangrove-holding countries in Goldberg's mangrove loss datasets and has a broader coverage of commodities sectors compared to the Eora database. (https://ceads.net/user/index.php?id=1274&lang=en). It can be a good addition for further analysis to improve the resolution of this study. Second, the mangrove loss footprint considers loss only, which does not account for the restoration efforts from these countries. Therefore, a consumer country that outsources its consumption to other countries may be able to compensate for these losses via successful mangrove restoration. Incorporating mangrove restoration efforts in future research requires improving remote sensing data to enable these estimates at a global scale. Lastly, better visualization of mangrove loss footprint can be applied to examine differences by landcover type. For example, to distinguish the values of mangrove ecosystem services or restoration potential, we can disaggregate the mangrove deforestation footprints into four domains: delta, estuary, lagoon, and open coast, based on their geomorphic and sedimentary settings, such as their proximity to coastal features. In the new mangrove typology maps by Worthington et al. (2020)[73], all deltaic and estuarine units are classed as terrigenous (i.e., dominated by minerogenic sedimentation from terrestrial sources), and lagoonal or open coast patches could be classed as terrigenous or carbonate (i.e., dominated by calcareous sedimentation). This distinction can help prioritize the values of the mangrove forests we lost and link them with their potential drivers through a global supply chain to compare their costs and benefits, which can bring about more precise policy recommendations.

2.4 Methods

The calculation of the mangrove loss footprint involves three main steps: 1) preparing mangrove forest loss per country (per pixel) per driver per epoch through GIS analysis, 2) constructing bilateral trade flows per driver per epoch, and 3) calculating mangrove deforestation embodied in trade. The flowchart below (Fig. 2.5) visualizes the steps with details.

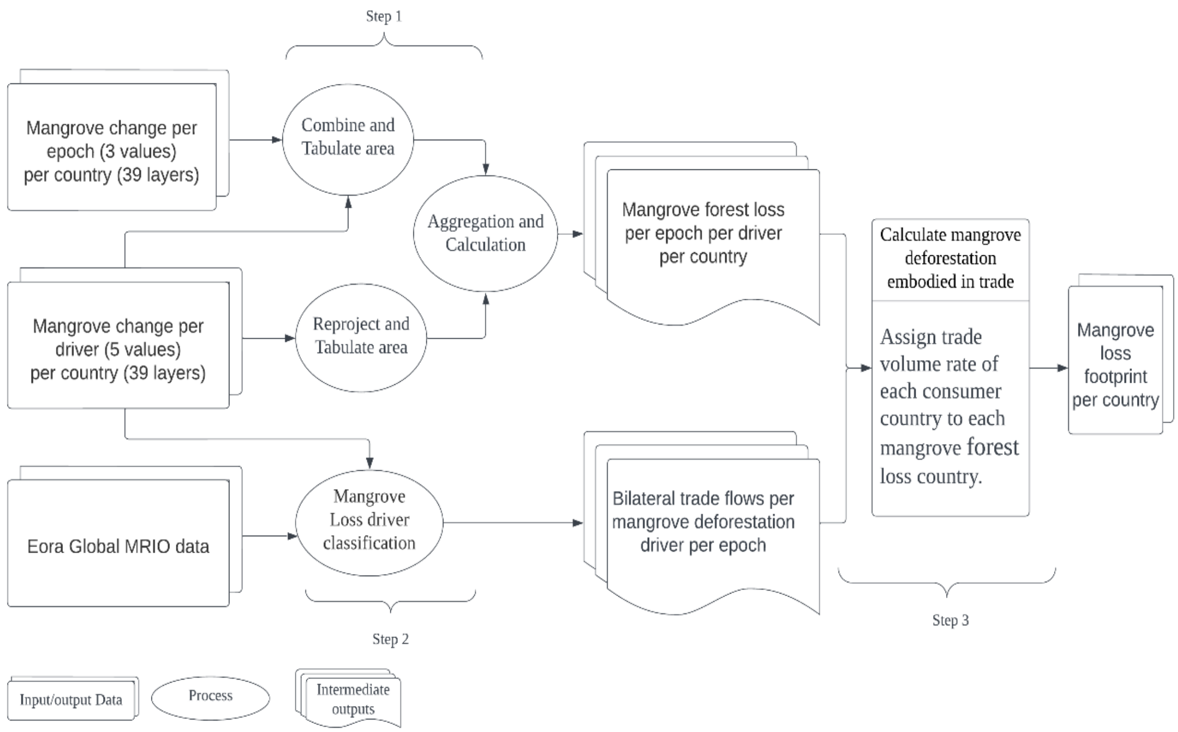


Figure 2.5 (Fig. 2.5): Flowchart of mangrove loss footprint mapping.

Step 1: Calculate mangrove loss per country (per pixel) per epoch per driver.

We use Goldberg et al.'s (2022) data for a GIS analysis to calculate mangrove loss per country per epoch per driver. The dataset is classified using high-resolution Google Earth images, random forest machine learning techniques, and a series of decision trees for several global-scale land use datasets. The final products include spatially explicit raster data with 30m*30m resolution per mangrove driver in three periods (2000-2005, 2005-2010, and 2010-2016) in 39 mangrove-holding countries. It groups mangrove loss drivers into five categories: commodity production (agriculture, aquaculture), settlement, erosion, extreme climatic events, and non-productive conversion. It also includes mangrove loss dataset per country per driver per epoch in 72 mangrove-holding countries. We use both products to create spatially explicit mangrove loss footprint maps and to understand their spatiotemporal dynamics.

The global extent of mangrove loss is based on the global map of mangrove extent produced by Giri et al. (2011). A Landsat-based NDVI anomaly algorithm is used to aggregate changes in mangrove greenness over time, using high-resolution images covering Landsat 5 TM and Landsat 7 ETM+ to measure pixels of loss. To identify the drivers associated with mangrove loss, a machine learning-based classification approach is first used to map land cover changes, using 1168 training points in three classes from mangrove forest in 2000 to consider conversion into wet soil, dry soil, and water for each loss pixel. Since spectral characteristics alone were insufficient to distinguish some land cover, a series of decision trees from multiple datasets for a decision tree model was used to separate land covers into five drivers. Therefore, the dataset contains three series of spatial raster data with 39 layers to depict mangrove loss at each epoch, for each driver, and with each soil type in 39 mangrove-holding countries. To calculate the mangrove loss per epoch per driver in each country, we batch GIS analysis for 39 country layers to combine mangrove loss data in each epoch and each driver and reproject these layers to World Robinson projection to tabulate the areas in each category. We then mosaic these raster layers for a cross-country map and use it for spatially explicit mangrove loss footprint mapping. The per country per driver per epoch dataset provided by Goldberg's dataset for 72 mangrove-holding countries is validated with the results in our analysis, and we directly used this dataset for per country mangrove loss footprint calculation.

Step 2: Identify mangrove drivers and their linkages with Eora.

We then follow the Hoang et al. (2021) method to link the drivers of mangrove loss with the Eora global multi-region input-output (MRIO) database to trace mangrove loss footprint. The complete Eora database covers 15000 industry sectors in 190 countries. The countries covered in both Eora and Goldberg's mangrove loss database are discussed in this chapter (n=34 for spatially explicit maps and 65 for country-level maps). Each country has its coverage of sectors ranging from 26 to 345. Since most of the mangrove-holding countries have 26 industries covered in Eora, only five countries (Vietnam, Thailand, Venezuela, Singapore, and Australia) have entire sectors covered. Therefore, we used Eora with 26 industries for this cross-country analysis. Moreover, although the sector resolution of the MRIO is high, the resolution of mangrove loss drivers is coarse, and only anthropogenic drivers are discussed because of the direct linkages with Eora based on the main knowledge.

We then aggregate the MRIO sectors into three groups of drivers of mangrove loss: commodities, human settlement, and non-productive conversion. The different industries/commodities are classified into the same driver related to mangrove loss in various areas in one country and with varying levels of impact. The aggregation of human settlement includes building infrastructure, such as roads, ports, and shipping channels, to support transport, shipping, etc. The non-productive conversion of mangrove loss is derived from Goldberg et al. (2022), which uses remote sensing images to overlap the human influence mask layer with the low density of the productive industry layer. It includes private household settlements for daily life support, recreational, cultural, or other service activities for non-commercial purposes, such as education, health, and social work. The commodities-driven mangrove loss covers a broad range of sectors, including long-term agriculture, aquaculture from shrimp farms, forestry, mining, and energy infrastructure, following Hoang et al (2021)'s definition of commodity driver in the deforestation footprint analysis. We also verify the distinct commodity drivers by comparing the commodity-driven mangrove loss from Goldberg et al. (2022) with the drivers of deforestation map by Curtis et al. (2018), to confirm that the commodities from Goldberg's datasets include various commodity types from Curtis such as agriculture, aquaculture, forestry, and other commodities.

Step 3: Mapping mangrove loss footprint

To map the mangrove loss footprint, which is the consumption-based mangrove loss, we follow the logic as equation 2.1.

$MLF = ML + I - E$ (2.1)

Mangrove forest loss footprint (MLF) is expressed in equation (1) and shows that ML is the mangrove forest cover loss in the production country, E is the mangrove loss embodied in exports, and I the loss embodied in imports. Mangrove loss (ML) is measured and calculated through Goldberg's driver datasets; the area of five drivers is in units as m^2.

Specifically, we first calculate the adjusted consumption based on Hoang's (2021) analysis.

$AC = \sum_{tj} L_{ij}^{rt} y_j^{ts} + \sum_{t\neq s,j} L_{ij}^{rt} y_j^{ts} - \sum_{t\neq s,j} L_{ij}^{rs} y_j^{st}$ (2.2)

Adjusted consumption (AC)= total consumption + imports - exports. L is the Leontief inverse, measuring the transformation between i sectors of origin in r export countries and j sectors of destination in s import countries. (r*i,s*j), y is the final demand of s import countries with j destination sectors. (s*j). t is both the last sale in the consumption and import term, and the country of final consumption in the export term.

We then decompose the total deforestation into the embodied deforestation in country s using the Eora MRIO model.

$F^s(Production) = \sum_{ri} f_i AC$ (2.3)

Where F^s (Production) is the total mangrove deforestation embodied in international trade driven by country s, f is mangrove deforestation intensity for each sector i (mangrove forest loss area from Goldenberg's data divided by gross output). AC represents adjusted consumption, which is measured in equation 2.2.

Finally, the spatial footprint analysis method calculates mangrove loss footprint M in country r driven by country s.

$$M^{S} = \sum_{hr} D_r^h \frac{\sum_i f_{hi} \sum_{tj} L_{ij}^{rt} y_j^{ts}}{\sum_i m_{hi}^r} \quad (2.4)$$

M^s represents spatial explicit mangrove forest loss map driven by country s (30m*30m). Mangrove forest loss map (D) by mangrove-holding countries r by driver h and embodied mangrove loss (numerator in eq.2.3 (fLy)) are in absolute values, and the embodied mangrove loss (fLy) is normalized by total mangrove loss m by each driver h in mangrove-holding countries r for each industrial sector i to downscale values from nations to pixels. The mangrove loss maps (D) are prepared in step 1 with the shapefile layers for each driver h in each mangrove-holding country r and mangrove deforestation intensity f for each production sector i.

2.5 Data and Code Availability

We combine three map datasets with the Eora global MRIO database to trace mangrove forest loss footprints. The main map is Goldberg's (2022) loss and driver maps, which contains two series of raster datasets of 39 countries in measuring the extent of mangrove loss (https://daac.ornl.gov/CMS/guides/CMS_Global_Mangrove_Loss.html)[5,51]. One depicts the mangrove loss raster with five drivers: commodity production (agriculture, aquaculture), settlement, erosion, extreme climatic events, and non-productive conversion; the other depicts the loss raster in three epochs: 2000–2005, 2005–2010, and 2010–2016. We also used Curtis (2018) to verify the commodity driver of mangrove loss layers (https://data.globalforestwatch.org/documents/gfw::tree-cover-loss-by-dominant-driver-2022/about), which should contain various commodities, including agriculture and aquaculture, and forestry identified in Curtis deforestation driver map[74]. This driver map identified the dominant drivers of tree cover loss in a 10km grid cell from 2001 to 2022. The dominant drivers are commodity-driven, shifting agriculture, forestry, wildfire, and urbanization. The last dataset is Eora Database, which is one of the most well-developed global multiregional input-output databases. This database describes the world economy in terms of the annual production, trade, intermediate consumption, and final consumption of 26 homogeneous sectors between and within 189 countries from 2000 to 2022[43,75]. The code for the mangrove loss footprint was developed in Matlab and Python to process and visualize. The primary datasets and code for visualization can be found on the GitHub repository, accessible at lwt852/mangrove footprint (github.com). Matlab code for mangrove loss footprint calculation in this study will be made available upon request.

CHAPTER 3: DRIVERS OF METACOUPLED MANGROVE LOSS FOOTPRINT ACROSS SPACE AND TIME

Abstract

Mangrove forests are vital ecosystems providing essential services like carbon storage, but their global decline has raised significant concerns. Population growth and international agricultural trade are key drivers of global deforestation, including mangrove loss. However, there is a substantial gap in understanding the specific causes and mechanisms of this decline, particularly during the era of globalization. This chapter applies the IPAT/STIRPAT model and the metacoupling framework to investigate the driving forces behind anthropogenic mangrove loss embedded in international trade across 187 countries from 2000 to 2016. The IPAT/STIRPAT analysis evaluates short-term drivers of the mangrove loss footprint, which is defined as the mangrove deforestation required to meet a country's domestic and external final demand. Our findings show a 1% increase in population and GDP per capita results in a 0.925% and 0.629% rise in the mangrove loss footprint, respectively. Through the metacoupling framework, we uncover mechanisms influencing countries' tendencies to consume mangrove resources beyond their borders, highlighting environmental responsibility leakage. Specifically, GDP per capita exhibits a significant positive elastic relationship with distant mangrove loss footprints, where a 1% increase in GDP per capita growth leads to more than a 1% rise in distant mangrove deforestation. Additionally, government effectiveness is a critical factor affecting adjacent mangrove loss footprints, underscoring effective governance's role in managing domestic and transboundary mangrove conservation. This pioneering study integrates geographical context to elucidate the spatiotemporal dynamics of mangrove loss driven by international trade, helping nations accurately assess their contributions to mangrove conservation and enhancing efforts toward sustainable development in a fair and just manner worldwide.

Keywords： mangrove loss footprint, metacoupling, IPAT/STIRPAT, panel analysis

3.1 Introduction

Mangrove forests are vital ecosystems offering storm protection, livelihood support, and high carbon storage[4,48,49,58,76,77]. In past decades, however, substantial declines in mangrove forests have happened globally, and identifying socioeconomic conditions associated with the losses is challenging because mangrove forests are located in complex social-ecological systems[13,57,61,62,78]. Affluence, measured as per capita gross domestic product (GDP), has often been posited as the main economic driving force for mangrove loss. Global analyses show that shrimp aquaculture and agriculture are also statistically significant drivers of mangrove loss[78]. However, other studies have found a more complex relationship between economic activities and mangrove existence. For example, Lagomasino et al. (2019) indicated that upstream urbanization, mining, and dam construction could affect sediment flow into mangrove forests and deliver harmful sediment to the forests' estuarine areas[79]. Hagger et al. (2022) found that loss drivers are also drivers of gain, and economic growth has different effects in different periods[62]. Further, other socioeconomic factors, such as community forestry, national regulatory quality, protected areas, and coastal population, are critical indicators affecting mangrove pressures and management interactions[54,61,62,80]. Among these studies, the far-reaching impacts of international trade specific to mangrove forests are lacking, and the underlying drivers attributed to mangrove loss embodied in the supply chain are also unclear.

Anthropogenic activities exert growing pressure on the mangrove environment locally and internationally, especially under the lens of globalization[5,6,16,51,52]. High-resolution remote sensing images have identified extensive land conversion of mangrove forests due to anthropogenic activities. For example, Thomas et al. (2017) indicated that anthropogenic activities between 1996 and 2010 caused 37.8% of mangrove conversion, and aquaculture/agriculture conversion are the most common activities (11.2%). Goldberg et al. (2020) Another study estimated an even greater intensity of mangrove conversion between 2000-2016; researchers calculated that over 60% of land conversion of mangrove forests globally was due to aquaculture and agriculture. Global studies synthesized hundreds of published studies and conducted regression analyses to understand the socio-ecological drivers of mangrove deforestation worldwide[57,62]. They also point to aquaculture and agriculture activities as the dominant drivers.

As drivers of global deforestation, aquaculture and agriculture are closely linked with demand through international trade[67,81–83]. For example, DeFries et al. (2010) indicated that agricultural exports are the main drivers of tropical deforestation. Li et al. (2015) found that trade structure of forest products matters. Agricultural exports can explain tropical deforestation due to the high opportunity costs that result from the replacement of forestlands and high demand from distant countries[81] to outsource forests from resource-intensive countries or industries. While these analyses do not establish causality, the correlations suggest that localized production for local markets is not the primary global driver of deforestation. Rather, international demand for products like agricultural goods and other products plays a significant role. Viewing this through the lens of globalization and international trade highlights how consumption driving mangrove loss can originate in other nations without mangrove loss.

Understanding mangrove loss has become possible by constructing global and multiregional input-output (GMRIO) models that can allocate production factors from trade to final consumption. These models have proliferated in recent years to measure the environmental impacts embodied in international trade, such as GHG emissions[84], land use, water[85,86], metal[87], and deforestation[67]. The modeling analysis is widely accepted as a valid quantitative method to measure virtual social and environmental impacts through the global supply chain[88,89]. It can also be applied to calculate the mangrove loss footprint (MLFP) that accounts for the mangrove loss embodied in international trade, and which helps to understand the in-situ loss of a country's final demand. Moreover, analytical techniques used to quantify the factors driving change in the impacts of trade on the environment have also been widely assessed for metal[87], water[85,86], land use[90], CO_2 emissions[84], and deforestation[91–93], through methods such as structural decomposition analysis, literature reviews, and questionnaires.[84,94]. Moreover, a growing body of literature has explored how global forces interact with global challenges. One application is the metacoupling framework, developed to understand socioeconomic and environmental interactions between distant, adjacent, and within coupled human-nature systems[10,28,30,47]. In addition to this framework, another application is the IPAT/STIRPAT model, which has been used to statistically explain how drivers such as population, affluence, technology, and other socioeconomic factors and also include their interactions influence environmental footprints[95–97]. These tools can help unveil the drivers of mangrove loss embodied in international trade.

This chapter aims to identify the drivers of global mangrove loss by studying the role of trade and its main driving factors through analysis of the worldwide supply chain. Past research on the economic drivers of mangrove loss has predominantly used cross-sectional analysis, offering only a static snapshot at a particular moment. This approach is limited as it fails to capture temporal and country-specific variations. In contrast, panel analysis, which examines time-series data across multiple countries, enables the detection of these variations that are otherwise hidden in cross-sectional studies and has yet to be widely applied to investigate mangrove forest loss dynamics. In addition, the role of spatial characters in the supply chain structure related to mangrove loss is also implicit and has yet to be discussed. Therefore, this chapter employs panel regression models and considers multiple socioeconomic variables and spatial characteristics to identify the dynamics and drivers of mangrove loss footprint, defined as the mangrove loss consumed to meet a country's (domestic and external) final demand. Specifically, the dynamics of the mangrove loss footprint are identified, focusing on investigating the geospatial dynamics of the footprint. We ask three research questions: (1) what are the geospatial and temporal dynamics of mangrove loss footprint; (2) which socio-economic variables are driving mangrove loss footprints, and (3) how do short-run elasticities of driving factors act to mangrove loss footprints? This is the first work to use an MRIO modeling approach and panel analysis to study the driving forces of mangrove loss through the global supply chain and understand the role of trade in global mangrove loss across space and time.

3.2 Results

3.2.1. Overview of mangrove loss footprint compared to mangrove loss (2000-2016)

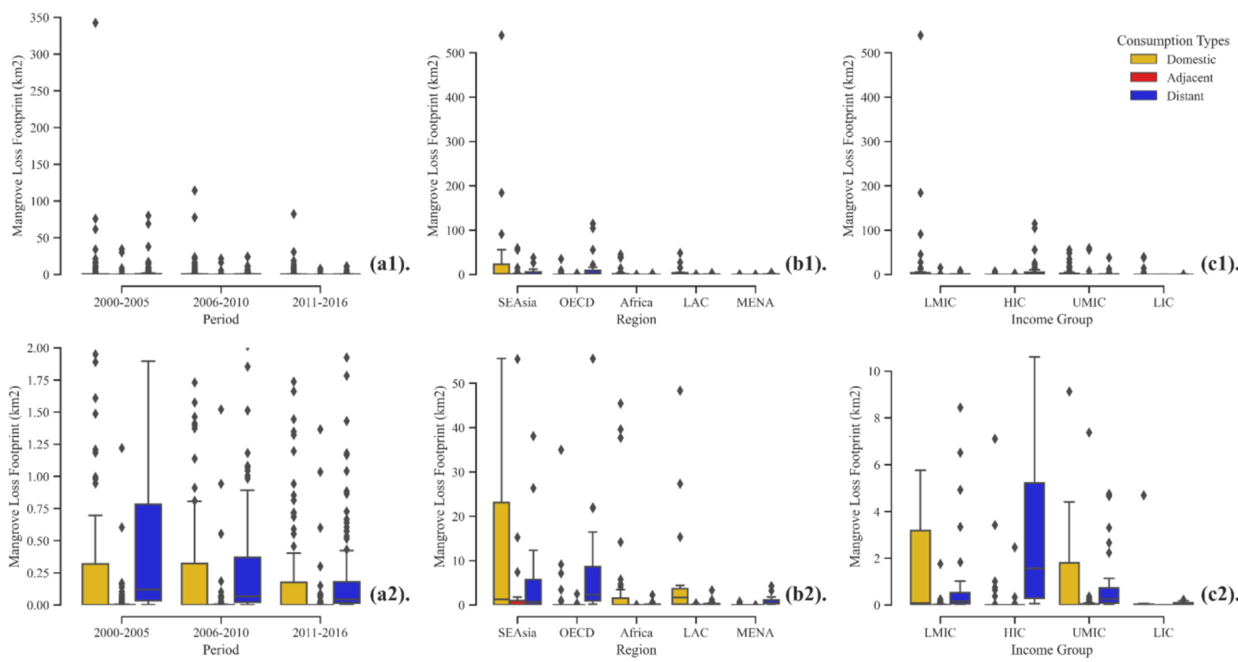


Figure 3.1 (Fig. 3.1): Distribution of mangrove loss footprint attributed to domestic, adjacent, and distant consumptions categorized by (a) Period, (b) Region, and (c) Income group.

Countries' regions and income groups follow the classification in the Sustainable Development Goals (SDG) Dashboard (https://dashboards.sdgindex.org/downloads). Regions named SE Asia, OECD, Africa, LAC, and MENA represent Southeast Asia, Organization for Economic Co-operation and Development Countries (OECD), Africa, Latin American Countries (LAC), and Middle East and North Africa (MENA), respectively. Oceania and East Europe are excluded from the visualization because their mangrove loss footprint is negligible. Income groups such as LMIC, HIC, UMIC, and LIC indicate lower-middle-income, high-income, upper-middle-income, and low-income countries. The first three sub-plots provide a comprehensive overview, highlighting the outliers within each category. The following three sub-plots zoom in on the boxplots, offering insights into each category's central tendencies. The order of the categories in the graphs is based on total mangrove loss footprint values in each bar. Moreover, the distribution of mangrove loss attributed to three consumption types is similarly visualized in Appendix Fig. SI3-1.

