Data Fusion, Hedonic Pricing, and Blockchains:
Lowering Investment Barriers for Sustainable Infrastructure

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Environmental Engineering)
in the University of Michigan
2022

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Dedication

I dedicate this dissertation to

my mother, my father, and my sister

for their constant support and unconditional love.

“Twenty years from now you will be more disappointed by the things that you didn’t do than by the ones you did do. Sail away from the safe harbor. Explore. Dream. Discover”

- Motivational poster in EWRE 126

Acknowledgements

First and foremost, I would like to express my sincere gratitude to my advisor Prof. Peter Adriaens for the continuous support of my Ph.D. study and research, for his patience, trust, knowledge, and enthusiasm. His guidance helped me explore uncharted waters of sustainability research and the writing of this dissertation. I could not have imagined having a better advisor and mentor for my Ph.D. study.

Besides my advisor, I would like to thank my dissertation committee: Prof. Ravi M. Anupindi, Prof. Jose F. Alfaro, and Prof. Christian M. Lastoskie, for their insightful comments and encouragement, but also for the fruitful discussions and stimulating questions which motivated me to widen my research from various perspectives. My gratitude also goes to Prof. Herek L. Clack, who supported and encouraged me during a time of transition in my life. Without his support and belief in me, it would not be possible to conduct this research and break new ground in the discipline of Environmental Engineering.

I thank my fellow lab mates and peers for the stimulating discussions and for the moral support both in research and in life. Under pandemic circumstance and the limited time, we had all the fun we could. To name a few: Dan, Mingyan, Qiyan, Kyle, Ettienne, Clyde, Leo, Merrisa, Alyssa, Kira, Kanchan, Rachel, and Anna. Special thanks to Dan Li who helped to with the visualization of decentralized oracle networks as well as providing knowledge on the subject area of causal inference.

Last but not the least, I would like to thank my family who have supported me every step of the way and encouraged my continued efforts. I could not have done this without you.

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Abstract

The United Nations Environment Program Finance Initiative as well as the National Academies of Science, Engineering, and Medicine recognize the need for financial innovations to facilitate transitioning to a sustainable society. To ignore financial solutions is to risk increasing environmental and social cost and the window to limit global warming under 1.5°C. Under-investment in infrastructure has resulted in significant deterioration in functionality and deficiencies in society's ability to meet present needs without compromising future generation needs from an environmental, social, and economic perspective. The American Society of Civil Engineers estimated that $5.9 trillion USD would be required to bring infrastructure to an adequate state and currently only 56 percent has been committed. This translates to an annual deficit of $259 billion USD from 2020 to 2029.

Aside from the built environment, investment deficits are found in incentivizing sustainable practices in agriculture as well. Yet, while government subsidies have attempted to guide these operations towards sustainable outcomes, the capital market instruments have not been executed in farming due to market and definitional frictions. This dissertation sought to achieve three goals: (1) to understand the economic value and environmental cost of unsustainable practices; (2) to explore the potential for technology-based financing models such as blockchain to facilitate sustainability-linked financing mechanisms; and (3) to demonstrate a proof-of-concept to operationalize agricultural outcomes-based financing using blockchain. The regional use case focused on agriculture in the sub-watersheds of the Great Lakes drainage area.

The work presented here leverages a number of methodologies to achieve these goals, including novel data fusion approaches, application of econometric theories, as well as blockchain-enabled funding and financing mechanisms. My initial approach applies data fusion and hedonic pricing to quantify the contribution of nitrogen and phosphorus loading on farmland sales transactions. The data sources and fusion process were derived from AcreValue, the United States Department of Agriculture's Gridded Soil Survey Geographic database and the United States Geological Survey's Spatially Referenced Regression on Watershed Attributes database. The results suggest that nutrient loading has significant positive influence on farmland prices such that prices increase with contamination and re-valuations of contaminating farmlands is required.

The following chapters leverage technology-based financing using blockchains and decentralized oracle networks to reduce investment barriers for sustainable systems. A framework is presented where trusted data from internet-of-things of infrastructure can inform financial transactions on-chain in an efficient manner. This section employs the Model method to justify and predict how blockchains and oracles can use infrastructure internet-of-things data to streamline performance-based financing mechanisms by creating trust and automation. A performance-based proof-of-concept to incentivize regenerative agriculture practices is then implemented on the Ethereum blockchain. This research element highlights the benefits of implementing performance-based incentives on a blockchain via Transaction Cost Economics (TCE) analysis. The combination of blockchain-based platforms and decentralized oracle networks not only show that payment processes are automated, reducing transaction costs, but also that multiple transaction steps in a typical pay-for outcomes program can be executed using a smart contract.

This work reveals the value of leveraging data streams, where insights are generated to understand the boundary conditions for the future design of sustainable infrastructure and practices. The findings of this study serve as a key input for technology-enabled financing models that can lower transaction costs and unlock new capital resources.

Chapter 1 Background and Motivation

Infrastructure is the physical and institutional backbone that supports society's competitiveness, economic growth, and, most importantly, its members' well-being and wealth generation. Typical examples of infrastructure include the transportation sector (e.g., roads, railways, airports, etc.), the energy sector (e.g., oil and gas, wind, solar, etc.), water and wastewater systems, social infrastructure (e.g., schools and hospitals), and natural infrastructure (e.g., agriculture). Without these infrastructures in place, society would not be able to meet the needs of both developed and emerging economies. However, with aging infrastructure in developed economies and rapid urbanization and population growth in emerging economies, the gap between infrastructure supply and demand has been as wide as ever before.

1.1 Current State of Infrastructure Finance

The American Society of Civil Engineers (ASCE) rates America's infrastructure a C-, stating general signs of deterioration with some significant deficiencies in conditions and functionality (American Society of Civil Engineers, 2021). An annual $259 billion USD financing deficit needs to be reconciled to bring domestic infrastructure to an "adequate" state[1]. Internationally, the finance gap is prevalent as well. The Organization for Economic Co-operation and Development (OECD) estimates annual infrastructure investments gap between 2.5 to 3 trillion USD (OECD,

[1] ASCE defines adequate as "…good to excellent condition; some elements show signs of general deterioration that require attention. A few elements exhibit significant deficiencies. Safe and reliable, with minimal capacity issues and minimal risk."

2020), with other organizations such as the Global Infrastructure Hub and the World Economic Forum finding comparable numbers. Traditionally, infrastructure financing has been serviced from public sources. Financing refers to the mechanisms by which investors get involved in projects, such as bonds, debt, or private equity. Funding is the collective of mechanisms or revenue that pay for the cost of this financing capital, such as taxes, fees (e.g., gas taxes), revenue (e.g. water rates), or other forms of revenue. Most of infrastructure is considered to be in the public domain, as positive societal externalities accrue from the use of such physical assets. However, a number of factors have caused a decrease in public funds directed towards infrastructure:

1. Lack of prioritization in budgets by the public sector:

The public sector, which is traditionally responsible for infrastructure, has multiple obligations to fund operations. Budget restrictions have limited and negatively impacted prioritization for both operations and maintenance as well as capital expenditure for closing this gap. This has led to decreased capital spending on infrastructure since the 1970s (McNichol, 2019).

2. Heavy burden imposed on public budgets:

Increased public deficits and public debt to GDP ratios have occurred in the past decade. The gross federal debt-to-GDP ratio rose from 91.2 in 2010 to 106.9 in 2019 (Trading Economics, 2020). In addition, misguided tax cut policies have reduced public budgets dramatically (McNichol, 2019). In the 2019 fiscal year, the infrastructure proposal of the United States Federal Government left a $1.3 trillion-dollar financing gap to fill (Leibenluft, 2018). Because of Covid-19 economic impacts in 2020, more than 700 cities in the United States have hit pause on critical infrastructure plans due to governments slashing expenses in order to remedy their depleted budgets (Romm, 2020). While economic recovery, the bipartisan infrastructure bill and the pending Inflation Reduction Act seek to inject fresh capital in public and private projects, the inefficiencies remain unless sustainable infrastructure and their performance metrics can be integrated in financing models and new forms of public private partnerships (PPP).

3. Reluctance to increase taxes for long term infrastructure projects:

At the federal level, increasing tax levies to fund infrastructure is not politically popular. In the US, for example, the gas tax for highway funding has not increased in decades, resulting in a projected $120 billion deficit in 2023 (Tax Foundation, 2022). At the city, county and state level, where most municipal bonds are issued, the use of fixed-income instruments backed by the taxing authority of the issuer puts pressure on the government entity's credit ratings and thus cost of capital (Weber et al., 2016).

4. Inefficient financing models:

Infrastructure is financed using a combination of long-term financing models such as bonds, private debt and equity, which do not allow for updates on the performance or risk profiles of these assets. The lack of real time risk adjustment in assets is often referred to as inefficient capital (say as opposed to stocks or other securities that offer short term reconciliation). In addition, the administrative structures of centralized intermediaries tend to increase the cost of capital as fees propagate in deal structuring. Expenses can be lowered by reforming the convoluted administrative machinery and through disintermediation (Weber et al., 2016).

The public sector has increasingly engaged with private sector market mechanisms under a wide range of public-private partnership contracts (Delmon, 2021; Loftus et al., 2019) to address the shortcomings mentioned. Private investments can access infrastructure via corporate finance or project finance. In corporate finance, the infrastructure is financed through the corporate balance sheet. The infrastructure sponsors collateralize the existing corporation's assets and cash flows to gain loans and credit provided by creditors and equity holders. However, corporate finance is subject to balance sheet contamination risk. When a new venture or project is large compared to a corporation's current size and the balance sheet is exposed to a higher degree of risk, or the new project is highly correlated to a company's core business, then in such cases, a project-finance based financial structure would be more ideal (Gatti, 2018a). In project finance, a long-lived, single-purpose, distinct legal entity is set up to construct, own, and operate a project off the balance sheet of the project sponsor (Finnerty, 2013; Gatti, 2018a). The entity is often referred to as a special purpose vehicle (SPV). The SPV raises funds through debt and equity securities on a limited-recourse or even a non-recourse basis, with the cash flow from the project servicing debt, equity, and operating expenses (Finnerty, 2013; Gatti, 2018a). The assets held by the SPV are used as collateral when default occurs.

A wide range of financing instruments, accessed through either corporate or project finance, are available to investors. Based on the risk and return profile, certain instruments can be more attractive to investors than others. Della Croce et al. (2015) have summarized the financing instruments and vehicles currently utilized and are shown in Table 1-I. Such instruments are often associated with high transaction fees, illiquidity, and high investment thresholds (Joffee, 2016). In addition, these instruments are becoming riskier as public entities are cash strapped. There is also evidence that suggests infrastructure funds and direct investment strategies do not promise stable returns or offer better risk-adjusted performance (Blanc-Brude, 2013). Innovation in financing instruments and methods are required to make investments in infrastructure much more desirable.

Table 1-I. Conventional infrastructure investment instruments and vehicle. Source: Della Croce et al. (2015)

<table>
<tr><th colspan="2">Modes</th><th colspan="2">Infrastructure Finance Instruments</th><th>Market Vehicles</th></tr>
<tr><th>Asset Category</th><th>Instrument</th><th>Infrastructure Project</th><th>Corporate Balance Sheet / Other Entities</th><th>Capital Pool</th></tr>
<tr><td rowspan="5">Fixed Income</td><td rowspan="3">Bonds</td><td>Project Bonds</td><td rowspan="2">Corporate Bonds, Green Bonds</td><td rowspan="3">Bond Indices, Bond Funds, ETFs</td></tr>
<tr><td>Municipal, Sub-sovereign bonds</td></tr>
<tr><td>Green Bonds, Sukuk</td><td>Subordinated Bonds</td></tr>
<tr><td rowspan="2">Loans</td><td rowspan="2">Direct/Co-Investment lending to Infrastructure project, Syndicated Project Loans</td><td>Direct/Co-investment lending to infrastructure corporate</td><td>Debt Funds (GPs)</td></tr>
<tr><td>Syndicated Loans, Securitized Loans (ABS), CLOs</td><td>Loan Indices, Loan Funds</td></tr>
<tr><td>Mixed</td><td>Hybrid</td><td>Subordinated Loans/Bonds, Mezzanine Finance</td><td>Subordinated Bonds, Convertible Bonds, Preferred Stock</td><td>Mezzanine Debt Funds (GPs), Hybrid Debt Funds</td></tr>
<tr><td rowspan="2">Equity</td><td>Listed</td><td>YieldCos</td><td>Listed infrastructure & utilities stocks, Closed-end Funds, REITs, IITs, MLPs</td><td>Listed Infrastructure Equity Funds, Indices, trusts, ETFs</td></tr>
<tr><td>Unlisted</td><td>Direct/Co-Investment in infrastructure project equity, PPP</td><td>Direct/Co-Investment in infrastructure corporate equity</td><td>Unlisted Infrastructure Funds</td></tr>
</table>

Innovative infrastructure financing methods have long been on the horizon; Its research and development have been accelerated by the SARS-CoV-2 pandemic as the world is being forced into a new normal. Other sources of financing and funding are required to reconcile the infrastructure financing gap. New instruments, vehicles, and business models can make alternative financing options available for infrastructure projects. Additional options, such as blockchains, may diversify the investor base by lowering the cost of capital and open new financing avenues for infrastructure development where investment gaps persist.

1.2 Blockchain Introduction

1.2.1 Fundamentals

Nakamoto (2008) presented the first idea of the blockchain for peer-to-peer payments without a financial intermediary. The three significant properties of blockchain enable decentralization, transparency, and immutability removes the need for a financial intermediary and addresses double-spending (i.e., spending money that has already been spent or spending money that you don't have). Decentralization means decision-making, information storage, transaction verification is distributed across the internet, so there is no single point of failure, centralized authority, or server. Blockchain is the data structure that efficiently facilitates decentralized storage and transaction verification where all relevant transaction data is aggregated into blocks that are chained to one another by the hash of a previous block. Hashing refers to the process of transforming input data to a fixed-sized string. The resulting fixed-sized string is the "hash". Hashing enables the tamper-evident characteristic of the blockchain, where any tampering of the input data will alter the resulting hash. The proof-of-work consensus algorithm ensures the decision that is accepted by the majority of computing power is recorded on the blockchain (Nakamoto, 2008; Wüst & Gervais, 2018). A voting process is initiated to append a new block (i.e., the decision or transaction that is accepted) to the blockchain. To obtain a voting right, evidence of spent resources must be shown. Simply put, you have to spend the time and resources to show that you are a trustworthy voter. In the case of the bitcoin blockchain, the time and resources considered is computing power. Transparency refers auditable transactions from broadcasting to the blockchain network (Nakamoto, 2008; Zelbst et al., 2020). All actors can query any transaction which increases accountability. The hashing of transactions and data alongside proof-of-work consensus makes information of the blockchain immutable or near-impossible to be tampered with.

Colloquially, the blockchain enables transactions like a traditional bank does. Table 1-II is a comparison of the functions of a bank versus a blockchain. There are four main functions that a bank offers: account and identity management, monetary transfer services, record management, and trust. Blockchains provides the same functionalities only by different mechanisms.

Table 1-II. Bank versus blockchain functionalities. Source: Akhtar et al. (2017).

	Account and Identity Management	**Service**	**Record Management**	**Trust**
Banks	Links personal information to bank account and verifies ownership	Transfers money and redeems money	Updates and tracks account balance	Provides services by professionals under regulations of government
Blockchains	Gives users autonomously created and managed identities	Sends funds between peers directly (P2P)	Updates every node, which keeps its own ledger (blockchain)	Provides trusted protocol which incentivizes actors to behave honestly

The blockchain data structure is also known as a distributed ledger technology. It is the underlying mechanism for record keeping and management without use of centralized authorities such as banks. The blockchain creates trust through consensus protocols such as the proof-of-work process mentioned above.

Along with these fundamental characteristics, blockchains today offer much more functionality than the original bitcoin blockchain such as programmability and accessing off-chain data. The Ethereum blockchain has a Turing-complete programming language (Solidity) built-in and is currently the second largest blockchain behind bitcoin in terms of market capitalization. The programming language is used to create "smart contracts". A smart contract is a piece of software that represents conventional papers contracts that carries out digital asset transactions according to certain conditions (Buterin, 2014). For example, if 5 blocks have been appended to the blockchain, then execute payment to Bob. Essentially, it is an if-then code execution. Table 1-III depicts the difference between a smart contract versus a traditional contract. Although programmable, blockchains by itself is not able to access data and computational resources in the real world. The next iteration of blockchain technology is the addition of oracles.

Table 1-III. Smart contracts versus conventional contracts. Adapted from Bennett et al. (2021).

	Smart Contracts	Conventional Contracts
Language	Computer code	Legal prose
Identity	Decentralized identities, wallets addresses	In-person signatures
Dispute Resolution	Consensus protocols	Judges, lawyers
Nullification	Hard or soft forking of blockchain	Legal enforcement
Payment	Peer-to-peer, automated execution based on certain pre-specified conditions	Financial intermediaries and IOUs
Escrow	Contract itself is the escrow	Reserves and liquidity in financial institutions

According to Chainlink[2], an oracle technology provider, oracles are "…entities that connect blockchains to external systems, thereby enabling smart contracts to execute based upon inputs and outputs from the real world." The combination of smart contracts utilizing oracles to access data off-chain for on-chain decision making is termed hybrid smart contracts (Breidenbach et al., 2021).

1.2.2 Opportunities for Sustainable Infrastructure

Uzsoki (2019) lays out the idea of utilizing blockchains for financing sustainable infrastructure projects given this technological innovation can lower transaction costs and cost of capital, as well as remove the need for intermediaries. Sustainable infrastructure assets tend to require higher

[2] https://chain.link/education/blockchain-oracles

capital outlay than traditional infrastructure, and often require reporting on the green performance. Therefore, the cost of capital issue is even more pressing than for traditional assets. The blockchain application helps to decrease this concern and allows for transparency in infrastructure performance. He proposes the advantages of digitizing of real-world assets and financial instruments on the blockchain (i.e., tokenization) and classifies these “tokens” as securities. Through tokenization, the traditional challenges of financing infrastructure may be address by the value propositions listed below:

1. Saving in costs related to public listing, transactions on secondary market, and operations
2. Improved transparency and accountability
3. Increased liquidity
4. Access to non-traditional capital providers
5. Lower counterparty risks
6. Shorten settlement time
7. Enabling small scale projects

A significant body of literature has addressed potential benefits from blockchain integration for data integration and privacy concerns in a smart cities’ context. However, there not only is a lack of empirical use cases to learn from (e.g., Tian et al. (2020)), but importantly a dearth of information on the potential for application in sustainable infrastructure financing. This knowledge gap is what my dissertation seeks to address. Research is lacking in understanding how blockchains can tangibly and positively impact our attempt to move to a more sustainable society.

1.3 Dissertation Structure

The finance gap and investment barrier for sustainable systems such as social (i.e., agriculture) and built infrastructure have resulted in significant deterioration in functionality and society's ability to meet future needs from an environmental, social, and economic perspective. Government subsidies have attempted to guide these operations towards sustainable outcomes, but the results are limited. Though capital market instruments are a promising solution to realize sustainable outcomes, uncovering the financial risks and uncertainties of sustainability is required. This work first applies data fusion using Geographic Information Systems (GIS) and hedonic pricing to quantify the contribution of nitrogen and phosphorus loading on farmland value. However, due to the fact that most pricing models have the potential to be biased and controlled by a central authority, decentralized decision-making on models and data is required in a trustworthy and transparent way. The following studies leverage blockchains and decentralized oracle networks to reduce investment barriers for sustainable systems. A framework is presented where trusted data from internet-of-things of infrastructure can inform financial transactions on-chain in an efficient manner. This section justifies how blockchains and oracles can use internet-of-things to streamline performance-based financing mechanisms by creating trust and automation. A performance-based proof-of-concept to incentivize regenerative agriculture practices is then implemented on the Ethereum blockchain. This research element highlights the benefits of implementing performance-based incentives on a blockchain via Transaction Cost Economics analysis. Figure 1-1 shows the flow chart of the subsequent chapters and their corresponding objectives.

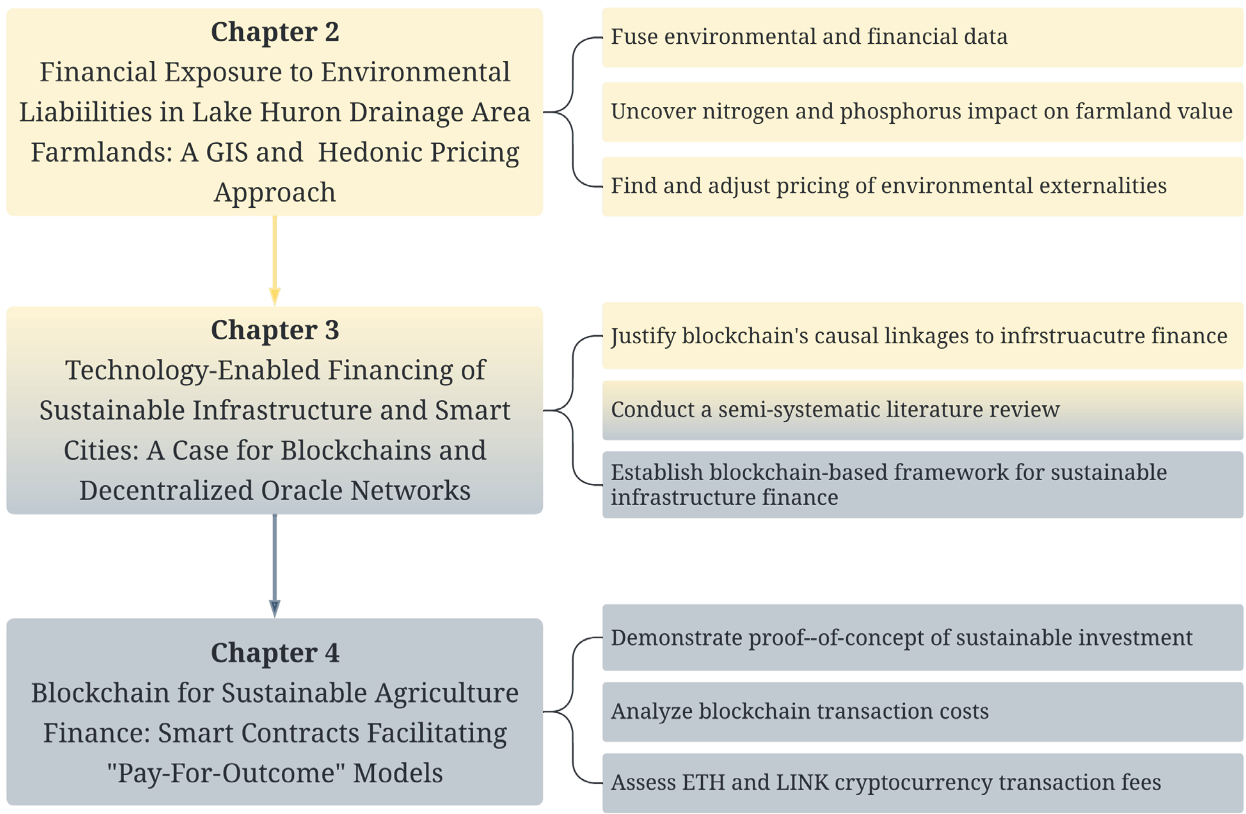

Figure 1-1. Flow chart and objectives of key chapters of dissertation.

This dissertation ventures out to price environmental externalities in Chapter 2. Chapter 3 discovers opportunities to leverage blockchains (not limited to tokens) and hybrid smart contracts for the financing of sustainable infrastructure. Then in Chapter 4, a pay-for-outcome proof-of-concept is carried out on the Ethereum blockchain. Ultimately, this work shows the lowering of the risks and uncertainties (i.e., barriers) of sustainable solutions for investors to more comfortably deploy capital à la Uzsoki (2019) and BIS Innovation Hub (2021). Chapter 5 concludes and discusses future research stemming from this dissertation.

Chapter 2 Financial Exposure to Environmental Liabilities in Lake Huron Drainage Area Farmlands: A GIS and Hedonic Pricing Approach

This chapter is published in *Agricultural Finance Review*.

Chung, K.H.Y. and Adriaens, P. (2022), "Financial exposure to environmental liabilities in Lake Huron drainage area farmlands: a GIS and hedonic pricing approach", *Agricultural Finance Review*, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/AFR-02-2022-0025

2.1 Introduction

Eutrophication, the process by which algae blooms occur leading to hypoxia and degradation of water quality, result from excess nutrient input. Several studies have shown that eutrophication in the Laurentian Great Lakes since the 1970s is a result of intensification of agriculture in the region (Baker et al., 2014; Kerr et al., 2016; Michalak et al., 2013). Shifting from excessive nutrient use on farms to more sustainable endeavors is required to reduce the adverse effects on the Great Lakes. Past government funding for large-scale ecosystem restoration has been limited in scale and impact (Vigmostad et al., 2005). Efforts to address excessive agricultural nutrient input through government subsidies in the Great Lakes are viewed to be not sustainable. Utilizing private sector capital to induce sustainable agricultural practices long-term requires risk pricing (Gregory et al., 2021; Kleimeier & Viehs, 2021). This study develops a data fusion method to combine agricultural nutrient data with farmland sales data and then analyzes the effect of excessive agricultural nutrient runoff on farmland value.

Keitzer et al. (2016) and Sowa et al. (2016) have shown that the amount of funding available from the U.S. Farm Bill to incentivize sustainable practices is insufficient to convert the land needed to sustainable practices with measurable improvements in the water quality of the Great Lakes. Sowa et al. (2016) point out that many sub-watersheds in the Saginaw Bay drainage area require more than 50% of agricultural land to adopt sustainable practices to see meaningful improvements in water quality. However, discrepancy exists to reach such a goal since only about 6% of planted corn acres in the State of Michigan participated in U.S. Farm Bill Conservation Programs (United States Department of Agriculture Economic Research Services, 2010). In addition, farmers who rely on temporary government subsidies are likely to revert to conventional agriculture practices, thus long-term adoption of sustainable practices remains a challenge (Ariana & Maria, 2018; Sahm et al., 2013). Much attention has been turned to the private sector to finance and induce incentives for sustainable practices as sentiment towards environmental, social, and governance (ESG) investing is growing rapidly (Forum for Sustainable and Responsible Investment, 2020).

According to U.S.Farmers & Ranchers in Action (2021), the private capital markets are by far the largest investors in the agricultural value chain, with institutional investors and retail investors totaling $973 billion USD. Of this total, approximately $442 billion USD are invested in farmland. The investments are committed through multiple types of avenues (e.g., funds, farm credit systems, commercial banks, etc.) which are exposed to unsustainable farming practices and environmental liabilities. Direct exposure is derived from farmland ownership, purchase of products grown on these lands, or farmland rented or leased, which represents up to 50% of farmland in many Great Lakes counties (Agricultural Collaborative Research Outcomes System, 2012). Despite such a large percentage of capital invested in farmland, it is not evident how environmental liabilities should be accounted for in farmland valuation or how investment capital should be conditioned for adoption of sustainable practices. Given the increasing interest from regulators in sustainable finance disclosures, from financial service providers to reduce their loan book liabilities, and from the agro-industry to deploy ESG practices, there is an increasing need to develop a sustainable risk-pricing approach for agricultural practices (Westchester, 2021; Willingham, 2021).

Environmental liabilities such as excessive nutrient inputs in surface waters causing derivative effects such as eutrophication, recreational damage, and environmental health effects aren’t typically considered in conventional farmland valuation approaches. Supply and demand models used to value farmland accounts for metrics such as number of farms supplied, number of farms demanded, USDA index of productivity, percentage of unemployed civil labor force, and farmland acres (Herdt & Cochrane, 1966). Other studies have expressed farmland value as the sum of the discounted expected future returns in a traditional capitalization model (Melichar, 1979). However, present value models do not adequately capture land values due to oversimplification and unaccounted speculative forces (Burt, 1986; Featherstone & Baker, 1987). Falk and Lee (1998) quantified the nonfundamental forces to explain overall farmland price dynamics. Macroeconomic variables such as interest rates, inflation, energy policies, and government payments can also affect land values (Kropp & Peckham, 2015; Moss, 1997). Devadoss and Manchu (2007) developed an empirical model that determines farmland value in Idaho and found that net farm income, crop yield, population, and credit availability increase farmland value. Zhang and Tidgren (2018) showed that real income, low interest rates, and prudent agricultural lending practices govern farm economics in land value, agricultural credit, and lending regulations. Sherrick (2018) showed that farmland value resiliency is mainly driven by treasury yields rather than by farm income. Basha et al. (2021) also observed that federal fund rate movements impact farmland values in the Midwest. Demographic factors such as urban area proximity, population density or opportunity to convert farmland to urban use are also important considerations that are often incorporated in farmland valuations (Capozza & Helsley, 1989; Guiling et al., 2009).

Featherstone et al. (2017) found that for Kansas land values forecasted with net farm income, the net present value model performs well. The authors indicate that farmland valuation research has incorporated many factors over the years and suggest that optimal model fit differs by location as well as time period. However, the impact of environmental liabilities in farm economics, investment, and procurement has not been considered in these prior models and little is known regarding their potential implications for risk-based farmland valuation.

Only a handful of literature study the financial relationship between environmental liabilities and agriculture. Beach and Carlson (1993) showed farmers to value water quality and safety when selecting pesticides. Whitehead (2006) found in a landowner survey that the respondents' willingness to pay increased for improved water quality. Grimes and Aitken (2008) used both sales price and tax valuation of land to investigate the value of water in a drought-prone farming region in New Zealand. Boisvert et al. (1997a) determined if productivity, location, and environmental contamination in the Susquehanna River Basin contributes to farmland value. Their study concluded that environmental vulnerability has a statistically-significant impact on the reduction of land values for corn production, based on dummy variables for nitrogen leaching and runoff potential from farmland as well as nitrogen leaching and runoff estimated from models published in (Boisvert et al., 1997b). Phosphorus leaching and runoff were not considered in the literature even though they are integral to causing eutrophication and degradation of water quality (Conley Daniel et al., 2009; Schindler et al., 2016). Research is required to shed light on how environmental contamination of commodity-agnostic nitrogen and phosphorus (i.e., nutrient runoff not limited to corn production) effect farmland value.

The current paper contributes to the knowledge on the impact of environmental contamination on farmland value, by fusing farmland sales data with environmental contamination data and valuing the environmental contamination via hedonic pricing. The method first fuses a highly geographically resolved farmland sales database (AcreValue) with modeled nitrogen and phosphorus data from the United States Geological Survey's Spatially Referenced Regression on Watershed Attributes (SPARROW) and the United States Department of Agriculture National Cooperative Soil Survey's database (gSSURGO) using geographic information system (GIS) spatial join mechanism. SPARROW greatly improves environmental contamination data resolution. The data fusion process combines financial and environmental data that were traditionally viewed as separate. With the fused data, the trend between farmland sales value and environmental contamination are analyzed. The hedonic price theory is applied to study the effects of environmental contamination on farmland sales value to improve insights for environmentally-conscious farmland purchases or investments. To the authors' knowledge, this is the first study to quantify the relationship between of environmental contamination and farmland value in the Lake Huron drainage area.

2.2 Conceptual Model and Hypotheses

2.2.1 The Conceptual Production Model

Boisvert et al. (1997a) proposed a conceptual agricultural production model. The model assumes that commodity production requires land and nutrient (or chemical) input, where OP_Q = output price and IP = input price (Beach & Carlson, 1993; Boisvert et al., 1997a; Kask & Maani, 1992). Farmland has productivity, Y, and an environmental index, G, of nutrient leaching or runoff. The expenditure on land, $L(Y,G)$, depends on Y and G. Productivity output is given by $Q = f(X, Y, G)$, where X is the nutrient input (assuming that $Q_x > 0$, $Q_y > 0$, $Q_G < 0$). Sale of Q produces income. The farm consumes a composite of good, C with a unit price of CP_C. The probability of nutrient runoff is denoted by P, where $0 \leq P \leq 1$. The unit cost of nutrient runoff or leaching, HP, has been interpreted as a farmer's payment for health care from becoming ill due to degraded water quality. Akin to a shadow price that accounts for the cost of farming, the expanded interpretation of *HP* could also be the cost of cleanup, water contamination fines, or legal liability for pollution. These costs or potential legal liabilities are a function of *X* and *G*, *H(X,G)*. Farm operations include a probability of contamination, *P(X,G)*. The utility function depends on health and *C*. In a healthy State *0*, $U_0 = U_0(0, C_0)$. In a state where environmental contamination occurs, denoted as State 1, $U_1 = U_1(H(X,G), C_1)$. The maximization of the utility problem is

$$(1)\ max[\,1\ - P(X,G)]\,U_0(0, C_0) + P(X,G)\,U_1(H(X,G), C_1)$$

such that,

State *0*:

$$(2)\ OP_Q Q = IPX + L(Y,G) + CP_C C_0$$

State *1*:

$$(3)\ OP_Q Q = IPX + L(Y,G) + CP_C C_1 + HP(H(X,G))$$

Letting $CP_C = 1$ and solving for C_0 and C_1 and substituting into the maximum utility equation, the problem is

$$(4)\ \max R = [\,1 - P(X,G)]\,U_0\left(0, OP_Q Q - IPX - L(Y,G)\right) + P(X,G)\,U_1(H(X,G), OP_Q Q - IPX - L(Y,G) - HP\big(H(X,G)\big))$$

First order conditions show the effects of individual variables. See Boisvert et al. (1997a) for complete derivations. Of particular interest are the first order conditions of G, nutrient runoff or leaching potential, on utility and *L(Y,G)*, the expenditure on land.

$$(5)\ \frac{\partial R}{\partial G} = -\frac{\partial P}{\partial G}(U_0) + (1-P)\left\{\frac{\partial U_0}{\partial C_0}\left[OP_Q\frac{\partial Q}{\partial G} - \frac{\partial L}{\partial G}\right]\right\} + \frac{\partial P}{\partial G}(U_1) + P\left\{\frac{\partial U_1}{\partial C_1}\left[OP_Q\frac{\partial Q}{\partial G} - \frac{\partial L}{\partial G} - HP\frac{\partial H}{\partial G}\right]\right\} = 0$$

Solve for $\frac{\partial L}{\partial G}$

$$(6)\ \frac{\partial L}{\partial G} = OP_Q\frac{\partial Q}{\partial G} + \frac{\left\{(U_1-U_0)\frac{\partial P}{\partial G}\right\}+\left\{-P\times HP\frac{\partial H\partial U_1}{\partial G\partial C_1}\right\}}{\left\{(1-P)\frac{\partial U_0}{\partial C_0}+P\frac{\partial U_1}{\partial C_1}\right\}}$$

2.2.2 Hypothesis

From the conceptual production model, the hypotheses to be tested centers on the influence of nutrient runoffs on farmland valuation. In null form, the hypotheses to be tested are:

Hypothesis 1. Nutrient runoff, G, is a factor influencing farmland values.

Hypothesis 2. $\frac{\partial L}{\partial G} < 0$ reflects the negative effect of nutrient runoff on output and its positive effect on the probability of a serious illness or other social costs. In equation (6), we assume that $\frac{\partial Q}{\partial G} < 0$. In addition, if $\frac{\partial P}{\partial G} > 0$, the first term in brackets is negative since $U_1 < U_0$. It is also reasonable that $\frac{\partial H}{\partial G} > 0$, leading to the second term in the numerator to be negative.

2.3 Study Area and Data

2.3.1 Study Area

This study focuses on Michigan farmland located in the Lake Huron major drainage area delineated in Figure 2-1. Detailed farmland parcel locations in Lake Huron's major drainage area. The basemap was compiled by Esri, CGIAR, USGS, Province of Ontario, Esri Canada, HERE, Garmin, FAO, NOAA, EPA, NPS, NRCan, and Parks Canada.. The area of eastern central Michigan's lower peninsula is one of the State's largest agricultural production regions, and Lake Huron suffers from nonpoint source pollution due to intense agriculture activities (Fales et al., 2016; Stow et al., 2014). Field crops in the region such as corn, soybean, oats, wheat, and sugar beets contribute to a total state agriculture economic productivity of $5.12 billion USD (Michigan Department of Agriculture & Rural Development, 2019).

2.3.2 Data Sources

Data for this study were procured from three major sources. Farmland sales transactions from 2014 to 2021 (n=432) and parcel information, including sale amount, location, makeup of land, and other attributes were collected from the AcreValue database. The parcel sizes are between 75 to 165 acres. Transactions including multiple parcels were included. AcreValue compiles public data sources ranging from deed records of land transactions, classifications of crop rotations and county assessor records (Ag-Analytics Technology Company, 2021). Land cover and soil horizon characteristics were obtained from the Gridded Soil Survey Geographic Database (gSSURGO) provided by the U.S. Department of Agriculture's National Cooperative Soil Survey. Data in gSSURGO was gathered by walking over the land, sampling and analyzing the soil (Soil Survey Staff, 2020). Data for nitrogen and phosphorus contamination was derived from the United States Geological Survey's Spatially Referenced Regressions on Watershed Attributes (SPARROW) model. SPARROW provides long-term mean-annual nitrogen (N) and phosphorus (P) constituent transport (i.e., load) for various land use, watershed characteristics, and types of nutrient sources for a given representative year (Saad et al., 2018).

SPARROW harmonizes four types of data: long-term mean-annual loads from sampling sites deployed in the field, stream and reservoir network information, total nitrogen and total, phosphorus source information, and environmental characteristics causing land-to-water delivery

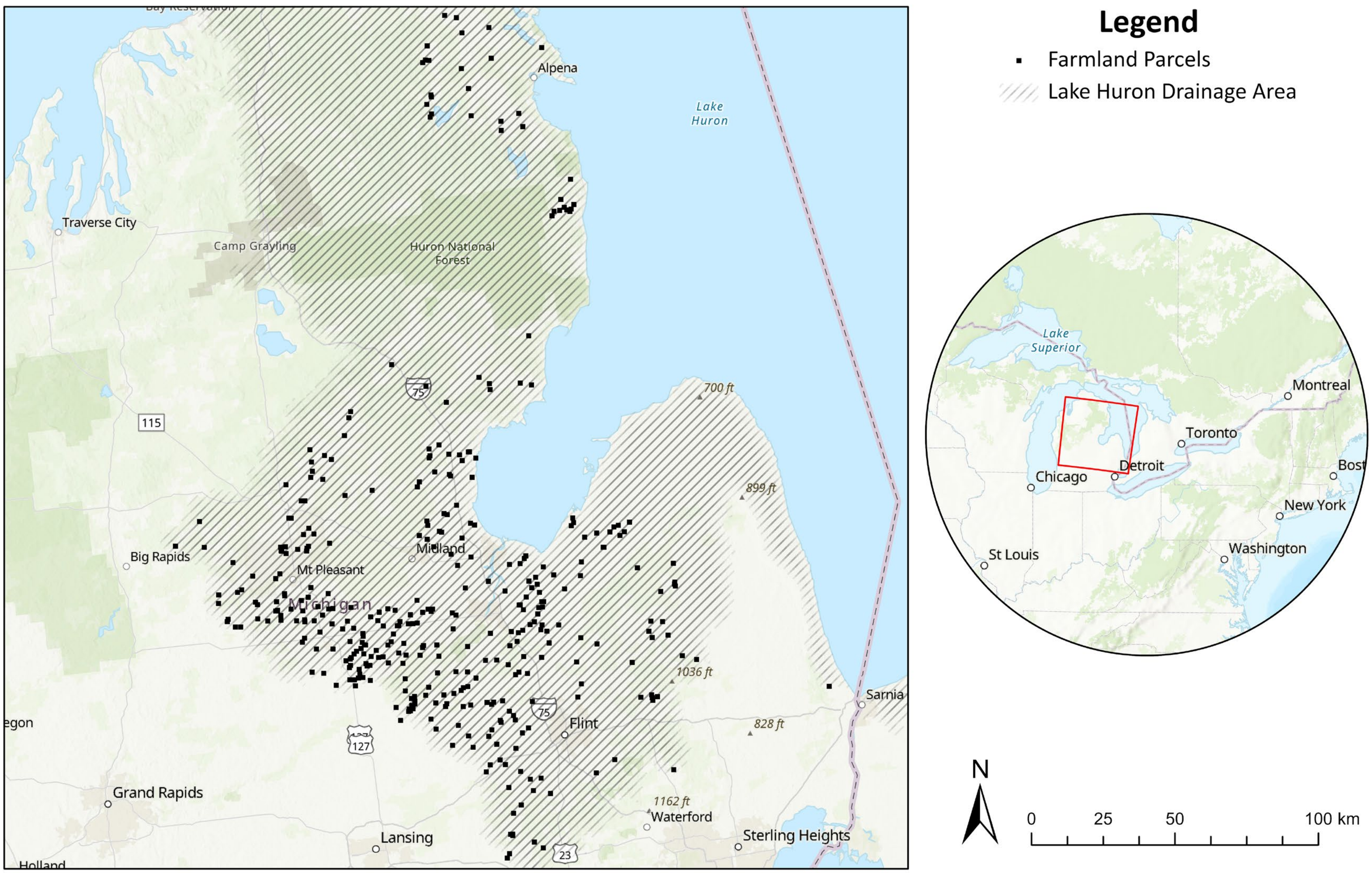

Figure 2-1. Detailed farmland parcel locations in Lake Huron's major drainage area. The basemap was compiled by Esri, CGIAR, USGS, Province of Ontario, Esri Canada, HERE, Garmin, FAO, NOAA, EPA, NPS, NRCan, and Parks Canada.

variability. Methods for load calculation and evaluation criteria are found in Saad et al. (2018). Vouk et al. (2018) and Robertson et al. (2019) describe the nitrogen and phosphorus source information. The final phosphorus model included six sources: wastewater treatment plants, urban/barren areas, farm fertilizers, manure, agricultural land, and forest/wetland areas. Agricultural land is defined as "all nonfertilizer and nonmanure sources in agricultural areas such as natural sources and increased erosion because of agricultural activities." Nitrogen is derived from five sources: wastewater treatment plants, urban/barren areas, farm fertilizers, manure, and atmospheric deposition. Natural sources of nitrogen were included in the fertilizer and manure terms. Farm fertilizer inputs were based on Ruddy et al. (2006)'s 2002 county-level estimates on the U.S. side of the border. Land use inputs such as agriculture land were based on catchment area in each general land type (i.e., urban, agriculture, or forested) designated in 2001 National Land Cover Data for the U.S. (Homer et al., 2007).

SPARROW calculates the absolute amount of nutrient contamination in kilograms as well as the amount of nutrient contamination normalized by catchment area (i.e., kilograms/acre). The findings are presented here using the normalized values since regulatory compliance is driven by units of concentration and is in line with the dependent variable of sale amount per acre. We also convert the normalized values to units of kilograms per acre to achieve consistency with the dependent variable. The results using absolute amount of nutrient contamination results are presented in the Appendices. Figure 2-2(a) shows the normalized nitrogen load and Figure 2-2(b) shows normalized phosphorus load. Maps and geocoding of farmland parcel coordinates with gSSURGO and SPARROW data in this study were created using ArcGIS® Pro Version 2.9.1 by Esri.