Substantial outliers are identified in the mangrove loss footprint, with an average decreasing trend from 2000 to 2016.

Mangrove loss is defined as the actual loss of trees on the ground in a country, while mangrove loss footprint measures the mangrove loss consumed to meet a country's final demand. Fig. 3.1 and Appendix Fig. SI3-1 measure the distribution of mangrove loss footprint (Fig. 3.1) and mangrove loss attributed to three consumption types. Firstly, they reveal a profusion of influential actors within each temporal epoch, with discernible diminishing trends over time. These outliers reveal the influential sway held by specific nations in shaping mangrove loss patterns across distinct periods, and they may have a substantial influence on OLS regression results to understand the socioeconomic divers[98,99]. Fig3.1-a2 reaffirms this trend, showcasing how mangrove loss exhibits a temporal decline, irrespective of domestic, adjacent, or distant consumption drivers.

Domestic consumption from SE Asia and lower-middle-income countries drives the highest mangrove loss footprint, and distant consumption from high-income countries is noticeable.

Southeast Asia as the epicenter of substantial mangrove loss and its footprints due to influential countries such as Indonesia, Myanmar, and Vietnam (Fig. 3.1, Appendix Fig. SI3-1 b1 and b2). These losses are primarily attributed to domestic and distant consumption factors, with adjacent consumption also playing a pivotal role. Moreover, Appendix Fig. S3-1-b1 and b2 show that African, Latin American, and OECD nations exhibit comparable magnitudes of mangrove loss. They also indicate that OECD countries maintain a more confined distribution while African and Latin American countries exhibit discernible outliers, potentially indicative of elevated mangrove loss footprints. Fig. 3.1 b1 and b2 indicate that the OECD countries have the highest mangrove loss footprint compared to African and Latin American nations. They are also significant consumers, second to Southeast Asian countries, which drove mangrove loss mainly through distant consumption. Contrastingly, Oceania and MENA countries have minimal contributions to mangrove loss, and MENA countries rely heavily on distant consumption, although their total mangrove footprint is small. In comparison, the loss footprint in African and Latin American countries is mainly driven by domestic consumption. Outliers of mangrove loss footprint in Fig. 3.1 are less than of mangrove loss in Appendix SI3-1.

Fig.3.1-c1 depicts a decreasing trend of mangrove loss from wealthy to poor economies, showing that high-income countries have the highest mangrove loss footprint while low-income countries have the lowest. Lower-middle-income countries had the most extensive mangrove loss footprint. However, this was due to two outliers, Indonesia and Myanmar, the countries with the largest mangrove loss footprint. Moreover, lower-middle and higher-middle income countries contain the major mangrove-holding countries, whose loss footprints are mainly driven by domestic

consumption to meet their needs, with noticeable distant consumptions. High-income countries have an astonishingly high level of distant consumption, explaining their mangrove loss footprint. In comparison, Appendix Fig. S3-1-c1 and c2 depict a nuanced phenomenon aligning with the environmental Kuznets curve[65], wherein mangrove loss is lowest in countries at both the low and high ends of the income spectrum. Mangrove loss peaks within lower-middle-income nations, extending to upper-middle-income countries. Notably, the lower-middle-income group harbors several outliers, indicative of influential nations (e.g., Indonesia, Myanmar, Vietnam) wielding pronounced mangrove losses. Most nations have comparable mangrove losses punctuated by sporadic outliers among the remaining income group categories. Compared to the high frequency of outliers in mangrove loss, outliers in mangrove loss footprints (Fig.3.1-c1) are far fewer.

3.2.2 Drivers of mangrove loss footprint

IPAT/STIRPAT model is robust in explaining mangrove loss footprint.

To assess what causally influences mangrove loss, we need to control for potential alternative explanations, a task for which regression is well suited. No analysis of observational data can eliminate alternative explanations, but a regression analysis with controlled influences suggested in the literature can offer strong evidence of what is driving environmental change. We start the regression analysis with the IPAT model using OLS. The results (Appendix SI3-2) indicate that the mangrove loss footprint can be explained by the total population and affluence level (GDP per capita) with R2=0.44. Population is a significant indicator, and ~30% of the cross-national variances for mangrove loss footprint can be explained in the most parsimonious model (i.e., population being the only explanatory variable). The coefficient of 0.896 indicates the 'inelasticity' that a one percent increase in population drives a 0.896 percent increase in mangrove loss footprint. This phenomenon was previously observed for direct CO_2 emissions and virtual water footprint at global and national scales[85,100], highlighting the importance of considering population change's impact on environmental degradation and policy discussions, including climate change negotiations, water scarcity mitigation policies, and pollution control efforts. In addition to population, affluence plays a significant role, as population and GDP per capita explain 44% of mangrove loss footprint. The coefficient of GDP per capita indicates that a one percent increase in GDP per capita drives a 0.626 increase in mangrove loss footprint. The following section explores the role of affluence in detail. The statistical significance of population and affluence level (reflected in GDP per capita) indicates the robustness of applying the IPAT model to explain mangrove loss footprint, which has been widely used in presenting an array of environmental degradations including energy use[95], CO2 emissions[100], land use[90], water consumption[85], and air quality[101]. However, OLS regression only reflects correlation and causally important variables can be dropped if the non-causal variables can capture the influence of the causal variable via a coincidence of correlation. Therefore, further analyses to expand the benchmark model from the IPAT and to address the causal interface are needed[98,99].

In addition to affluence and population, foreign investment share and gross capital formation share are critical.

We expand the bench IPAT model by adding socio-economic exploratory variables through four estimation approaches: OLS, random effect, fixed effect, and first differencing regressions to find other critical indicators. The full model to explain the mangrove loss footprint is expanded with three additional variables representing institutions, investment rate, and external investment share. They are government effectiveness, gross capital formation, and foreign inflow shares of GDP. These three variables are significant in explaining the mangrove loss footprint with at least 10% significance in regressions and cover most categories of variables with a reasonable variance inflation factor (VIF) to avoid collinearity among variables. Adding these variables expands the R2 of the bench model to 0.5, improving the prediction power of the previous model. Table 2.1 reports the regression results of the full model for three dependent variables: mangrove loss footprint (MLFP), domestic, and external MLFP. The full model explains MLFP and external MLFP but does not fully explain domestic MLFP regressions. For these regressions, the standard errors are much higher than the coefficients of the variables, indicating regression instability. Hausman tests indicate fixed effect, and the first, differencing regressions are more favorable among four regressions in models. Their test statistics, which were obtained from pooled OLS estimation, F statistics from the random effects approach, and their significance (prob >chi squared) are listed in Appendix SI3-4. All six regressions have a more significant F statistic compared to the Hausman specification testing statistics from pooled OLS. This is due to the random effects approach, which allows for the estimation of the augmented regression. Thus, the unobserved country heterogeneity is correlated with at least one of the explanatory variables.

Measures	MLFP				Domestic MLFP				External MLFP			
	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	FE	FD	FE	FD	FE	FD	FE	FD	FE	FD	FE	FD
log_pop	0.840^{**}	0.774^{**}	0.962^{***}	0.925^{***}	-0.581	-1.114	0.183	-1.010	0.678^{***}	0.624^{***}	0.646^{***}	0.636^{***}
	(0.323)	(0.322)	(0.362)	(0.334)	(1.633)	(1.608)	(1.982)	(1.776)	(0.245)	(0.238)	(0.219)	(0.214)
log_gdppc	0.685^{***}	0.575^{***}	0.745^{***}	0.629^{***}	-1.064	-0.902	-1.022	-0.969	1.005^{***}	0.862^{***}	1.013^{***}	0.943^{***}
	(0.205)	(0.181)	(0.225)	(0.193)	(0.753)	(0.707)	(0.954)	(0.978)	(0.155)	(0.124)	(0.148)	(0.145)
log_forci_inper			0.0677	0.0556^{**}			0.0775	0.241^{**}			0.0496^{**}	0.0243
			(0.0419)	(0.0277)			(0.164)	(0.114)			(0.0241)	(0.0171)
log_gcf_per			0.201	-0.00610			0.116	-0.383			0.271^{***}	0.221^{**}
			(0.173)	(0.151)			(0.533)	(0.444)			(0.0919)	(0.0976)
log_gov			-0.107	0.150			-1.571	-2.062^{*}			0.556^{*}	0.681
			(0.514)	(0.593)			(1.109)	(1.109)			(0.321)	(0.450)
t1	1.400^{***}		1.523^{***}		0.390		0.736		1.516^{***}		1.597^{***}	
	(0.0922)		(0.0823)		(0.465)		(0.502)		(0.0779)		(0.0666)	
t2	0.775^{***}	0.0591^{*}	0.799^{***}	0.0408	0.0820	-0.0724	0.200	-0.163	0.807^{***}	0.0277	0.810^{***}	0.0187
	(0.0666)	(0.0314)	(0.0736)	(0.0389)	(0.363)	(0.157)	(0.430)	(0.226)	(0.0548)	(0.0248)	(0.0534)	(0.0259)
_cons	-22.61^{***}	-0.679^{***}	-25.88^{***}	-0.734^{***}	19.80	-0.166	7.595	-0.265	-24.12^{***}	-0.734^{***}	-25.23^{***}	-0.777^{***}
	(5.337)	(0.0483)	(6.160)	(0.0464)	(30.93)	(0.226)	(37.02)	(0.261)	(4.104)	(0.0408)	(3.508)	(0.0400)
N	470	312	422	273	157	100	137	84	470	312	422	273

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.1: Domestic, external, and the total mangrove loss footprints versus GDP per capita, population, and three indicators of interest: gross capital formation (GCF) share in GDP, government effectiveness, and foreign inflow investment share of GDP.

All variables in table 3.1 are all in the natural logarithm format. Samples (N) include mangrove loss footprint in 159 countries in three periods: 2000-2005 (t1),2006-2010 (t2), and 2011-2016 (t3). FE and FD represent fixed effects and first differencing regressions.

From Table 3.1, the significance and the positive coefficients of foreign inflow share of GDP in the full model (Table 3.1, model2) and the parsimonious model (Appendix SI3-1) indicate that a one percent increase in the growth rate of foreign inflow direct investment share to its domestic GDP, 0.056 percent growth of trade-adjusted mangrove loss would occur (table 3.1, model2). The significance indicates that the percentage of direct monetary investment from foreign investors in the domestic economy is vital in driving the nation's mangrove loss footprint, emphasizing that the mangrove loss embodied in global demand is attributed to a country's economic openness. Moreover, it is statistically significant in models explaining mangrove loss embodied in international trade, with 5% significance (Table 3.1, model 4), emphasizing that economic dependence on external investors drives domestic mangrove losses embodied in international trade. In particular, a one percent increase in foreign investment share growth in GDP leads to a 0.241 percent growth increase in domestic mangrove loss footprint. The economic dependence on foreign investors has a worse impact on the domestic mangrove loss footprint, indicating that other countries' environmental responsibilities are transferred to the mangrove-holding countries through their investments in international trade, leading to mangrove loss.

Gross capital formation (GCF) share of GDP, described as the industry investment rate, has been identified as a better substitute for affluence in explaining environmental footprints[85,87]. Our analysis echoes the conclusion and identifies it as an essential determinant of the mangrove loss footprint. As shown in Appendix SI3-2, GCF's share of GDP has a 10% significance in random and fixed effect regressions. Although out of 10% significance in Table 3.1, model 2, in explaining the total mangrove footprint (MLFP), that GCF percentage explains the external MLFP within 1% confidence in Table 3.1, model 6. The high significance indicates that countries' consumption of capital formation to facilitate their economic development, such as investments in infrastructure, capital, transportation, etc., can drive external mangrove loss through the global supply chain, after controlling the GDP per capita. In particular, external MLFP-GCF elasticity indicates a strong coupling: a 1% increase in growth of the GCF share was associated with a 0.221% growth increase in the external mangrove loss footprint (table 3.1, model 6).

3.2.3 Distant MLFP has a significantly positive and 'elastic' relationship with GDP per capita, while adjacent MLFP has a U-shape relationship driven by influential actors.

We then decompose the MLFP-affluence relationship, Fig. 2a presents the first differencing regression results between (1) affluence, (2) both affluence and its quadratic form, (3) the full model, and adjacent, distant, and total mangrove loss footprint (MLFP). Adjacent or distant MLFP is defined as the nearby and distant mangrove loss that the focal country's final consumption drive. The regressions for domestic MLFP were not conducted because the model was unstable due to high standard errors. The result indicates adjacent and distant MLFPs perform differently toward affluence (shown as GDP per capita), and affluence is a significant driver in explaining these MLFPs. Moreover, Fig. 3.2-b-d visualizes the scatter points and their fitted lines between GDP per capita growth and different MLFPs' growth, which presents a more direct and intuitive demonstration of first differencing regressions and details the MLFP-GDP per capita relationship in different MLFPs.

Firstly, the coefficient for GDP per capita growth (log_gdppc) and its quadratic term (log_gdppc_sq) are significant and positive for distant mangrove loss footprint growth in the first differencing regressions, suggesting an 'elastic' and "U shape" relationship. Both affluence-related coefficients are larger than 1, indicating one percentage change of affluence can bring about a sensitive and proportional shift in distant mangrove forest loss. A ‘U-shape’ relationship suggests that the growth of mangrove loss footprint changes over the range of affluence growth. Regression (8) is an example that only accounts for population and affluence; distant mangrove loss footprint growth reaches the lowest point when the GDP per capita growth is -0.262. In other words, the growth of distant mangrove loss footprints reduces when a country’s GDP per capita decreases by more than 23% over two periods. Large-scale economic recession helps alleviate the distant mangrove loss change, and distant MLFP can be alleviated by 43.5% when GDP per capita decreases by 23%. In contrast, if the country’s GDP per capita decrease is less than 23%, or affluence increases between two periods, distant mangrove loss footprint growth increases. Moreover, the elastic relationship is identified in Fig. 3.2d, where the fitted line has a very slight U shape. The scatter plots are mainly shown as an increasing trend because of outlier points, such as Zimbabwe on the left end. It has a large-scale economic recession with the lowest GDP per capita growth values, while its distant MLFP change is also low.

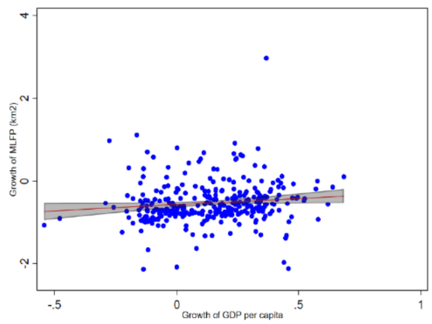
Regarding the affluence-MLFP relationship in adjacent countries, the quadratic form of affluence (log_gdppc_sq) growth affects adjacent mangrove loss footprint with a positive and significant coefficient at 10% confidence, indicating a potential U-shaped line to explain the relationship. However, as shown in Fig. 3.2c, their scatter points between the growth of adjacent MLFP and affluence growth are sporadic, and the U-shaped line is dragged by several points with high adjacent MLFP values at both ends. On the left end of the economic recession (GDP per capita growth < 0), countries such as the Arab Emirates and Liberia firmly shape the U-shape with high growth of adjacent MLFP. On the right end of economic expansion (GDP per capita growth>0), countries such as Myanmar drag the relationship as a potential U-shape with high growth of adjacent MLFP.

3.2.4 Gross capital formation is key to distant adjacent mangrove forest loss footprint (MLFP), while government effectiveness is critical to adjacent MLFP.

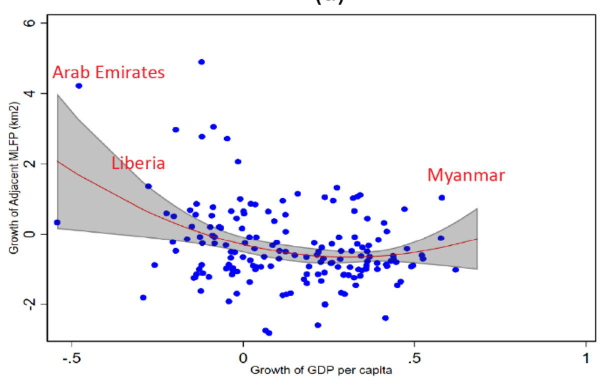
	MLFP			Adjacent MLFP			Distant MLFP		
	afl	afl+2	all	afl	afl+2	all	afl	afl+2	all
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log_gdppc	0.473**	0.466**	0.614***	-0.799	-0.784	-0.716	0.858***	0.901***	1.083***
	(0.187)	(0.189)	(0.189)	(0.751)	(0.775)	(0.626)	(0.128)	(0.151)	(0.159)
log_gdppc_sq		-0.242	-0.536		1.915	2.876*		1.718**	1.261*
		(0.589)	(0.569)		(1.897)	(1.512)		(0.853)	(0.744)
log_pop			0.898***			2.044			0.745***
			(0.331)			(1.433)			(0.210)
log_forei_inper			0.0535*			0.00157			0.0245
			(0.0282)			(0.108)			(0.0169)
log_gcf_per			0.0170			-0.106			0.149*
			(0.153)			(0.458)			(0.0801)
log_gov			0.193			3.403***			0.574
			(0.583)			(1.154)			(0.405)
N	312	312	273	166	166	142	312	312	273

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

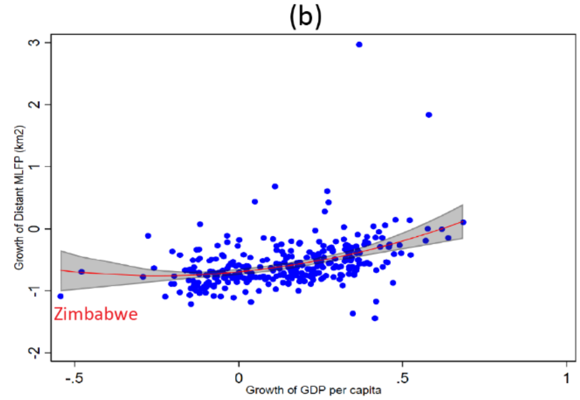
(a)



(b)



(c)



(d)

Per capita GDP growth rate — Fitted values — 95% confidence interval

Figure 3.2 (Fig. 3.2): (a) First differencing regressions for adjacent, distant, and total mangrove loss footprints run with (1) affluence, (2) affluence and its quadratic form, and (3) the full model: GDP per capita and its quadratic form, population, and variables of interest: Gross capital formation (GCF), foreign inflow investment shares of GDP, and government effectiveness.

They are all in the natural logarithm format. Samples (N) include mangrove loss footprint in 159 countries in 2000- 2005, 2006- 2010, and 2011-2016. The affluence variables, GDP per capita, and its quadratic form were centered by subtracting its sample mean as a common step to avoid collinearity in the model. (b-d) Growth rates of total, adjacent, and distant mangrove loss footprint (MLFP) versus GDP per capita growth. The sample covers 312 country-period observations in 187 countries from 2000- 2005, 2006- 2010, and 2011-2016. The growth rates are calculated using differenced natural logs between two periods. The shaded area represents the 95% confidential interval under robust estimations.

Regressions (6) and (9) in Fig. 3.2a show that the driving factors explain how adjacent and distant MLFPs differ except for population and affluence. Regression (6) indicates that a one-percent improvement in the focal country’s government effectiveness can exponentially drive mangrove loss footprint change in adjacent countries (3.4) with 1% confidence. This larger than one coefficient between adjacent MLFP and government effectiveness indicates a very sensitive and elastic relationship that a tiny improvement of government effectiveness can greatly impact its adjacent country’s mangrove loss. In comparison, affluence-related indicators, including gross capital formation, representing the focal country’s investment in industries, capitals, and infrastructures, significantly drive distant mangrove loss footprint change, after controlling GDP per capita and its quadratic form.

3.3 Discussion

Population growth and international agricultural trade are recognized as primary drivers of global deforestation, including mangrove forests[78,81]. However, existing studies have not specifically examined the impact of international trade on global mangrove deforestation. Our study breaks new ground by examining the underlying forces of mangrove loss linked to international trade, termed the mangrove forest loss footprint. We aim to understand the specific characteristics that influence a country's mangrove forest loss through the global supply chain.

Drawing on a comprehensive literature review, we apply the IPAT/STIRPAT model to statistically dissect these driving forces, focusing on population, affluence (measured by GDP per capita), and socio-economic factors such as institutional quality, investment rates, and external investment shares. Panel data analysis underscores the robustness of the IPAT/STIRPAT model in explaining the mangrove forest loss footprint, highlighting population and affluence as key drivers of global mangrove loss displacement. Additionally, we employ the metacoupling framework to explore how spatial interactions across regions influence this process. Our findings reveal that GDP per capita exerts varying impacts on adjacent and distant mangrove loss footprints, showing a positive and elastic relationship particularly evident in explaining distant mangrove loss. Moreover, effective governance in a focal country can influence neighboring nations' mangrove loss dynamics, while investments in capital formation, infrastructure, and industries drive mangrove loss in distant countries. Empirical case studies below further substantiate these conclusions, providing on-the-ground validation of our analytical framework.

3.3.1. The mangrove-holding countries should work collaboratively to manage their distinct mangrove forests.

Numerous empirical studies highlight the spatial spillover impacts, or 'leakage,' of conservation policies across neighboring regions. For instance, Angelsen (2008) reviewed the literature on REDD and forest protection policies, revealing that conservation efforts in one area may inadvertently increase deforestation activities elsewhere[102]. This phenomenon is evident in Sumatra, Indonesia, where protected areas displace human populations, leading to intensified exploitation activities in surrounding regions[66]. Similarly, in the Peruvian Amazon, while forest concessions have reduced deforestation rates due to stringent timber legislation, deforestation outside these zones has escalated because the need from the market has not decreased, but seek elsewhere to satisfy their material needs[103]. This displacement effect underscores the complex interactions between protected and exploited areas, highlighting the unintended consequences of conservation policies[104] on its neighboring regions.

Limited studies have been identified on spatial spillover regarding mangrove forests nationally. However, various regional cooperation networks, such as ASEAN, the Western Indian Ocean, and the Mesoamerican Mangrove and Seagrass Network, play crucial roles in addressing regional mangrove conservation needs because the dense and complex root system of mangrove forests along the coastal line is hard to be separated by the political borders. These networks, often initiated by non-profit organizations, facilitate coordinated efforts for biodiversity monitoring and conservation across regions, contributing significantly to global mangrove protection initiatives.

3.3.2. Countries with high economic capability can take higher responsibilities for worldwide mangrove forests.

Due to the rise of globalization, remote regions exporting products often face cascading effects of land use displacement to meet global demands. Changes in land use allocation within supply chains can trigger conservation challenges in distant areas, where environmental impacts are difficult to measure promptly. Wiedmann & Lenzen (2018) highlight that a significant proportion (10%-70%) of environmental and social impacts occur elsewhere due to consumption patterns driven by higher-income countries, exacerbating ecological intensity and social disparities in low-income nations[89].

Our study affirms a concerning trend in mangrove forest loss, primarily driven by distant consumption and intensified by fierce competition for land between mangrove ecosystems and other land-use types. For instance, emerging markets for commodities like palm oil, shrimp/fish farming, and urban development incentivize local stakeholders to convert mangrove areas for short-term economic gains[4]. The global supply chain facilitates these conversions across distant countries, underscoring the cascade effects of globalization[66].

Furthermore, our research identifies high-income and OECD countries as exerting elastic positive impacts on distant mangrove forest loss, necessitating greater responsibility for mangrove conservation efforts. For example, mangrove forests have benefited from the conservation projects from non-governmental organizations and governments on the ground through international collaborations, including (a) the International Union for Conservation of Nature(IUCN) Mangrove Specialist Group, which is an expert-led body that provides conservation and inhabitation assistance to local restoration projects worldwide; (b) the International Blue Caron Initiative, which works on climate change mitigation through restorations that bring together research institutions and governments around the world; and (c) the Global Mangrove Alliance(GMA), which partnered 19 NGOs together to help identify global mangrove strategies and priorities. These initiatives rely on contributions from high-income and OECD countries to mitigate the adverse impacts of mangrove loss driven by international trade and consumption.

In summary, our analysis offers a rigorous quantitative approach to assess environmental leakage via international trade, confirming that local mangrove loss is influenced by global forces such as international trade spanning geographical boundaries. This pioneering study employs the metacoupling framework and IPAT/STIRPAT theory to uncover the socio-economic drivers of mangrove loss across different spatial and temporal dimensions. Moreover, it serves as an empirical application of the metacoupling framework to human-nature systems involving mangroves, complementing the established IPAT/STIRPAT theory.

3.4 Methods

To assess how humans transform the mangrove forest and identify the forces driving these changes, we can apply mathematical models to quantitatively assess the stressors, such as the IPAT/STIRPAT model[96]. The IPAT model is a systematic approach to understanding human stressors of environmental changes. It has been successfully utilized to investigate the main driving forces of many environmental issues, such as energy use[95], CO2 emissions[100], land use[90], water consumption[85], and air quality[101]. Briefly, the model stands for Impact = Population * Affluence*Technology or I = PAT (eq. 3.1). Taking mangrove loss as an example, it represents Mangrove-loss = Population (P) * GDP / capita (A)* Technology (T) / GDP * Mangrove-loss / Technology.

Technology in the STIRPAT model quantifies the impact per unit of economic activity, encompassing factors like investment, domestic industry values (e.g., agriculture, fisheries, timber), and agent consumptions (e.g., households, non-governmental organizations). The extended STIRPAT model (eq. 2) transforms the original framework into an expanded version, typically employing natural logarithms for parameter estimation. The stochastic error term e is crucial in precisely defining the responsiveness of environmental impacts to each driving force[95,100,105,106].

$$I = aP^bA^cT^de \quad (3.1)$$

$$\ln I_i = a + b(\ln P_i) + c(\ln A_i) + e_i \quad (3.2)$$

In the STIRPAT model, we estimate constants and coefficients, where "e" represents the error term. Each coefficient serves as an empirical measure of 'ecological elasticity,' indicating how environmental impacts (dependent variables) respond to driver changes (independent variables). Coefficients in natural logarithmic form demonstrate the proportional change in the dependent variable resulting from a one-percent change in an independent variable, holding other factors constant. A coefficient of 1.0 (or -1.0) indicates 'unit inelasticity,' meaning the impact changes proportionately to the driving force. Coefficients >1.0 (or <-1.0) signify a 'positive (or negative) elastic' relationship, where the impact changes more rapidly than the driving forces. Coefficients <1.0 but >0 (or >-1.0 but <0) denote 'inelasticity,' where the impact changes in lesser proportion to the driving force. Unlike IPAT's assumption of a=b=c=d=1, the STIRPAT model empirically tests hypotheses of anthropogenic drivers, revealing varying levels of elasticity/inelasticity across population, affluence, and technology.

3.4.1 Constructions of model parameters

Dependent variable: mangrove deforestation footprint

We use the trade-adjusted mangrove loss (named mangrove loss footprint (MLFP)) as the dependent variable, which measures the mangrove deforestation dynamics embodied in international supply chains. The mangrove loss footprint describes the mangrove forest loss associated with a country's final demand (domestic and external). It is calculated by linking human-induced mangrove loss in the real world and their in-situ mangrove drivers (e.g., commodities, human settlement, non-productive conversion) with industry sectors in the multi-regional input-output table (MRIO) by applying the Leontief demand-pull model. We used Eora, a well-acknowledged MRIO database, to trace mangrove loss drivers within the global supply chains. EORA describes the world economy in terms of the annual production, trade, intermediate consumption, and final consumption of 26 homogeneous sectors between and within 189 countries from 2000 to 2021, which allows a direct comparison between the sectors in different countries[43,75]. The central tenet of the model is the input-output market balance:

$$x = AX + Y \quad (3.3)$$

In eq. 3, "X" represents a vector of total output, "A" is a technical coefficient matrix, and "AX" denotes a matrix describing the intermediate flows of "n" commodities within a global economy comprising "r" regions. Additionally, "Y" is a matrix representing final demand. The balance equation asserts that for each commodity, the total output equals the sale of commodities for intermediate production added to the sales for final use.

then we have the consumption-driven format:

$x = BY,\ B = (I - A)^{-1}$ (3.4)

In eq. 4, the $(I\text{-}A)^{-1}$ is the Leontief inverse matrix, indicating that both direct and indirect money from other countries sum to meet one final monetary consumption. Each element "b_ij" signifies the direct input of commodity "i" per unit output of "j."

$D = F * (I - A)^{-1} * y_1$ (3.5)

The mangrove loss footprint D of an arbitrary final demand y_1 can be calculated by eq. 5. where matrix "F" delineates the input of mangrove loss into the production of each respective sector. In our case, we consider three drivers from Goldberg’s mangrove loss dataset: commodities, settlement, and non-productive conversion.

Natural log transformation is performed for mangrove loss footprint to achieve normal distributions and a straightforward interpretation of the coefficients. Understanding global mangrove deforestation footprints is pivotal in formulating regulatory policies and science-based interventions to safeguard forests and biodiversity across diverse hotspots.

Independent variables

It is plausible that the human stressors that drive mangrove ecosystem changes interact; therefore, we apply the IPAT/STIRPAT model to estimate the contribution of each hypothesized factor in driving mangrove loss footprint.

We include GDP per capita to represent affluence[78] and a quadratic term of GDP per capita to capture the potential ameliorating effects of affluence at high levels. We also include population, the other core socio-economic indicator from the IPAT/STIRPAT model. Besides GDP per capita and population, investment (GDP share of Gross Capital Formation (GCF)) (investment rate), foreign direct investment(inflow and outflow share of foreign direct investment of GDP)[78,81], the share of industry and household value added in GDP (reflecting the structure of the economy)[85,87], domestic agricultural, fishing, and forestry added value(reflecting the domestic resource availability)[3,51,57,74], urban population, population density, female population[107] , and time trend may be critical determinants of a country's MLFP. So, we also tested them as explanatory variables. We obtained these socioeconomic indicators from World Development Indicators(https://databank.worldbank.org/source/world-development-indicators#advancedDownloadOptions). These independent variables are in natural logarithmic form to follow the specifications of the IPAT/STIRPAT model, and their metadata details are in the Appendix table SI3-4.

Moreover, studies suggest that institutional factors impact deforestation[57,62,108], that government effectiveness can lead to different trade barriers, tariffs, and embargoes to leverage the international trade's impact on the focal natural resources, and that can degrade the ability to implement conservation or economic development policies and laws in the focal country[109]. Therefore, we add governance indicators, government effectiveness, and corruption from the World Governance Indicators[110]. The variables range from -2.5 to 2.5, which represents the effectiveness of the countries' governments from low to high. We add 3 to turn values into all positive numbers and transform them into the natural logarithmic form in the model. In total, we collect 14 independent variables.

3.4.2. Panel estimation of socio-economic drivers of mangrove loss footprint (MLFP).

We employ panel analysis to estimate the short-run elasticity of MLFP concerning key socio-economic drivers. Given the limited periods (three) of existing mangrove loss data from Goldenberg et al., the co-integration and stationarity tests cannot be applied. Therefore, we use different regressions in panel analysis to find the optimal bench model.

Let y_{it} denote the dependent variable in our regression analysis for country i at period t. Let x_{it} be the $1 \times K$ row vector of the explanatory variable and c_i represent the country-specific unobserved heterogeneity (also called fixed effects). As y_{it} is continuous over the range of the real line, it is not too restrictive to use a linear panel data model to examine the relationship between y_{it} and x_{it}.

$y_{it} = \beta_1 + x_{it2}\beta_2 + x_{it3}\beta_3 + \cdots + x_{itK}\beta_K + c_i + t + u_{it}$ (3.6)

Or in vector form

$y_{it} = x_{it}\beta + c_i + t + u_{it}$ (3.7)

where $\beta = (\beta_1, \beta_2, \dots, \beta_K)'$ is the $K \times 1$ parameter vector and u_{it} is the idiosyncratic error term.

Two important questions need to be addressed regarding our panel data analysis. The first one is what variables to be included in xit. We follow the theoretical model (IPAT/STIRPAT) to select various variables and test their significance. Another critical issue in the panel data analysis is the correlation between ci and xit. Suppose our selected explanatory variables are properly exogenous because they are uncorrelated with the unobserved heterogeneity. In that case, the random-effects approach is attractive as it accounts for the variance of the additive error term ci+uit. On the other hand, if we suspect that some or all of the explanatory variables are correlated with the unobserved heterogeneity, then the fixed-effects approach is appealing as it eliminates the fixed effects by demeaning the data. It is also well-known that the fixed-effects estimation method cannot identify the parameters associated with time-constant variables. The primary interest in this chapter focuses on the effects of time-varying variables, although some geographical variables, which are time-constant, might also be of some interest[111].

Variables selection

Natural log transformations are performed on the dependent and independent variables to achieve normal distributions and a straightforward interpretation of the coefficients. The variables are tested, and constants, coefficients, and error terms are estimated using Stata 15.1. Based on IPAT/STIRPAT theory, we select affluence and population as the fundamental variables in the benchmark model, reflected as population and GDP per capita. Moreover, these two variables are validated through a stepwise algorithm to be included as the benchmark model. Employing the stepwise algorithm, we set entry and removal probabilities at 0.01 and 0.05, respectively, in testing the independent variables through OLS regression. As a result, except for population and GDP per capita, the other 12 variables are dropped due to their lack of statistically significant effects on the dependent variable. The resulting benchmark model from stepwise calculation fits the traditional IPAT theory, and the identified multicollinearity effect in the benchmark model is minor, with the highest variance inflation factor (VIF) for any factor in the model being only 1.03.

However, stepwise statistical-significance-based processes have been criticized for their inflation of regression coefficients on selected variables, bringing bias and potential for missing significant variables, especially when the sample size is not large[112]. We then apply four regressions: OLS, fixed effect, random effect, and first differencing to find the potential socio-economic variables to add to the bench model. The estimation equation for measuring the impact of per capita GDP (affluence), population, and other socio-economic indicators on mangrove loss footprint (MLFP) following the IPAT/STIRPAT model. In addition to population and affluence-related indicators, we test variables according to the literature review. In particular, we include institutional indicators, such as corruption and government effectiveness, and technology indicators, including investment rate, external investment share, economy structure, and domestic resource availability. The details of the variables are included in the Supplementary Table. The equation is as follows:

$$log\_y_{it} = \beta_1 + (log\_A_{it2})\beta_2 + (log\_P_{it3})\beta_3 +$$
$$(log\ \_x_{it4})\beta_4 \ldots + (log\ \_x_{itK})\beta_K + c_i + t + u_{it} \quad (3.8)$$

$log\ \_y_{it}$ denotes the logarithmic form of MLFP. *Log_A* is the logarithmic form of per capita GDP at purchasing power parity, measured in 2015 international dollars. The subscript i denotes the individual observations (that is, countries in this study); t denotes the period with three observations of 2000-2005 (t1), 2006-2010 (t2), and 2011-2016 (t3). β_2 is the MLFP–GDP elasticity. $\beta_3$is the MLFP-population elasticity. Time dummies are included to control for time-specific effects. Intercepts c_i are country-fixed effects that are included to control for time-invariant factors (for example, geography and resource endowment) that may affect the rates of the MLFP. Besides GDP per capita and population, other socio-economic indicators are included in $log\ \_x_{it4-k}$ and we test them as explanatory variables separately and find potential indicators with statistical significance to include in the bench model. The final full model is decided based on two criteria: the possibility of including the most variety of variables in different categories with statistical significance. The variance inflation factor (VIF) of the model is reasonably lower than five to avoid collinearity of variables.

Model Specification Test

We employ the Hausman testing statistic to compare the regression results from the random and fixed-effects estimation. A large value of the Hausman statistic suggests that the fixed-effects estimator is more reliable, and the random-effects estimator is inconsistent.

We also note the differences in the magnitudes of the estimates of variables of interest in random and fixed effect estimations. Thus, it is of interest to investigate which estimation method is more reliable. We use the regression-based Hausman specification test to choose between the random and fixed effects model[113]. In particular, we write out the following augmented regression equation.

$y_{it} = x_{it}\beta + \underline{x}_i\varphi + a_i + u_{it}$ (3.9)

where $\underline{x}_i$ is the time averages of x_{it} for country i. It should be mentioned that if x_{it} includes time-constant variables z_i, then $\underline{x}_i$ should not include these variables to avoid multicollinearity in our augmented model. OLS or random effects can estimate the above regression equation. A joint test of $\varphi = 0$ is asymptotically equivalent to the test of random effects assumption that c_i is uncorrelated with $x_i = (x_{i1,} x_{i2}, \dots, x_{iT})$. If we fail to reject the null hypothesis that $\varphi = 0$, then random effects estimator is more attractive. If we reject the null, which means there are statistically significant differences between the random effects estimator and the fixed effects estimator, the fixed effects method delivers a consistent estimator while the random effects estimator is inconsistent.

First Differencing Method

The fixed effects estimation effectively removes the time-invariant country-specific fixed effects by demeaning all variables. An alternative approach to eliminate the fixed effects is first differencing (FD hereafter). Mathematically FD is equivalently to the OLS estimation of Δy_{it} on Δx_{it} , where $\Delta y_{it} = y_{it} - y_{it-1}$ and Δx_{it} is similarly defined. Under the strict exogeneity assumption on the regressors, both FE and FD estimators give consistent estimates of the underlying parameters.

The popularity of the FD method is partially explained by its power to give casual interpretations. From the formula, we can see that the coefficients β measure how does y_{it} change associated with the change in x_{it}. In our context, we would like to use the FD estimator to evaluate the impacts of various economic variables on the mangrove loss footprint.

While both FE and FD provide consistent estimates, there are differences between these two estimators regarding their asymptotic efficiency. It has been shown that the fixed effects estimator is more efficient when $\{u_{it}\}_{t=1}^{T}$ is a white noise process. On the other hand, the FD estimator has an advantage in efficiency if $\{u_{it}\}_{t=1}^{T}$ follows a random walk or, equivalently, it is a unit root process. As indicated in many empirical studies, it is most likely that the true dynamics of $\{u_{it}\}_{t=1}^{T}$ is neither a white noise process nor a unit root process but something in between. There are serial correlations among $\{u_{it}\}_{t=1}^{T}$ but they are not a I(1) process. For the following statistical analysis, both FE and FD estimators are reported.

In our case, we used first differencing regressions for discussions. The specific regression model follows:

$$\Delta log\_y_{it} = \beta_1 + (\Delta log\_A_{it})\beta_2 + (\Delta log\_P_{it})\beta_3 +$$

$$(\Delta log\ \_Gov_{it})\beta_4 + (\Delta log\ \_GCF_{it})\beta_5 + (\Delta log\ \_Foreign_{it})\beta_6 + c_i + \ t + u_{it} \quad (3.10)$$

This regression structure is the same as eq. 8. The only difference lies in the variables are turned into the value difference between two periods, that is , $\Delta \log\ \_y_{it} = \log\ \_y_{it} - \log\ \_y_{it-1}$. And the independent variables are similarly defined.

Additional specifications of the model

The extension of the study is to understand the socio-economic driving forces of mangrove loss footprint (MLFP) across space. We decompose the focal country’s MLFP based on their geographic information and categorize them as domestic, adjacent, and distant mangrove loss footprints. Countries that share political boundaries with the focal country are adjacent; others are classified as distant countries. By definition, mangrove loss footprint measures mangrove loss embodied in international trade, which measures the loss the focal nation's consumption can drive. Accordingly, adjacent MLFP measures mangrove loss that the focal country's consumption can drive in the nearby countries, and so does distant MLFP. It follows

$$MLFP = MLFP_{domestic} + MLFP_{adjacent} + MLFP_{distant} \quad (3.11)$$

CHAPTER 4: UNVEILING COMPLEMENTARITIES BETWEEN MANGROVE RESTORATION AND GLOBAL SUSTAINABLE DEVELOPMENT GOALS

Abstract

Indonesia, renowned as the most mangrove-rich nation, is committed globally to restoring 600,000 hectares of mangrove forests by 2024. Although mangrove restoration has many influences beyond simply increasing the extent, its effects have yet to be systematically evaluated. Our study conducts a comprehensive network analysis to investigate the synergies between mangrove restoration and global Sustainable Development Goals (SDGs) achievements by exploring their interactions between 41 mangrove socio-ecological system (SES) metrics and SDGs at the 17 Goals and 118 indicator levels. This investigation follows the 'product space' method in economics and creates the 'Mangrove-SDG space' to assess each metric pair's co-occurrence and comparative advantages with validated stability. Our analysis unveils a tripartite structure, encompassing socio-economic and environmental clusters, each significantly contributing to global sustainability and a distinctive mangrove cluster tied to land attributes. At the Goal level, mangrove loss showcases robust synergies with SDGs 12 (Responsible Consumption and Production) and 13 (Climate Change), and mangrove metrics such as tropical storm frequency and mangrove change, indicating strong interdependences between mangrove forests and SDGs, that improved performance of climate change and responsible consumption can greatly enhance mangrove forests' performance such as in alleviating mangrove loss and reducing tropical storms. Moreover, our analysis underscores the central roles played by 'bridge' Goals, which indicator-level space proves how they warrant prioritization because of their cascade synergistic enhancements across widely interconnected indicators, triggering systematic positive improvements. Turning to Indonesia, we advocate a strategic shift from solely expanding mangrove extent to focusing on four critical policy priorities: effective nitrogen management, enhancing Ramsar site efficiency, optimizing logistic performance, and addressing urban population conditions. These priorities are pivotal to seeking

complementarities between Indonesia's international sustainability commitment and fostering mangrove restoration success.

Keywords: Sustainable Development Goals, Mangrove Governance, Complementarities, Policy Priorities, Indonesia,

4.1 Introduction

Mangrove forests play a vital role in sustaining ecosystems at both local and global scales. This salt-tolerant ecosystem found in the intertidal regions of tropical and subtropical coastlines provides a habitat for wildlife, traps nutrients within dense root systems, nourishes marine wildlife, and serves as a carbon sink that contributes significantly to global climate regulation[4]. Healthy marine ecosystems can support local livelihoods and assist in eradicating poverty. Consequently, prior studies have found that mangrove forests broadly influence various socio-economic aspects of society, including substantial economic and ecological benefits[1,114,115]. For example, preventing further mangrove loss could potentially avoid nearly 424 $MtCO_2e$ by 2030 globally, equivalent to 6% of emissions generated by land use change in 2019[116].

However, conserving the world's mangrove forests is a complex issue with various challenges. As the human population increases, especially in coastal communities, mangrove forests have experienced a net loss in recent decades[16,50,51]. Studies have indicated that as high as 35% of the world's mangrove areas in the 1980s-1990s had already been deforested, and the current yearly mangrove deforestation rate is from 1%-8%[4]. On the other hand, the natural condition of mangrove forests and their complex root system make it challenging to allocate property rights efficiently for proper management. Privatizing mangrove areas has implied socio-ecological impacts[117], such as worsening the loss of ecosystem services from mangroves and increasing socioeconomic inequality in local communities by favoring inefficient and unsustainable allocation of resources[118]. Therefore, conserving mangroves is hard to achieve and is closely linked with the efficiency of mangrove management and the quality of mangrove governance.

Moreover, identifying mangrove forests and the extent of their underlying drivers has long presented challenges attributable to a combination of natural and human-induced factors.

Mangrove forests thrive exclusively in the intertidal zone, bridging the gap between coastal and terrestrial landscapes. Their existence is intricately intertwined with the land's natural ebb and flow. It is inherently susceptible to shifts induced by rising sea levels and the erosive forces of large-scale disturbances such as stronger storms and ocean acidification. Furthermore, the spatial distribution of mangroves exhibits considerable variation due to divergent abiotic environments, forest structures, species diversity, and more, each varying across regions and nations[54]. This high geographical variability serves as a fundamental driver of mangrove deforestation, consequently leading to the loss of crucial ecosystem services, such as carbon sequestration, on a global scale[116]. Conversely, the triumphs achieved in expanding mangrove extent and the concurrent enhancement of ecosystem services through restoration projects have spurred the emergence of national and regional policies geared toward mangrove conservation and rehabilitation. Mangrove forests are widely mentioned by at least 45 countries in their national plans to tackle climate change[119], 28 countries in their restoration pledges, and approximately 62 countries in their national biodiversity plan[120,121] for global sustainability. For example, Indonesia proposed a mangrove rehabilitation target to restore 600,000 ha by 2024, in line with the UN Decade of Ecosystem Restoration 2021-2030--a strong commitment made by the global conservation community to increase mangrove cover by 20% by 2030[116]. Similarly, China’s national mangrove action plan aims for restoration of 18,800 ha before the year 2025 to support the livelihoods of coastal communities and absorb carbon dioxide[122].

The intricate dynamics characterizing changes in mangrove forest habitats encompass an array of factors, including ongoing rehabilitation and conservation initiatives, juxtaposed against mangrove degradation and deforestation resulting from natural climatic fluctuations and anthropogenic logging activities. This complexity introduces significant uncertainties in quantifying mangrove forest extent and its proximate drivers, directly impacting the assessment of the effectiveness of mangrove conservation policies. Notably, compared to the large quantity of global-scale data available for mangrove forest coverage and change, the field lacks robust, time-sensitive, and consistent datasets capable of addressing the geographical variations in mangroves, encompassing different geomorphic settings, species types, and drivers essential for tailoring conservation and restoration strategies for effective policy interventions[54,123,124]. This extends to unanswered questions regarding how macro-scale mangrove conservation policies influence global sustainability.