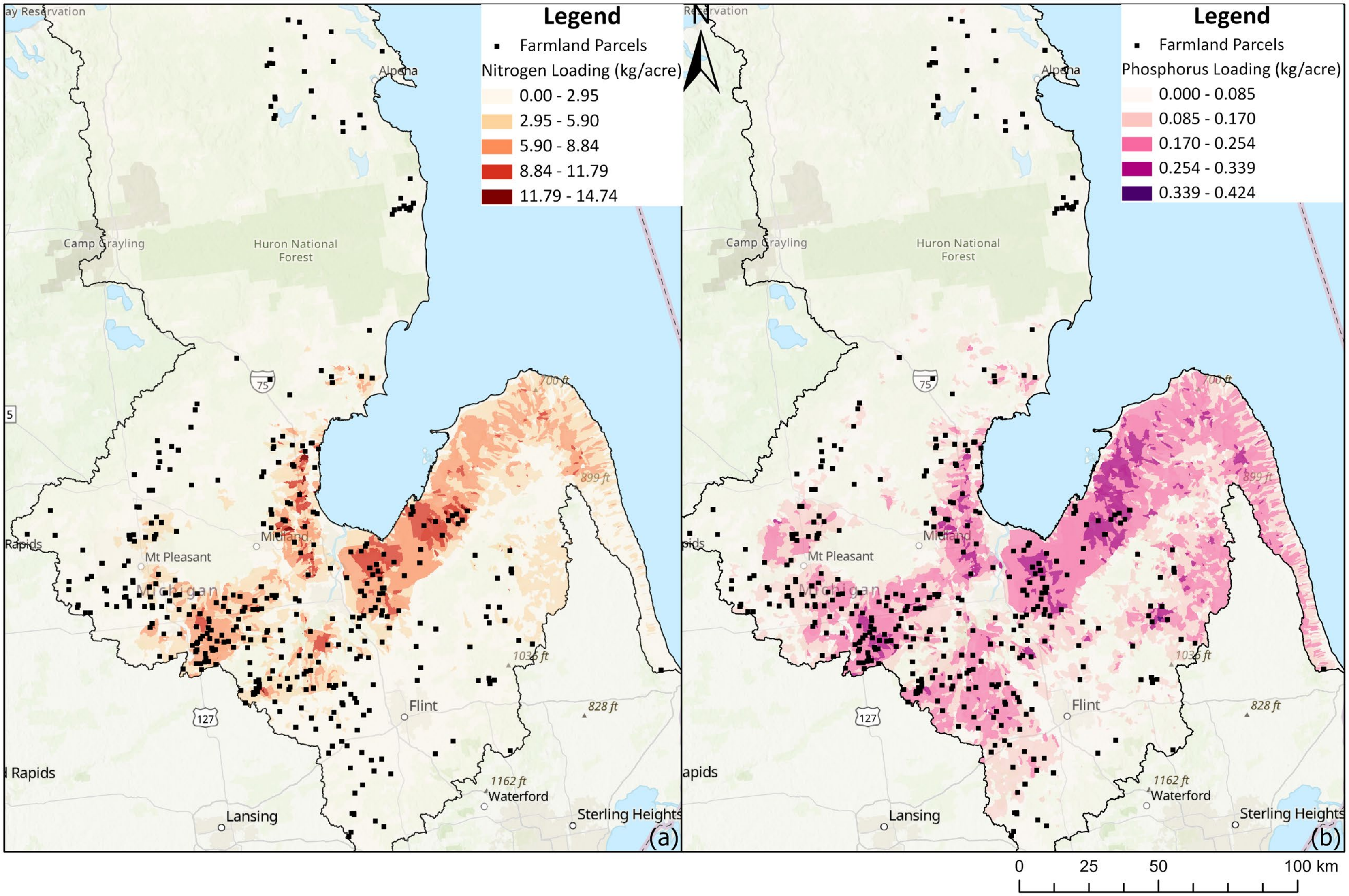

Figure 2-2. Lake Huron's major drainage area (a) nitrogen loading and (b) phosphorus loading. The basemap was compiled by Esri, CGIAR, USGS, Province of Ontario, Esri Canada, HERE, Garmin, FAO, NOAA, EPA, and NPS.

2.4 Production Model Specifications

2.4.1 Features of the Production Model

The transaction sale amount per acre of farmland reported by AcreValue is the dependent variable. Following the conceptual production model, the features include land productivity features, built production characteristics, and environmental contamination features (Boisvert et al., 1997a). Summary statistics for all features are provided in Table 2-I. Absolute nitrogen loading and phosphorus loading summary statistics can be found in Table A-I in Appendix A.

Table 2-I. Summary Statistics

	Unit	Mean	Std	Min	Max
Dependent Variable					
Sale amount per acre	\$/acre	3536.09	2301.61	63.00	13709.0
Environmental Contamination					
N loading	kg/acre	3.948	3.126	0.052	12.162
P loading	kg/acre	0.080	0.044	0.001	0.159
P loading (*Agricultural land*)	kg/acre	0.074	0.037	0.001	0.145
Land Productivity					
Average NCCPI	Unitless	56.99	10.54	17.0	86.0
Cultivated land % of parcel	%	0.874	0.15	0.04	1.0
Forest area % of parcel	%	0.05	0.07	0.0	0.31
Grassland area % of parcel	%	0.02	0.06	0.0	0.66
Soil organic carbon (SOC)	g/m^2	6775.625	2696.31	1388.0	23018.0
Root zone depth	cm	114.96	35.18	23.0	150.0
Root zone available water storage	mm	148.71	63.02	28.0	315.0
Soil loss tolerance factor	tons/acre year	4.61	0.57	1.0	5.0
Drought vulnerability	Binary	0.61	0.49	0.0	1.0
Well drained	Binary	0.17	0.38	0.0	1.0
Poorly drained	Binary	0.81	0.40	0.0	1.0
Prime farmland if drained	Binary	0.63	0.48	0.0	1.0
Not prime farmland	Binary	0.06	0.25	0.0	1.0
Farmland of local importance	Binary	0.10	0.30	0.0	1.0
Built Production					
Acres	acre	99.94	25.73	75.04	164.05
Noncropland area % of parcel	%	0.03	0.05	0.0	0.21
Developed area % of parcel	%	0.01	0.02	0.0	0.1
Representative slope	%	1.89	2.43	0.0	15.90
Distance to city	m	11936.71	6389.56	1556.05	39204.28

The average National Commodity Crop Productivity Index (NCCPI) is a metric based on an interpretation using "natural relationships of soil, landscape, and climate factors to model the response of commodity crops" (United States Department of Agriculture, 2008). The production of crops is directly related to the tillable area on the land parcel given by the *Cultivated land % of parcel* feature. *Forest area as a percent of parcel* as well as *Grassland area as a percent of parcel* indicate habitat land use potential inside the parcel. *Soil organic carbon (SOC)* is the organic carbon concentration in the soil of depth 0 to 30 cm. *Root zone depth* is the soil profile depth where water and nutrients can be extracted. *Root zone available water storage* is the volume of crop available water, based on the soil components, that can be stored within a soil profile. *Soil loss tolerance factor* is the erosion extent where soil quality can be retained. The *Drought vulnerability* dummy indicator suggests whether soils have available water storage within the commodity crops root zone that is less than or equal to 152 mm. The *Well drained* and *Poorly drained* dummy indicators refer to the frequency and duration of moisture saturation period of natural drainage conditions of the soil.

Farmland classification, indicating land productivity, is also provided in the gSSURGO database. Classes include *Prime farmland if drained*, *Not prime farmland*, and *Farmland of local importance*. The baseline class of "All areas prime farmland" is omitted. The built environment features include basic land properties such as *Acres* and *Representative slope*. *Acres* is the total area of the parcel of farmland and *representative slope* is the weighted average slope gradient of all soil components in the map unit. *Noncropland area % of parcel* indicates potential recreational land use inside the parcel. *Developed area % of parcel* indicates the proportion of the parcel covered by buildings and production accessories. Distance to city indicates the straight-line distance to the closest city as designated by the State of Michigan. *N loading* is nitrogen runoff from fertilizer according to the SPARROW model. Phosphorus has two main sources from farmland, fertilizer (*P loading*) and natural sources such as increased erosion due to agriculture activities *(P loading Agricultural land*).

2.4.2 Empirical Model

Hedonic pricing is a common causal inference method for non-market valuation of ecosystem services and natural resources. The theoretical foundation is given by Rosen (1974) where the author exhibits individual choices in market equilibrium. Let X = (x_1, x_2,…, x_n), where n is the number of features of a differentiated market good. The equilibrium price p can be discovered by the dynamics of utility-maximizing consumers and profit-maximizing producers in a perfectly competitive market. The fundamental hedonic equation is $p = h(X)$, where h may take up various functional forms and represents the relationship between a good's price and its features. The price is regressed on all features thus obtaining a marginal influence of each feature denoted as $p_n = \frac{\partial h(X)}{\partial x_n}$. Selection of the functional form h has little theoretical basis (Ma & Swinton, 2012; Nickerson & Zhang, 2014). Given that the skewness of sale amount per acre from the AcreValue dataset was moderate (Figure B-1 in Appendix B) and log-transformation caused the dependent variable to become highly skewed (Figure C-1 in Appendix C), no additional scaling or transformation was conducted for hedonic regression.

The results of the hedonic pricing model were considered in the context of the production model proposed by (Boisvert et al., 1997a) assuming productivity Q and unit cost of runoff HP. Since the model is a causal inference between non-market inputs and transaction value, the input features have value as proxy indicators for pricing mechanisms. Indeed, ESG data such as environmental features are increasingly considered as alternative data inputs in financing and valuation models given their material risk to the asset being financed (Freiberg et al., 2020). Recent reports indicate the value of ESG to be up to 5 basis points (bps) in loans or 23 bps for green bond issuances (Adler, 2019; Great Lakes St. Lawrence Governors & Premiers, 2021). Given that farm operations are predominately financed using farm credit, private loans, and securities sales from the Farm Credit Funding Corporation (Farm Credit, 2017), ESG risk-adjusted pricing mechanisms of environmental externalities may have implications on the equilibrium price p of a farm asset and the unit price CPC of consumption and operations. In other words, the hedonic pricing model approach may be interpreted as a baseline inference for price adjustment when the features impacting transaction price are quantified with an improved understanding of the costs and benefits associated with agricultural practices. One way to operationalize this concept is by estimating a shadow price of environmental or nutrient risk on the cost of operations or revenue as proposed by Shaik et al. (2002).

2.5 Results and Discussion

2.5.1 Distribution of farmland sale amount per acre versus nutrient loading

AcreValue, gSSURGO, and SPARROW data originate from multiple databases. Fusion of data in the financial realm (i.e., AcreValue's farmland sale amount per acre) with environmental data (i.e., gSSURGO and SPARROW) was required. As seen in Figure 2-1, AcreValue parcel longitude and latitude were geocoded onto a base map of the State of Michigan. gSSURGO and SPARROW data were subsequently fused with AcreValue data with ArcGIS® Pro via spatial join. A spatial join merges the attributes of multiple layers based on the geolocation of features in the different layers. By merging financial transactions with environmental data, a statistical analysis of the relationship between both types of datasets can be carried out.

A preliminary analysis based on spatial geolocation of two independent datasets was conducted first to gain insights in underlying trends of land transactions and contaminant loading. Figure 2-3 shows the distribution of farmland sale amount per acre versus nitrogen loading. Nitrogen loading amount is categorized into five bins, ranked from low to high loading, based on the SPARROW model values. An overall trend shows that the mean farmland sale amount per acre (horizontal dashed lines) increases with nitrogen loading into Lake Huron. Compared to the lowest nitrogen loading category (between 0.04 to 2.47 kg/acre), the higher nitrogen loading categories coincided with an increase in transactional value amount per acre at a 99.9% significance level ($p < 0.01$) (Table 2-II). These results indicate that contamination levels impart an increase in farmland transactional value of up to $1,730.14/acre when nitrogen loading increases from the lowest [0.04 - 2.47 kg/acre] loading to the [7.32 - 9.74 kg/acre] category. Although the highest nitrogen loading category [9.74 - 12.16 kg/acre] showed increased farmland value, the increase was not significant at the 10% level.

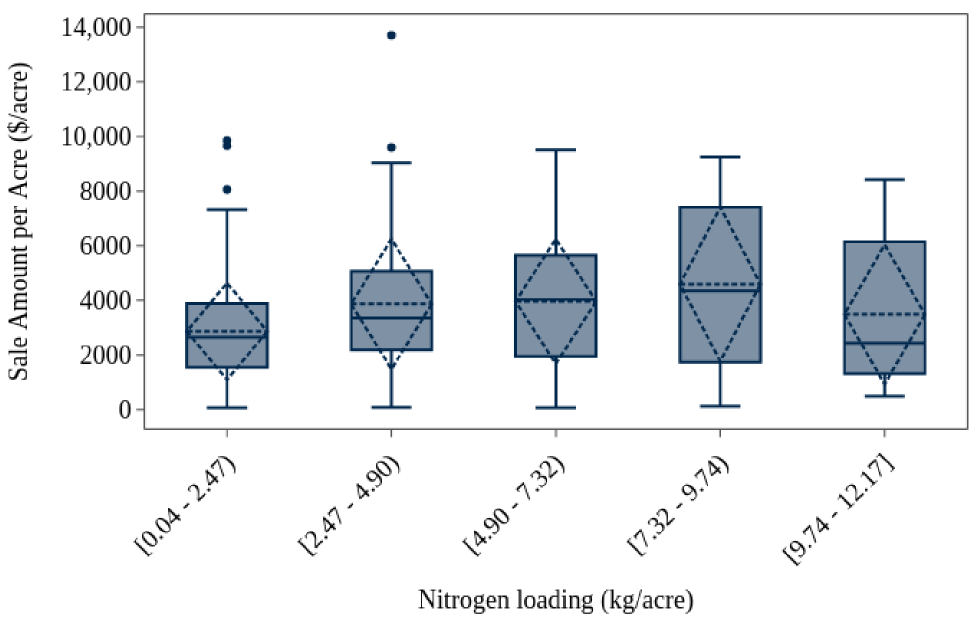

Figure 2-3. Distribution of sale amount per acre ($/acre) versus fertilizer nitrogen loading (kg/acre). The box-and-whisker plot (solid lines) display the distribution of sale amount per acre for each nitrogen loading category. The dashed-lined rhombuses indicate the mean (horizontal

dashed line) and standard deviation (vertical tips of rhombus) of sale amount per acre for each nitrogen loading category.

Data in Figure 2-4 and Figure 2-5 illustrate farmland sale amount per acre versus phosphorus loading from fertilizer and agricultural land, respectively. Both sources of phosphorus indicate similar trends to nitrogen, namely that: farmland value and nutrient contamination have a positive correlation. The increased farmland value in higher loading categories compared to low phosphorus loading were all significant (p <0.01) (Table 2-II). Farmland transactional value increased up to \$1,816.60/acre when phosphorus increases in loading from the [0.001 - 0.033 kg/acre] category to the [0.128 - 0.159 kg/acre] category. For phosphorus loading from agricultural land, a \$2,338.83/acre increase was observed if loading increased from the lowest to the highest category. To generate a more informed analysis of the causal effect of nitrogen and phosphorus loading on farmland value, additional features were included to carry out hedonic regression.

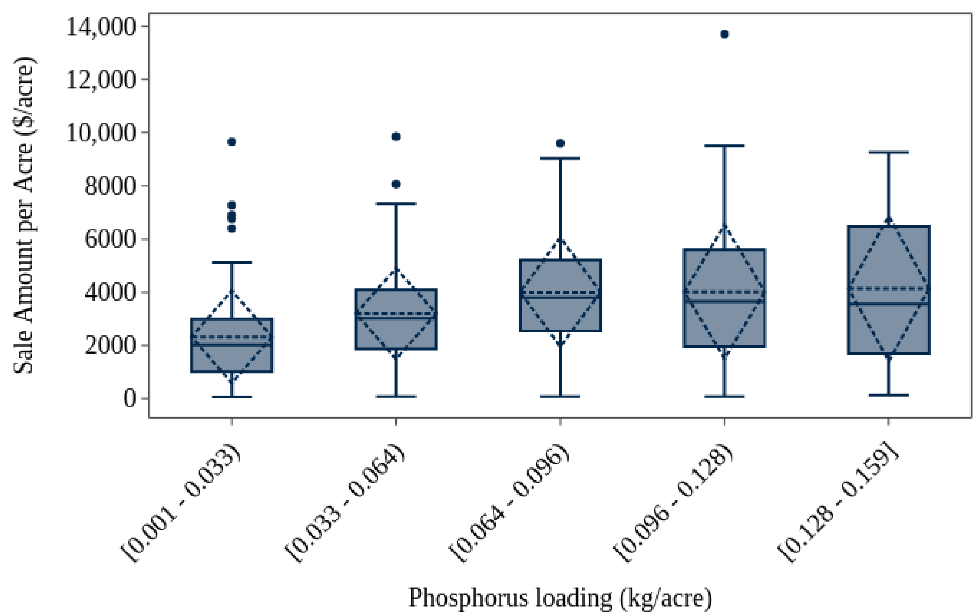

Figure 2-4. Distribution of sale amount per acre (\$/acre) versus fertilizer phosphorus loading (kg/acre). The box-and-whisker plot (solid lines) display the distribution of sale amount per acre for each nitrogen loading category. The dashed-lined rhombuses indicate the mean (horizontal dashed line) and standard deviation (vertical tips of rhombus) of sale amount per acre for each nitrogen loading category.

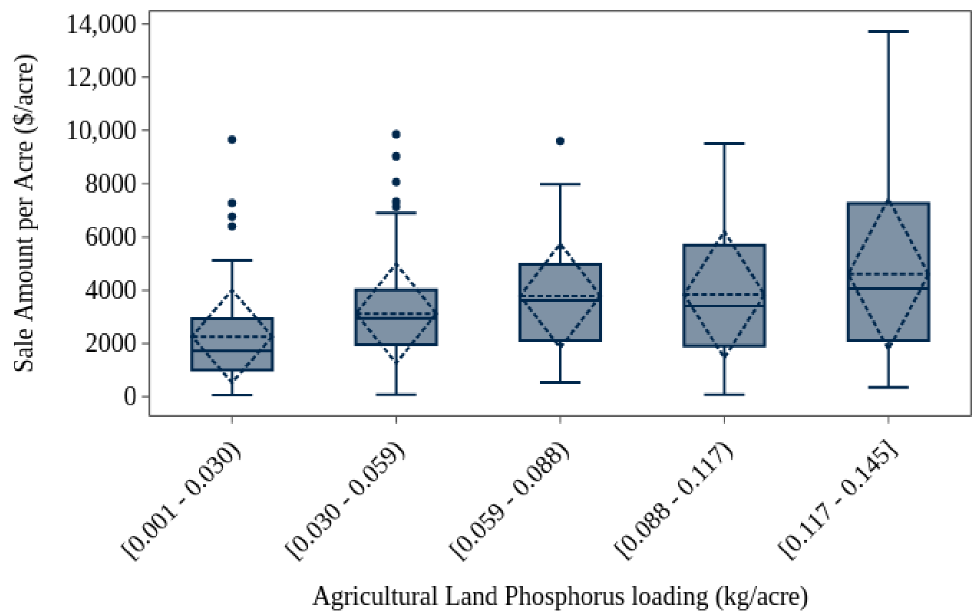

Figure 2-5. Distribution of sale amount per acre ($/acre) versus fertilizer phosphorus loading (kg/acre). The box-and-whisker plot (solid lines) display the distribution of sale amount per acre for each nitrogen loading category. The dashed-lined rhombuses indicate the mean (horizontal dashed line) and standard deviation (vertical tips of rhombus) of sale amount per acre for each nitrogen loading category.

Table 2-II. Farmland environmental contamination loading category versus mean sale amount per acre

Nitrogen loading			**Phosphorus loading**			**Phosphorus loading (Agricultural land)**		
Loading category (kg/acre)	Mean Sale Amount ($/acre)	*p*-value	**Loading category (kg/acre)**	Mean Sale Amount ($/acre)	*p*-value	**Loading category (kg/acre)**	Mean Sale Amount ($/acre)	*p*-value
0.04 - 2.47	2866.46	-	**0.001 - 0.033**	2318.07	-	**0.001 - 0.030**	2261.15	-
2.47 - 4.90	3866.64***	1.27e-4	**0.033 - 0.064**	3192.45***	1.13e-3	**0.030 - 0.059**	3122.59***	3.41e-3
4.90 - 7.32	3961.60***	6.14e-5	**0.064 - 0.096**	4002.58***	8.00e-8	**0.059 - 0.088**	3787.58***	2.22e-6
7.32 - 9.74	4594.60***	4.94e-8	**0.096 - 0.128**	4015.30***	6.02e-7	**0.088 - 0.117**	3831.76***	3.74e-6
9.74 - 12.16	3486.91	1.37e-1	**0.128 - 0.159**	4134.67***	9.56e-7	**0.117 - 0.145**	4599.98***	6.60e-8

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

2.5.2 Hedonic Pricing

The hedonic pricing model considers additional features to estimate more granularly the influence of nutrient contamination on farmland transaction value. Pairwise Pearson's correlation coefficients (Figure D-1 in Appendix D) and variance inflation factors (Table E-I and Table E-II in Appendix E) show strong evidence of multicollinearity in the nitrogen and phosphorus loading data. Thus, hedonic regression was conducted on nitrogen and phosphorus loading sources separately. The F-statistic for both nitrogen and phosphorus regression indicate significance of the selected features (Table F-I in Appendix F).

Estimated coefficients for both nitrogen and phosphorus contamination are shown in Table 2-III. The second and fourth column indicate whether the coefficient estimates are statistically significant ($p < 0.10$). The results indicate that nitrogen and phosphorus loading coefficients are significant features and thus Hypothesis 1 (nutrient runoff is a factor influencing farmland values) cannot be rejected. Hedonic regression coefficients for absolute nitrogen and phosphorus loading can be found in Table G-I in Appendix G. Both nitrogen and phosphorus runoff, whether from fertilizer or agriculture land, increase farmland sale amount per acre.

In land productivity features, *Cultivated land % of parcel*, *Root zone depth*, and *Not prime farmland* in farmland classification are significant to the models. *Cultivated land % of parcel* has a prominent effect on farmland sale amount, contributing to an increase in farmland values with a same order of magnitude those observed from contamination in Table 2-II. This is corroborated by the findings of previous studies that crop production from farmland (future cash flows) is a major determinant of farmland value (Devadoss & Manchu, 2007; Featherstone et al., 2017; Miao et al., 2016). Land designated as Not prime farmland resulted in a reduction in a major reduction in sale amount per acre between $1181.89/acre and $1340.26/acre. Prime farmland is defined by the U.S. Department of Agriculture and inventoried by the Natural Resource Conservation Service to be used to produce the United States' food supply, and hence a revenue-generating asset (United States Department of Agriculture). *Root zone depth* significantly affects soil productivity as it is a measurement of the depth within a soil horizon which crop roots can extract water and nutrients (Dobos et al., 2012). For the centimeter increase in *Root zone depth* characteristic, the increase in farmland sale amount per acre may be in the range of $11.70/acre to $12.14/acre. As the acreage of a parcel increases, a decrease in sale amount can be observed. Ma and Swinton (2012) saw similar results in south-western Michigan where larger parcel acreage decreased sale price by 3% per 10 acres increase in area. Huang et al. (2006) also reached similar conclusions for Illinois where farmland values declined as parcel size increased. Boisvert et al. (1997a) provided a possible explanation that inflated bids for smaller parcels may occur as farmers try to expand ownership in a specific area.