Nations and organizations have invested efforts in estimating how mangrove forests can contribute to international sustainable development. For example, The United Nations' Sustainable Development Goals (SDGs) proposed in 2015 represent an ambition to foster inter-governmental efforts to achieve sustainable development by 2030. This comprehensive framework includes 17 interlinked Goals and over 200 indicators, including those related to mangrove forests. Moreover, the United Nations[125], along with many international and regional non-profit initiatives [126–129], has listed arrays of ecosystem services that mangroves can provide in achieving specific SDGs, including the discussion on how potential loss could impede SDG achievement[130] and how mangrove restoration may facilitate progress[131]. Studies have also addressed the mechanisms of how mangrove forests affect certain SDGs, such as Goal 14 (life underwater) in coastal management [132] or in specific regions such as Kenya [133] and Indonesia [116]. These efforts help document the interlinkages between mangroves and specific SDGs in certain areas. However, these understandings of the interactions between mangrove conservation and SDG achievement remain qualitative and unilateral. Governance structure, environmental contexts, and socio-economic conditions can influence their complex interactions. The missing of their broader context and interconnectedness may lead to biased policymaking and distort the overall achievement of the SDGs, along with mangrove conservation.

This chapter investigates the complementarities between mangrove conservation and sustainable development Goals by comprehensively and systematically connecting mangrove metrics with sustainable development Goals at coarse and fine levels through expanding the application of the 'product space' concept in economics. The product space approach, derived from the revealed comparative advantages (RCA) of products, can be used to compare the economic specialization pattern in economics. By measuring the shared production capability between products' economic activities, named as 'proximity,' 'product space' can illustrate the similarity of the productive ability of products (such as infrastructure, labor, capital, etc.), indicating which products share similar production capabilities and are more likely to be efficiently produced simultaneously, which represents the complementarities of products. This concept has been applied in constructing 'SDG spaces'[134–136], measuring the complementarities between SDGs and indicators at global and national levels with a more stable structure and a substitute understanding of SDG pairs' synergies compared to the traditional interpretation. Furthermore, to explore the application of 'product space' in conservation policy implications, especially in mangrove conservation, which has confronted data discrepancy in quality and quantity, we apply the concept to understand the complementarities and structures between mangrove-related indicators and SDGs. The complementarity measurment of the performances of mangrove conservation outcomes and sustainable development goals can provide science-based knowledge on what metrics have similar requirements to work together synergistically, considering efficiency and overall outcomes. The high synergetic proximity between the pairs of SDGs and mangrove metrics displaying a robust network connection is more likely to exhibit synergies: enhancing one goal can positively improve another. Moreover, this integrated approach to quantitatively discussing the structure and relationship between mangroves and the SDGs provides a powerful tool for systematically assessing their interactions by identifying co-benefits and synergies, establishing actionable priorities for nations to achieve mangrove-sustainable development, and providing more robust policymaking than focusing solely on specific aspects of SDGs.

In the Mangrove-SDG space, a well-connected goal, target, or indicator is central to developing numerous other goals or indicators. A less connected goal may need more synergies to avoid slow progress. The study will answer the following questions: (1) What is the global mangrove-SDG space at goal and indicator levels? (2) Compared to existing methods, Is the mangrove-SDG space stable for long-term policymaking? (3) How do countries prioritize policies based on the space to reach the maximum benefits toward overall mangrove sustainability? To address these questions, our approach involves the construction of three distinct tiers within the Mangrove-SDG space employing diverse datasets. The initial two tiers of these spaces amalgamate SDG data at the goal level with two sets of mangrove data: one emanating from two sources of mangrove loss data and the other encompassing various metrics of mangrove socio-ecological system. The third tier of the Mangrove-SDG space encompasses SDG data at the indicator level, intricately interwoven with the metrics related to the mangrove socio-ecological system. By constructing three tiers of space, we can test the stability of spaces with different datasets and understand the complementarities in mangrove sustainability at multiple resolutions. Subsequently, we visually represent these intricate network structures and undertake an in-depth network analysis to identify and delineate clusters and ascertain the core-periphery dynamics. We also embark on comparative analysis to discern and quantify the relative stability levels exhibited by the Mangrove-SDG spaces in contrast to correlation coefficient networks. Through these processes, our study can provide policymakers with quantitative tools and insights into achieving sustainable mangrove development and advancing the broader SDGs. It will also enhance understanding of the interconnections between mangrove forests and sustainable development, paving the way for more effective and efficient policymaking.

Table 4.1: Concept clarification between product space and Mangrove-SDG space.

	Product Space	Mangrove-SDG Space
Network	the relatedness or proximity between products traded in the regional market	The complementarities or proximity between measurements of two policies (mangrove-related metrics and SDGs) in a given regional level
Nodes	Products	SDGs + mangrove metrics
Edges	the similarity of productive ability required to produce two products within a given region	the complementarities between each node pair, reflecting the environment similarity to incubate the performance of each node.

4.2 Results

4.2.1 Unveiling the Mangrove-SDG Nexus: A Multi-Dimensional Exploration

The goal-level ‘Mangrove-SDG space’ encompasses 17 SDG goals and two pivotal mangrove loss indicators, namely GMW_loss and Gold_loss, to represent Global Mangrove Watch (GMW) and Goldenberg (Gold), aggregating to 19 nodes, intertwined by a web of 183 synergetic interactions. These two datasets are well-acknowledged sources of global mangrove forest cover data, with one having an overestimate and the other having an underestimate of the real-world mangrove loss[6,51]. Employing an unsupervised classification algorithm, we partition this space into two clusters, discernibly categorized as socio-economic development-related goals, denoted as the 'pink group,' and environmental progress-related objectives, represented by the 'green group.' The division is effective because the modularity value of the division is 0.361. This value is used to measure partition quality and falls within a range of 0.3 to 0.7, which is empirically recognized as an effective partition. The relatively modest modularity value means that all nodes within this space, encompassing the two mangrove loss indicators and the 17 SDGs, are closely interlinked, emphasizing the intricate interplay among elements spanning society, the economy, and the environment.

The proximity between the two mangrove loss indicators is the highest, denoted as 0.94, reflecting the level of similarity of the two datasets in the space regardless of sources and the stability of the space. They are within the environmental-related cluster, underscoring their extensive synergies with environmental-related SDGs. Specifically, they exhibit the highest intense synergies in the space with 12 (Responsible Consumption and Production) and 13 (Climate change) (Fig. 4.1-a2), which are strongly synergized with SDG 14 (Life Below Water). They are the most substantial synergies in the environmental cluster as the core nodes (yellow edges in Fig. 41-a1).

Furthermore, enhancing these two mangrove loss indicators can result in synergies with SDGs 2 (Zero Hunger), 8 (Decent Work and Economic Growth), 10 (Reduced Inequalities), and 15 (Life on Land), as they merge within the same cluster, forming a network of robust synergies. SDG 15 (Life on Land) sits at the periphery, with a few tenuous synergistic connections to the core nodes. In contrast, SDGs 2 (Zero Hunger), 8 (Decent Work and Economic Growth), and 10 (Reduced Inequalities) are similarly equidistant from the core of the environmental-related cluster. However, they are in the center of the space with significant betweenness centrality values. These SDGs assume the role of 'bridges' within this space, serving as conduits linking nodes in both clusters. Enhancing these two goals can profoundly augment overall sustainability performance, given their extensive synergistic interactions across the space.

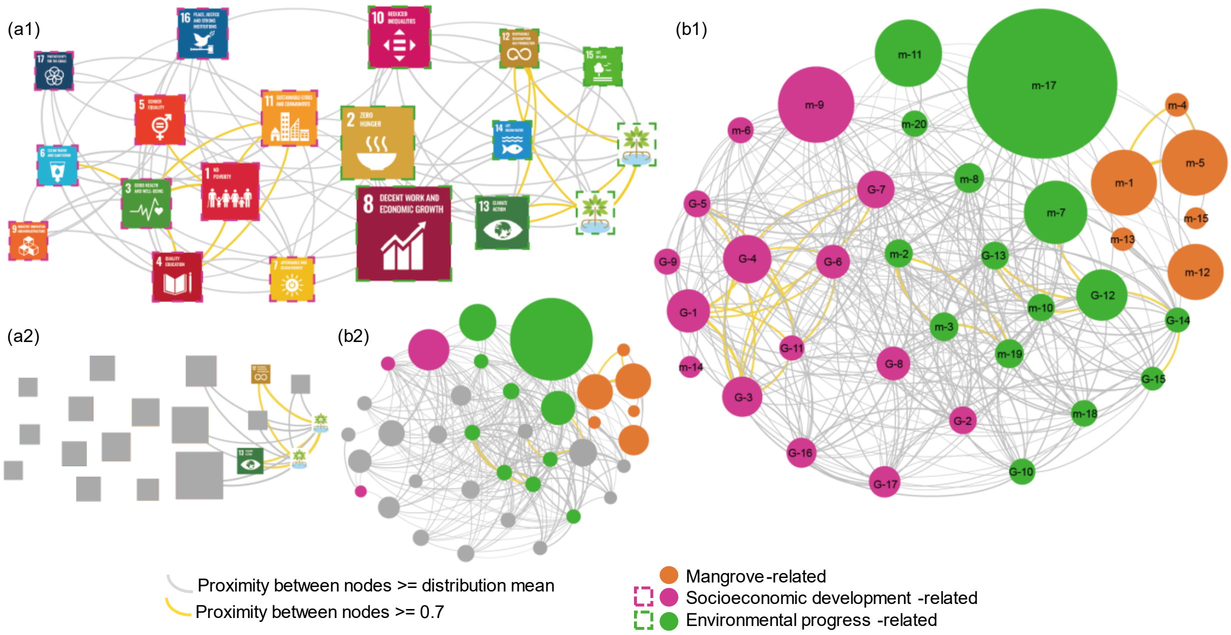


Figure 4.1 (Fig. 4.1): A Multidimensional Nexus of goal-level 'Mangrove-SDG' space: a1. 'Mangrove-SDG space,' shaped by two mangrove loss data sources. a2. Synergies between mangrove loss and the associated SDGs. b1. Extending the 'Mangrove-SDG space,' with all mangrove metrics. b2. Synergic interactions between mangrove metrics and their SDGs.

4.2.2 Augmenting Insight through Goal-Level 'Mangrove-SDG Space'

The goal-level Mangrove-SDG space enriched with a comprehensive array of mangrove metrics constitutes an expansion of prior efforts to categorize interactions to explore more nuanced insights into mangrove sustainability. As depicted in Fig. 4.1-b1, the space encompasses 20 metrics specific to mangroves and 17 SDGs comprising 37 nodes with 690 synergistic connections. This analysis is an amplified version of the prior goal-level space because the nodes from the preceding space, encompassing SDGs and mangrove loss indicators, are located similarly in this space, with similar classification results. For instance, m-3 (GMW mangrove loss), housed within the environmental-related cluster, clusters with SDGs 12 (Responsible Consumption and Production), 13 (Climate Change), 14 (Life Below Water), and 15 (Life on Land)—mirroring the configuration of the goal-level realm, with their interconnected synergies reinforced by significant proximity (≥0.7).

Our analysis introduces a more intricate web of details concerning mangrove metrics. For example, the core of the environmental cluster embraces mangrove loss and other mangrove metrics, including m-7 (Marine Protected Area (MPA) staff capacity), m-10 (Nationally Determined Contributions (NDC) commitments), alongside m-2 (mangrove change) and m-19 (tropical storm frequency). These mangrove-specific indicators converge with mangrove loss, accentuating their potential to drive transformative improvements in mangrove conservation and the performance of related SDGs within the environmental cluster. Notably, mangrove loss exhibits its most robust synergies with mangrove change and tropical storm frequency, signifying that lower storm occurrences and increasing mangrove areas can significantly mitigate mangrove loss. Additionally, NDC commitments exhibit strong synergies with SDG 12 (Responsible Consumption and Production) and SDG 13 (Climate Change), suggesting that international cooperation encouraging countries to reduce emissions can substantially improve climate change and prompt responsible consumption in industries.

Nevertheless, differences are also discernible. First, an additional cluster takes shape, comprising six mangrove-related metrics. The unsupervised clustering technique indicates the elusive nature of these indicators, rendering them challenging to align with either of the primary clusters within the Mangrove-SDG space. These metrics include m-1 (mangrove area in 2016), m-4 (mangrove gain), m-5 (country area in 2016), m-12 and 13 (total number and area of Ramsar sites), and m-15 (the cumulative sum of night light growth). Given their real-world implications, these metrics are intrinsically tied to land areas, diverging from global sustainability metrics rooted in socio-economic and environmental considerations. Furthermore, within the socio-economic cluster, three mangrove indicators find their niche: m-14 (night lights growth), m-6 (varieties of Democracy), and m-9 (the economic complexity index). Notably, m-6 and m-14 occupy the periphery of the socio-economic cluster, characterized by modest betweenness values. Conversely, m-9 stays close to both environmental-related and mangrove-related clusters. It has a high betweenness centrality value of 31.54 with synergies connected in three clusters and can be named the ‘bridge’ indicator.

The significance of these 'bridge' indicators lies in their potential to bolster the growth of their associated indicators, which has a profound influence over the entire network. Consequently, these indicators merit prioritization in future policy considerations. In addition to m-9, m-17 (historical sea level rise) and m-11 (Indigenous property tenure) emerge as prominent 'bridge' metrics, underpinned by the highest betweenness centrality values—76.02 and 27.05, respectively. Sea level rise, with an extensive nexus encompassing indicators from three distinct clusters, emerges as a quintessential bridge uniting 11 mangrove metrics with 15 SDGs. This pivotal role accentuates its potential to catalyze broader transformations. Similarly, Indigenous property tenure, straddling the boundary between the mangrove metric cluster and the environmental-related domain, forges a network of connections encompassing nine mangrove metrics and six SDGs. The 15 connections underscore that enhancing Indigenous property tenure relative to other land types within a nation can profoundly influence mangrove sustainability, invigorating environmental and overall sustainability clusters.

4.2.3 Consistency and Complexity in Indicator-level Mangrove-SDG Space

The integrity of the indicator-level Mangrove-SDG space echoes the stability observed in goal-level spaces, laying the groundwork for pinpointing pivotal indicators for future policy implications concerning SDG and mangrove sustainability achievements. This space materializes through the discernment of synergies amid its distribution mean (0.45), encompassing 115 nodes that comprise 20 mangrove-related metrics and 95 SDG indicators. Impressively, the intricate interplay engenders a staggering 6580 interconnecting edges. Much akin to goal-level spaces, the architecture of this indicator-level realm bears semblances yet discernibly elevates the complexity scale owing to its granular metric inclusions. The parallelisms manifest across three dimensions.

First, indicator-level space can be subdivided into three distinct clusters. The first cluster encompasses all six mangrove indicators, while the remaining two are delineated as socio-economic-oriented and environmentally focused clusters. The socio-economic cluster comprises a relatively smaller subset of mangrove indicators (4), whereas the environmental-related cluster encompasses most of these indicators (10). Second, Fig. 4. 1-b2 and Fig. 4. 2-b demonstrate the consistency of all mangrove metrics vis-à-vis the goal-level expanse. These metrics assume their designated positions, creating significant synergies and relationships. For example, the interaction of three specific measures related to m-1, the area of mangroves in 2016, m-4, the increase in mangrove area from 2007 to 2016, and m-5, the country area in 1996 shows strong connections and synergies that help achieve specific goals and indicators in the mangrove sector. Finally, the quintessential core-periphery dynamics persist for the bulk of SDG and mangrove indicators. Consider the four socio-economic clustered mangrove-related indicators, distant from the core, primarily positioned as a bridge connecting the socio-economic and environmental enclaves or close to the mangrove cluster.

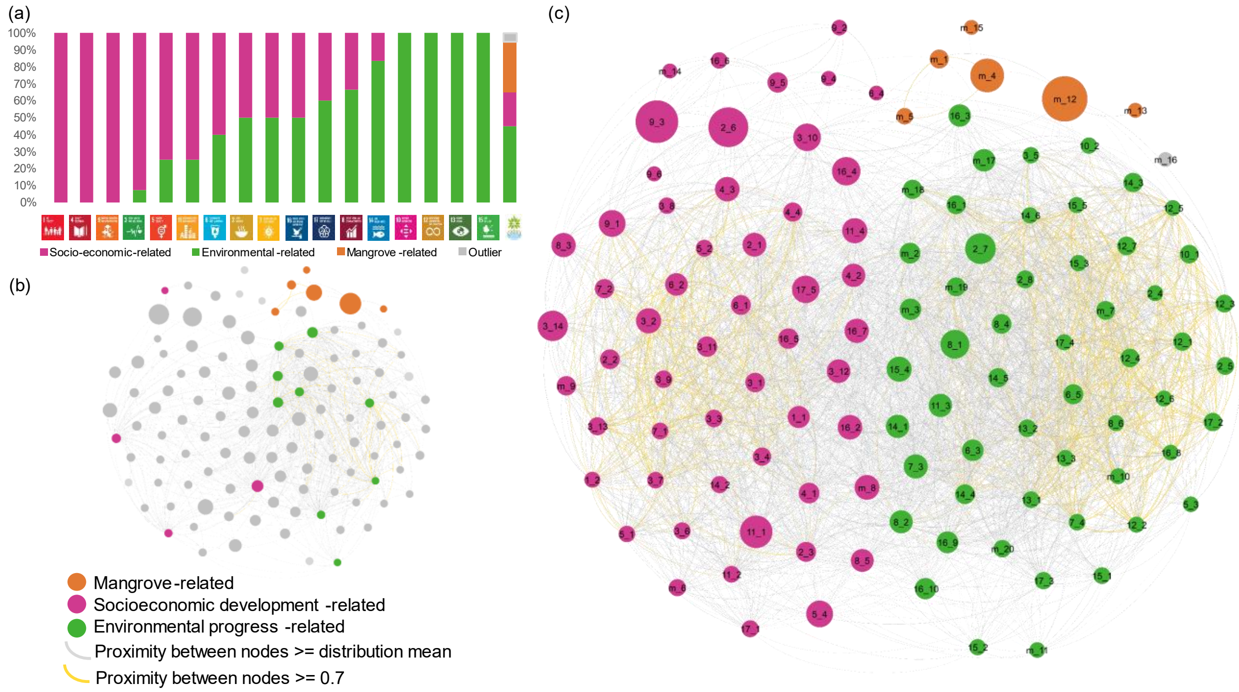


Figure 4.2 (Fig. 4.2.): a. Percentage chart depicting cluster distribution of SDG indicators and mangrove metrics. b. Graphical portrayal of synergies binding mangrove metrics and their associated SDG indicators. c. Indicator-level Mangrove-SDG space with the entirety of mangrove metrics.

The indicator-level space embraces intricacies, unraveling the strategy for prioritizing SDG and mangrove indicators toward sustainable accomplishments. On a more detailed level, the interaction between m-2 and m-3, changes and loss in mangrove areas during 2007 to 2016 shows significant connections with various SDG indicators, which are central in linking economic and environmental aspects. These indicators include Sustainable Nitrogen Management, Adjusted GDP Growth, Satisfaction with Public Transport, Property Rights, and Statistical Performance. The connection between mangrove loss and these central SDG indicators shows that tracking mangrove loss is key to monitoring global sustainability. The connection between mangrove loss and these 'bridge' SDG indicators indicates that mangrove loss can be a representative indicator of global sustainability monitoring. Reducing mangrove loss can improve these SDG indicators. These central indicators can also trigger positive ripple effects, leading to improvements across a network of interconnected indicators, which in turn helps in achieving overall sustainability goals. Furthermore, the dynamic of mangrove changes and loss is encapsulated by m-19 (Tropical storm frequency). Consistent with the goal-level space, the proximity unravels the essence of drivers governing mangrove loss and change during 2007-2016. This demonstrates that natural storm disturbances can unleash cataclysmic impacts on mangroves. This interdependence indicates a pressing need for informed policymaking by emphasizing climate change mitigation, given its potential to directly influence mangrove loss and change, thus paving the way for resilient mangrove sustainable development.

4.2.4 SDG-Mangrove spaces across scales are more stable than correlation coefficient networks.

The consistency of goal- and indicator-level spaces with different mangrove metrics has proven the stability of 'Mangrove-SDG space' regardless of data sources, quality, quantity, and resolution in the above analysis. We also embark on a comprehensive comparison by constructing both the correlation coefficient structure and the space utilizing goal-level and indicator-level data encompassing mangrove and SDG data from 1996 to 2007 and 2007 to 2016. Our objective is to scrutinize their network stability, shedding light on the reliability of our constructed space compared to the most common way to measure synergies between variables (correlation coefficient). To gauge the stability of the networks, we employ matrix norms and calculate the discrepancies in norms between the most recent network structures and their respective earlier counterparts. The results, as delineated in Table 4.1, reveal the stability of the space. The goal-level SDG space of 1996-2007 differs by a mere 6.93%, and the indicator-level SDG space shows an 8.4% divergence from its 2007-2016 equivalents. In stark contrast, the correlation structure confronts more substantial changes, with the goal-level coefficient network of 1996-2007 displaying a 12.26% disparity from the 2007-2016 network. Similarly, the indicator-level coefficient networks exhibit a 12.57% difference across the two temporal periods.

Table 4.2: Mangrove-related network similarity comparison at goal-level and indicator-level between 1996-2007 and 2007-2016.

Norm difference	Goal-level space	Indicator-level space
Correlation network (in percentage)	12.26	12.57
SDG space network (in percentage)	6.93	8.4

4.3 Discussion

4.3.1 The enduring stability observed in the structure of SDG-mangrove spaces across scales and time can systematically monitor long-term mangrove sustainability progress and provide countries with case-by-case pathways.

The complexities surrounding the conservation of global mangrove forests, compounded by the absence of reliable, timely, and uniform data on mangrove extent and influencing factors, pose significant obstacles to the systematic, long-term monitoring of these ecosystems and their contributions to global sustainability. The stable ‘Mangrove-SDG space,’ spanning both coarse and fine resolutions and across time, emerges as a potent tool for policymakers, offering solutions to the challenges above, irrespective of data quality and quantity constraints.

First, the stability of our crafted space is significant in the long-term policy planning for mangrove sustainability efforts (e.g., in response to climate change). These policies emphasize the importance of feedback, where policy actions have a lagged performance to the system. A network structure that maintains stability over time is critical, offering tools to visualize, monitor, evaluate, and interpret the dynamics of real-world policy responses and problems. In this regard, it holds the potential to act as a cornerstone for facilitating efficient, sustainable development strategies and robust mangrove conservation efforts with sound science-driven solutions to complex decision-making processes.

Second, the stability elucidates that not all goals, indicators, or mangrove metrics share equal prospects for improvement. For instance, two nodes with high proximity are more likely to require similar external resources because the proximity metric quantifies the similarity in external resources required for attaining two distinct nodes, such as capital investment, technological innovation, and organizational governance. This convergence in resource requirements facilitates efficient resource utilization. Thus, when a country excels in achieving one goal, it is inclined to extend its efforts to pursue its connected nodes in the Mangrove-SDG space with a high-intensity edge to foster sustainability on a broader scale.

Moreover, specific indicators at the peripheral positions encounter more challenges to improve because they are connected with few synergies in the space and may need to navigate through the 'bridge' goals as they occupy peripheral positions. Hence, 'bridge' nodes are of paramount importance. These 'bridge' metrics establish connections among different clusters characterized by numerous weak synergies with other nodes and lay the groundwork for a comprehensive and systematic approach to measuring and evaluating policies to achieve overall sustainability progress and mangrove conservation success. These 'bridge' elements can address and elucidate various dynamics, including (1) the mechanisms by which countries attain comparative advantages in specific goals relative to others, and (2) how countries make determinations regarding the development of goals or metrics, and whether other goals or metrics can be aligned synergistically to advance overall sustainability within the realm of SDGs and mangroves. Consequently, the intricate network topology of the space acts as a 'dictionary' for understanding the synergy of metrics, enabling policymakers to set priorities and initiate constructive dynamics for future development. Using Indonesia as a case study, we illustrate how the goal-level and indicator-level space with mangrove metrics can effectively inform targeted policy-making processes in the nation[116].