Table 2-III. Hedonic regression results explaining farmland sale amount per acre (n=432)

	Nitrogen loading		Phosphorus loading		Phosphorus loading (Agricultural land)	
	Coefficient	*p*-value	Coefficient	*p*-value	Coefficient	*p*-value
SPARROW						
Nitrogen loading	75.22*	0.099	-	-	-	-
Phosphorus loading	-	-	9583.78***	0.005	11680***	0.003
Environmental Production and Consumption Variables						
Average NCCPI	-1.96	0.871	-5.82	0.631	-5.63	0.642
Cultivated land % of parcel	3736.65***	0.001	3890.95***	0.001	3967.27***	0.001
Forest area % of parcel	-409.24	0.832	535.83	0.784	705.90	0.719
Grassland area % of parcel	952.31	0.662	1453.88	0.504	1644.46	0.450
Soil organic carbon	0.05	0.420	0.03	0.591	0.03	0.525
Root zone depth	12.14**	0.013	12.08**	0.013	11.70**	0.016
Root zone available water storage	-4.06	0.355	-3.23	0.461	-3.38	0.438
Soil loss tolerance factor	-56.81	0.785	-65.85	0.750	-51.40	0.803
Drought vulnerable	718.59	0.140	764.27	0.115	701.51	0.146
Well drained	949.96	0.296	882.29	0.329	845.04	0.349
Poorly drained	576.56	0.541	441.38	0.639	387.40	0.680
Prime farmland if drained	296.73	0.423	259.78	0.480	306.96	0.402
Not prime farmland	-1340.26**	0.025	-1249.91**	0.036	-1181.89**	0.048
Farmland of local importance	-166.64	0.698	-160.26	0.707	-128.04	0.764
Built Production and Consumption Variables						
Acres	-9.12**	0.031	-8.37**	0.047	-8.15*	0.053
Noncropland area % of parcel	62.82	0.980	842.69	0.742	1065.68	0.678
Developed area % of parcel	-573.74	0.916	1136.70	0.835	1297.05	0.812
Representative slope	86.73	0.210	85.10	0.215	78.56	0.252
Distance to city	`-0.017	0.319	-0.02	0.381	-0.012	0.476
Constant	-944.34	0.666	-1383.10	0.527	-1613.30	0.462
R^2	0.174		0.184		0.186	

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

Closer inspection of the nitrogen and phosphorus coefficients is required to evaluate Hypothesis 2 (i.e., negative effect of nutrient runoff, $\frac{\partial L}{\partial G} < 0$). Table 2-III shows the marginal increases in nutrient contamination led to an increase in farmland value. The farmland sale amount per acre increases by \$7.52/acre per 0.1 kg/acre increase in fertilizer nitrogen loading. Similarly, increases of \$958.38/acre and \$1,168/acre in farmland sale per acre were observed in response to 0.1 kg/acre of marginal increase in fertilizer phosphorus sources and natural sources, respectively. The effects of nutrient contamination on farmland price are more pronounced in the phosphorus models than in the nitrogen model and may be due to the fact that phosphorus is a common limiting nutrients in crop production (Walker & Syers, 1976). When phosphorus is readily available, farmlands are more productive (Faucon et al., 2015; Wang et al., 2014). An increase in phosphorus non-point source loss to the environment can be directly attributed to the initial amount of phosphorus fertilizer applied (Reid et al., 2018; Vadas et al., 2009). The models suggest that increase in nutrient contamination leads to higher transactional sale value, thus leading us to reject the null of Hypothesis 2.

This result appear to indicate that the cost of nutrient runoff or leaching, *HP*, interpreted in Boisvert et al. (1997a) as a farmer's payment for health care from becoming ill due to degraded water quality, or the cost of mitigation and potential liability for pollution hazards, is not internalized or adequately priced in the economic models of the farmland transaction market. The increased output and thus higher land value, paired with the increased use of fertilizers in agricultural production results in unaccounted costs from environmental damages. To the extent that unpriced environmental degradation results from agricultural activities, increased agricultural production does not account for the negative implications and impacts for society.

2.5.3 An Argument for Shadow Pricing of the Environmental Risk of Agriculture

The Natural Resource-based View of the Firm, first proposed by Hart (1995) and updated 15 years later (Hart & Dowell, 2010) , considers management of the natural environment as a resource for sustainable competitive advantage in the production process. The argument in the theory is that environmental resources input or damage to the environment should be considered in the valuation of a firm, whether a corporation or a farm. The price of environmental resources or damage, when internalized, is referred to as shadow prices (Shaik et al., 2002). Shadow pricing quantifies off-balance sheet reduction either of revenue from the farm when treated as an undesirable output, or as an increased cost of reducing pollution, thus impacting future cash flows, profitability, and implied land value. The decrease in the value of productivity and profitability results in reduced farmland valuation per acre based on the productivity model, since costs, *HP,* increase or revenue*,* OP_QQ, decrease. While we have not calculated the shadow prices for fertilizer runoff in the Lake Huron drainage area, the shadow pricing models presented by Shaik et al. (2002) serve to illustrate the cost nitrogen pollution in agriculture.

Using the difference between aggregate nitrogen inputs and nitrogen removal from production across all crops in Nebraska, Shaik et al. (2002) estimated the average direct and indirect shadow prices of $0.91 and $2.21 (in 1936 dollars) per pound of nitrogen pollution abatement over the time period of 1936 to 1997. The range represents the opportunity cost of revenue for nitrogen removal on a per-pound basis while sustaining the same level of agricultural production. When nitrogen was treated as a cost of production, the average shadow prices of $1.73 and $1.95 (1936 dollars) per pound in the 1936-1997 timeframe. After adjusting 1936 dollars to 2021 with an average inflation rate of 3.56% per year using the Bureau of Labor Statistics data, and converting pounds to kilograms, shadow prices for nitrogen pollution alone range from $40.60 - $98.59 per kg nitrogen fertilizer as a revenue opportunity cost or \$77.18 - \$87.00 per kg for additional abatement costs.

Given that the economically optimum nitrogen application rate to farmland in the Lake Huron drainage area is 74.84 kg/acre (Kaatz, 2019), the shadow price of fertilizer runoff is estimated to be on the order of \$3,038.50 - \$7,378.48 per acre. These data should be adjusted in the future to account for nitrogen fertilizer shadow pricing effects in the Lake Huron drainage area. Since shadow price is interpreted as a production cost, and future cash flow generation is one determinant of land value, fertilizer-adjusted risk pricing of the land asset would exert a downward pressure on the market value of farmland based on the income capitalization model (Featherstone et al., 2017). If farm credit organizations and private lenders seek to reduce the liability of nutrient risk on their loan books, interest rate adjustments or other incentives in the loan structure would be necessary to drive sustainable behavior. Given that interest rate is a stronger determinant of land value than crop yield and cash flow (Basha et al., 2021; Sherrick, 2018), a sustainability-linked loan product based on pollution disclosures from farm operations will open up market mechanisms to scale sustainable financing of agriculture.

Conclusion and Environmental, Social, and Governance (ESG) Investing Implications

In this paper, a data fusion and hedonic pricing approach of nutrient contamination was developed for farmlands located in the Lake Huron drainage area. The empirical evidence indicates that the sale amount per acre of farmland is influenced by nitrogen and phosphorus loading on the surrounding environment. The value of the farmland is also determined by land productivity features such as cultivated percentage of parcel and root zone depth. Land classification by USDA and parcel size are influencing factors in farmland price as well. The conceptual production model proposed by Boisvert et al. (1997a) suggests that land value should theoretically decrease as nutrient contamination in the environment increases. This effect was not observed based on the parcels and contamination data used in our study. The contribution of this paper is that nitrogen and phosphorus loading increase farmland transaction price, showing that nutrient contamination from farmland is not "correctly priced" in the market. Adjustments for these environmental liabilities should be taken into consideration to incentivize adoption of more sustainable practices such as regenerative agriculture.

Approximately $442 billion out of $973 billion USD of institutional investor and retail investor capital in the agriculture sector are invested in farmland (U.S.Farmers & Ranchers in Action, 2021). Given the assumption in the conceptual production model (Boisvert et al., 1997a) that environmental contamination may be viewed as health care costs or potential legal liability, it is not evident whether the invested amount in farmland takes into account these costs and liabilities. Given the increasing focus of sustainable financing in financial transactions (e.g., Task Force on Climate-Related Financial Disclosures and the emerging Task Force on Nature-Related Financial Disclosures), capital markets actors such as lenders, investment banks, and pension funds are actively seeking to reduce ESG liabilities on balance sheets and in investment portfolios.

This study contributes to the literature that environmental contamination has not been accounted for to reflect the costs and liabilities of water pollution and eutrophication from farming operations. Further research is required to apply shadow pricing models to inform repricing of farmland. Spatial dependencies and omitted variables bias issues were not addressed in this study and will be considered in future work to improve upon the current hedonic pricing model.

Chapter 3 Technology-Enabled Financing of Sustainable Infrastructure and Smart Cities: A Case for Blockchains and Decentralized Oracle Networks

This chapter is submitted to Technological Forecasting and Social Change.

3.1 Introduction

Infrastructure comprises the necessary physical and institutional human-centric assets that sustain a society's competitiveness, economic growth, and, most importantly, its members' well-being. In its most recent report, the American Society of Civil Engineers (ASCE) gave the United States infrastructure a C- rating, stating that it "…shows general signs of deterioration and requires attention. Some elements exhibit significant deficiencies in conditions and functionality, with increasing vulnerability to risk" (American Society of Civil Engineers, 2021). To achieve a state of good repair for United States infrastructure by 2029, the costs is estimated at $5.9 trillion USD, where about 44 percent is yet to be covered. This translates to an annual deficit of $259 billion USD from 2020 to 2029. It should be noted that the added cost for resiliency to adjust for climate change impacts was not included in this assessment, and has been argued to add approximately 4% to 25% of future capital needs (Hallegatte et al., 2019).

The infrastructure finance gap is also observed internationally. The World Economic Forum estimated that the annual deficit in infrastructure investments would be $5 trillion USD globally (Boehm et al., 2021). In addition, the Global Infrastructure Hub, a G20 Initiative, estimated the global infrastructure investment needs to be $94 trillion USD between 2016 and 2040, an average of approximately \$3.76 trillion USD of investments per year (Global Infrastructure Hub, 2017). The OECD estimates annual infrastructure investments gap between 2.5 to 3 trillion USD (OECD, 2020). The McKinsey Global Institute reports that the world needs to spend an aggregate \$69.4 trillion USD between 2017 and 2035 to match the projected global GDP growth. This would amount to an annual deficit of roughly \$3.7 trillion USD (Woetzel et al., 2017).

Infrastructure projects exhibit several key features that make the funding and financing challenging. Significant up-front, largely illiquid, long-term capital is required for development and construction, leading to a high barrier for entry for investors (Weber et al., 2016). The long service and economic life of an infrastructure asset require on-going operations and maintenance budgets increasing investment risks (Gatzert & Kosub, 2016). These capital investments need to be funded to service debt obligations to bonds and loans, as well as – project dependent – dividend payouts, to equity investors, either from tax revenues, fees, or alternative revenue sources. The extended operating expense (OPEX) horizon and sizable capital expenditures (CAPEX), along with debt service requirements and internal rate of return (IRR) expectations of invested capital make risk-adjusted financing of infrastructure critical. Furthermore, conventional infrastructure financing structures often take years to execute and incur high transaction costs (Jansen & Tuijp, 2021; Jin et al., 2016). With high risks of market failure on one hand, and infrastructure being regarded as a public good on the other, government provisions, support for loss guarantees, and other risk-mitigating mechanisms such as regulations have been central to the provision of core economic infrastructure (Chen & Bartle, 2017).

Increasingly, private sector financing and market mechanisms are engaged to finance and operate infrastructure under an increasingly broad suite of public-private partnership contracts (Delmon, 2021; Loftus et al., 2019). Typically, these contracts require the government sector to pay the private operator on the basis of pre-agreed key performance indicators (KPIs), while under certain lease or co-financing conditions allowing the private sector to monetize the value of the asset (e.g., toll roads). As infrastructure is becoming smarter, resulting from the integration of digital infrastructure such as ubiquitous sensing, edge processing, and telecommunications hubs, the opportunity to further monetize value via data markets is creating more complexity in contract and delivery agreements. This is in part due to the shift from traditional construction supply chains to data-driven value networks with digital technology partners, requiring new counterparty risk transfer, allocation, and verification arrangements. Due to investor demand and regulatory requirements for environmental, social and governance (ESG) integration, the collection of alternative data on infrastructure performance adds new urgency, including the tracking of sustainability features such as carbon emissions, water, air quality, and social equity indicators. While the upfront cost and maintenance of these smart assets is expected to increase, the opportunity for long term operational performance, new value capture methods, data monetization, and opportunities for lowering the cost of financing through contract automation is driving the market towards efficient financing mechanisms (Adriaens & Ajami, 2021; Adriaens et al., 2021). This is commonly referred to as digital delivery of infrastructure (Skowron & Flynn, 2019).

Together with an increasing interest in infrastructure financing and funding mechanisms (National Academies of Sciences & Medicine, 2022), blockchain is being considered as a technology to lower the cost of capital, increase data transparency and transaction efficiency, and enhance capital liquidity (Uzsoki, 2019). As a distributed ledger technology (DLT), blockchains can facilitate direct, peer-to-peer transactions without an intermediary or central decision maker such as a bank. It prevents double spending and validates transactions while keeping immutable public records of activities on-chain (Tapscott & Tapscott, 2016). Blockchain provides many benefits and solutions such as visibility, traceability, and workflow automation in supply chains, verifiable identity and credentials management in record keeping and document signing, as well as enabling a unique digital representation of a real-world asset on the blockchain in a process called tokenization (IBM Corporation, 2020). The tokenization of assets, a digitization method to allow retail investor participation in financing, is an increasingly common use of blockchain technology and has many applications, including participation in an investment fund, proof of intellectual property and artwork ownership, as well as representation of the equity and debt used for financing an infrastructure project or portfolio (Laurent et al., 2018; Sazandrishvili, 2020; Tian et al., 2020; Uzsoki, 2019).

Despite positive sentiment and expectations towards the potential benefits of blockchain (Mnif et al., 2021; Saberi et al., 2018), its adoption has been slower than expected and implementations on a larger scale are still rare (Clohessy et al., 2019; Gartner, 2021). Common barriers include regulatory uncertainty (Prewett et al., 2020), a steep technological learning curve (Oberhauser, 2019), as well as unfavorable user experience (Glomann et al., 2020). In addition, factors such as cryptocurrency instability (Iwamura et al., 2019), introduction of new organizational governance models (Batubara et al., 2018), and the question as to whether blockchain can deliver true decentralization in decision-making (Chu & Wang, 2018) present barriers to adoption. Nonetheless, the limits on conventional financing for delivering infrastructure have resulted in predictions that blockchain adoption is inevitable and will play a major role in major industry sectors (Belchior et al., 2021; Bhushan et al., 2020). One of the most visible practical implementations in the area of financing infrastructure is Project Genesis, a blockchain-based tokenization of green bonds that allows retail investors to buy into environmentally sustainable projects, while being provided with transparent data that the project delivers on the intent of the bond financing (BIS Innovation Hub, 2021).

The expectations of blockchain technology adoption is particularly relevant with the sustainability of infrastructure and smart cities becoming central to the discussion and priorities on climate transitioning and resilience (Cousins & Hill, 2021; United States White House Briefing Room, 2021). The International Organization for Standardization (2019) defines sustainability as meeting the needs of the present without compromising future generation needs from an environmental, social and economic perspective. The provision of universal access to infrastructure services, such as clean water and sanitation, and affordable green energy are central tenets. To reconcile sustainability and infrastructure, innovative financing mechanisms accounting for climate and sustainability are required (UNEP Finance Initiative, 2021). A key challenge is that the financing of sustainable, resilient infrastructure such as smart stormwater systems, electric and autonomous vehicle transportation, and energy-efficient buildings have is more challenging as compared to their traditional counterparts (Canas da Costa & Popović, 2020; Meltzer & Constantine, 2018). The generally higher upfront costs and higher perceived technology risks associated with more environmentally-conscious solutions tend to be barriers for financing (Meltzer & Constantine, 2018). While the capital cost of green solutions are lowering, increasing the financial attractiveness of sustainable infrastructure by reducing the cost of capital still requires further investigation (Kling et al., 2021). Risk premiums should be lowered such that infrastructure projects are more adequately hedged against their downside risks (Codosero Rodas et al., 2019; Li & Liao, 2018).
A substantial body of research exists on the opportunities for blockchain applications in smart cities in general and in the operations of energy systems, yet there is a knowledge gap at the intersection of sustainability, infrastructure financing, and blockchain-enabled investment

mechanisms. Adams and Tomko (2018) state that research is needed before the promises of blockchains as an enabler of traceability and environment governance can become reality because these projects remain conceptual and proponents have "glossed over detailed discussions". For sustainable infrastructure and smart cities to be financed through blockchain, a justification of this integration, and an understanding of the technical tools as well as the premise and limitations to enable adoption, are required. The current study addresses three central research questions: (1) What are the emerging areas of research in infrastructure finance, sustainable infrastructure and smart city finance mechanisms, and blockchain technology applications? (2) How does blockchain enable sustainable infrastructure and smart city financing? (3) What are the implications for sustainable infrastructure and smart cities? The research explores the opportunity to utilize decentralized oracle networks (DON) with blockchains for monitoring, reporting and verification (MRV) of sustainable infrastructure asset performance to automate pay-for-performance mechanisms, and reduce risks and cost of capital in sustainable infrastructure investments. To the authors' knowledge this is the first study to integrate decentralized oracle networks for financing sustainable infrastructure and contributes to the literature on sustainable infrastructure finance and investments.

3.2 Materials and Methods

Establishing new theory based on distinct disciplines will be required to address the knowledge gap focus of this paper. This is carried out through building and combining meticulously selected literature and sources of information. The research method to be employed is therefore aligned with that of a conceptual research article, which Jaakkola (2020) characterizes it as creating new theory by building on concepts and data tested through empirical research. Conceptual papers offer integrated frameworks and directions of future inquiry by unearthing new connections among constructs and providing logical associations between them (Gilson & Goldberg, 2015). As opposed to empirical research, there is no specific research design for conceptual papers. However, this study will use the commonly accepted model methodology approach, which is characterized by identifying unexplored connections and justifying causal linkages between constructs to build a theoretical framework to predict relationships between disparate subjects (Jaakkola, 2020). Researchers are able to explore emerging phenomena where data is not readily available. The model approach to address the research questions is shown in Figure 3-1.

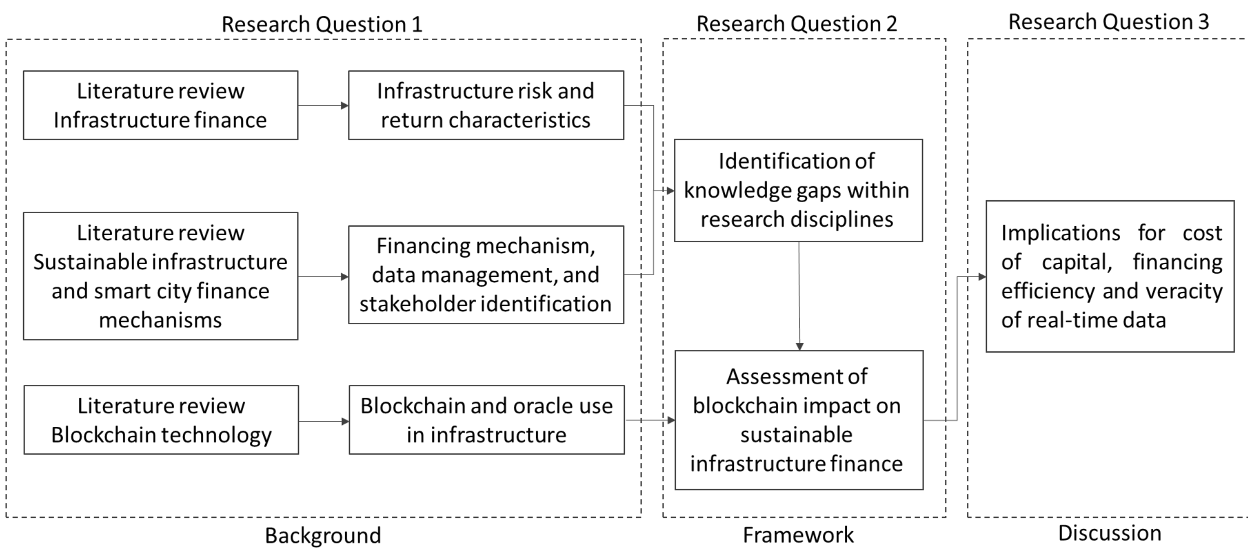

Figure 3-1. The model approach followed in this study to explain and predict relationships between infrastructure finance, sustainable infrastructure and smart cities financing mechanisms, and blockchains and oracles to provide insights in technology-enabled financing of sustainable infrastructure.

The literature review process recognizes the current knowledge on the risk and return characteristics of infrastructure finance, mechanisms in financing sustainable infrastructure and smart cities, and applications of oracles and blockchain in the existing literature. Since the three areas of study are drawn from a wide range of literature, a semi-systematic literature review is conducted to address research question 1. Semi-systematic literature reviews are used to scope an area of study and its gradual evolution over time (Snyder, 2019). This method captures theories and common challenges defined within a domain. Meticulously designed search strings were used to identify relevant literature in the areas of study. The manuscripts and documents were evaluated according to the following criteria: (a) literature was limited to those published from 2013 to 2022; (b) unfitting titles and abstracts were excluded. The selection data sources, search strings, and process are shown in Figure 3-2. Relevant professional expert reports from the National Academies of Sciences, Engineering, and Medicine, the Global Infrastructure Hub, EDHEC Infrastructure Institute, World Bank, and Quantified Ventures that do not typically show up in the academic databases Scopus and Web of Science search results were manually added to the literature review stack.