4.3.2. The massive mangrove loss and the effects of restoration projects in Indonesia can be reflected in the Mangrove-SDG spaces.

Indonesia, renowned as the most mangrove-rich nation globally, boasts the largest expanse of mangrove forests, covering 22% of the total global mangrove area.[56] Notably, it ranks among the trio of countries, alongside Australia and the United States, with the most substantial annual carbon sequestration potential and extensive coverage of coastal ecosystems[2]. These mangrove ecosystems are crucial connecting points between Indonesia's people and its natural environment. However, a concerning trend emerges as approximately 800,000 hectares of these vital ecosystems have been cleared and converted over the past three decades[54]. This concerning trajectory is depicted in Figure 3-a, illustrating the goal-level Mangrove-SDG space with Indonesia's sustainability performance color-coded. Within this space, we observe the central placement of critical metrics—m-2, m-3, and m-19—representing mangrove loss, mangrove change, and tropical storm frequency spanning 2007 to 2016. They are situated in the heart of the global sustainability clusters, as indicated by the pink-shaded circle, reflecting their suboptimal performance within Indonesia during the same period.

In response to this loss of a precious ecosystem, policymakers and various non-governmental stakeholders have voiced the urgent need for mangrove conservation and restoration. In collaboration with Eurasia, Brazil, the US, Canada, and India, Indonesia has emerged as a global leader in implementing restoration solutions. Together, they are working towards restoring 15 million hectares of peatlands by 2030 and a staggering 350 million hectares of forests and wetlands by 2050. This concerted effort is projected to reduce nearly five gigatons in emissions annually, marking 30% of the natural climate solution mitigation opportunity by 2030[137]. This significant endeavor could benefit a substantial coastal population of 74 million people and contribute to national emissions reductions of up to 16%[54,137]. We identify the progress in Fig. 3a and b through the above-average performance of Indonesia in m-4: mangrove gain, which can reflect the direct mangrove extent success of Indonesia's leading restoration projects worldwide. However, neither graph shows the direct synergetic connections with SDG goals or indicators, and its connections with strong synergies are discussed in 3.2.2. Moreover, despite these noble and ambitious efforts, it is essential to acknowledge that many large-scale restoration initiatives have faced challenges and encountered low success rates. The reasons behind these hurdles are multifaceted, including limited ecological understanding, inadequate representation of subnational governments in mangrove governance, and ineffective monitoring and evaluation mechanisms. These factors collectively underscore the complex landscape of mangrove conservation and the pressing need for holistic and well-informed strategies to succeed in these critical endeavors.

The Mangrove-SDG spaces indicate a policy priority transformation from mere mangrove extent gain to its synergized 'bridge' indicators.

Our analysis explores different perspectives to explain the failure of mangrove restoration projects in consideration of Indonesia's overall sustainability performance. As shown in Fig 3-a, m-4, representing mangrove gain between 2007 and 2016, which usually increases due to rehabilitation and restoration projects, is strongly synergized with m-1 and m-5, representing the original natural habitat of mangrove forests and the country's administrative area. They have reached a proper performance (green dots). Moreover, the two land-based metrics are relatively independent in the goal-level and indicator-level spaces (Fig. 3-a and b) and relate to merely a few goals or indicators. However, when we dig into their synergized nodes with solid connections (proximity > 0.45), shown in Table 4.2, they are 2-7(Sustainable Nitrogen Management Index), m-12 (Ramsar Sites' Area), m-17 (Historic Sea Level Rise), 11-1 (Urban Population Living in the Slums), and 9-3 (Logistics Performance Index). These indicators are the most significant 'bridge' indicators in the spaces, either in goal- or indicator-level spaces, with the highest betweenness centrality values. The performance of these indicators can have the most potent influence in the space, indicating that mangrove forest gain can be affected by the poor performance of these 'bridge' indicators from a broader perspective considering the overall sustainability. However, it has not reached a proper performance now.

These 'bridge' indicators are still poorly performed (pink dots) in Indonesia, which indicates their potential to impede the performance of mangrove forest gain and impact the efficacy of mangrove conservation projects. Except for the urban population living in the slums, the other 'bridge' indicators are below average. In one way, the improvements of mangrove forests have their limits, which are strongly strained and synergized by the natural habitat of mangrove forests and the country's administrative areas. Policies focusing merely on the increase in mangrove extent have limits because natural conditions set the natural habitat of mangrove forests. Too many resources poured into increasing the mangrove forest extent may result in lower resource efficiency. In another way, mangrove forest gain can be weakly influenced or impacted by those weak synergized 'bridge indicators. The policy should prioritize those 'bridge' indicators more, especially poorly performed ones. These 'bridge' indicators' improvements can directly be synergized with mangrove gain performance. Moreover, they have deciding roles to the overall sustainability with positive cascading effects for many other sustainability-related indicators, including mangrove conservation success.

Table 4.3: The robust synergies directly and indirectly related to mangrove restoration projects in Indonesia.

Source	Target	Link intensity (Proximity)	Target's betweenness centrality
m-4 (mangrove gain in 2007-2016)	m-5 (country's administrative area in 1996)	0.8	9.43
	m-1(mangrove coverage in 2016)	0.77	24.18
	m-13 (Area of Ramsar listed Wetlands)	0.48	183.68
m-1(mangrove coverage in 2016)	m-13 (Area of Ramsar listed Wetlands)	0.54	183.68
	9-3 (Logistics Performance Index: Quality of trade and transport-related infrastructure (worst 1-5 best))	0.48	167.32
	11-1 (Urban Population Living in the Slums)	0.47	105.46
	M-17 (Historical sea level rise)	0.47	45.97
	2-7 (Sustainable Nitrogen Management Index)	0.46	94.50
m-5 (country's administrative area in 1996)	m-13(Area of Ramsar listed Wetlands)	0.52	183.68
	11-1 (Urban Population Living in the Slums)	0.47	105.46
	9-3 (Logistics Performance Index: Quality of trade and transport-related infrastructure (worst 1-5 best))	0.48	167.32

Priority 1: Sustainable Nitrogen Management Index

As shown in Fig 4.3-b, indicator 2-7 (Sustainable Nitrogen Management Index) is in the middle of global sustainability-related clusters (red circle with dashed line), between the environmental-related cluster and the socio-economic cluster. Moreover, it is placed close to m-2 (Mangrove change), m-3 (Mangrove loss), and m-19 (Tropical storm frequency) in 2007-2016, along with two SDG indicators: 15-4 (Permanent deforestation percentage) and 8-1 (Adjusted GDP growth), which were poorly performed in Indonesia in 2007-2016. However, these indicators have a high potential to decide Indonesia's future sustainability because of their location, which can act as the 'bridge' between socio-economic and environmental clusters, contributing to the overall achievement of sustainable development. Firstly, they are close in the space, indicating their improvements require similar external incentives, such as policy, institutions, resources, etc. Policy priorities on improving any of these indicators can bring enhancements of their related 'bridge' indicators because of similar policy stigma and external environment requirements. Secondly, these indicators have a broad range of coverage of synergies and can potentially bring positive cascading effects to the whole system. For example, 2-7 is synergized with 78 indicators, including ten mangrove metrics and 68 SDG indicators. The broad coverage of synergy indicates that its improvement can help enhance these indicators, consisting of about half of all indicators (135). Moreover, these 78 indicators include 'bridge indicators, and their improvements can generate broad indirect synergies with their connected indicators.

Priority 2: Ramsar Sites' Area

Similar situations can be applied to m-12 (Ramsar Sites' Area) (purple circle), 9-3 (Logistics Performance Index) (blue circle), and 11-1 (Urban Population Living in the Slums) (yellow ring). Although they are relatively located at the periphery of global sustainability clusters, their high betweenness centrality values indicate their influential roles in acting as 'bridge' indicators. For example, the mangrove metric: Ramsar sites' total area has the highest betweenness centrality value as 183.7, synergizing with 15 indicators whose betweenness centrality values are also high. Policy prioritizing expanding Ramsar sites to have more marine ecosystems protected by the global conservation alliance can improve other 'bridge' indicators' performance with a broad influence on enhancing marine protected areas' management capacity, reducing poverty, maintaining mangrove extent, etc. In one way, these wetland areas in Indonesia, protected by the Ramsar Convention, played an essential role in safeguarding biodiversity and providing valuable ecosystem services. Meanwhile, their total area can serve as a critical indicator in monitoring the formidable challenges in preservation due to the intricate interplay of natural factors, such as climate change and environmental degradation, and anthropogenic influences, such as urbanization and resource extraction from poverty.

Priority 3: Logistics Performance Index (LPI)

Similarly, 9-3 (Logistics Performance Index (LPI): Quality of trade and transport-related infrastructure) also has a high betweenness centrality value of 167.3 with low performance in Indonesia and is synergized with other poorly performed indicators, including m-14 (Night-time Lights Growth), m-6 (Varieties of Democracy (VDEM)), and m-9 (Economic Complexity Index (ECI). The LPI measures a country’s logistics efficiency and performance, including customs procedures, infrastructure quality, and international shipments. The interplay of democracy, economic complexity, and the growth of night-time lights can serve as mangrove metrics relevant to mangrove conservation efficiency, and mangrove deforestation drivers augment a nation’s logistics capabilities and facilitate trade and economic growth.

A well-functioning democracy may lead to more effective enforcement of laws related to mangrove protection, and citizen participation and transparency allow citizens to voice concerns for sustainable practices in mangrove preservation. Moreover, transparent governance with institutional effectiveness is characterized by greater accountability, reduced corruption, and improved regulatory frameworks, which create an environment conducive to efficient logistics operations with smoother trade flows and logistical processes, streamlined customs procedures, and reliable infrastructure investments. In addition, economic complexity, referring to a more diversified economy that can produce diverse and intricate products, indicates less dependency on specific resources such as mangrove forests for financial gains and may lead to a greater emphasis on sustainable resource management. Meanwhile, a complex economy is built upon a network of interconnected industries and specialization, which fosters the development of more sophisticated supply chains and manufacturing processes. These advancements improved logistics practices, including efficient transportation networks, streamlined customs procedures, and increased capability to handle complex trade transactions. Lastly, the growth of night-time lights often indicates urbanization and economic development. Rapid urbanization can pressure coastal ecosystems, including mangrove forests, due to infrastructure development and land reclamation. In contrast, a well-managed urbanization process can bring the coexistence of mangrove conservation with planning and zoning regulations to prevent encroachments and urban expansion. At the same time, urbanization expansion indicates the evolvement of logistics infrastructure and capabilities, that infrastructure investment in transportation, ports, and distribution networks are driven by the need to support economic growth, and in return, leads to improved logistics efficiency and performance. These indicators are synergized with each other, and any improvement can help augment the enhancements of others. Policy prioritized on these indicators can help improve mangrove conservation success in mangrove extent gain and overall sustainability performance.

Priority 4: Urban Population Living in the Slums

Noticeably, 11-1 (Urban Population Living in the Slums) performed well compared to other ‘bridge’ indicators discussed above and compared to its synergized indicators in the yellow circle. Since this ‘bridge’ indicator performed better, we anticipate future improvements in its connected indicators including m-6 (Varieties of Democracy (VDEM)), m-8 (BDH2020), m-9 (Economic Complexity Index (ECI)), and m-11 (Indigenous Land Tenure), as well as a potential improvement of its nearby indicators, especially those with poor performance, such as 11-2 (New HIV Infections) and 2-3 (Prevalence of Wasting in Children under five years of age). Improvements to eradicate poverty in city slums and reduce inequality can generate synergies with enhancements in various aspects, such as improving the diversity of economic products with a more diversified economy, better-functioning democracy governance for natural resources management, better-performed institutions to reduce biodiversity loss, and more indigenous land tenures. Moreover, it can generate indirect enhancements such as health care, democracy conditions, children's education, etc. Policy priorities on the urban population in the slums can bring about improvements to a broad range of aspects for mangrove conservation and overall sustainability, and policies to ensure the indicator's performance can monitor the advances of its related indicators, leading to a more sustainable future in Indonesia.

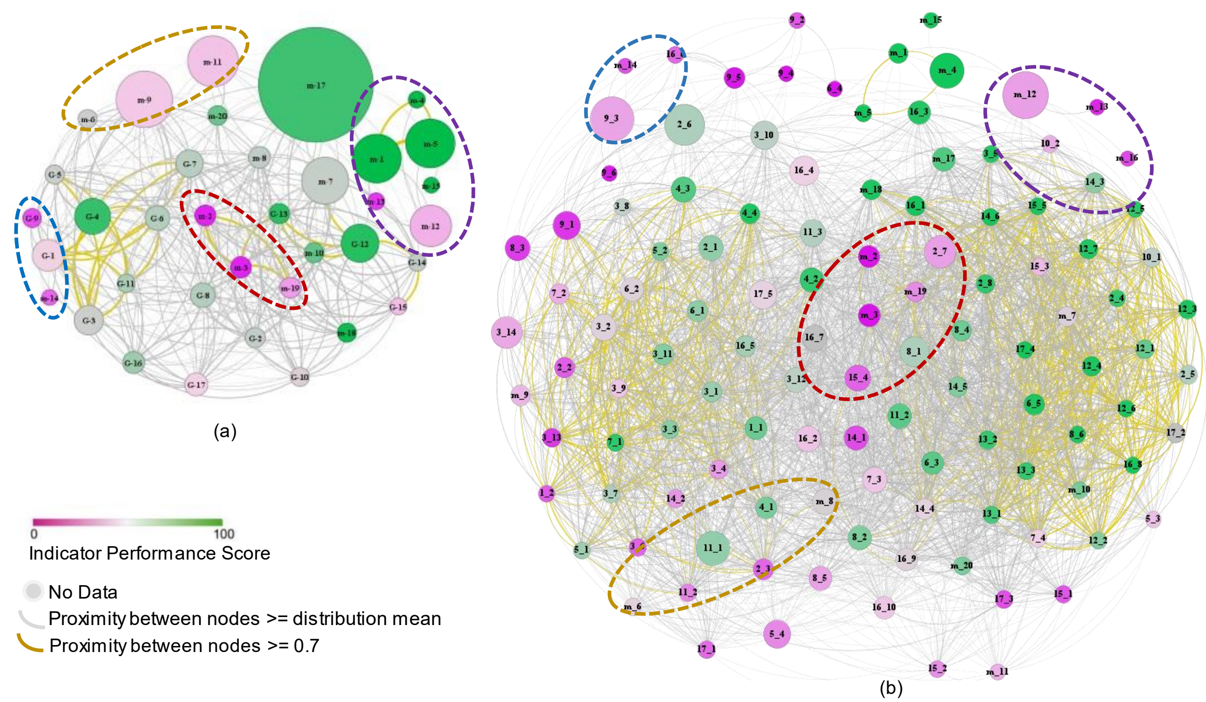


Figure 4.3 (Fig. 4.3.): a. Goal-level space projected to Indonesia's sustainability performance score as the node color. b. Indicator-level space projected to Indonesia's performance score as the node color. The node color is to visualize the sustainability performance in Indonesia between 2007 and 2016, and node size is scaled by each node's centrality betweenness value in its spaces.

4.4 Conclusions

Our study adopts an integrated network modeling approach to discuss the complementarities between sustainable development and mangrove governance. We construct global 'Mangrove-SDG spaces' by harnessing the framework of 17 SDGs, 95 indicators, and 21 mangrove metrics spanning 109 countries. Leveraging network science methodologies, we identify core-peripheral relationships, community compositions, and network structures within these spaces, offering insights into their complementarities across goal and indicator levels. Furthermore, we examine the robustness of the space by comparing it to correlation coefficient networks built on historical data and evaluating their matrix norms. Mangrove-SDG spaces exhibit stability, which indicates their relative resilience to data variations stemming from diverse data sources, quantities, and qualities encountered during data collection, preparation, and analysis phases.

This adaptability and stability to evolving real-world environmental complexities is paramount, underlining the significance of informed and effective decision-making processes. For example, unveiling complementarities between sustainable development and mangrove governance from ‘Mangrove-space spaces’ prioritize policies to focus on ‘bridge’ factors that facilitate the optimal performance with the most achievements from the systematic perspective. Moreover, the stable structure empowers long-term policy planning for sustainability efforts, offering tools to systematically monitor, evaluate, and analyze the performance of policy outcomes with lagged feedback.

Considering these advantages, we offer valuable insights into country-level strategies and pathways to promote sustainable development and mangrove conservation, using Indonesia as an illustrative example. The nuanced structure and complementarities embedded within Mangrove-SDG spaces empower countries to craft context-specific strategies rooted in benchmarking their sustainability performance. For Indonesia, this entails a strategic shift from the sole expansion of mangrove extent to a concentrated emphasis on four pivotal areas: adept nitrogen management, bolstering Ramsar site efficiency, optimizing logistical performance, and addressing urban population dynamics.

However, as a noteworthy limitation of the method, it does not offer specific policy actions to improve the performance of these prioritized indicators, and policymakers still need their expertise to devise practical strategies to implement the policy recommendations. Future studies can provide more discussions on the potential feasibility and challenges of implementing these ‘bridge’ indicators in specific country settings and explore their policy pathways through comparative studies between countries, considering political, economic, and social factors (e.g., governance structure, financial conditions, culture settings, etc.) for practical policy implementation.

4.5 Methods

The methodology includes the construction and network analysis of ‘Mangrove-SDG spaces’ while emphasizing validating their stability. The subsections discuss them in detail.

4.5.1 Mangrove-SDG space

Mangrove-SDG space assesses the complementarities among SDGs and mangrove governance metrics from the 'product space' concept[138,139] and its application in measuring SDG interactions[134–136]. We construct three levels of Mangrove-SDG space using different datasets. The first two levels of spaces incorporate SDG goal-level data with two sets of mangrove data: 1) two sources of mangrove loss data and 2) full mangrove socio-ecological system metrics. The third level of mangrove-SDG space covers SDG indicator-level data with full mangrove SES metrics. All levels of SDG spaces are constructed and analyzed following the method below.

We define the 'Mangrove-SDG space' as a network framework encompassing inter- and intra-connections (edges) among SDG indicators and mangrove-related data (nodes). The concept of 'proximity,' signifying the degree of closeness between nodes in this analytical space, serves as the primary metric for identifying synergies within the network. Interactions marked by higher proximity values, closer to 1, denote pronounced synergies within the space. We delineate a proximity threshold by utilizing the mean from the network proximity distribution, setting aside low-proximity interactions to focus on complementarities with high intensity [134,135].

Mathematically, proximity is a quantifiable measure of the co-occurrence of comparative advantages in pursuing different objectives. It is succinctly expressed as the conditional probability that a specific region can achieve one goal more effectively when it demonstrates superior performance in accomplishing another goal. This proximity, denoted as θ (g, g'), is formally defined as:

$$\theta(\mathrm{g},\mathrm{g}') = \min\{\mathrm{P}(\mathrm{RCA}(\mathrm{i},\mathrm{g}) > 1)|\mathrm{RCA}(\mathrm{i},\mathrm{g}') > 1), \mathrm{P}(\mathrm{RCA}(\mathrm{i},\mathrm{g}') > 1)|\mathrm{RCA}(\mathrm{i},\mathrm{g}) > 1)\}$$

$$= \frac{\sum_{\mathrm{i}} \mathrm{I}(\mathrm{RCA}(\mathrm{i},\mathrm{g}) > 1)|\mathrm{I}(\mathrm{RCA}(\mathrm{i},\mathrm{g}') > 1)}{\max\{\sum_{\mathrm{j}} \mathrm{I}(\mathrm{RCA}(\mathrm{i},\mathrm{g}) > 1), \sum_{\mathrm{j}} \mathrm{I}(\mathrm{RCA}(\mathrm{i},\mathrm{g}') > 1)\}} \tag{4.1}$$

Here, RCA(i, g) represents the revealed comparative advantage of country i in achieving mangrove metrics/SDG goal/indicator: g. The variables i' and g' encapsulate all countries and metrics/goals/indicators. The indicator function, I(·), yields 1 when the specified condition is met and 0 otherwise.

$$\mathrm{RCA}(\mathrm{i},\mathrm{g}) = \frac{\frac{\mathrm{x}(\mathrm{i},\mathrm{g})}{\sum_{\mathrm{g}'} \mathrm{x}(\mathrm{i},\mathrm{g}')}}{\frac{\sum_{\mathrm{i}'} \mathrm{x}(\mathrm{i}',\mathrm{g})}{\sum_{\mathrm{i}',\mathrm{g}'} \mathrm{x}(\mathrm{i}',\mathrm{g}')}} \tag{4.2}$$

Furthermore, x(i, g) signifies the developmental status of metric/goal/indicator g in country i. The symbol $\sum$ represents summation across various indices. For example, $\sum_{g'} x(i,g')$represents the sum of the development level of all metrics/goals/indicators in country i, $\sum_{i'} x(i',g)$is the sum of the development level of g in all countries. $RCA(i,g)>1$ indicates that region i has a revealed comparative advantage in g compared to its other capabilities.

The culmination of this rigorous calculation results in a matrix for the Mangrove-SDG spaces, encompassing dimensions of 19x19, 38x38, and 116x116, corresponding to the goal-level space with two mangrove loss data, with all mangrove metrics and indicator-level space, respectively. Notably, the non-diagonal elements within this matrix effectively encapsulate the essence of complementarity between pairs of goals and indicators.

4.5.2 Network Analysis

Our analytical approach encompasses the calculation of community partition and betweenness centrality to unveil the network's aggregation tendencies and delineate the core-periphery structure. A robust community structure manifests as dense connections within groups and relatively sparser connections bridging distinct groups. To quantify this structure, we rely on modularity, a parameter measuring the deviation between the number of edges within a group and the anticipated count in randomly generated equivalent networks[140]. Modularity assumes a constant value within the -1 to 1 range, with higher values signifying a more pronounced community structure.

The Louvain algorithm, an unsupervised heuristic technique, facilitates the identification of optimal community partitions. This algorithm operates iteratively, cycling through two phases until convergence is achieved. In the initial phase, nodes are reallocated between communities to maximize the modularity value within each group. The subsequent step involves forming and amalgamating communities into super-nodes to establish an interconnected network. Within communities, nodes exhibit a high degree of complementarity, fostering synergistic interactions. In contrast, inter-community nodes showcase diminished synergy within the space[141].

To delve into the core-periphery dynamics, we employ Ulrik Brandes' algorithm to compute the betweenness centrality of both goals and indicators[142]. The results are then visualized within the network, with node size reflecting their betweenness centrality. In Mangrove-SDG networks, nodes characterized by higher betweenness centrality wield more substantial influence, as they serve as vital connectors facilitating synergistic interactions across many nodes.