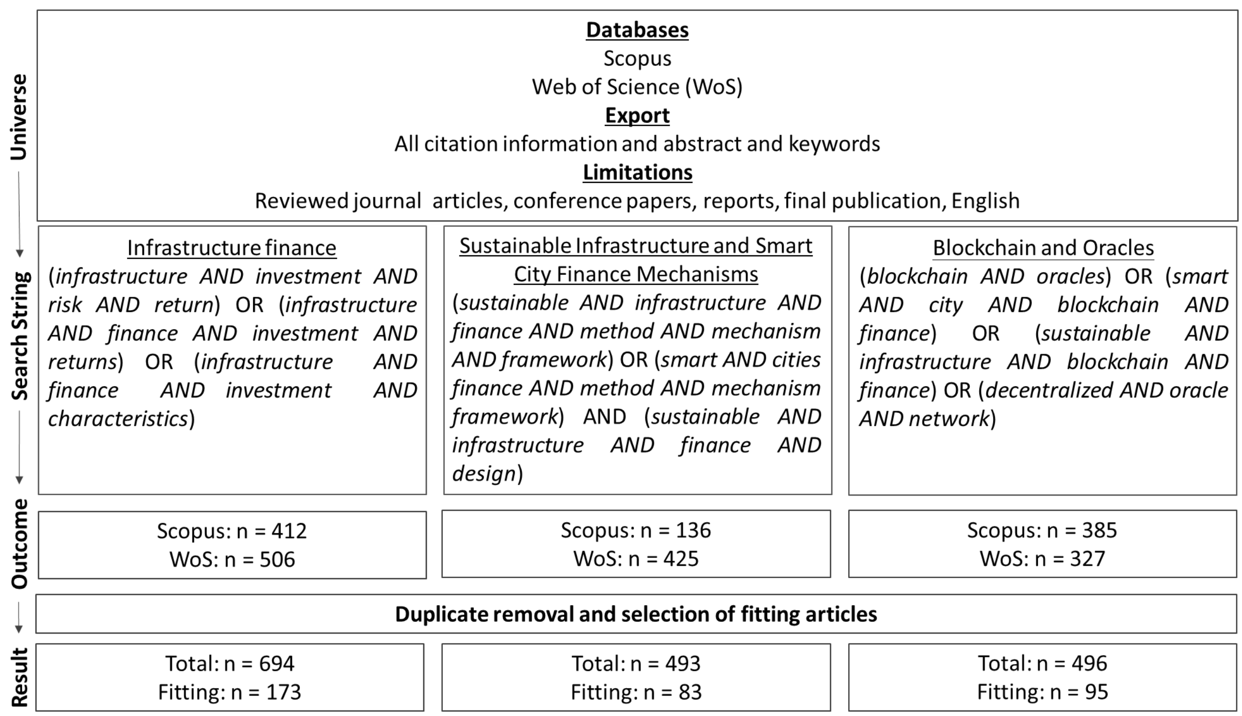

Figure 3-2. Semi-systematic quantitative literature review for three distinct areas of study: infrastructure finance, sustainable infrastructure and smart cities financing mechanisms, blockchain and oracles. n is the number of literatures from Scopus and Web of Science and does not include professional expert reports.

After the literature review process, the key insights and knowledge gaps are assessed via the model research design to uncover the opportunities and value propositions that blockchain and oracle technologies present for risk-return profiles of infrastructure assets and sustainable infrastructure and smart cities financing mechanisms without the use of empirical data. By making the connections between disciplinary areas, the impact of blockchain and oracles on sustainable infrastructure financing is evaluated to address the implications for technology-enabled financing of sustainable infrastructure.

3.3 Literature Review

3.3.1 Infrastructure Finance

One of the earliest definitions of infrastructure, described by Jochimsen (1966), is "the sum of all material, institutional and personal assets, facilities, and conditions available to an economy based on the division of labor and its individual economic units that contribute to realizing the assimilation of factor remuneration, given an expedient allocation of resources." Infrastructure has become an attractive alternative investment class for institutional investors due to several commonly perceived characteristics such as low volatility in high-risk market environments, steady income, diversification from equity markets, and value as an inflation hedge (Duclos, 2019; Weber et al., 2016). However, given the wide range of industry types, organizational models, and regulations that compose infrastructure, the risk-return profile of infrastructure must be carefully considered. A recent World Bank survey of 6343 public infrastructure projects from 129 developing countries during the period from 1987 to 2020 shows adoption of a wide range of contractual forms from user charge tariffs and tolls (2211), fixed annuity (440), availability-based variable annuity (239), revenue share (85), fixed tariff purchase agreements (3167) and other hybrid mechanisms (World Bank Group, 2021).

Contrary to a simple sector-based analysis of investment characteristics, the risk-return profile of infrastructure depends on a multitude of factors (e.g., business models, partnership models, etc.)

(Figure 3-3). One of the most critical differentiators between assets is the unique contractual agreements of infrastructure projects that determine the risk-return profile of the investment (Weber et al., 2016). Figure 3-3 illustrates the internal rate of return (IRR) of two similar physical assets, categorized in the same subsector, each at a different stage of their project life cycle with different embedded contractual structures. For an operational asset with an availability payment-based public-private partnership (PPP) structure that is not highly leveraged, and where the public participant is fiscally and politically stable, minimal market risk is assumed by the private party. The expected return would range from 5% to 9%. The other physical asset, although a monopoly and regulated, is subject to demand-side risk as the business model is user financed as opposed to budget financed. The increased risk leads to an expected return of 9% to 14%. While the two assets are physically identical and both operational, their risk-return characteristics vary.

Investors gain access to infrastructure through direct placement deals, listed and unlisted funds, which have not performed up to the commonly perceived characteristics due to misunderstood or mixed risk profiles of assets under management (Amenc et al., 2017; Blanc-Brude & Gupta, 2020). Additionally, traditional investment vehicles utilized are often associated with high transaction fees, illiquidity, and high investment thresholds (Joffee, 2016). Andonov et al. (2021) rejected the hypothesis that closed private fund investments in infrastructure delivers more stable and diversified cash flow than other alternative asset classes. PPP tend to command a much higher price as compared to public procurement of infrastructure, resulting from large risk transfers, how the private sector treats risk, and the performance uncertainty of the public-private organizational contract (Makovšek & Moszoro, 2018). Existing infrastructure indices and funds aggregate financial vehicles based on industry sector. This does not distinguish between the contractual and regulatory characteristics that inform risks and returns, nor does it take into account factors that may distort the investment characteristics of the underlying infrastructure, leading to a deviation from expected infrastructure investment outcomes (Blanc-Brude, 2013). The structure and components of infrastructure indices can also be skewed, which leads to the question of whether such benchmarks can capture any general infrastructure qualities or valuations (Bianchi et al., 2017; Blanc-Brude, 2013).

Venture capital and private equity funds investing in infrastructure are predicated on information asymmetry with the asset owner, often leading to adverse selection decisions, and therefore utilizes convertible securities to mitigate the impact of risks (Tripathi, 2021). The lack of accurate valuation of infrastructure assets has led to a mis-match between the available long-term source of capital and the infrastructure asset to be financed finance (Rossi & Stepic, 2015). Climate-resilient infrastructure has an additional layer of financing difficulty due to the higher upfront capital costs, higher perceived technology performance risks, as well as unaccounted costs of stranded assets of investing in climate-conscious solutions (Lindsay et al., 2021; Meyer & Schwarze, 2019). Thus, improving the transparency of infrastructure performance metrics is seen as an important advancement for innovations in infrastructure project financing (Herrmann & Spang, 2020; Roelofs, 2019). The advent of so-called cyberphysical systems (CPS) and integration of internet-of-things (IoT), with its value proposition to increase data availability on infrastructure performance improves the "informational efficiencies" and pricing strategies of conventional infrastructure (Liu & Fukushige, 2020; Sugrue & Adriaens, 2022; Teng et al., 2021). This information can then be incorporated in performance-driven models such as risk transfer finance, securitization against cash flows or asset valuation, and business-to-business market instruments.

Infrastructure I	Operational Availability-based Finance No market risk	• Assets with regulated, long-term availability-based PPP contracts – no/minimal market risk (demand or price) • Grantor of revenue is a recognized public body in stable country • Low or medium leverage
Infrastructure II	Operational User-based Finance Market risk	• Monopoly, regulated, but exposed to market risk (e.g., user financed) • Revenues yield from day one – possibly high leverage • Regulatory risk owing to periodic regulatory changes and/or unstable government

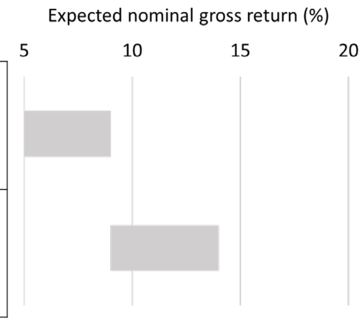

Figure 3-3. Physically identical Infrastructure I and Infrastructure II have different risk-return characteristics based on project life-cycle stage and contractual agreements. Adapted from Weber et al. (2016).

3.3.2 Sustainable Infrastructure and Smart City Finance Mechanisms

Smart cities projects and sustainable infrastructure require a rethinking of the revenue models as well as financing instruments and delivery contracts. For example, does the asset have direct or indirect value capture models that can be used as collateral for financing? Can data be monetized or used to offset project risk by giving better insights in operations and maintenance costs? Is public financing an option or will private co-financing be required? In this section, smart cities and sustainable infrastructure will be discussed synonymously, based on the premise and value proposition of smart cities to improve the ESG quality of infrastructure services. These non-traditional value systems require new stakeholders, with knowledge that tends to be available only to specialized investors and asset classes, typically at a higher expected rate of return than can generally be afforded through public funding mechanisms. Federal loan programs such as the Transportation Infrastructure Finance and Innovation Act (TIFIA) provide guarantees or credit for projects including intelligent transportation systems, but most smart infrastructure is financed using debt and grants, or co-financed by private sector operators. Akomea-Frimpong et al. (2021) showed that PPP were applied in infrastructure to address poverty alleviation, urban development, and waste management. Gonzalez-Ruiz et al. (2019) employed the mezzanine debt mechanism in PPPs, capturing financial value by converting debt into equity shares, to finance a wastewater treatment plant. The Tax Increment Financing (TIF) model has been shown to be promising to attract private capital in the development of core infrastructure for smart cities or to revitalize economically blighted areas. These financing structures are based on setting up a geographically-defined tax district whose tax revenues are generated by future increase in property value and applied to the cost of financing (Malhotra et al., 2020).

More recently, private, IoT-driven operational models are trickling into public infrastructure systems and are changing the funding and credit landscape by catalyzing so-called efficient financing. The efficient infrastructure finance model relies on regular updates of information on the status and use of the physical asset. Literature indicates that a wide range of PPP is employed, where delivery of the service often involves construction of the underlying asset and payment is made based on infrastructure performance and availability of the service (Gundes, 2022; Haran et al., 2013; Leviäkangas et al., 2013; Selim et al., 2018). Information technology (IT) enables efficiency by automating pay-for-performance, unlocking new cash flows, increase operational efficiency and thus reduce costs (e.g., Sugrue and Adriaens (2022)). In addition, IT provides an opportunity for alternative data to be integrated in financing mechanisms, including ESG indicators for long-term sustainable value accrual (Ferrarez et al., 2020). Appropriate benchmarks are required to establish accurate and precise performance indices for them to be included in financing models (Codosero Rodas et al., 2019; Sengupta et al., 2018; Wang et al., 2020).

The integration of ESG, sustainable outcomes or other impact data in the financing of infrastructure has been explored in asset valuations and investment returns (Lu et al., 2015). Green outcomes or other impact data in the financing of infrastructure is already starting to influence the narrative around asset valuations, and investment returns, and cost of capital considerations (Kovarik et al., 2020; Selim et al., 2018; Wener, 2019). For example, the refinancing of traditional bonds for roads using sustainability or social bonds has been shown to result in coupon discounts of 2-3%. Green municipal bonds for water, energy, mass transit or housing infrastructure have been shown to result in a pricing discount of up to 23 basis points (bps) (Li & Adriaens, 2021). Corporate bonds issued by companies with leading ESG ratings are discounted up to 12 bps (Li & Adriaens, 2022). Jakob et al. (2016) purport that carbon pricing could simultaneously reduce greenhouse gas emission and generate substantial public revenues to cover infrastructure development needs. Tirumala and Tiwari (2022) introduce a financing-facility based mechanism that pools low-cost funds from investors at the national or local level to support projects that meet the UN Sustainable Development Goals for the Ocean. Monetary provisions from the facility engages either large impact projects or individual projects through concessional financing, credit enhancements, or "blue" bonds issuances.

To avoid greenwashing of sustainable infrastructure, there is a requirement for independent measurements and assessment of ESG performance metrics for the infrastructure to qualify as a social, green, or sustainable investment. As a result, new business and financing models have been proposed to implement sustainable financing, including through green bonds (Baker et al., 2018; Jeremy & Neil, 2020; Zimmerman et al., 2019), "pay-for-success" models such as environmental impact bonds (EIBs) (Brand et al., 2021; Salzman et al., 2018), green asset-backed securitization (Agliardi, 2021; Berrou et al., 2019; Demidov, 2022), sustainability-linked loans or bonds (Ionescu, 2021; Kölbel & Lambillon, 2022), and new P3 contract structures (Cheng et al., 2021; Hebb, 2019; Hendricks et al., 2018; Hoeft et al., 2021). Pay-for-success or performance-based models measuring outcomes have become favored financing models for smart cities and sustainable infrastructure as it provides asset-specific risk allocations preferrable to all parties involved (Lindsay et al., 2021). Performance-based financing integrates real assets with digital infrastructure assets, such as sensors, communication infrastructure, edge computing and data centers (Adriaens et al., 2021; Uckelmann et al., 2011).

The integration of digital infrastructure and sensors in sustainable infrastructure and smart cities includes the development and design of a digital twin of the physical asset to explore human-infrastructure interaction and use, new revenue opportunities from data monetization, and better performance tracking and tracing (Adriaens, 2021). Brand et al. (2020) uses stochastic hydro-financial watershed modeling to estimate cost savings from hedging against environmental risk with sustainable infrastructure that informs the financial terms of an environmental impact bond. The study also discusses risk reduction techniques for investors such as extending the bond length, using bond guarantees, or cost sharing among stakeholders. Chitikela and Simerl (2017) highlights the flexibility and efficient conductibility of renewing water infrastructure by performance contracting. Performance contracting is a budget-neutral approach to asset renewal as the savings incurred after the asset renewal can be used to service the outstanding debt. Hence, performance of the renewed infrastructure is used as a debt service criterion. A similar approach was piloted under the Clean Development Mechanism (CDM) to finance a small hydropower plant in Colombia (Duque et al., 2016). Under CDM, sustainable infrastructure developed in emerging economies is credited and financed by industrialized countries, whereby each ton of CO_2 reduced from the sustainable infrastructure becomes a Certified Emission Reduction sold to industrialized countries and traded in the carbon market. Samer and Zahran (2017) uses the "Program-for-Results" mechanism to minimize government spending on costly infrastructure in the implementation stage of a project. The "Program-for-Results" mechanism links disbursements from the World Bank to the crediting country based on the achievement of performance indicators of the infrastructure. The performance benefits can also achieve favorable conditions on the cost of financing (Giráldez & Fontana, 2022). All revenue streams are dependent on veracity and trust in the infrastructure performance data and information. Other information used to indicate performance achievement include environmental sustainability metrics such as stormwater runoff reduction and forest restoration (Brand et al., 2021). Ferrarez et al. (2020) provides 42 additional sustainability indicators, categorized across the ESG pillars for infrastructure.

A generalized model for pay-for-performance is shown in Figure 3-4 and includes: the project provider who delivers the service, investors in the project, payors (including users), and external third-party evaluators. The investors provide up-front capital to initiate or scale a sustainable infrastructure project. The project provider carries out construction of the piece of infrastructure after receiving the up-front capital. The payor of the project makes fixed or variable interest payments to the investors. External evaluators quantify and verify the sustainable infrastructure performance. According to the measurements, an additional payment accrued from cost savings or other revenue generations to the investors can be triggered when overperformance occurs. In the case of underperformance, payors of the project can invoke a clawback from the investors, hedging against performance risks. This mechanism, as all other performance-based funding and financing structures, is dependent on the veracity, timeliness, and transparency of data, which has led to the opportunity for blockchain and oracles.

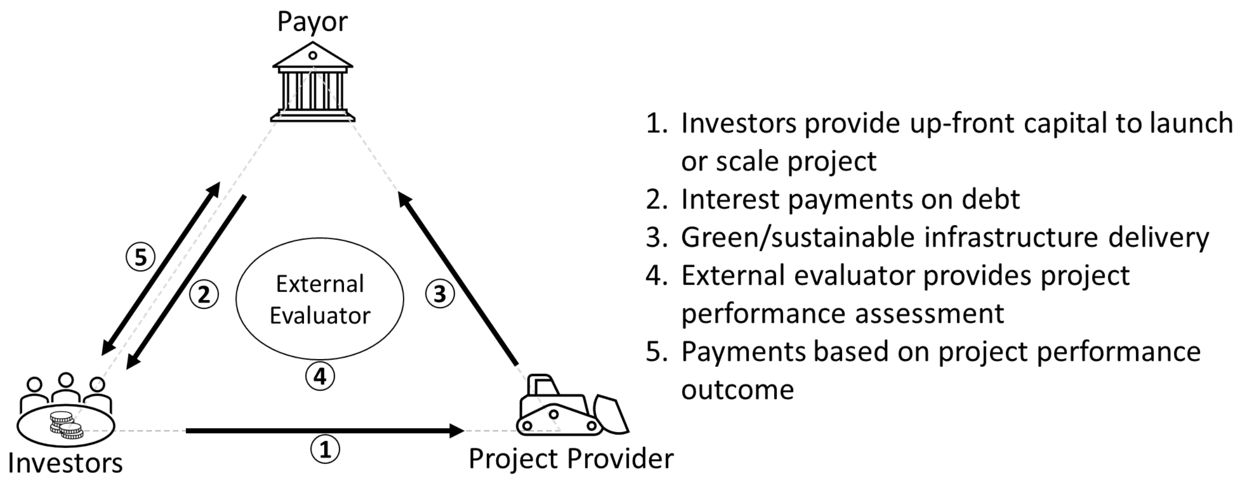

Figure 3-4. A visual representation of the performance-based financing mechanism. Adapted from Quantified Ventures (2021).

3.3.3 Blockchain and Oracles

The idea of blockchains rose to prominence as the underlying technology of Bitcoin, the world's largest cryptocurrency. Nakamoto (2008) introduced the technology as peer-to-peer timestamped transactions that are aggregated by hashing the transactions into a continuous, proof-of-work record, addressing the double-spend problem without a financial institution. Blockchains are viewed as a promising technology for smart cities and sustainable infrastructure because it enables network participants to exchange data, allows for transparent communication, and affords new decentralized transaction models. Given that conventional practices in the IoT era, such as cloud-based computation and storage, may be at risk as a single-point of failure or have privacy concerns, the integration of blockchain and IoT has led to innovative decentralized applications that includes smart finance, smart cities, and smart energy grids (Chen et al., 2022). In infrastructure construction and development, current information management practices are subject to fraudulent behaviors. Zhang et al. (2021) present a framework to address the malpractices using blockchain and smart contracts, enabling around-the-clock services, integration of data analysis algorithms, and security and stability within the management system. Other common use cases of blockchain are for solving administration and transaction disputes in construction projects (Mohammed et al., 2021). Sanka et al. (2021) forecasted blockchain adoption, reporting that blockchain-enabled projects entered the pilot stage in 2017 to 2018 while currently moving to production phase, and will gain more mainstream adoption by 2025.

The literature of blockchain-based solutions, data aggregation, and performance management for smart cities include applications for security, city services and management requirements (Bagloee et al., 2021; Bhushan et al., 2020; Hakak et al., 2020; Majeed et al., 2021). Woo et al. (2021) describe the application of blockchain technology for building energy performance MRV and to verify carbon credit market disclosures. Several studies have proposed the use of blockchain technology to finance infrastructure. Moseley (2018) proposed utilizing blockchain-based debt financing of infrastructure. By representing bonds on the blockchain as smart contracts, this blockchain-based digital bond could be used as an alternative instrument for the financing of the project by lowering investment entry barriers and increasing investment vehicle liquidity. Tian et al. (2020) describe the opportunity for blockchain to tokenize infrastructure equity as an alternative to traditional debt financing, improving transaction efficiencies. Project Genesis has released two blockchain based green bond tokenization platforms to allow retail investors to participate in financing infrastructure and receive information on the green performance returns (BIS Innovation Hub, 2021). Although blockchains are adept at native cryptocurrency token accounting and transactions, the cited studies do focus on the mechanisms or effects of utilizing real-time data from off-chain environments. The blockchain by itself is siloed from the outside world and its capabilities are severely limited (Mühlberger et al., 2020).

Oracles have been introduced in various forms to overcome this limitation. Oracles are the bridges that connect off-chain computational resources and data to the mainchain infrastructure, such as smart contracts where execution of transactions are conditional to real-world events (Poblet et al., 2020). However, as a source of external data to a decentralized system, oracles are increasingly seen as a point of centralized vulnerability (Sheldon, 2021). A particular form of oracle that addresses the issue of single-point failure is the decentralized oracle. Decentralized oracles allows users to prove data provenance and verify statements about such data with zero-knowledge (ZK) (Zhang et al., 2020). Park et al. (2021) describes a framework for a privacy-preserving oracle system that converts signed data in a legacy web server into a zk-SNARKs proof and provides a smart contract to verify. The on-chain processing is verified and automated through smart contracts while data owner privacy remains protected. Adler et al. (2018) introduced a decentralized oracle, Astraea, based on a voting mechanism that decides the truth or falsity of propositions, making adversary oracle manipulation difficult. Cai et al. (2022) improves upon Astraea by implementing peer prediction-based scoring with non-linear staking, to improve the veracity of off-chain data transfer to the blockchain. The scoring scheme is designed so voters uniquely maximize their expected score by honest reporting of data. Breidenbach et al. (2021) introduced the concept of hybrid smart contracts, a general framework for augmenting existing smart contract capabilities by integrating off-chain computing resources. Hybrid smart contracts constitute an on-chain component and off-chain component consisting of executing programs running on a decentralized oracle network (DON). DONs facilitate a highly trustworthy layer of support for hybrid smart contracts and other oracle-dependent systems by means of decentralization, cryptographic tools, and cryptoeconomic guarantees. DON usage has been predominantly providing decentralized price feeds to Decentralized Finance (DeFi) applications (Kaleem & Shi, 2021).

In infrastructure applications, Osterland and Rose (2021) utilizes oracles to maintain an audit certificate of a significant amount of data from German waterway transportation on the ledger while tracing and proving the aggregated data. Albizri and Appelbaum (2021) applies decentralized, automated, and consensus-based oracles in the Business Process Management (BPM) model of a smart contract and IoT-governed supply chain. Here, the decentralized oracle paired with IoT exists as a data providing and transmitting layer for supply chain provenance. Nguyen et al. (2019) built an oracle server to utilize drought-index data for agricultural insurance applications in Southeast Asia.

3.4 Discussion and Implications

Extending from the literature review, a blockchain-based framework utilizing DONs to gain insight from information on infrastructure performance and other data metrics to inform and automate mechanisms in sustainable infrastructure and smart cities finance is established. The framework provides the logical connection and justification for why blockchain is primed to facilitate performance-based infrastructure financing and how it improves infrastructure investment representation, transparency, and allows infrastructure to become more financially attractive. CPS and IoT harness data collected from infrastructure to inform investments and more readily bridge the infrastructure finance gap.

3.4.1 Connections between infrastructure finance, sustainable infrastructure and smart cities financing mechanisms, blockchains and oracles

The sustainable infrastructure and smart city use case coupled to financing linked to traceable and verifiable impact metrics is particularly well suited for blockchain-enabled finance. A key requirement is the availability of data and processed information, capturing the various data layers, types, and scope of the asset (Gürdür Broo et al., 2022; Sepasgozar et al., 2021). The digital rendering of the physical asset has the capacity to inform sustainability considerations for operation, future states of infrastructure health and the potential for data markets and monetization (Ramu et al., 2022). The infrastructure finance literature highlights the lack of accurate benchmarks and valuation metrics for direct investments, listed infrastructure, and unlisted infrastructure. In sustainable infrastructure and smart cities financing mechanisms, the pay-for-success or performance-based model provides asset-specific performance indicators and risk management profiles desirable to all stakeholders. A sustainable, highly interoperable, and trust-inducing data backbone for environmental performance-based financing can be facilitated via blockchain technology (Suhail et al., 2022). The blockchain literature review highlights the value propositions such as efficiency in transactions, trust and transparency, and automation. In addition, decentralized oracles are the interface between the blockchain and off-chain resources and data. The oracles enable specific transactions to execute on-chain based of the data retrieved from infrastructure IoT sensors.

The use of blockchain is suited for performance-based financing mechanisms as it provides trust and transparency for all parties involved in a project, “allowing mutually mistrusting entities to exchange financial value and interact without relying on a trusted third party” (Wüst & Gervais, 2018). For performance-based financing of sustainable infrastructure, evaluating project feasibility, selecting developers, and financing, operating, and MRV in the post-construction phase of a project lifecycle requires intricate coordination from various actors as well as their reaching of consensus. Currently, an external evaluator is required to assess performance against established and contractually agreed metrics. However, trust in institutions, evaluators, and rating providers has been a challenge due to recent performance lapses, security breaches, and cost, thus exposing limitations to these intermediaries (Busch et al., 2015; Jonsdottir et al., 2022; Nicole & Robert, 2013). Legacy accounting systems and mechanisms are deemed insufficient to avoid information asymmetry resulting from heterogeneity and fragmentation of data flows (Gatti, 2018b; Sclar, 2015). High MRV costs and counterparty risks associated with "greenwashing" of infrastructure assets to fit the ESG narrative have impacted the financing and development of sustainable infrastructure (Baldi & Pandimiglio, 2022; He et al., 2021). Depending on whether the infrastructure performance data require public verifiability, a public or private permissioned blockchain could be used.

The integration of sustainable infrastructure IoT information with blockchain-based financial transactions is challenging. Data availability can be switched on and off by a data provider or a centralized web server, negatively affecting the benefit of blockchain, such as decentralization (Sheldon, 2020). Single "trusted" data sources frequently impede transparency and accountability (Kaulartz, 2018; Niya et al., 2018). Decentralizing single sources of trust or single points of failure is a core consideration for blockchain use cases to build more resilient accounting systems (Lockl et al., 2020; Sicilia & Visvizi, 2019; Zachariadis et al., 2019). Although blockchains are the backbone for automated smart contracts, their on-chain functions are insular and expensive to execute (Pierro & Rocha, 2019). Blockchains are siloed or blocked off from the outside world and very expensive to append (Zarir et al., 2021). These shortcomings constrain the blockchain to maximally benefit from real-world data and computational resources off-chain.

To facilitate performance-based financing for infrastructure, smart contracts will be required that can combine on-chain and off-chain modules in a decentralized approach. This can be realized via hybrid smart contracts and DONs, which are efficient blockchain-agnostic interfaces to off-chain resources (Figure 3-5). As opposed to conventional smart contracts that only govern on-chain activities, hybrid smart contracts expand conventional smart contract functionality by integrating off-chain resources in a trusted and confidentiality-preserving fashion (Basile et al., 2021;

Breidenbach et al., 2021; Cai et al., 2022). By combining the highly secure properties of smart contracts anchored on the mainchain with the off-chain capabilities of DONs, a bevy of opportunities arise for applications in sustainable infrastructure finance. Hybrid smart contracts constitute several modules: on-chain components and an off-chain nodes, and an "executable" that is running on the oracle nodes (Breidenbach et al., 2021). Executables are programs that run autonomously, continuously, and initiate adapters. They utilize adapters that link the oracle nodes to external resources for advanced functionalities. They then send the requested information over another adapter back to the hybrid smart contract on-chain (Figure 3-5). DONs retrieve data from its compatible off-chain source with different trust models or transparency requirements for a wide range of applications (Gouiaa et al., 2022; Kaleem & Shi, 2021; Shi et al., 2021). The oracle networks communicate verified and trusted data to hybrid smart contracts using a verification committee where corruption is dissuaded with cryptoeconomic incentives.

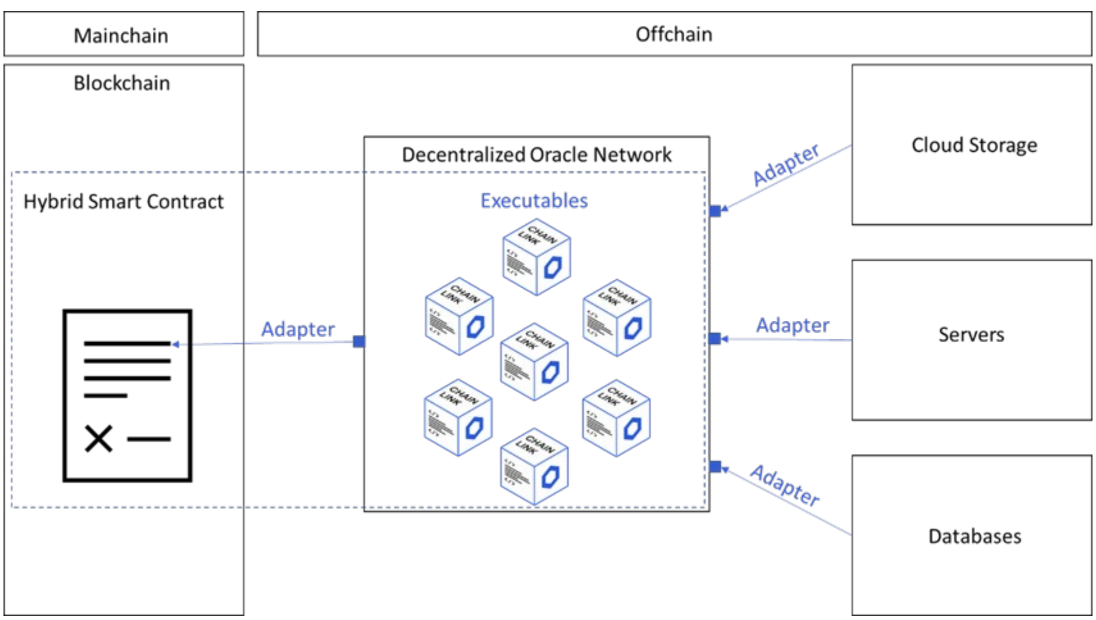

Figure 3-5. Visualization of a decentralized oracles network pulling off-chain data on chain to a hybrid smart contract (Adapted from Breidenbach et al. (2021)). The DON accepts requests from the hybrid smart contract and the executables initiates the adapters to query data from off-chain resources and passes the requested information back on to the blockchain. The direction of data flow carried out by adapters are indicated by the arrows.

Carrying out performance-based financing (e.g., environmental impact bond or other performance-based contracts) on the blockchain with DON technology shifts the stakeholder relationships of Figure 3-4. The investors provide up-front capital directly to the infrastructure project provider to initiate construction. The asset owner, typically a public utility or government entity, makes interest payments directly to the investors. The payment processes are done peer-to-peer without the need of financial intermediaries. With infrastructure IoT-based performance data accessed and verified through DONs, third-party external evaluators are reduced in their roles, or no longer required. The off-chain collected infrastructure performance measurements are used as inputs to the smart contract on-chain for automatic execution of payouts conditioned on cost savings and other revenue generated from overperformance or risk-hedging in underperforming circumstances (Figure 3-6). All parties, including the public, will have access to read and audit the smart contract agreements as well as the performance data. Introducing a transparent data MRV and automated transaction mechanism can reduce the cost of capital and allow for improved risk management in sustainable technology and its associated financial transactions.

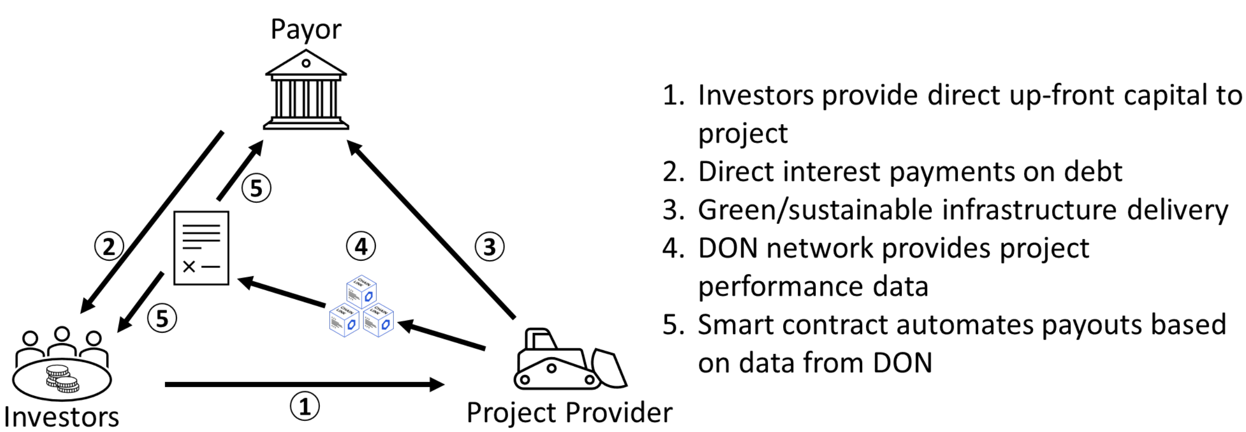

Figure 3-6. Visualization of the performance-based financing mechanism via the blockchain and decentralized oracle network (DON) technology.

3.4.2 Implications of DONs and Hybrid Smart Contracts for Sustainable Financing of Infrastructure

This paper set out to define a conceptual framework for sustainable infrastructure and efficient financing by drawing on risk and return expectations of the investor on one hand, and new business and revenue models of the owner and operator of the infrastructure delivery method on the other. The framework primarily centers around pay-for-performance models, which depend on veracity, transparency of performance metrics, and accountability of individual actors (Gupta et al., 2021). The pay-for-performance model can include tokenized bonds, sustainability-linked bonds, or other KPI-initiated transaction methods. The framework conceptualizes how data from sustainable infrastructure and smart cities IoT can inform transactions on the blockchain through distributed oracle networks and hybrid smart contracts (Figure 3-7). The DONs take advantage of decentralized data aggregation and distributed computing to securely process information and payment contracts. Applications of distributed oracle networks to aggregate climate data for infrastructure compliance, investor decision-making, insurance underwriting and risk rating are in the process of being implemented by blockchain technology companies (e.g., Wolfberg and Adriaens (2021)). The integration of digital technologies such as distributed ledger technology, IoT, and econometrics in a DON architecture can enhance trust, transparency, and efficiency. It has implications for data flow which underpins pay-for-performance financing, engagement of stakeholders, and the wide adoption of sustainable infrastructure.

Implementation of Data Flow and Pay-for-Performance Financing

The framework of blockchain-enabled performance-based financing of sustainable infrastructure is shown in Figure 3-7. The first step involves the collection, aggregation, and processing of data from infrastructure assets, using application specific IoT devices such as smart meters for measuring stormwater levels and bridge sensors (Bartos et al., 2018; Zhang et al., 2016). Potential data fusion or scaling by using remote sensing and various surveying techniques may be included.

The data is securely stored on web servers, databases or “meta-registries” (Bartos et al., 2018; Schletz, Franke, et al., 2020; Zhang et al., 2016). In these systems, machine learning algorithms can be utilized for identifying data errors, accurately filling data gaps, and enabling verification (Marjani et al., 2017; Troutman et al., 2017). Digital signatures subsequently added to confirm the precision and accuracy of data (Sporny et al., 2022). These data infrastructures’ application programming interfaces are essential to enable real-time data queries from DONs adapters, bridging legacy systems to blockchains. In MRV procedures, DON committees may be used to verify and medianize data from providers (Breidenbach et al., 2021). This approach minimizes storage and performing computations on-chain while maximizing trust when changes occur in the off-chain environment. Once the off-chain data is provided to the hybrid smart contract, transactions can be executed based on agreed upon conditions. For example, if an application is the blockchain-based environmental impact bonds of the DC Water Stormwater Infrastructure improvement (Quantified Ventures, 2021), automated payouts and transactions can be initiated from a hybrid smart contract between the stakeholders based on the reduction percentage of stormwater runoff that is queried from stormwater IoT sensors by DONs.

Implication for Engagement of Stakeholders

By executing performance-based financing of sustainable infrastructure, all actors participating in the infrastructure project would be represented with a decentralized identity (DID) on the blockchain containing a unique ID, a public cryptographic key, and other attribute descriptions of the digital identity (Avellaneda et al., 2019; Davie et al., 2019; Li et al., 2019). A decentralized trust web is established through the verifiable credentials of decentralized identifiers (Lux et al., 2020). DIDs contains a stakeholder’s unique characteristics such as location and KYC information without third-party custody (Rivera et al., 2017; Takemiya & Vanieiev, 2018). The application of

DIDs in the performance-based financing example (Figure 3-6) represents the payor, the investors, and the project provider that each interacts with the hybrid smart contact on the blockchain. All DIDs are referenced on a blockchain to increase tamper-resilience and immutability of the data (Schletz et al., 2022). Furthermore, DID-based systems remove the need for any centralized governing authority to handle personal credentials and information, improving trust and communications in a cost-effective way (Hyperledger, 2021; Li et al., 2019; Sporny et al., 2021).

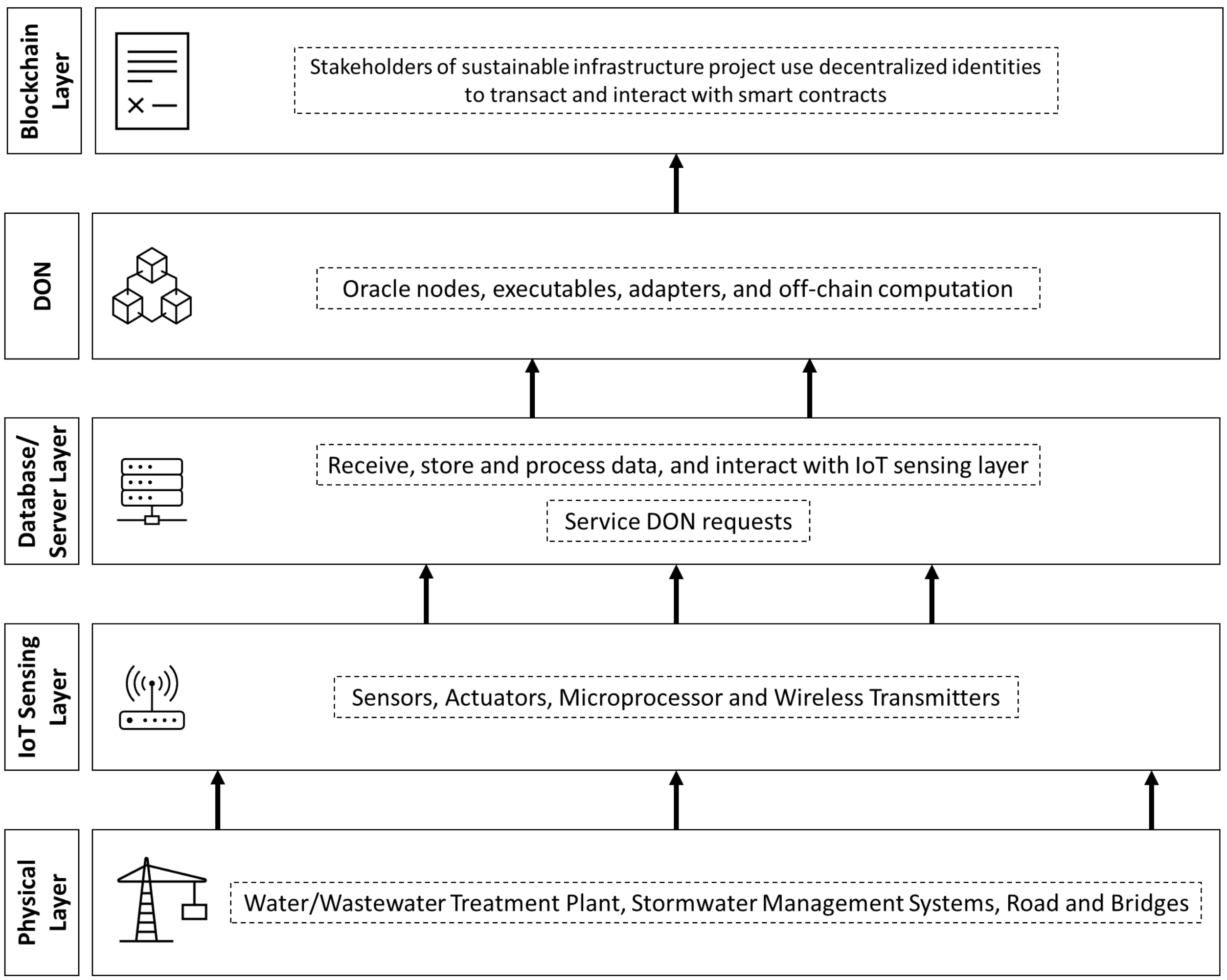

Figure 3-7. Overview of the different components of an infrastructure IoT-Oracle-Blockchain impact financing process

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3.5 Conclusion

The financing gap for sustainable infrastructure assets is largely due to a mismatch between the risk-return profile of the source of financing and the business model of the infrastructure asset. The funding or revenue-generating capacity of infrastructure, as well as its cost structure, inform its valuation and risk profile, and thus the financing sources that best meet the needs. Traditional infrastructure investment characteristics as well as performance benchmarks for investors often deviate from the conventional sentiment of infrastructure as a market-decoupled, stable-yield generating asset. This, in turn, increases the already-elevated risk premium of sustainable infrastructure and lowers its financial attractiveness. This paper argues for the use of blockchain technology and decentralized oracle networks (DONs) to better indicate infrastructure risk profiles and reduce the cost of capital for the financing of sustainable infrastructure and smart cities.

The contribution of the research design model is threefold: First, the paper reviews existing literature in infrastructure finance, performance-based sustainable infrastructure, and smart cities financing mechanisms, and blockchain and oracle technology. Second, a rationale and justification are argued for the adoption of blockchain-based sustainable infrastructure finance. The paper describes a holistic view to integrating all the currently disjointed data flows and breakdown of confidence in centralized institutions into a shared and interoperable "internet of infrastructure data" architecture. This concept reconciles data segments from various infrastructure systems, digital signatures for data authentication, DONs, decentralized identities, and trust minimization processes. Third, the architecture builds on blockchains, DONs and IoT technologies to ensure complete data traceability over the sustainable infrastructure financing process by representation of real-world asset performance or conditions on the blockchain and automating transactions between DIDs of stakeholders in a trusted and transparent approach. DONs enable off-chain data to be brought on-chain while addressing centralization concerns of single data sources. Through these features, the combination of blockchains and DONs improves data quality, availability, and transparency.

The integrated data flow framework and digitization of the assets improve coordination of decentralized governance among stakeholders in performance-based financing of sustainable infrastructure. As more trusted data sources become available for digital twins of infrastructure assets, data granularity and opportunities for cross-validation will increase, along with performance transparency and accountability. The integration of DONs will accelerate adoption of blockchain-enabled financing, and integration of DIDs for all stakeholders will benefit auditability and verifiability for counterparties. More decentralized, reliable and verifiable retrieval of data serve the purpose of reducing the cost of capital to a cost similar to that of software (blockchain), conferring a discount in the bond and debt market, or introducing new revenue streams through the data markets and managed data platforms (e.g., stormwater flows, traffic management, communication services, data processing services). Ultimately, transaction efficiencies will increase and a more trusted and accurate depiction of the underlying asset for investors to evaluate will be available, lowering the risk premium of sustainable infrastructure. Blockchains that integrate the use of DONs link stakeholders with their investment incentives and real-time infrastructure performance data streams offers efficient financing to close the infrastructure finance gap.

Chapter 4 Blockchain for Sustainable Agriculture Finance: Smart Contracts Facilitating “Pay-For-Outcome” Models

4.1 Introduction

Excess nutrient input to natural waters can lead to eutrophication, the process by which algae blooms occur leading to subsequent hypoxia and degradation of water quality. Eutrophication in the Great Lakes region has been shown to be a result of increased agriculture activities (Baker et al., 2014; Kerr et al., 2016). Due to the degradation of water quality and excess nutrient input, water and wastewater treatment plants need to be upgraded or refurbished to meet usage standards straining local government budgets.