The SDG space is subsequently visualized, where network nodes represent goals and indicators, while edges symbolize pairwise proximity links. To create these visualizations, we employ the Force Atlas and Fruchterman-Reingold layouts. Both layouts are underpinned by force-directed algorithms, simulating the behavior of physical systems to attain a stable configuration. In this analogy, graph nodes represent particles, while the edges connecting them act as springs or electrical charges. Consequently, nodes with extensive connections gravitate towards the central regions of the graph, while those with fewer linkages find placement towards the periphery. All these network analysis techniques are executed using Gephi 0.10.0, a robust tool designed explicitly for network analysis, either directly or through Gephi plugins[143].

4.5.3 Stability Validation

Our study *compares* stability levels between Mangrove-SDG spaces and correlation networks across two distinct time spans: 1996-2006 and 2007-2016. Correlation networks gauge similarity in performance between nodes based on changes in data, influencing the overall network structure via alterations in correlation coefficients between nodes. In contrast, Mangrove-SDG spaces measure similarities in the external environment fostering node performance, which may exhibit less variability with minor changes in node values. For instance, *increasing* nitrogen efficiency could promptly alter food production enhancements in the correlation network. *In contrast, such* efficiency improvements might not substantially impact Mangrove-SDG spaces due to their construction based on shared external factors like technology, resources, and capital that nurture efficiency improvements.

Mathematically, stability comparison involves quantifying disparities in network structures between the two time spans using matrix norms. Matrix norms serve as mathematical tools to measure matrix structures' "magnitude" or "size", facilitating comparison of network structures. Networks with similar matrix norm values indicate comparable structures. The resultant differences between network structures across periods are assessed relative to a reference network established during 1996-2006, expressed as a proportion. Specifically, this equation is formulated for goal-level comparisons to highlight the extent of network variations between the specified time intervals.

$$\Delta Norm = \frac{((Norm(N_{0716}) - Norm\,(N_{9606}))\times 100}{Norm(N_{9606})} \quad (4.3)$$

Here, N represents either the correlation network or Mangrove-SDG space concerning goal-level mangrove metrics and SDG goals. A smaller ΔNorm signifies a lesser disparity in network structures, while an elevated value denotes a more substantial divergence. This analytical process is executed within the Matlab Version R2021a.

4.6 Data and Code Availability

Data from 17 SDGs and the scores of 95 indicators across 177 countries were sourced from the SDG Dashboard[144] (https://dashboards.sdgindex.org/downloads) within the Sustainable Development Report 2022. This extensive database spans 2000 to 2021 and has been meticulously normalized, encompassing a scale of 0 to 100. Here, a score of 0 denotes the lowest performance, while a perfect score of 100 signifies an apex of sustainability achieved by 2030.

The architecture of the goal-level mangrove SDG space was meticulously devised utilizing SDG data from 2016, the year with the most recent mangrove metrics data. Concurrently, the most recent data on mangrove loss was gleaned from two distinct sources. The first originates from the Global Mangrove Watch 1996-2016 dataset, curated by the UNEP World Conservation Monitoring Centre (WCMC) (http://data.unep-wcmc.org/datasets/45) for 2016[6]. However, it's noteworthy that this source may err on the side of overestimation in certain regions. The second source, known as Goldenberg's estimate, calculated mangrove forest loss in 71 mangrove-holding countries during three periods, and we used the most recent period from 2011 to 2016[51]. This dataset (https://daac-news.ornl.gov/global-mangrove-land-cover-change-loss-drivers) is somewhat conservative, revealing an underestimation of loss compared to the GMW dataset in specific areas[5]. This reflects a more subdued estimation of mangrove loss. Country-specific data was acquired from the Global Administrative Areas Database (GADM) (https://gadm.org/data.html).

To unlock the panoramic insights of the mangrove landscape, encompassing drivers and hotspots of both loss and gain, a comprehensive assortment of metrics was culled from a plethora of sources, consolidated within the reference chapter following link: https://www.nature.com/articles/s41467-022-33962-x#data-availability[58,62]. A deliberate curation selected 41 indicators deemed representative of the entire spectrum of mangrove SES-related metrics from 1996 to 2016 across 109 countries. This selection was meticulously divided, comprising 21 indicators for 1996-2007 and an additional 21 indicators for 2007-2016. Each of these metrics underwent rigorous normalization to fit the 0-100 range, with a score of 0 earmarking the nadir of performance and a perfect score of 100, symbolizing a pinnacle of sustainability aspired for by 2030. The supplementary table has meticulously elucidated this normalization process's nuances and intricacies, including sign changes for four indicators to fit into the criteria that 100 means better sustainability achievement by 2030, and 19 indicators used 5th and 95th bounds as their maximum and minimum because of the existence of extreme values. In response to the dual timeframes of mangrove metrics, the SDG goal and indicator data were strategically anchored within the average years of 2001 and 2011, representing the average years of 1996-2007 and 2007-2016 of mangrove metrics data, respectively. This research is hosted on the GitHub repository, accessible at lwt852/mangrove SDG space (github.com), where the comprehensive research code is made available.

CHAPTER 5: SYNTHESIS

Abstract

Current governance approaches for mangrove ecosystems include state-owned, community-based, market-based, and co-management models, each with contextual advantages and drawbacks. However, managing mangroves, which exist naturally in both terrestrial and coastal zones, becomes complex in a globalized context, especially with the rise of international trade. Environmental leakage, such as mangrove loss, through global supply chains is a significant concern due to the valuable ecosystem services provided by mangrove forests. Despite the importance, few studies have explored how mangrove governance intersects with international trade. In this dissertation, Rosenbaum's (2000) market concept is integrated with the metacoupling framework to systematically examine global market-related interactions of mangrove human-nature systems within and across geographic borders. This includes intracoupling (interactions within systems), pericoupling (interactions between adjacent systems), and telecoupling (interactions between distant systems). Drawing on this market-based metacoupling framework (Chapter 1) and empirical analyses (Chapters 2-4), I propose governance recommendations for policymakers. These insights aim to guide nations in reframing their mangrove-related policies to consider the cross-border interactions of mangrove human-nature systems, thereby promoting both mangrove conservation and global sustainability goals.

5.1 Mangrove Governance Overview

Mangrove governance presents a complex challenge due to mangrove ecosystems spanning terrestrial and marine environments, crossing political boundaries, and having interconnected root systems. Consequently, conservation and governance efforts require collaboration and negotiation among diverse stakeholders and agencies. Three main types of mangrove governance systems are recognized from Ostrom's (1990) framework on property rights regimes. State governance, which has been predominant historically involves experts setting common ecological and social goals to address natural resource and social issues, sometimes at the expense of local needs. Community-based governance has emerged as a response to the inflexibility of state governance, prioritizing local needs and empowering communities to manage their resources more flexibly and responsively. Market-based governance takes a different approach, believing that rational human ingenuity can effectively utilize resources once the government establishes specific rules, market environments, and principles. It emphasizes individual rights and aims to create markets for environmental goods regulated by government administrators. Additionally, co-management between state and community regimes involves shared responsibility and authority between governments and local communities to manage natural resources jointly[145].

These governance models highlight different approaches to balancing ecological sustainability, social equity, and economic development in mangrove ecosystems. Each model offers unique strengths and challenges, influencing how governance frameworks are structured and implemented to ensure effective mangrove conservation and management.

5.1.1 State-ownership governance

State-ownership governance, centered on publicly owned protected forests and national parks, wields substantial authority and accountability in mangrove conservation. These protected areas are recognized for their effectiveness in mitigating local mangrove loss, particularly in regions with weak regulatory frameworks. However, their impact can be compromised by inadequate enforcement and compliance with environmental laws. Studies indicate that socioeconomic pressures often drive local officials to disregard conservation policies in favor of personal gain through corruption and bribery, especially in economically vulnerable communities[61].

Moreover, the establishment of protected areas can paradoxically contribute to deforestation in adjacent regions[7,66,146]. For instance, in Sumatra, Indonesia, while local mangroves within protected areas may be preserved, deforestation rates have accelerated in surrounding areas due to displaced populations and increased economic activities seeking opportunities beyond the reserves[147].

The governance of mangrove forests is further complicated by the involvement of multiple agencies with divergent policies and priorities[148]. This vertical and horizontal policy fragmentation leads to enforcement ambiguities and competition among administrative bodies, undermining effective mangrove management. In regions like Western Africa, these governance challenges are exacerbated by the proliferation of institutions managing mangrove resources, often resulting in bureaucratic inefficiencies and ineffectual governance structures.

Addressing these governance complexities requires cohesive strategies that integrate stakeholder collaboration, robust enforcement of environmental regulations, and harmonized policies across administrative levels. By enhancing governance coherence and accountability, it becomes possible to sustainably manage mangrove ecosystems, effectively balancing conservation goals with socioeconomic development imperatives.

5.1.2 Community-based governance

Community-based governance emphasizes that participation and resource sharing are governed by local residents, and these community-driven governance systems place the conservation power of the decision-making process and implementation on local people[149]. Studies indicate that these self-governance systems have brought mangrove conservation success because the local community members are more knowledgeable about their culture and power structures and those of their nearby communities. It can effectively create communications and collaborations among communities and achieve a system of local autonomy[150–152]. For example, studies in coastal Ecuador found that community-based mangrove concessions can protect mangrove fisheries that are weakly managed by the State[151]. In addition, a meta-analysis of 69 cases of community-based management indicated that 58% of them were considered as successful on their ecological sustainability criteria[153]. Moreover, Chhatre & Agrawal (2009) found that differences in the ownership of forest commons are connected with their quality, and greater rule-making autonomy at local levels leads to a higher quality of forests, such as higher carbon sequestration[154] .

However, community-based governance experiences are hard to establish and maintain at the local scale and hard to promote at a national scale. The success of community-based conservation needs local community leaders to play significant roles in establishing and maintaining trust among communities and consistently promoting the awareness of mangrove values among community members. These requirements are hard to maintain and easy to break[150,155]. In addition, the success of self-governance structures relies on their possibility to enforce rules, including norms and regulations, to build up the self-autonomy system[145,156]. These norms and regulations are based on local culture, community power structure, and joint agreement on the mangrove conservation strategies depending on local facts of mangrove existence and status, which are hard to implement in different places with different cultural, social, and biophysical settings.

5.1.3 Market-based governance

Market-based approaches in mangrove governance, such as carbon credits, payments for ecosystem services, and certified 'mangrove friendly' products, rely heavily on supportive governance frameworks provided by state ownership and community-based governance. These frameworks establish legislative environments and garner local community support necessary for successful implementation and enforcement. However, the benefits and drawbacks of state-owned and community-based governance can either facilitate or hinder the effectiveness of market-based solutions in addressing environmental challenges like the tragedy of the commons. For instance, the REDD (Reducing Emissions from Deforestation and Forest Degradation) programs exemplify market-based governance aiming to incentivize forest conservation through payments for ecosystem services and carbon sequestration. Angelsen (2010) identified obstacles such as corruption and unclear property rights that limit the effectiveness of REDD programs across different scales. Moreover, spatial spillover effects observed in REDD implementation highlight how incentivizing conservation in one area may inadvertently increase deforestation elsewhere[102,157].

Privatizing property rights to individuals or corporate entities in environmental resource management, like air and water, presents practical challenges due to their transboundary nature[158]. Similar issues are evident in other market-based initiatives where administrative oversight is crucial for creating, managing, and enforcing rules and incentives. The effectiveness of these economic mechanisms in promoting conservation success varies and requires rigorous evaluation. For example, Liu & Yang (2013) suggested that the economic benefits and local livelihood support of Payment for Ecosystem Services (PES) require further investigation using an integrated ecosystem services framework. Studies generally show PES schemes provide 50% higher benefits than costs, but outcomes vary with local conditionss[159,160]. In addition, Yost et al. (2020) found that local villagers in China viewed programs like the Grain-to-Green Program unfavorably due to dissatisfaction with compensation conditions, underscoring the need for PES designs that align with local socio-economic realities for better acceptance and effectiveness[161]. In conclusion, while market-based governance offers innovative solutions to environmental challenges, its implementation must navigate complexities such as regulatory frameworks, local contexts, and unintended consequences. Addressing these challenges requires ongoing research and adaptive management strategies to maximize environmental and socio-economic benefits effectively.

5.1.4 Co-management

Due to the complex nature of mangrove conservation involving multiple stakeholders, there is growing interest in polycentric and multi-level governance models, such as co-management. These models facilitate understanding and managing complex governance systems by integrating decision-making across various arenas, including self-governance, cooperation, coordination, and conflict resolution[162]. Polycentric governance involves multiple decision-making arenas, encompassing levels of administration within governments (national, district, village) as well as regional and international collaborations. Horizontal governance levels entail interactions and collaborations among diverse actors, including government agencies, inter-governmental organizations, private sectors, local communities, and civil societies, each influenced by institutional designs and functions[163].

Theoretically, co-management is considered potentially more effective than state-owned or community-based systems because it combines legislative power with local decision-making, enhancing enforcement and communication among stakeholders. However, practical challenges hinder its implementation. For instance, in Kenya, distrust toward the central government due to corruption complicates community engagement in conservation efforts[163]. Moreover, the involvement of multiple stakeholders often leads to diffusion of responsibility and increased coordination costs, making it difficult to hold actors accountable and prevent free-riding behaviors. For example, insufficient monitoring of conservation outcomes has been noted where stakeholders have focused on reporting activities rather than ensuring long-term effectiveness[164]. Addressing these challenges requires building trust among stakeholders, improving coordination mechanisms, and fostering genuine commitment to shared conservation goals. Effective co-management hinges on balancing power dynamics, ensuring transparency, and promoting active participation from all involved parties to achieve sustainable mangrove conservation outcomes.

5.2 Mangrove Governance is Complex

The mangrove ecosystem provides vital ecosystem services such as economic support for fisheries and shrimp farming, coastal protection against erosion, and significant carbon sequestration capabilities[3]. These services underscore the importance of mangrove forests, recognized globally by coastal communities and international civil societies whose livelihoods depend on them. Efforts for global restoration, conservation, and sustainable development often hinge on the preservation or degradation of mangrove forests across different regions. Numerous studies highlight the potential for restoring mangrove forests, aligning with UN Sustainable Development Goal 14, which emphasizes the sustainable management and protection of marine and coastal ecosystems. This goal aims to support the livelihoods of island communities and safeguard marine resources, crucially including mangrove habitats. Despite these efforts, evaluating global mangrove conservation and restoration projects remains challenging, particularly in relation to UN SDGs, due to the complex interactions and trade-offs between different goals and targets. Furthermore, the effectiveness of both local and international conservation initiatives remains uncertain, often requiring substantial time and resources with varying degrees of progress.

Mangrove governance under globalization is complex, involving various forms such as state ownership, self-governance, privatization, and co-management. External actors like NGOs, private sectors, and academia play critical roles facilitated by global financial and trade flows, often creating governance vacuums outside existing systems[165]. Policies by international NGOs and external actors may oversimplify local dynamics, leading to distrust and perceptions of unfairness among communities [150–152]. In comparison, effective conservation relies on inclusive community-based governance, but conflicts arise when local governance is displaced by external priorities, exacerbating power imbalances and disrupting mangrove socio-ecological systems[166,167]. Global value chains complicate governance further, interconnecting remote areas through globalization. While firms improve supply chains with standards, less is understood about how external actors influence these processes and local conservation outcomes[168,169]. Governance for sustainability faces challenges in balancing diverse interests and achieving legitimacy amid pluralistic visions[165]. Issues include knowledge deficits, divergent interests, weak legitimacy, policy incoherence, and data transparency across multiple jurisdictions.

5.3 Implications for Applying Metacoupling Framework to Mangrove Sustainability

My dissertation investigates the spatial dynamics, drivers, and complementarities of mangrove human-environment systems using the metacoupled interactions framework. This framework categorizes interactions within and across geographic borders into intracoupling, pericoupling, and telecoupling types, systematically integrating socio-economic and environmental factors. It employs analytical components like sending, receiving, and spillover systems and flows and feedback to characterize these interactions.

Chapter 1 introduces the metacoupling framework, which provides a structured approach to understanding how international trade influences global mangrove ecosystems. Chapters 2 and 3 focus on empirical analyses: Chapter 2 measures the mangrove loss footprint—mangrove loss attributable to meeting a consumer country's final demand—using remote sensing and input-output models to track changes from 2000 to 2016. Chapter 3 delves into the drivers of mangrove loss within global supply chains at the national scale. Chapter 4 uses Indonesia as a case study to explore policy pathways for successful mangrove conservation and sustainable development, emphasizing synergies with conservation strategies and sustainable development goals. Based on these findings, the dissertation proposes the following enhanced mangrove governance strategies under the metacoupling framework, aiming to integrate socio-economic drivers, environmental impacts, and international trade dynamics for effective conservation and sustainable development. This structured approach enhances our understanding of the complexities within mangrove ecosystems and provides actionable insights for policy-makers and managers at both local and global levels.

5.3.1 Data transparency is essential for monitoring mangrove dynamics and ensuring accountability among consumers and producers

The governance challenge in ensuring effective mangrove sustainability under globalization stems from governance institutions' inherent difficulties in providing transparent and legitimate decision-making processes. The persistent knowledge gap about detecting and understanding environmental externalities, especially spatial spillovers, is central to these challenges, particularly regarding their causes and broader impacts. This complexity is exacerbated by the diverse ecological settings of mangrove forests, which span coastal and terrestrial landscapes, each characterized by unique abiotic conditions, forest structures, and species diversity. Despite the availability of global-scale maps depicting mangrove forest coverage and change, there remains a critical shortage of robust, timely, and consistent datasets that account for these geographic variations. This limitation hinders the development and implementation of tailored conservation and restoration strategies crucial for addressing local-specific drivers of deforestation[54]. While localized studies contribute valuable insights into socio-ecological interactions and driver identification, their methodological disparities and varying spatial and temporal resolutions pose challenges for comparison and synthesis. To comprehensively grasp the dynamics of mangrove ecosystem change and effectively mitigate deforestation impacts, efforts must focus on integrating and harmonizing diverse datasets and findings from local to global scales[13]. This approach is essential for developing holistic strategies that account for the multifaceted drivers of mangrove loss and promote sustainable governance practices across regions and countries.

It's noted that international assessment models play a crucial role in quantifying the economic benefits of mangroves, encompassing areas such as blue carbon[1,2,14,49,170,171], coastal restoration[116,172–174], and tourism[175], while also addressing the impacts of their loss, such as forest fragmentation[58,176–178], across various scales from local to global. My dissertation contributes to the field by examining how mangrove forest lands are impacted by global supply chains. Specifically, I calculate and map a spatial-temporal dataset to measure the mangrove loss on the ground attributed to consumption embodied in international trade at high resolution, named mangrove loss footprint. Additionally, I develop the socio-economic models to explain the driving forces of the mangrove loss footprint within and across the space. The models and datasets are instrumental in elucidating drivers from both consumer and producer perspectives, essential for crafting effective conservation strategies that recognize the diverse nature of mangrove ecosystems. To enhance this process, there is a critical need for an authoritative platform that can visualize and compare existing datasets and assessment results. Such a transparent monitoring platform would facilitate the tracking, monitoring, and comparing mangrove forest changes. This transparency can also significantly improve public awareness of mangrove conservation issues, thereby clarifying the responsibilities of both consumers and producers in mitigating the impacts of global supply chains on mangrove ecosystems.

5.3.2 Mangrove sustainability is integral to global sustainability efforts, necessitating a systematic approach that guides science-based policymaking

While mangrove ecosystems offer significant ecosystem services and restoration potential, their natural habitats are limited. Attempts to restore mangrove forests beyond these habitats have shown low success rates and inefficiencies. For instance, Indonesia aims to restore 600,000 hectares of mangroves by 2024, aligning with the UN Decade of Ecosystem Restoration 2021-2030—an ambitious goal reflecting global conservation commitments but facing challenges as studies suggest only 30% of suitable lands in Indonesia are identified for restoration[116].

Effective mangrove governance requires a holistic approach that integrates sustainability considerations rather than treating them in isolation. Systematic thinking and science-based knowledge are essential for guiding policies. I developed a 'mangrove-SDG space' framework in my dissertation to assess synergies between mangrove conservation outcomes and Sustainable Development Goal (SDG) performance, using Indonesia as a case study. This framework advocates a strategic shift from solely expanding mangrove extent to prioritizing four key policy areas: effective nitrogen management, enhancing the efficiency of Ramsar sites, optimizing logistics, and addressing urban population pressures. For example, improving nitrogen management can enhance land use efficiency, mitigating competition for land and reducing incentives for mangrove deforestation. These priorities are crucial for aligning Indonesia's sustainability commitments with successful mangrove restoration efforts and achieving policy coherence across environmental and developmental goals.

Moreover, international collaborations have been instrumental in meeting global commitments such as UN SDGs, Aichi targets, and national climate plans. For instance, the Ramsar Convention facilitates the designation and protection of wetlands, including mangrove forests, through cooperation among national authorities. NGOs play a crucial role in these efforts, supporting local projects through expertise, technical assistance, and conservation aid. Examples include the IUCN Mangrove Specialist Group, the International Blue Carbon Initiative for climate mitigation, and the Global Mangrove Alliance for global strategies. Despite these efforts, current collaborations often focus on specific priorities and may overlook the potential leakage of policies to other sustainability issues. Recognizing and addressing environmental externalities in high-level collaborations can enhance understanding of mechanisms, improve management strategies, and contribute to global sustainable development goals.

5.3.3 Systematic planning within and across space in mangrove conservation policies is needed.

Policymakers must carefully consider external actors' geographic influences in mangrove governance before implementing policies. Evidence from the dissertation reveals that neighboring and distant countries exert different pressures on mangrove loss in countries with significant mangrove coverage. Neighboring countries contribute to mangrove forest loss due to stricter domestic governance effectiveness. For instance, conservation policies in Sumatra, Indonesia, such as protected areas, unintentionally increase deforestation in surrounding areas like Vietnam by displacing populations and attracting economic activities[66]. On the other hand, distant countries drive mangrove loss in these nations through economic growth, particularly via domestic investment in capital formation. For example, our study shows that U.S. consumption patterns have driven Honduras to expand commodity lands, leading to mangrove deforestation from 2000 to 2016. Local remote sensing studies confirm this trend, linking mangrove loss in Honduras to shrimp pond construction over the past three decades[68,69]. These high-income countries significantly impact economically vulnerable distant nations with rich resources but weak governance.

Many studies have observed that international collaboration focusing on specific regions may bring about spatial spillover to other regions. For example, protected areas, REDD programs, and strict law enforcement in one region can transfer environmental degradation to other places[66,146,157]. Therefore, systematic planning before policy implementation, considering various actors' geographic dynamics, can enhance program efficiency and effectiveness. Addressing spatial spillovers from economically strong distant actors through high-level collaborations can deepen understanding of underlying mechanisms, improve management strategies, and advance global sustainable development goals.

In conclusion, traditional approaches to mangrove governance—state-owned, community-based, market-based, and co-management—often fail to adequately address the impacts of external actors within their socio-ecological systems. This governance gap underscores the need for systematic frameworks to tackle sustainability challenges like mangrove conservation. My dissertation applies the metacoupling framework, offering a comprehensive approach to understanding how human-nature interactions, especially influenced by international trade, shape mangrove dynamics within and across space. Empirical analysis highlights spatial spillovers in mangrove loss driven by international trade, revealing distinct patterns and mechanisms among adjacent and distant countries. Based on these findings, I propose three governance recommendations: enhancing transparency in mangrove conservation methods, focusing on integrating data and methods comprehensively, setting up authoritative platforms for data and method sharing in sustainability initiatives, and incorporating spatial considerations into policymaking for more effective policy outcomes. These measures aim to empower decision-makers to craft policies that better address the complexities of mangrove ecosystems in a globalized context.