To date, regenerative agriculture incentives to reduce negative impacts rely on market push-based programs, including “pay-for-practice” incentives led by federal or local governments or philanthropic entities that pay agriculture producers. Examples include the Conservation Reserve Program Field Border Buffer Initiative, the Environmental Quality Incentives Program Organic Initiatives, and the Conservation Stewardship Program. Due to funding priorities and public budget deficits, push-based mechanisms are not a sustainable long-term solution for catalyzing wide adoption and scaling of regenerative agriculture (USDA, 2022). The U.S. Farm Bill incentivizes are not sufficient to convert the required area of land to sustainable practices to see noticeable improvements in the water quality of the Great Lakes (Keitzer et al., 2016; Sowa et al., 2016). Over 50% of agricultural land in the Saginaw Bay drainage area need to take up sustainable practices to see meaningful improvements in water quality (Sowa et al., 2016). However, the

United States Department of Agriculture Economic Research Services (2016) shows approximately only 8% of planted corn acres around the Great Lakes took part in U.S. Farm Bill Conservation Programs. Studies have also shown that farmers are likely to return to conventional agriculture practices when temporary government subsidies end (Ariana & Maria, 2018; Sahm et al., 2013). Capital market incentives are potential solutions for long-term sustainable practices adoption as environmental, social, and governance (ESG) sentiment grows (Gernego et al., 2022; Makarenko et al., 2022). New market-based approaches are being developed for climate change mitigation, ensuring clean water, and halting biodiversity loss to achieve the United Nation's Sustainable Development Goals (Salzman et al., 2018; Sattler et al., 2013). The case study below is an example of such an approach.

4.1.1 Case Study

The Soil and Water Outcomes Fund is an innovative market-based approach implemented by the Iowa Soybean Association and Quantified Ventures to incentivize sustainable practices (Cargill, 2020). Investor capital is pooled in the fund for farmers to utilize for transitioning to more environmentally friendly practices, leading to reduced nitrogen and phosphorus concentrations in water, and more carbon retained in soils. The beneficiaries of the improved water quality and increased carbon sequestration pay out the fund investors. Considering multiple outcome metrics and identifying the corresponding beneficiaries enables the fund to pay out much more desirable per-acre payments than existing government programs to farmers. The mechanisms of the "pay-for-outcome" (PFO) regenerative agriculture incentive model are visualized in Figure 4-1. As of 2021, the fund has incentivized a 260% reduction in CO_2-equivalents, and a 28% and 27% reduction in nitrogen and phosphorus leakage, respectively, compared to the baseline "business-as-usual" practices (Soil and Water Outcomes Fund, 2021).

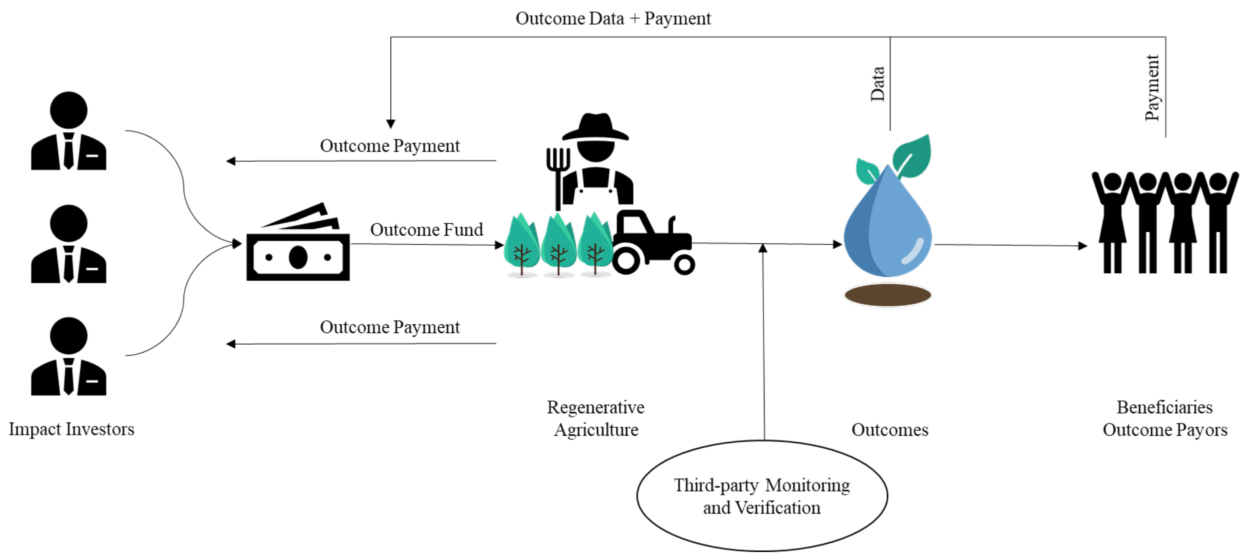

Figure 4-1. Outcome-based regenerative agriculture financing model (adapted from Quantified Ventures).

4.1.2 Literature Review

Performance-based incentives arise due to governance constraints in conventional approaches identified by Transaction Cost Economics (TCE). In his seminal paper "The Nature of the Firm", Ronald Coase analyzed how transaction costs lead to the existence of firms and theorized firm and market dynamics (Coase, 1937). Williamson (1975, 1981) drew insights from Coase's work and formalized as well as operationalized the theory of Transaction Cost Economics (TCE). TCE examines complex transactions between economic entities that have bounded rationality and are subject to opportunism. The costs of the transaction are influenced by asset specificity, uncertainty, and frequency of the transaction (Ménard et al., 2008). Transaction costs are defined as "costs associated with the activities that are not directly productive but are engaged in only as a consequence of the need to coordinate exchange among the transactors." (Masten, 2021).

The case study illustrates transaction costs in a PFO setup including evaluation of model feasibility, engagement with willing farmers, identification of outcome beneficiaries as well as partnering with a third-party to monitor and verify the outcomes require effective communication, coordination, and agreement from multiple entities (Hernández, 2017; Martin & Clapp, 2015; Quantifies Ventures, 2021; Ranjan et al., 2020). Measuring outcomes often requires considerable effort in data procurement and subsequent analysis. In addition, the validity of measurements are frequently disputed (Lancefield & Gagliardi, 2016). Lack of consensus on the data typically are due to not knowing whether the desired results have actually been achieved and how much the outcomes were a direct result of the implemented changes. Pay-for-outcome financing models can also be costly and risky due to a lack of standardization while simultaneously producing unpredictable outcomes. The beneficiaries don't always accrue the expected outcomes, and thus the financiers may be under-rewarded for their investments, especially when the result is hard to achieve or monitor (Brand et al., 2021). Another major impediment to widespread adoption of outcome-based financing, is that the cost of developing the financing structure, which oftentimes represent a significant percentage of the debt issuance, leading to high transaction fees, illiquidity, and high cost of capital that create barriers to investment (Joffee, 2016; Strong & Preston, 2017). This has been a challenge for issuance of impact bonds which exhibits risks and uncertainty around performance metrics, the cost of forecasting and measurement infrastructure, in addition to developing and structuring the contractual agreement (Brand et al., 2021).

Considered a high-intensity incentive framework, PFO mechanisms can also introduce gaming and issues of commitment that weaken the incentives and simultaneously increase the administrative transaction cost (Musso & Weare, 2020). The costs and benefits of what has been referred to as "incentive intensity" is illustrated in Figure 4-2 (Musso & Weare, 2020). The figure communicates that: (1) as incentive intensity increases, costs and benefits of performance management increase as well, (2) difficulty of measurement or demands for accountability could narrow the efforts to a singular goal which could limit the benefits of higher incentive intensities, (3) marginal costs increase is larger than benefit or incentive intensity increases. With increasing incentive intensities, the legitimacy of the key performance indicators is likely to be called into question. Data tampering and manipulation can occur to achieve desired outcomes. Thus, more resources and effort are required to corroborate the data veracity thereby increasing overall costs and expenses. For a more in-depth discussion, please refer to (Musso & Weare, 2020).

Distributed ledger technology (DLT) known more commonly as blockchain has the potential to disrupt many sectors of the economy, addressing the informational and transactional inefficiencies of firms and organizational models (Tapscott & Tapscott, 2016). The decentralized characteristic of blockchain in conjunction with trust generation through cryptographic algorithms, direct peer-to-peer interactions, and minimized counter-party risk has deep implications for the field of economics (Abadi & Brunnermeier, 2018; Catalini & Gans, 2020; Evans, 2014). While blockchains are appealing and there has been ample research on cryptocurrencies and specific

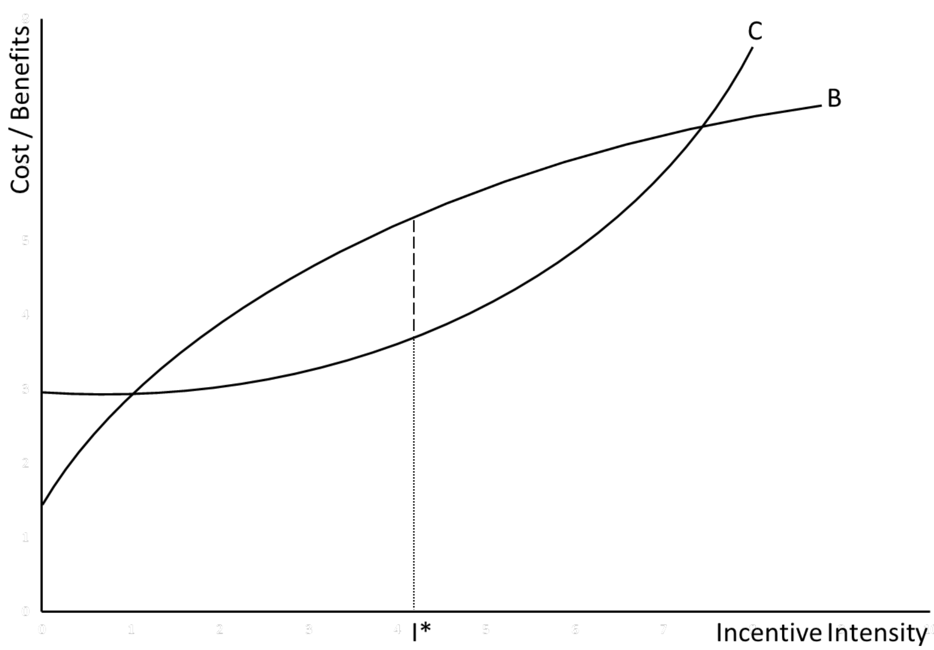

Figure 4-2. The cost and benefits of achieving performance or specified outcomes as incentive intensity increases. The total benefits exceed the costs by the greatest amount at optimal incentive intensity at I. Source: Musso and Weare (2020).*

applications of blockchain, the dearth of literature on blockchain applications for environmental governance is more skeptical (M. Bublitz et al., 2019; Rocha et al., 2021). These authors argue that the potential benefits of blockchain are still largely aspirational, and do not cite empirical studies. This sentiment follows the broader recognition of the technology's future potential. For example, Gartner (2021) argues that blockchain adoption has been slower than expected. Saberi et al. (2018) point out that the current cycle of blockchains falls in the "Peak of Inflated Expectation" phase where expectations of the technology are likely inflated, and an understanding of the limitations and pitfalls is required. The limitations and challenges include technical expertise and knowledge, scalability, privacy and security, and regulatory standards (Mendling et al., 2018; Swan, 2015). In their study on cryptogovernance in environmental management, Adams and Tomko (2018) state that substantial research is needed before the promises of blockchains and smart contracts can become reality as most projects remain conceptual and proponents have glossed over detailed discussions. Pisa (2018) cautions against unrealistic expectations of blockchains during the blockchain hype and cites overlooked obstacles in practical adoption. The same author also suggests utilizing blockchain in an application-specific approach since value propositions of blockchains vary greatly across use cases. In Howson et al. (2019)'s study on utilizing blockchains for payment for ecosystem services to incentives carbon sequestration, the authors suggested that more case-specific demonstrations and critique are needed for future recognition and adoption blockchain-based solutions.

To address the knowledge gaps mentioned above, the current study examines performance-based incentives and blockchain-based financing through the lens of transaction cost economics. We contend that blockchain-based financing mechanisms are able to address the transaction cost shortcomings in performance-based incentives. We further present a proof-of-concept (POC) using blockchain to facilitate pay-for-outcome (PFO) financing models and environmental governance in regenerative agriculture. We hypothesize how blockchains can positively shift the cost and benefit curves of TCE analysis of performance-based incentive approaches and of a blockchain-based PFO mechanism. In the POC, we employ a blockchain wallet addresses, an Ethereum smart contract for value distribution, the Accuweather application programming interface (API), and an Chainlink oracle-link between these the smart contract and weather data from Accuweather. It illustrates the transaction cost reductions and limitations in a blockchain-based PFO financing mechanism for regenerative agriculture incentive scheme, such as the outcome-based fund described earlier.

As a market-based approach, the blockchain-based structure has the potential to be more cost effective than conventional "pay-for-practice" approaches for conservation. In addition, because blockchain-enabled transactions lower the cost of capital and automate third-party verification, the process should be more cost effective than non-blockchain PFO mechanisms, thus lowering the barriers for regenerative agriculture adoption. The methods and tools utilized as well as the hypotheses of the study are described in Section 4.2. Section 4.3 discusses how blockchains can increase the net benefit of PFO mechanisms from a TCE perspective, as well as the scalability, limitations, and implications of the presented blockchain POC. Section 4.4 concludes and discusses the implications of the study. To the best of the authors knowledge, this is the first paper to examine transaction costs of integrating blockchain technology for performance-based incentives in regenerative agriculture. By utilizing the TCE framework, this study shows how blockchains will be the driving force for a sustainable future by reducing costs and efficiently managing transactions.

4.2 Methods and Hypotheses

The Solidity smart contract can be found on GitHub[3]. First, the use case is setup in the context of a blockchain-based PFO scheme. Then the method and tools are discussed. The tools consist of two main components: (1) the Ethereum Kovan testnet as the underlying blockchain with three Ethereum wallet accounts and a hybrid smart contract and (2) precipitation data is accessed through the Accuweather Chainlink oracle data provider. Each component is described below.

4.2.1 Use Case

The use case tests whether a unique wallet (farmer) can be rewarded for outcomes such as reduction in fertilizer (nutrient) leaching using a blockchain-enabled smart contract. The POC setup of the financing scheme is one representative farmer who carries out regenerative practices. Payments are made to the farmer from the Soil and Water Outcomes Fund to incentivize and sustain regenerative practices. The beneficiaries purchase the positive outcomes of the regenerative practices. The proceeds are paid back to the fund investors. In the POC, precipitation data (Accuweather API) was used a proxy for nutrient input since it is a strong predictor of nutrient input in water bodies (Elrashidi et al., 2013; Sinha et al., 2017). Nitrogen or phosphorus sensors are not widely deployed in agricultural field practices. For the demonstration location this study, no real-time water quality data is available and oracles for interacting with water quality APIs do not exist.

[3] https://github.com/Enveblockchain/Ag_payforoutcome

4.2.2 The Ethereum Blockchain

The Ethereum blockchain is programmable and decentralized applications can be written in the Turing-complete language, Solidity (Buterin, 2014). The core technology of the POC application is an Ethereum hybrid smart contract. The public identities on the Ethereum are made up of wallet "accounts". User private keys give rights to access externally owned accounts (EOAs) and the smart contract have addresses themselves termed contract accounts (CAs). Messages and transactions can be sent between any account holding a balance by signing transactions. CAs code executes when deployed on the blockchain and writes to internal storage (Buterin, 2014). EOAs or other CAs can call accessible functions on the smart contracts to initiated transactions (Bashir, 2018)

The PFO setup was instantiated by creating three EOAs and one hybrid smart contract on the Ethereum blockchain. The hybrid smart contract initiates a data request from the off-chain resources and the oracle receives and processes the request (Caldarelli et al., 2020). The EOAs represent the financier, the farmer, and the beneficiaries. The hybrid smart contract governs the PFO transaction and was written and compiled in the Remix integrated development environment (Remix, 2022). The contract was then deployed on the Kovan testnet using the injected web3 provider (i.e., Metamask). For illustration purposes, the contract was written in a straight-forward manner without security considerations.

The variables are the payout incentive (outcome_Payment), the precipitation in the specified location over the past 24 hours (precip24), and the three addresses of the capital provider (Financier), the farmer (ServiceProv), and the beneficiaries (Gov) defined as the payable hashes of their respective EOAs. The state variables also include a storage for the unique oracle request identifier (loccurcondition_RID) and the oracle job identifier (loccurcondition_jobId). An oracle job specifies a series of tasks that needs to be carried out to procure off-chain data and send the data back on-chain to the smart contract. The reserved function (receive) paired with the payable modifier allows ether to be deposited into the smart contract. The first function (withdrawFromContractBalance) enables the farmer to withdraw capital held in the smart contract (i.e., the up-front capital to enable farmers to implement regenerative agriculture practices from the financier). The next set of functions allows the beneficiaries to make payments (addBenefitPayment) that only the financier can withdraw (getBenefitPayment). The next set of functions initiates and completes the request-and-receive cycle that retrieves off-chain outcome data through an oracle. requestLocationCurrentConditions sends the data query as well as the payment for oracle services. Next, fulfillLocationCurrentConditions is the receive function that can only be called by the oracle that executed the data query with the unique oracle request identifier, in this case, loccurcondition_RID. Upon the call-back, the off-chain data is stored in the functions storeLocationResults and storeCurrentConditionsResults. The outcome metric that informs who receives the PFO payment is stored in storeCurrentConditionResult (precip24). The last function (outcomePayment) transfers the PFO payment to the financier if the desired outcome is achieved. The function enables transfer to the financier's wallet if the precipitation amount, just received on-chain by the callback mechanism, remains lower than a specific threshold.

The example geographic coordinate location does not, for the proof-of-concept application, have nitrogen or phosphorus sensors deployed in the field. No real-time water quality data are publicly available at the time of this writing. In addition, oracles that have executables and adapters for interacting with water quality APIs do not exist. Due to the limiting factors mentioned above, precipitation data from the Accuweather executables and adapters is used as a proxy for nutrient input into water bodies. Precipitation has been shown to be an accurate predictor for nutrient input under "business-as-usual" fertilizer use. Sinha et al. (2017) showed that due to climate-change induced precipitation increase, riverine total nitrogen loading will also increase by 19 ±14%. Nutrient inputs would need to decrease by 33 ±24% to offset the increase. Elrashidi et al. (2013) found that total soil nutrient loss from agricultural nonpoint sources were greater in wet years (i.e., more precipitation) than in dry years. Hence, in our POC, precipitation will be used as a proxy performance metric for nutrient input into water bodies.

4.2.3 Chainlink Oracle

Linking the off-chain Accuweather precipitation data to the Ethereum hybrid smart contract is realized using Chainlink oracles. The hybrid smart contract makes a request to the Chainlink oracle through a sendChainlinkRequest that sends the request and LINK amount to the specified oracle address. The transferAndCall function imported within the ChainlinkClient contract from the ERC677 protocol, enables transfer of LINK tokens to the governing oracle contract and simultaneously initiate actions based on data from the sendChainlinkRequest. The actions include calling the onTokenTransfer function in the receiving oracle contract, which communicates the request from the ChainlinkClient to off-chain oracle nodes. The oracle contract communicates by emitting an OracleRequest event that has the request specifications from the client hybrid smart contract. The emitted event is monitored and recorded by the off-chain oracle node which initiates a job request to the Accuweather API. Once data is retrieved from Accuweather, the off-chain node calls the fulfillOracleRequest function in the oracle contract to move the requested data back on-chain. In fulfillOracleRequest, it uses the callback contract address initially defined in the hybrid smart contract to return the result to the ChainlinkClient. The sequence of actions is visualized in Figure 4-3.

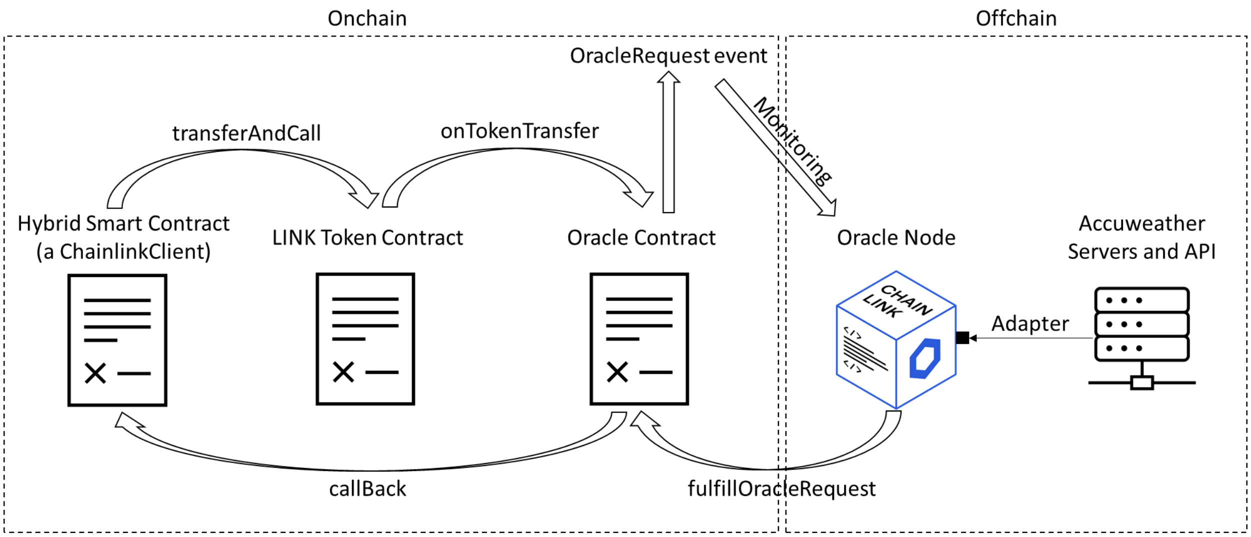

Figure 4-3. Data flow from on-chain request to off-chain fulfillment.

4.2.4 Accuweather Application Programming Interface (API)

The AccuWeather API provides users access to location-based weather data via a RESTful web interface. REST, or REpresentational State Transfer, is an data access standard for applications on the web to communicate with on aother (Codecademy, 2022). Given an API key, the user can search for a specific location with geographic coordinates, postal codes or city names using the Locations API, which responds with a location key. The location key that is returned can be used to access other API endpoints such as current conditions or daily forecasts weather data APIs.