BIBLIOGRAPHY

1. Himes-Cornell, A., Pendleton, L. & Atiyah, P. Valuing ecosystem services from blue forests: A systematic review of the valuation of salt marshes, sea grass beds and mangrove forests. Ecosystem Services 30, 36–48 (2018).

2. Bertram, C. et al. The blue carbon wealth of nations. Nat. Clim. Chang. 11, 704–709 (2021).

3. Richards, D. R. & Friess, D. A. Rates and drivers of mangrove deforestation in Southeast Asia, 2000–2012. PNAS 113, 344–349 (2016).

4. Friess, D. A. et al. The State of the World's Mangrove Forests: Past, Present, and Future. Annual Review of Environment and Resources 44, (2019).

5. Goldberg, L., Lagomasino, D., Thomas, N. & Fatoyinbo, T. Global declines in human‐driven mangrove loss. Glob. Change Biol. 26, 5844‐5855 (2020).

6. Bunting, P. et al. Global Mangrove Extent Change 1996–2020: Global Mangrove Watch Version 3.0. Remote Sensing 14, 3657 (2022).

7. Meyfroidt, P. et al. Middle-range theories of land system change. Global Environmental Change 53, 52–67 (2018).

8. Meyfroidt, P., Rudel, T. K. & Lambin, E. F. Forest transitions, trade, and the global displacement of land use. PNAS 107, 20917–20922 (2010).

9. Kunstadter, P., C. F. Bird, E. & Sabhasri, S. Man in the Mangroves: The Socio-Economic Situation of Human Settlements in Mangrove Forests. (1986).

10. Liu, J. Integration across a metacoupled world. Ecology and Society 22, (2017).

11. Liu, J. et al. Coupled human and natural systems: The evolution and applications of an integrated framework. Ambio 50, 1778–1783 (2021).

12. Liu, J. et al. Framing Sustainability in a Telecoupled World. Ecology and Society 18, (2013).

13. Sasmito, S. D. et al. Effect of land-use and land-cover change on mangrove blue carbon: A systematic review. Global Change Biology 25, 4291–4302 (2019).

14. Gevaña, D. T., Camacho, L. D. & Pulhin, J. M. Conserving Mangroves for Their Blue Carbon: Insights and Prospects for Community-Based Mangrove Management in Southeast Asia. in Threats to Mangrove Forests (eds. Makowski, C. & Finkl, C. W.) vol. 25 579–588 (Springer International Publishing, Cham, 2018).

15. Friis, C. Telecoupling. (Springer Berlin Heidelberg, New York, NY, 2019).

16. Thomas, N. et al. Distribution and drivers of global mangrove forest change, 1996–2010. PLOS ONE 12, e0179302 (2017).

17. Friis, C. et al. From teleconnection to telecoupling: taking stock of an emerging framework in land system science. Journal of Land Use Science 11, 131–153 (2016).

18. Carrasco, L. R., Chan, J., McGrath, F. L. & Nghiem, L. T. P. Biodiversity conservation in a telecoupled world. Ecology and Society 22, (2017).

19. Viña, A. et al. Temporal Changes in Giant Panda Habitat Connectivity Across Boundaries of Wolong Nature Reserve, China. Ecological Applications 17, 1019–1030 (2007).

20. Carlson, A. K., Taylor, W. W., Rubenstein, D. I., Levin, S. A. & Liu, J. Global Marine Fishing across Space and Time. Sustainability 12, 4714 (2020).

21. Zhao, Z., Cai, M., Connor, T., Chung, M. G. & Liu, J. Metacoupled Tourism and Wildlife Translocations Affect Synergies and Trade-Offs among Sustainable Development Goals across Spillover Systems. Sustainability 12, 7677 (2020).

22. Kapsar, K., Frans, V. F., Brigham, L. W. & Liu, J. The metacoupled Arctic: Human–nature interactions across local to global scales as drivers of sustainability. Ambio 51, 2061–2078 (2022).

23. Barbieri, P., MacDonald, G. K., Bernard de Raymond, A. & Nesme, T. Food system resilience to phosphorus shortages on a telecoupled planet. Nat Sustain 5, 114–122 (2022).

24. Chung, M. G. Complex Interactions among Ecosystem Services, Human Well-Being, and Their Linkages to Telecoupling Processes. (2020).

25. Chung, M. G. & Liu, J. International food trade benefits biodiversity and food security in low-income countries. Nat Food 3, 349–355 (2022).

26. Dou, Y. et al. Understanding How Smallholders Integrated into Pericoupled and Telecoupled Systems. Sustainability 12, 1596 (2020).

27. da Silva, R. F. B. et al. Socioeconomic and environmental effects of soybean production in metacoupled systems. Sci Rep 11, 18662 (2021).

28. Liu, J. An Integrated Framework for Achieving Sustainable Development Goals Around the World. Ecol. Econ. Soc. 1, (2018).

29. Liu, J. Forest Sustainability in China and Implications for a Telecoupled World: China and a Telecoupled World. Asia & the Pacific Policy Studies 1, 230–250 (2014).

30. Liu, J. et al. Nexus approaches to global sustainable development. Nature Sustainability 1, 466–476 (2018).

31. Liu, J. et al. Complexity of Coupled Human and Natural Systems. Science 317, 1513–

1516 (2007).

32. Liu, J. et al. Coupled Human and Natural Systems. 36, 12 (2007).

33. Carter, N. et al. Coupled human and natural systems approach to wildlife research and conservation. Ecology and Society 19, (2014).

34. Rosenbaum, E. F. What is a Market? On the Methodology of a Contested Concept. Review of Social Economy 58, 455–482 (2000).

35. Agrawal, A. & Yadama, G. How do Local Institutions Mediate Market and Population Pressures on Resources? Forest Panchayats in Kumaon, India. Development & Change 28, 435–465 (1997).

36. Song, A. M., Dressler, W. H., Satizábal, P. & Fabinyi, M. From conversion to conservation to carbon: The changing policy discourse on mangrove governance and use in the Philippines. Journal of Rural Studies 82, 184–195 (2021).

37. Agrawal, A. Common Property Institutions and Sustainable Governance of Resources. World Development 29, 1649–1672 (2001).

38. Geldmann, J., Manica, A., Burgess, N. D., Coad, L. & Balmford, A. A global-level assessment of the effectiveness of protected areas at resisting anthropogenic pressures. PNAS 116, 23209–23215 (2019).

39. M.R., B., N., L., T., H. & E., M. Governing Mangroves: Unique Challenges for Managing Indonesia’s Coastal Forests. (Center for International Forestry Research (CIFOR), 2017). doi:10.17528/cifor/006595.

40. Lee, S. Y. From blue to black: Anthropogenic forcing of carbon and nitrogen influx to mangrove-lined estuaries in the South China Sea. Marine Pollution Bulletin 109, 682–690 (2016).

41. Spalding, M. World Atlas of Mangroves. (Routledge, 2010).

42. Waldron, A. et al. Reductions in global biodiversity loss predicted from conservation spending. Nature 551, 364–367 (2017).

43. Lenzen, M. et al. International trade drives biodiversity threats in developing nations. Nature 486, 109–112 (2012).

44. Moran, D. & Kanemoto, K. Identifying species threat hotspots from global supply chains. Nature Ecology & Evolution 1, 0023 (2017).

45. Kitzes, J. et al. Consumption-Based Conservation Targeting: Linking Biodiversity Loss to Upstream Demand through a Global Wildlife Footprint: Global wildlife footprint. Conservation Letters 10, 531–538 (2017).

46. Waldron, A. et al. Targeting global conservation funding to limit immediate biodiversity declines. PNAS 110, 12144–12148 (2013).

47. Liu, J. Leveraging the metacoupling framework for sustainability science and global sustainable development. National Science Review 10, (2023).

48. Friess, D. A. Ecosystem Services and Disservices of Mangrove Forests: Insights from Historical Colonial Observations. Forests 7, 183 (2016).

49. Adame, M. F. et al. Future carbon emissions from global mangrove forest loss. Global Change Biology 27, 2856–2866 (2021).

50. Alban, J. D. T. D., Jamaludin, J., Wen, D. W. de, Than, M. M. & Webb, E. L. Improved estimates of mangrove cover and change reveal catastrophic deforestation in Myanmar. Environ. Res. Lett. 15, 034034 (2020).

51. Goldberg, L., Lagomasino, D., Thomas, N. & Fatoyinbo, T. Global Mangrove Loss Extent, Land Cover Change, and Loss Drivers, 2000-2016. ORNL DAAC (2022) doi:10.3334/ORNLDAAC/1768.

52. Bunting, P. et al. The Global Mangrove Watch—A New 2010 Global Baseline of Mangrove Extent. Remote Sensing 10, 1669 (2018).

53. Hamilton, S. E. & Casey, D. Creation of a high spatio-temporal resolution global database of continuous mangrove forest cover for the 21st century (CGMFC-21). Global Ecology and Biogeography 25, 729–738 (2016).

54. Worthington, T. A. et al. Harnessing Big Data to Support the Conservation and Rehabilitation of Mangrove Forests Globally. One Earth 2, 429–443 (2020).

55. Giri, C. Frontiers in Global Mangrove Forest Monitoring. Remote Sensing 15, 3852 (2023).

56. Giri, C. et al. Status and distribution of mangrove forests of the world using earth observation satellite data. Global Ecology and Biogeography 20, 154–159 (2011).

57. Bhowmik, A. K., Padmanaban, R., Cabral, P. & Romeiras, M. M. Global Mangrove Deforestation and Its Interacting Social-Ecological Drivers: A Systematic Review and Synthesis. Sustainability 14, 4433 (2022).

58. Howard, J., Andradi-Brown, D. A., Hagger, V., Sasmito, S. D. & Bosire, J. Editorial: Drivers of mangrove forest change and its effects on biodiversity and ecosystem services. Front. For. Glob. Change 5, 989665 (2022).

59. Hansen, M. C. et al. High-resolution global maps of 21st-century forest cover change. Science 342, 850–853 (2013).

60. Olson, D. M. et al. Terrestrial Ecoregions of the World: A New Map of Life on Earth: A

new global map of terrestrial ecoregions provides an innovative tool for conserving biodiversity. BioScience 51, 933–938 (2001).

61. Turschwell, M. P. et al. Multi-scale estimation of the effects of pressures and drivers on mangrove forest loss globally. Biological Conservation 247, (2020).

62. Hagger, V. et al. Drivers of global mangrove loss and gain in social-ecological systems. Nat Commun 13, 6373 (2022).

63. Darling, E. S. et al. Social–environmental drivers inform strategic management of coral reefs in the Anthropocene. Nat Ecol Evol 3, 1341–1350 (2019).

64. Thomas Rudel. Reforesting the Earth: The Human Drivers of Forest Conservation, Restoration, and Expansion (Society and the Environment) | Mitpressbookstore. (Columbia University Press, 2023).

65. Meyer, A. L., VAN KOOTEN, G. C. & WANG, S. Institutional, social and economic roots of deforestation: a cross-country comparison. The International Forestry Review 5, 29–37 (2003).

66. Lambin, E. F. & Meyfroidt, P. Global land use change, economic globalization, and the looming land scarcity. Proceedings of the National Academy of Sciences 108, 3465–3472 (2011).

67. Hoang, N. T. & Kanemoto, K. Mapping the deforestation footprint of nations reveals growing threat to tropical forests. Nature Ecology & Evolution 1–9 (2021) doi:10.1038/s41559-021-01417-z.

68. Chen, C.-F. et al. Multi-Decadal Mangrove Forest Change Detection and Prediction in Honduras, Central America, with Landsat Imagery and a Markov Chain Model. Remote Sensing 5, 6408–6426 (2013).

69. UNEP. Mangrove forest cover fading fast. Thematic focus: Ecosystem management, Disasters and conflicts, Climate change https://na.unep.net/geas/getUNEPPageWithArticleIDScript.php?article_id=103 (2013).

70. Wiedmann, T. & Lenzen, M. Environmental and social footprints of international trade. Nature Geoscience 11, 314–321 (2018).

71. Eastman, J. R., Toledano, J., Crema, S. & Singh, R. Phase 3 Extension to the Mapping of Tropical Pond Aquaculture, Mangroves and Coastal Wetlands. (2020).

72. Huo, J., Meng, J., Zheng, H., Parikh, P. & Guan, D. Achieving decent living standards in emerging economies challenges national mitigation goals for CO2 emissions. Nat Commun 14, 6342 (2023).

73. Worthington, T. A. et al. A global biophysical typology of mangroves and its relevance for ecosystem structure and deforestation. Sci Rep 10, 14652 (2020).

74. Curtis, P. G., Slay, C. M., Harris, N. L., Tyukavina, A. & Hansen, M. C. Classifying drivers of global forest loss. Science 361, 1108–1111 (2018).

75. Lenzen, M., Moran, D., Kanemoto, K. & Geschke, A. Building Eora: A Global Multi-Region Input–Output Database at High Country and Sector Resolution. Economic Systems Research 25, 20–49 (2013).

76. Aye, W. N., Wen, Y., Marin, K., Thapa, S. & Tun, A. W. Contribution of Mangrove Forest to the Livelihood of Local Communities in Ayeyarwaddy Region, Myanmar. Forests 10, 414 (2019).

77. Romañach, S. S. et al. Conservation and restoration of mangroves: Global status, perspectives, and prognosis. Ocean & Coastal Management 154, 72–82 (2018).

78. Barbier, E. B. & Cox, M. Does Economic Development Lead to Mangrove Loss? A Cross-Country Analysis. Contemporary Economic Policy 21, 418–432 (2003).

79. Lagomasino, D. et al. Measuring mangrove carbon loss and gain in deltas. Environ. Res. Lett. 14, (2019).

80. Neumann, B., Vafeidis, A. T., Zimmermann, J. & Nicholls, R. J. Future Coastal Population Growth and Exposure to Sea-Level Rise and Coastal Flooding - A Global Assessment. PLoS ONE 10, (2015).

81. DeFries, R. S., Rudel, T., Uriarte, M. & Hansen, M. Deforestation driven by urban population growth and agricultural trade in the twenty-first century. Nature Geosci 3, 178–181 (2010).

82. Li, L., Liu, J., Long, H., de Jong, W. & Youn, Y.-C. Economic globalization, trade and forest transition-the case of nine Asian countries. Forest Policy and Economics 76, 7–13 (2017).

83. Chaves, L. S. M. et al. Global consumption and international trade in deforestation-associated commodities could influence malaria risk. Nat Commun 11, (2020).

84. Duarte, R., Pinilla, V. & Serrano, A. Factors driving embodied carbon in international trade: a multiregional input–output gravity model. Economic Systems Research 1–22 (2018) doi:10.1080/09535314.2018.1450226.

85. Wang, R., Hertwich, E. & Zimmerman, J. B. (Virtual) Water Flows Uphill toward Money. Environmental Science & Technology 50, 12320–12330 (2016).

86. Hou, S., Xu, M. & Qu, S. The “Gravity” for global virtual water flows: From quantity and quality perspectives. Journal of Environmental Management 329, (2023).

87. Zheng, X., Wang, R., Wood, R., Wang, C. & Hertwich, E. G. High sensitivity of metal footprint to national GDP in part explained by capital formation. Nature Geoscience 11, 269–273 (2018).

88. Marques, A. et al. Increasing impacts of land use on biodiversity and carbon sequestration driven by population and economic growth. Nature Ecology & Evolution 3, 628–637 (2019).

89. Wiedmann, T. & Lenzen, M. Environmental and social footprints of international trade. Nature Geoscience 11, 314–321 (2018).

90. Weinzettel, J., Hertwich, E. G., Peters, G. P., Steen-Olsen, K. & Galli, A. Affluence drives the global displacement of land use. Global Environmental Change 23, 433–438 (2013).

91. Erasmus K. H. J. zu Ermgassen et al. Addressing indirect sourcing in zero deforestation commodity supply chains. Science Advances (2022).

92. van Vliet, J. Direct and indirect loss of natural area from urban expansion. Nat Sustain 2, 755–763 (2019).

93. Lambin, E. F. et al. The role of supply-chain initiatives in reducing deforestation. Nature Clim Change 8, 109–116 (2018).

94. Brolin, J. & Kander, A. Global trade in the Anthropocene: A review of trends and direction of environmental factor flows during the Great Acceleration. The Anthropocene Review 2053019620973711 (2020) doi:10.1177/2053019620973711.

95. York, R., Rosa, E. A. & Dietz, T. STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. Ecological Economics 46, 351–365 (2003).

96. Dietz, T. Drivers of Human Stress on the Environment in the Twenty-First Century. Annual Review of Environment and Resources 42, 189–213 (2017).

97. Ehrlich, P. R. & Holdren, J. P. IMPACT OF POPULATION GROWTH: Obstetrical & Gynecological Survey 26, 769–771 (1971).

98. Dietz, T., Frey, R. S. & Kalof, L. Estimation with Cross-National Data: Robust and Nonparametric Methods. American Sociological Review 52, 380 (1987).

99. Dietz, T., Kalof, L. & Frey, R. S. On the Utility of Robust and Resampling Procedures1. Rural Sociology 56, 461–474 (1991).

100. Dietz, T. & Rosa, E. A. Effects of population and affluence on CO2 emissions. PNAS 94, 175–179 (1997).

101. Cramer, J. C. Population growth and air quality in California. Demography 35, 45–56 (1998).

102. Moving Ahead with REDD: Issues, Options and Implications. (Center for International Forestry Research, Bogor, Indonesia, 2008).

103. Oliveira, P. J. C. et al. Land-Use Allocation Protects the Peruvian Amazon. Science 317, 1233–1236 (2007).

104. Robalino, J. A., Pfaff, A. & Sanchez-Azofeifa, A. Estimating spatial interactions in deforestation decisions. in Biodiversity Economics (eds. Kontoleon, A., Pascual, U. & Swanson, T.) 92–114 (Cambridge University Press, 2001). doi:10.1017/CBO9780511551079.006.

105. Liu, J., Daily, G. C., Ehrlich, P. R. & Luck, G. W. Effects of household dynamics on resource consumption and biodiversity. Nature 421, 530–533 (2003).

106. Bradbury, M., Peterson, M. N. & Liu, J. Long-term dynamics of household size and their environmental implications. Popul Environ 36, 73–84 (2014).

107. Crow, B. & Carney, J. Commercializing Nature: Mangrove Conservation and Female Oyster Collectors in The Gambia. Antipode 45, 275–293 (2013).

108. Barbier, E. B. & Burgess, J. C. The Economics of Tropical Deforestation. Journal of Economic Surveys 15, 413–433 (2002).

109. Deacon, R. T. Deforestation and the Rule of Law in a Cross-Section of Countries. Land Economics 70, 414–430 (1994).

110. Kaufmann, D., Kraay, A. & Mastruzzi, M. The Worldwide Governance Indicators : Methodology and Analytical Issues. https://openknowledge.worldbank.org/handle/10986/3913 (2010).

111. Frank, K. A., Lin, Q. & Maroulis, S. J. Embracing Essential Discourse in Educational Policy about Causal Inferences from Observational Studies: Towards Pragmatic Social Science.

112. Ioannidis, J. P. A. Why Most Discovered True Associations Are Inflated. Epidemiology 19, 640–648 (2008).

113. Wooldridge. Econometric Analysis of Cross Section and Panel Data. 741 (2010).

114. Siikamaki, J., Sanchirico, J. N. & Jardine, S. L. Global economic potential for reducing carbon dioxide emissions from mangrove loss. Proceedings of the National Academy of Sciences 109, 14369–14374 (2012).

115. Ricke, K., Drouet, L., Caldeira, K. & Tavoni, M. Country-level social cost of carbon. Nature Clim Change 8, 895–900 (2018).

116. Sasmito, S. D. et al. Challenges and opportunities for achieving Sustainable Development Goals through restoration of Indonesia’s mangroves. Nat Ecol Evol 7, 62–70 (2023).

117. Adger, W. N. & Luttrell, C. Property rights and the utilisation of wetlands. Ecological Economics 35, 75–89 (2000).

118. Ferreira, A. C., Borges, R. & de Lacerda, L. D. Can Sustainable Development Save

Mangroves Sustainability 14, 1263 (2022).

119. Deng, Z. et al. Comparing national greenhouse gas budgets reported in UNFCCC inventories against atmospheric inversions. Earth System Science Data 14, 1639–1675 (2022).

120. Landgap Report - Homepage. LAND GAP https://www.landgap.org/.

121. International Day for the Conservation of the Mangrove Ecosystem. https://www.unesco.org/en/days/mangrove-ecosystem-conservation.

122. China to build and restore 18,800 hectares of mangrove by 2025. http://english.www.gov.cn/statecouncil/ministries/202008/28/content_WS5f490ae4c6d0f7257693b3cb.html.

123. Slobodian, L., Rodriguez Chaves, M., Nguyen, L. T. P. & Rakotoson, L. N. Legal Frameworks for Mangrove Governance, Conservation and Use : Assessment Summary. (2018).

124. Maynard, J. et al. Mangrove Cover Change between 1996 and 2016 near River-Ocean Outlets: A Global Analysis to Identify Priority Rivers for Conservation. (2019). doi:10.6084/m9.figshare.8094245.v2.

125. ITFFF. Mangroves for sustainable development. United Nations Western Europe https://unric.org/en/mangroves-for-sustainable-development/ (2022).

126. Mangroves for the Future. Shorthand https://social.shorthand.com/IUCNAsia/jCGOFQxB26/mangroves-for-the-future.html.

127. Mangroves4SDGs. https://www.mangroves4sdgs.com/sdgs.

128. Mangroves Conservation and Sustainable Development Goals (SDGs). https://www.insightsonindia.com/environment/unique-ecosystems-degradation-and-management/mangrove-ecosystem/mangroves-conservation-and-sustainable-development-goals-sdgs/.

129. Seymour, F. & Busch, J. Forests and SDGs: Taking a Second Look. (2017).

130. Krause, T. & Tilker, A. How the loss of forest fauna undermines the achievement of the SDGs. Ambio 51, 103–113 (2022).

131. Can restoring mangroves help achieve the Sustainable Development Goals? | IUCN. https://www.iucn.org/news/forests/201703/can-restoring-mangroves-help-achieve-sustainable-development-goals.

132. Friess, D. A. et al. SDG 14: Life below Water – Impacts on Mangroves. in Sustainable Development Goals: Their Impacts on Forests and People (eds. Katila, P. et al.) 445–481 (Cambridge University Press, 2019). doi:10.1017/9781108765015.016.

133. Obiene, S., Shilabukha, K., Muga, G., Ojwang, L. & Owuor, M. A. Understanding of

Sustainable Development Goals among communities living adjacent to mangroves in Kenya. WIO J. Mar. Sci. 59–73 (2022) doi:10.4314/wiojms.si2022.1.5.

134. Gong, M., Yu, K., Xu, Z., Xu, M. & Qu, S. Unveiling complementarities between national sustainable development strategies through network analysis. Journal of Environmental Management 350, 119531 (2024).

135. Gong, M. et al. SDG Space: Revealing the Structure and Complementarities among Sustainable Development Goals in China. Fundamental Research S2667325824000256 (2024) doi:10.1016/j.fmre.2024.01.005.

136. Yu, K., Song, Y., Lin, J. & Qu, S. Evaluating complementaries among urban water, energy, infrastructure, and social Sustainable Development Goals in China. Journal of Environmental Sciences 149, 585–597 (2025).

137. Wolosin, M. Exponential Roadmap for Natural Climate Solutions. (2022).

138. Hidalgo, C. A., Klinger, B., Barabási, A.-L. & Hausmann, R. The Product Space Conditions the Development of Nations. Science 317, 482–487 (2007).

139. Alabdulkareem, A. et al. Unpacking the polarization of workplace skills. Sci. Adv. 4, eaao6030 (2018).

140. Newman, M. E. J. Modularity and community structure in networks. Proc. Natl. Acad. Sci. U.S.A. 103, 8577–8582 (2006).

141. Blondel, V. D., Guillaume, J.-L., Lambiotte, R. & Lefebvre, E. Fast unfolding of communities in large networks. J. Stat. Mech. 2008, P10008 (2008).

142. Brandes, U. A faster algorithm for betweenness centrality*. The Journal of Mathematical Sociology 25, 163–177 (2001).

143. Mathieu Bastian, S. H. Gephi: An Open Source Software for Exploring and Manipulating Networks. International AAAI Conference on Weblogs and Social Media https://aaai.org/papers/00361-gephi-an-open-source-software-for-exploring-and-manipulating-networks/ (2009).

144. Launch of Sustainable Development Report 2022: “From Crisis to Sustainable Development: the SDGs as Roadmap to 2030 and Beyond” – Global MOOC and Online Education Alliance. https://mooc.global/gma/launch-of-sustainable-development-report-2022-from-crisis-to-sustainable-development-the-sdgs-as-roadmap-to-2030-and-beyond/.

145. Ostrom, E. Governing the Commons: The Evolution of Institutions for Collective Action. (Cambridge University Press, 1990).

146. Meyfroidt, P. & Lambin, E. F. Forest transition in Vietnam and displacement of deforestation abroad. Proc Natl Acad Sci U S A 106, 16139–16144 (2009).

147. Burgess, R., Hansen, M., Olken, B. A., Potapov, P. & Sieber, S. The political economy of deforestation in the tropics. 40 (2012).

148. Feka, Z. N. Sustainable management of mangrove forests in West Africa: A new policy perspective? Ocean & Coastal Management 116, 341–352 (2015).

149. Datta, D., Chattopadhyay, R. N. & Guha, P. Community based mangrove management: A review on status and sustainability. Journal of Environmental Management 107, 84–95 (2012).

150. Beitl, C. M. Adding Environment to the Collective Action Problem: Individuals, Civil Society, and the Mangrove-Fishery Commons in Ecuador. World Development 56, 93–107 (2014).

151. Beitl, C. Decentralized mangrove conservation and territorial use rights in Ecuador's mangrove-associated fisheries. bms 93, 117–136 (2017).

152. Beitl, C. M., Rahimzadeh-Bajgiran, P., Bravo, M., Ortega-Pacheco, D. & Bird, K. New valuation for defying degradation: Visualizing mangrove forest dynamics and local stewardship with remote sensing in coastal Ecuador. Geoforum 98, 123–132 (2019).

153. Pagdee, A., Kim, Y. & Daugherty, P. J. What Makes Community Forest Management Successful: A Meta-Study From Community Forests Throughout the World. Society & Natural Resources 19, 33–52 (2006).

154. Chhatre, A. & Agrawal, A. Trade-offs and synergies between carbon storage and livelihood benefits from forest commons. Proceedings of the National Academy of Sciences 106, 17667–17670 (2009).

155. Beitl, C. M. Cockles in Custody: The Role of Common Property Arrangements in the Ecological Sustainability of Mangrove Fisheries on the Ecuadorian Coast. 29.

156. Ostrom, E. A General Framework for Analyzing Sustainability of Social-Ecological Systems. Science 325, 419–422 (2009).

157. Angelsen, A. Policies for reduced deforestation and their impact on agricultural production. PNAS 107, 19639–19644 (2010).

158. Dryzek, J. S. 6. Leave It to the Market: Economic Rationalism. The Politics of the Earth (Oxford University Press, 2012).

159. Liu, J. & Yang, W. Integrated assessments of payments for ecosystem services programs. PNAS 110, 16297–16298 (2013).

160. Yang, W. et al. Nonlinear effects of group size on collective action and resource outcomes. Proc Natl Acad Sci U S A 110, 10916–10921 (2013).

161. Yost, A. et al. Mechanisms behind concurrent payments for ecosystem services in a Chinese nature reserve. Ecological Economics 169, 106509 (2020).

162. Oberlack, C. et al. Polycentric governance in telecoupled resource systems. Ecology and Society 23, (2018).

163. Nunan, F. Navigating multi-level natural resource governance: an analytical guide. Natural Resources Forum 42, 159–171 (2018).

164. Thompson, B. S. The political ecology of mangrove forest restoration in Thailand: Institutional arrangements and power dynamics. Land Use Policy 78, 503–514 (2018).

165. Friis, C. Telecoupling. (Springer Berlin Heidelberg, New York, NY, 2019).

166. Partelow, S., Glaser, M., Solano Arce, S., Barboza, R. S. L. & Schlüter, A. Mangroves, fishers, and the struggle for adaptive comanagement: applying the social-ecological systems framework to a marine extractive reserve (RESEX) in Brazil. E&S 23, art19 (2018).

167. Powell, N. & Osbeck, M. Approaches for understanding and embedding stakeholder realities in mangrove rehabilitation processes in Southeast Asia: lessons learnt from Mahakam Delta, East Kalimantan. Sust. Dev. 18, 260–270 (2010).

168. Bolwig, S., Ponte, S., Toit, A. D., Riisgaard, L. & Halberg, N. Integrating Poverty and Environmental Concerns into Value-Chain Analysis: A Conceptual Framework. Development Policy Review 28, 173–194 (2010).

169. Dauvergne, P. & Lister, J. Big brand sustainability: Governance prospects and environmental limits. Global Environmental Change 22, 36–45 (2012).

170. Sasmito, S. D. et al. Mangrove blue carbon stocks and dynamics are controlled by hydrogeomorphic settings and land-use change. Global Change Biology 26, 3028–3039 (2020).

171. Howard, J. et al. Clarifying the role of coastal and marine systems in climate mitigation. Frontiers in Ecology and the Environment 15, 42–50 (2017).

172. Valle, A. del, Eriksson, M., Ishizawa, O. A. & Miranda, J. J. Mangroves protect coastal economic activity from hurricanes. PNAS 117, 265–270 (2020).

173. Arifanti, V. B. et al. Contributions of mangrove conservation and restoration to climate change mitigation in Indonesia. Global Change Biology 28, 4523–4538 (2022).

174. Lee, S. Y., Hamilton, S., Barbier, E. B., Primavera, J. & Lewis, R. R. Better restoration policies are needed to conserve mangrove ecosystems. Nat Ecol Evol 3, 870–872 (2019).

175. Spalding, M. & Parrett, C. L. Global patterns in mangrove recreation and tourism. Marine Policy 110, 103540 (2019).

176. Chaplin-Kramer, R. et al. Global modeling of nature’s contributions to people. Science 366, 255–258 (2019).

177. Bryan-Brown, D. N. et al. Global trends in mangrove forest fragmentation. Sci Rep 10,

7117 (2020).

178. Goal 2. End Hunger, Achieve Food Security and Improved Nutrition, and Promote Sustainable Agriculture. in A New Era in Global Health (ed. Rosa, W.) (Springer Publishing Company, New York, NY, 2017). doi:10.1891/9780826190123.0013.

APPENDIX A: SUPPORTING DOCUMENTS OF CHAPTER 2

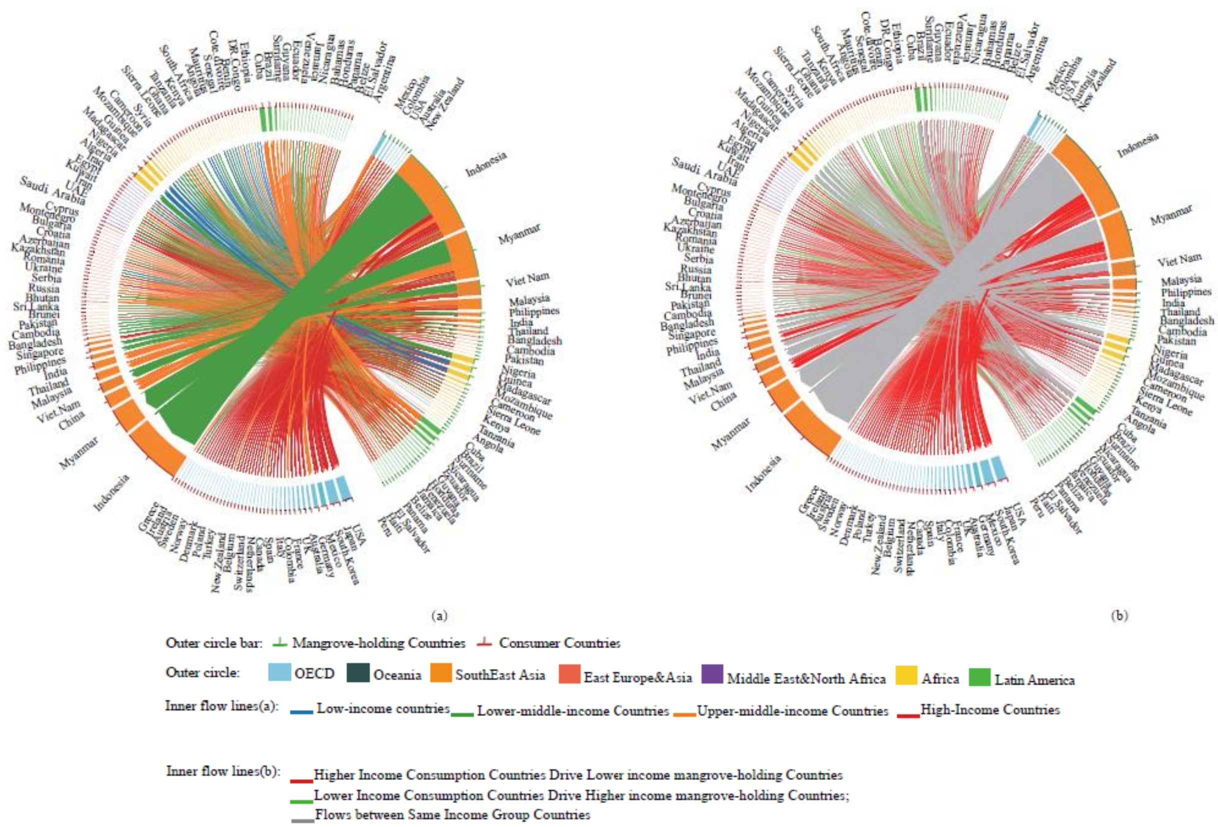


Figure S2-1: Mangrove loss footprint flows (km2) between mangrove-holding and consumer countries in 2000-2016. Mangrove loss footprint flows (km2) between mangrove-holding and consumer countries in 2000-2016 with two visualization ways. (a) the flow color represents the consumer country's economic status, and (b) the flow color represents how mangrove forest resources flow between countries of different economic statuses. Mangrove-holding countries are marked by green in their outer circle bar, and consumer countries by red. The arc length of the circle indicates the sum of consumption exported and imported between the mangrove-holding and consumer countries. The arc color of the circle indicates the region of countries, which is ordered by their geographic location.

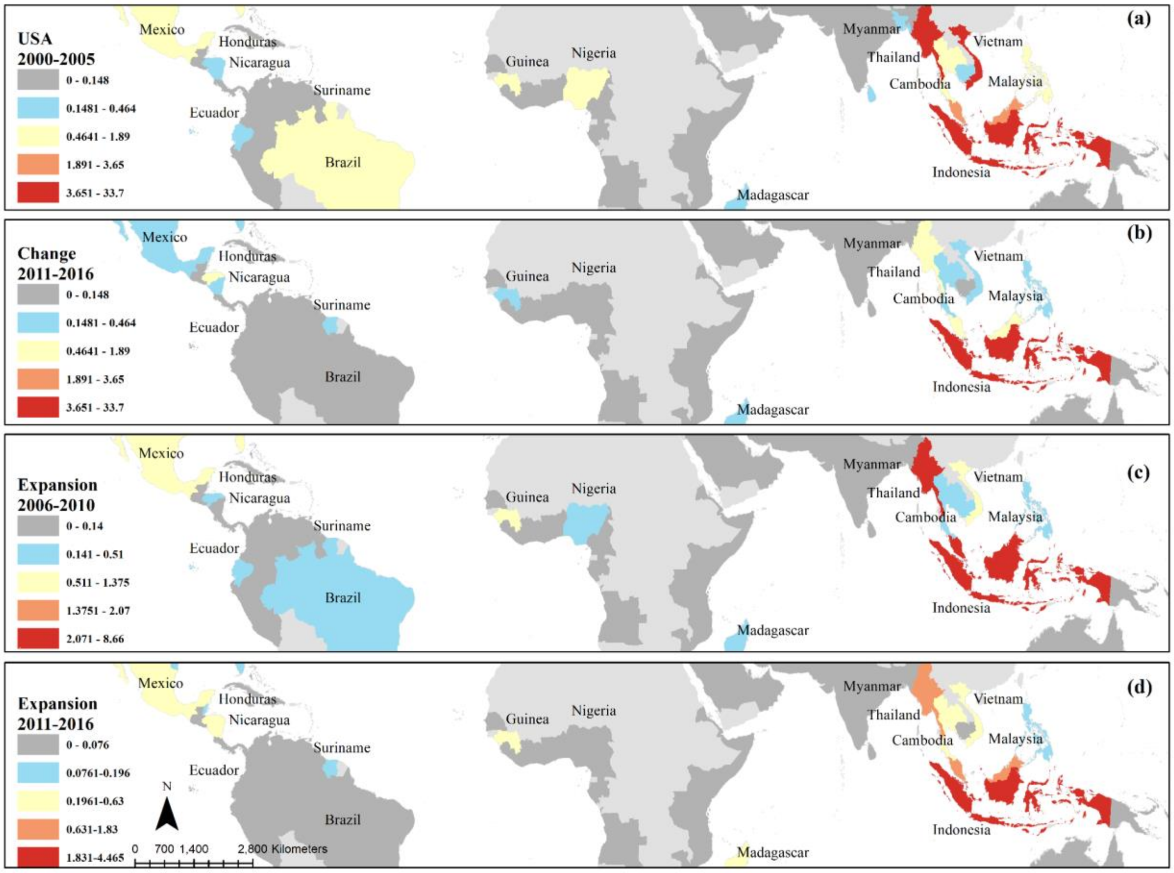


Figure S2-2: Maps of Mangrove loss footprints (km2) in 65 mangrove-holding countries driven by USA's consumption. Maps of Mangrove loss footprints (km2) in 65 mangrove-holding countries driven by USA's consumption to compare the changes (a) and (b) and expansion (a), (c), and (d) in three epochs (2000-2005, 2006-2010, 2011-2016) at the country level.

APPENDIX B: SUPPORTING DOCUMENTS OF CHAPTER 3

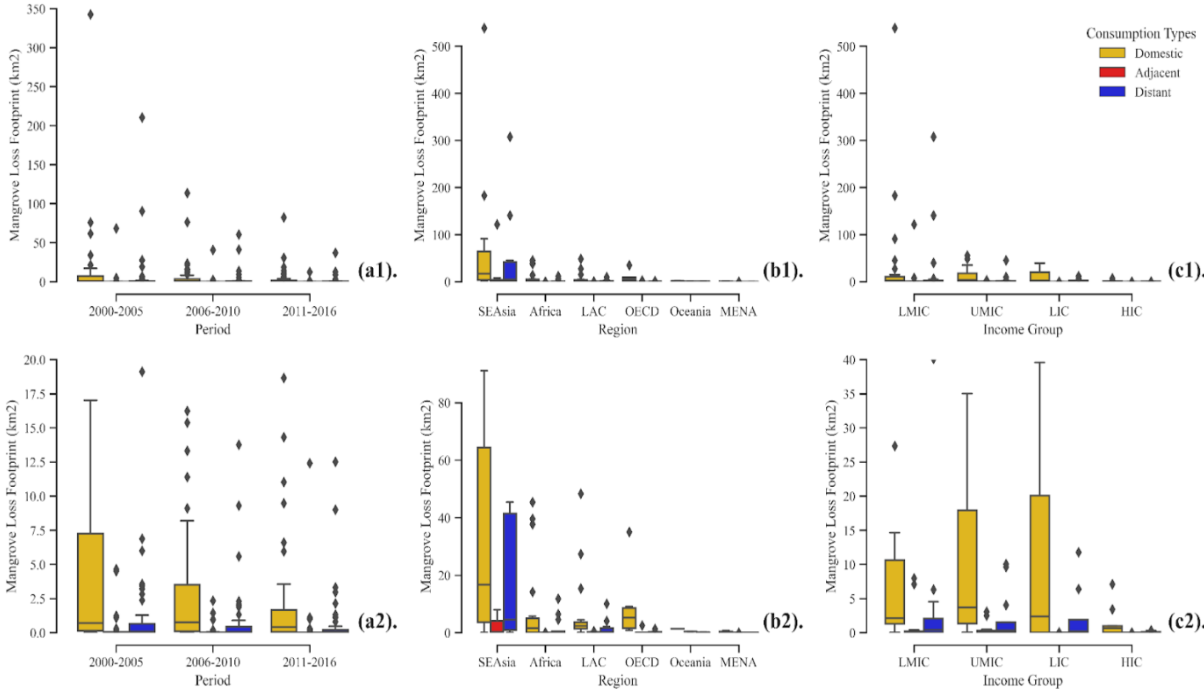


Figure S3-1: Distribution of mangrove loss attributed to domestic, adjacent, and distant consumptions categorized by (a) Period, (b) Region, and (c) Income group. Distribution of mangrove loss attributed to three consumption types categorized by (a) Period, (b) Region, and (c) Income group. Countries' regions and income groups follow the classification in the Sustainable Development Goals (SDG) Dashboard (https://dashboards.sdgindex.org/downloads). Regions named SE Asia, Africa, LAC, OECD, Oceania, and MENA represent South East Asia, Africa, Latin American Countries (LAC), Organization for Economic Co-operation and Development Countries (OECD), Oceania, and Middle East and North Africa (MENA), respectively. Income groups such as LMIC, UMIC, LIC, and HIC indicate lower-middle-income, upper-middle-income, low-income, and high-income countries. The first three sub-plots provide a comprehensive overview, highlighting the outliers within each category. The next three sub-plots zoom in on the boxplots, offering insights into each category's central tendencies. The arrangement to order the categories in graphs is based on values in each bar.

Table S3-1-1: Benchmark regression model through stepwise algorithm in backward method.

Number of obs	=	470
F(2, 157)	=	91.62
Prob > F	=	0.0000
R-squared	=	0.4444
Root MSE	=	1.8033

(Std. Err. adjusted for 158 clusters in id)

log_mlfp	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
log_pop	.8965265	.0797395	11.24	0.000	.7390259	1.054027
log_gdppc	.6264071	.0866526	7.23	0.000	.4552519	.7975623
_cons	-22.19753	1.59266	-13.94	0.000	-25.34333	-19.05173

Table S3-1-2: VIF of benchmark regression model through stepwise algorithm in backward method.

Variable	VIF	1/VIF
log_gdppc	1.03	0.974890
log_pop	1.03	0.974890
Mean VIF	1.03	

Table S3-2-1: Estimates of bench model run in OLS, random effect, fixed effect, and first differencing regressions plus foreign inflow percentage share of GDP.

	(1) OLS	(2) RE	(3) FE	(4) FD
log_pop	0.971***	0.938***	1.057***	0.853***
	(0.0782)	(0.0772)	(0.314)	(0.308)
log_gdppc	0.637***	0.662***	0.672***	0.538***
	(0.0899)	(0.0862)	(0.209)	(0.182)
log_forei_inper	0.166*	0.0824**	0.0749**	0.0519**
	(0.0934)	(0.0355)	(0.0375)	(0.0229)
t1	1.389***	1.443***	1.468***	0
	(0.0842)	(0.0671)	(0.0813)	(.)
t2	0.705***	0.770***	0.787***	0.0434
	(0.0696)	(0.0501)	(0.0669)	(0.0353)
_cons	-24.44***	-24.09***	-26.13***	-0.696***
	(1.536)	(1.566)	(5.080)	(0.0453)
N	454	454	454	296

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table S3-2-2: Estimates of bench model run in OLS, random effect, fixed effect, and first differencing regressions plus GCF percentage of GDP.

	(1)	(2)	(3)	(4)
	OLS	RE	FE	FD
log_pop	0.987***	0.922***	0.719**	0.805**
	(0.0728)	(0.0752)	(0.363)	(0.345)
log_gdppc	0.618***	0.641***	0.760***	0.728***
	(0.0926)	(0.0955)	(0.227)	(0.182)
log_gcf_per	-0.105	0.236*	0.284*	0.0981
	(0.449)	(0.134)	(0.161)	(0.139)
t1	1.454***	1.468***	1.471***	0
	(0.104)	(0.0758)	(0.0889)	(.)
t2	0.827***	0.783***	0.799***	0.0676*
	(0.0640)	(0.0480)	(0.0696)	(0.0347)
_cons	-24.01***	-24.22***	-22.36***	-0.730***
	(2.231)	(1.674)	(5.929)	(0.0447)
N	435	435	435	285

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table S3-3: Hausman test statistics for the six models are in Table 4.1.

	(1)	(2)	(3)	(4)	(5)	(6)
F statistics from Pooled OLS	6.99	4.59	8.49	5.30	59.88	61
F statistics from random effect regression	31.87	17.04	27.33	15.06	119.36	166.56
Prob > chi2	0.0000	0.0007	0.0000	0.0017	0.0000	0.0000

Table S3-4: List of independent variables in regressions.

Name in the regressions	Categories	Indicator Name
gdppc	Affluence	GDP per capita (constant 2015 US$)
pop	Population	Population, total
gcf	Affluence	Gross capital formation (constant 2015 US$)
agri_value	Affluence	Agriculture, forestry, and fishing, value added (constant 2015 US$)
pop_urban	Affluence	Rural population
pop_femal	Population	Population, female
agri_per	Technology (Domestic resource availability)	Agriculture, forestry, and fishing, value added (% of GDP)
forei_inper	Technology (external investment share)	Foreign direct investment, net inflows (% of GDP)
forei_outper	Technology (external investment share)	Foreign direct investment, net outflows (% of GDP)
house_per	Technology (economy structure)	Households and NPISHs final consumption expenditure (% of GDP)
gcf_per	Technology (investment rate)	Gross capital formation (% of GDP)
industry_per	Technology (economy structure)	Industry (including construction), value added (% of GDP)
gov_effect	Institutions	Government Effectiveness
corrup	Institutions	Control of Corruption