4.2.5 Hypotheses

Under TCE, the increased intensity of incentives may improve performance but very likely at the expense of higher governance and administrative costs, while simultaneously inducing malicious behavior such as gaming schemes (Musso & Weare, 2020). Using qualitative graphical analysis, the impact of transactional, governance, and contextual factors affect changes in the cost and benefit curves can be explored (Figure 4-2). The cost curve may shift up from C_0 to C_1 for incentive mechanisms that request public accountability due to measurement ambiguity, leading to increase in cost of monitoring, measuring, reporting, and auditing. Other costs include assessing the viability of performance-based setup, communication and coordination with willing farmers, as well as engaging beneficiaries. In PFOs, measurement devices, sensors, and other IoT equipment may be set up in remote locations, limiting physical access, incurring unreliable data due to tampering or sensors going offline (Sicari et al., 2015). Hence, redundancies in deployment of data aggregation and edge computing systems may be required, increasing cost. The third-party verifier would also be a potential for a single, centralized point of failure. Counter-party risk and low trust in centralized entities, such as evaluators and rating providers increase transaction costs further (Nicole & Robert, 2013; Tang et al., 2013; Tomasic & Akinbami, 2011). Given the upward shift in cost, the net benefits of performance-based incentives would decrease. In cases where above accountability issues are exacerbated or even participating actors work to game the performance metrics, the cost curve could increase to C_2, reducing any net benefits to zero. In these extreme cases, the use to use of performance-based incentives should be called into question (Figure 4-4). Our hypothesis is that blockchain-based technologies can shift the cost curve PFO management practices down from C_0 to C_3 (Figure 4-4). This is primarily due to the properties of smart contract programmability enabling automation (Puri et al., 2021) where conditional decision-making based on off-chain data such as those collected using IoT can be automated and streamlined (Christidis & Devetsikiotis, 2016; Jiang et al., 2019). Smart contracts enforce commitment through automated transaction execution based on performance outcomes, reducing uncertainties (inducing a shift from C_0 to C_3). Since blockchains provide benefits such as immutability and transparency, the need for third-party monitoring, verification, and fund management is removed, further reducing costs.

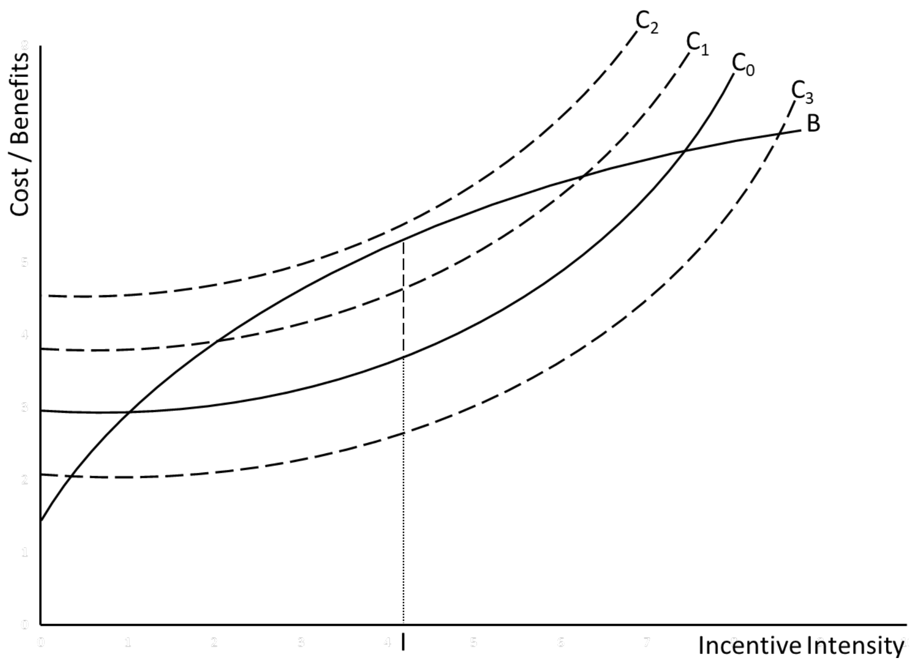

Figure 4-4. Effects of curve shifts on the cost of performance-based incentives shifts in cost curve. Adapted from Musso and Weare (2020).

4.3 Results and Discussion

To illustrate the potential and limitations of the POC, the paper applies a blockchain-enabled process to the Soil and Water Outcomes Fund market-based incentive mechanism described in Figure 4-1. The POC has three characteristics that are applicable for the use case of regenerative agriculture incentives. First, smart contracts make payments tamper-proof. In hybrid smart contract presented in this study, the farmer who receives the incentive payment is defined as the state variable ServiceProv. The contract address cannot be modified once it is deployed on the blockchain. This means that any transaction initiated by the transfer function will be sent to the correctly designated recipient. While the smart contract in this proof-of-concept includes only one farmer, the number of participating farmers can be conveniently scaled to include an arbitrary number of recipient addresses. The hybrid smart contract serves as a trusted monetary distribution escrow, ensuring payments are received by the correct recipients and timely settlement is achieved. Second, an immutable record of all transactions occurring from the pay-for-outcome scheme is etched in Ethereum blockchain. These records are visible and can be queried by anyone with an internet connection since the Ethereum blockchain is a public ledger. Third, the smart contract allows for flexible timing of transactions as long as it remains funded by the investors. The smart contract acts as an escrow from which farmers can withdraw a pre-specified amount. Payments cannot be voided or stopped by an individual authority thus the farmers in this case can depend on timely deliveries of funds.

Fallback functions that terminate the contract can also be built-in the contract in case of any extreme weather conditions that may distort or effect monitoring outcomes. Such functions will only activate or trigger if certain abnormal (i.e., out of range) conditions occur. They could then be called by any participating entity after reaching an agreement on terminating of the contract. Outcomes for PFO scheme can be extended to other metrics and do not have to be limited to nutrient reduction as long as suitable metrics or proxies can be defined, particularly for conservation performance payments (Dickman Amy et al., 2011; Engel, 2016).

4.3.1 Proof of Concept Blockchain Payment

The POC addresses financing issues by lowering transaction costs for all payment processes. The PFO transaction comprises five steps executed on a blockchain: (1) the deployment of the smart contract, (2) the initial investment from the financier that send and stores funds in the smart contract representing the Soil and Water Outcomes Fund, (3) the farmer transfer funds locked in the smart contract to their wallet, (4) initiate the request-and-receive cycle including Link token payment to the Accuweather Chainlink oracle, (5) based on the outcome of the data from Accuweather, the beneficiaries send funds to the smart contract for the financiers to withdraw. For all these function calls and executions require Ether to run and Link to access the oracle services.

Transaction fees are not proportional to the amount of Ether being transferred. Function calls required gas fees in gwei. Only when accessing the Accuweather oracle services are Link tokens required. Table 4-I shows that when testing the POC on the Koven testnet in April 2022, all transactions combined (shown in Figure 4-3), totaled 0.00889559 ETH. This is equivalent to $26.52 USD in total to execute the pay for outcome transaction (Table 4-I). Given that this includes the potential transfer of funds across the globe, agnostic of national boundaries, a tamper-proof benefit distribution mechanism based on Accuweather, and an immutable record of the whole process, the operational transaction costs will be considered lower than the incentive being paid for regenerative agriculture adoption. Additionally, the POC shows that PFOs can be executed on a blockchain in a series of streamlined trusted transactions. Capital providers are less hesitant to invest if they can be assured that funds are transparently delivered to the right entity and the return on investment is based on environmental outcome conditionality.

Table 4-I. Ethereum blockchain transaction fees for the PFO smart contract in April 2022

Transaction	Ether	US Dollar equivalent (~$2982.13)
Smart contract deployment	0.00818347	$24.40
Outcomes fund investment	0.00004737	$0.14
Farmer incentive payment	0.00007878	$0.23
Weather data procurement	0.00048011	$1.43
Outcome payment	0.00010586	$0.32
Total	0.00889559	$26.52

The transaction fees in Figure 4-4 and Table 4-I capture data aggregation, smart contract execution, verification, and payout components associated with PFO schemes. The cost of negotiating payout schemes for farmers are not considered and neither were the development costs, hence the focus was on execution of key operational elements. It has been argued that the cost of software-driven execution is on the order of 30 basis points (0.3% of contract value) versus 150 basis points (1.5% of contract value) for traditional execution with intermediaries (Wolfberg, 2022). While there is no empirical validation, it is unclear whether the savings can be realized. A recent use case for blockchain tokenization of energy infrastructure argues for similar cost savings (Tian et al., 2020). While the results of the blockchain-enabled funding and financing are appealing in theory, the POC indicate several obstacles in practice. For example, the dependence on cryptocurrencies as the medium of exchange leads to additional barriers. An Ethereum smart contract can only transfer Ethereum Virtual Machine-compatible cryptocurrency such as Ether (ETH), Link (LINK), and Polygon (Matic). Wrapped tokens and coins that allow cross-chain/multichain functionality remain underdeveloped and are subject to hacks. All participating entities in the POC that use fiat currency like the US dollar would need to convert it to ETH using crypto-exchanges or procure ETH through mining or staking. The payment recipients would also need to convert the cryptocurrency to US dollars. Currently, the most straight-forward way to convert crypto to fiat, and vice versa, is through a crypto-exchange that requires a bank account that complies with know-your-customer (KYC) and anti-money laundering (AML) procedures, which add to the barriers of setting up and scaling the PFO mechanism. In the conversion process, the crypto-exchanges charge fees as well. Factors such as the payment method, order amount, volatility of the market conditions and the exchange's liquidity determine the fees in the process, adding uncertainty to the process. Lastly, the fluctuation of cryptocurrency value remains a concern. This could raise the cost of payments unexpectedly if cryptocurrency value compared to the US dollar grows exponentially.

4.4 Conclusions and Implications

The POC in this study shows the potential as well as the limitations of applying blockchains to PFO schemes in regenerative agriculture. Blockchains provide a bevy of advantages for PFO schemes. The transactions are tamper-proof, the blockchain maintains an immutable record of how funds were distributed in the past, and payments are made timely. Several obstacles exist in practice for all participating parties in the PFO scheme to benefit from blockchain use. If technological literacy is lacking, a fair distribution of funds is arbitrary and subject to centralized actors such as the smart contract writer and deployer. Furthermore, dependence on cryptocurrencies as the medium of exchange when cryptocurrencies are not yet widely accepted leads to additional barriers.

Conditionality for the PFO scheme was based on precipitation data from Accuweather. Precipitation was used as a proxy for water quality as previous studies have shown a strong correlation between the two metrics. With the combination of smart contracts, oracles, and environmental data, the PFO scheme becomes self-enforcing, thus, the scalability of this type of incentive mechanism is high due automation. However, nutrient monitoring in water such as nitrogen and phosphorus is not readily available at low cost. As such monitoring stations are sparse and currently there is no existing oracle that provides in water quality data from off-chain APIs. Future development of such oracles is needed for a more accurate and precise PFO scheme facilitated on the blockchain. The financial efficiency and sustainability that smart contracts provide is evident in this study. It lowers the transaction cost to below $30 for such a complex PFO scheme while bringing about tamper-proof benefit distribution and an immutable record of all transactions.

Blockchains provide trust, transparency, and transaction automation. Costs are reduced with tokenized securities through disintermediation and automation which, in turn, reduces size and liquidity requirements (Schletz, Nassiry, et al., 2020). Costs of financing utilizing blockchain-based securities can be reduced from an estimated 150 basis points (bps) to 30 bps (Wolfberg, 2022). Chen and Volz (2021) posited that blockchains can mobilize financial resources for sustainable infrastructure investments by minting green bonds at low cost on the blockchain and accessing certain markets through security tokens. This will allow small and mid-size enterprises (SMEs) to issue debt directly, cutting out the expensive services and fees of centralized financial institutions. By examining several financial institutions that have applied blockchain technology to bonds issuances, Pana and Gangal (2021) concluded that blockchains effect cost reduction by shortening the length of the settlement processes as well by decreasing the number of intermediaries. Pufahl et al. (2021) uses blockchain technology to address trust and efficiency across the agriculture supply chain, where payment failure, insufficient visibility, and high costs of obtaining information frequently occurs.

According to the Forum for Sustainable and Responsible Investment (2020), investors are already considering ESG factors in $17 trillion USD worth of assets and the market capitalization in this space will continue grow. Institutional investor sentiment to use a holistic approach to seek opportunities that advance environmental and social issues are dependent on the veracity and transparency of the underlying data, such as those associated with the use of proceeds of green (Li & Adriaens, 2021), sustainability or other bond issuances, or corporate bonds offered by leading ESG rated companies (Li & Adriaens, 2022). Piñeiro-Chousa et al. (2021) showed investor sentiment extracted from social networks positively influences the green bond returns, where the use of proceeds is dedicated to projects that seek to address climate change and water management. Zeidan (2022)'s sentiment analysis on finance professionals on ESG investing revealed that the strategy space, internal and external transaction costs, and data quality remain obstacles for integrating ESG into financial portfolios. With the increased appetite for sustainable investing, this will certainly benefit the growth of regenerative agriculture as the agriculture sector contributes 24% of the total CO_2-equivalent greenhouse gases emitted annually and is also a major contributor to low water quality (Bosch et al., 2014; IPCC, 2014; Nsenga Kumwimba et al., 2018). Tokenized green bonds recently proposed by the Bank of International Settlements indicates that not only can retail investors participate in green financing, but blockchain-enabled transparency on the green use of proceeds is communicated to all stakeholders (BIS Innovation Hub, 2021). Whether these automated transactions will lower the cost of capital for the issuer remains to be seen.

Chapter 5 Conclusions and Future Recommendations: Asset Pricing and Blockchain-based Solutions for Sustainable Infrastructure Financing

The analytical tools and techniques used in this dissertation produced novel insights to the price of environmental contamination, why blockchain technology is suitable for facilitating sustainable investments, and how blockchains can reduce transaction costs. These insights inform the valuation of sustainable infrastructure, de-risking the assets and lowering the investment barrier for private capital to bridge the finance gap in society's transition to a sustainable future.

Large amounts of capital reside in pension funds, sovereign wealth funds, and private equity firms with investment mandates and risk-return expectations that are well-aligned with sustainable infrastructure investment profiles. Sidelined capital in ESG-oriented private equity funds are projected to reach $11 trillion by 2026 (Eccles et al., 2022). Private capital has been slow to enter the sustainability initiatives due to uncertainty surrounding environmental/climate risks, asset performance, and internal rates of return (IRR) that do not meet investor expectations. This "dry powder" can be deployed to cover the infrastructure finance gap, particularly if environmental externalities and potential transaction costs are revealed for risk-pricing.

The data fusion and hedonic pricing approach in Chapter 2 revealed a misprice of environmental externalities in farmland value. Shadow pricing utilizing existing literature data from a proxy region was used to adjust for the externalities. For more accurate adjustments and pricing, empirical shadow pricing of the study areas will be required in the future. While the shadow pricing was implied using data from a study on farmlands in a different region, this work should be place-based to more accurately reflect the nitrogen and phosphorus risk pricing of these farmland assets. To improve the linkage of farm nutrient loading risk with cost of financing, and thus creating efficient financing opportunities as proposed in my research, the increasing deployment of IoT in farming will serve to better inform performance updates from the real assets. This opportunity is currently under review in a grant application to the Great Lakes Protection Fund, in which sending infrastructure from the Saginaw Bay Monitoring Consortium will be leveraged to connect performance in the physical and financial context. Based on my work on the integration of off-chain data (such as those derived from environmental sensors) onto a smart contract execution on chain (Chapter 3), it will become possible to fund and finance farming activities using green loans and ESG-linked agricultural bonds for more sustainable farming operations. Other potential research topics can be how shadow pricing can be accounted for in derivatives pricing in the Black-Scholes formula for options. The data fusion technique can be combined with other causal inference methods such as propensity score matching to discover the impact of environmental risks on financial securities such as municipal bonds and public company stocks.

Chapter 3 showed qualitatively how blockchains can be utilized in for sustainable infrastructure by using the Model method and a semi-systematic literature review approach. Future research directions can include pairing the proposed framework with the tokenization of real assets to close the financing gap. The premise of integrating digital infrastructure in farming or built assets with blockchain-based financing mechanisms will still take time to be realized. As Chapter 3 indicated, the conceptual model for linking off-chain performance data with on-chain smart contracts for efficient financing is just starting to emerge. My work provides a framework of future directions in this financial policy realm but asks significant questions as to the likelihood and speed of adoption in the practice. The potential barriers limiting or slowing adoption is as follow: a steep blockchain technology learning curve, underdeveloped policies on data privacy and cybersecurity, and trust in transitioning from using subject experts and consultants in the decision-making process versus consenting to automated execution through a smart contract. Nevertheless, the feasibility of the approach was demonstrated in Chapter 4 for an application in farming.

Chapter 4 provided a proof-of-concept of performance-based incentives for regenerative agriculture that revealed the value propositions of blockchains: low transaction fee, and increased trust and transparency. The study uses an existing oracle network to bring off-chain environmental data for on-chain decision making. The benefits of blockchain in terms of transaction cost economics were discussed in a qualitative manner. Future work will require a quantitative approach by first identifying the frictions that exist in incentive-based governance structures and finding the correct metric for measuring said friction. Once the friction metric is identified, causal inference models can be implemented to see if blockchain will actually be able to lower transaction costs. In addition, identifying the proportion that financial transaction fees make up the total transaction cost should also be carried out in future endeavors.

There are also other ample research opportunities with oracles, smart contracts, and Transaction Cost Economics. In the near-term, building oracles for the Environmental Protection Agency's Storm Water Management Model (SWMM) can be used to bring simulated green infrastructure performance metrics on-chain to inform financing mechanisms. Oracles can also host pricing models such as those developed in Chapter 2. Long term developments include interfacing smart contracts with internet-of-things technology developed in the Department of Civil and Environmental Engineering. The Center for Digital Asset Finance can be a hub to host decentralized oracle networks for financing sustainable infrastructure and smart cities in the future.

Insights from real asset valuation and application of financial technology developed in this dissertation presents a pathway and innovative opportunities for financing of sustainable infrastructure. In times when the negative impacts of climate change are imminent, bold and aggressive solutions are needed to accelerate our efforts in transitioning to an equitable and sustainable society.

Appendices

Appendix A Summary statistics for absolute nitrogen and phosphorus loading

Table A-I. Summary statistics for absolute nitrogen loading and phosphorus loading

	Unit	Mean	Std	Min	Max
Environmental Contamination					
N loading	kg	12465.29	31030.27	4.82	324242.10
P loading	kg	224.26	481.38	0.15	5315.71
P loading **(Agricultural land)**	kg	199.41	394.51	0.13	4376.25

Appendix B Distribution of Sale Amount per Acre

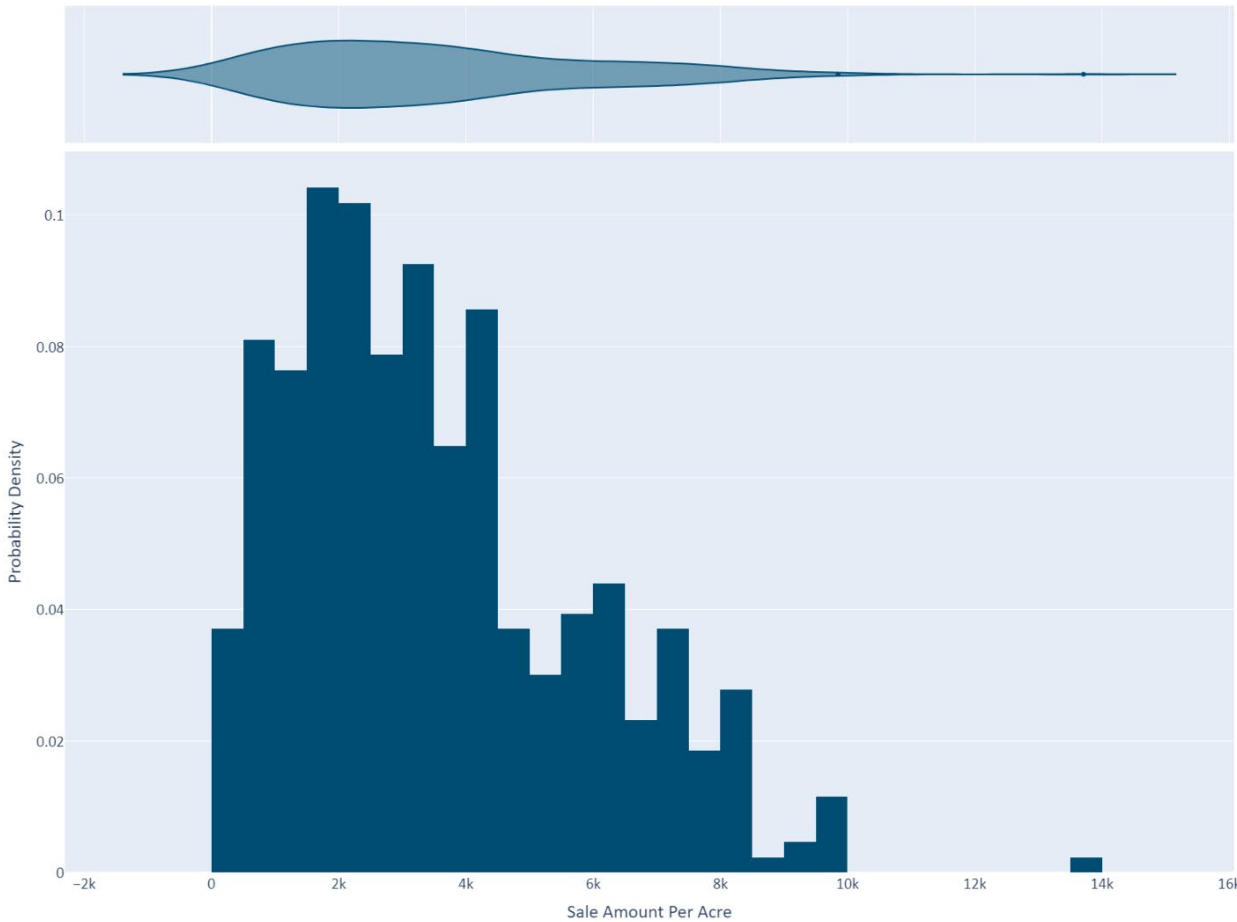

Figure B-1. Distribution of sale amount per acre (skewness = 0.799)

Appendix C Distribution of log-transformed Sale Amount per Acre

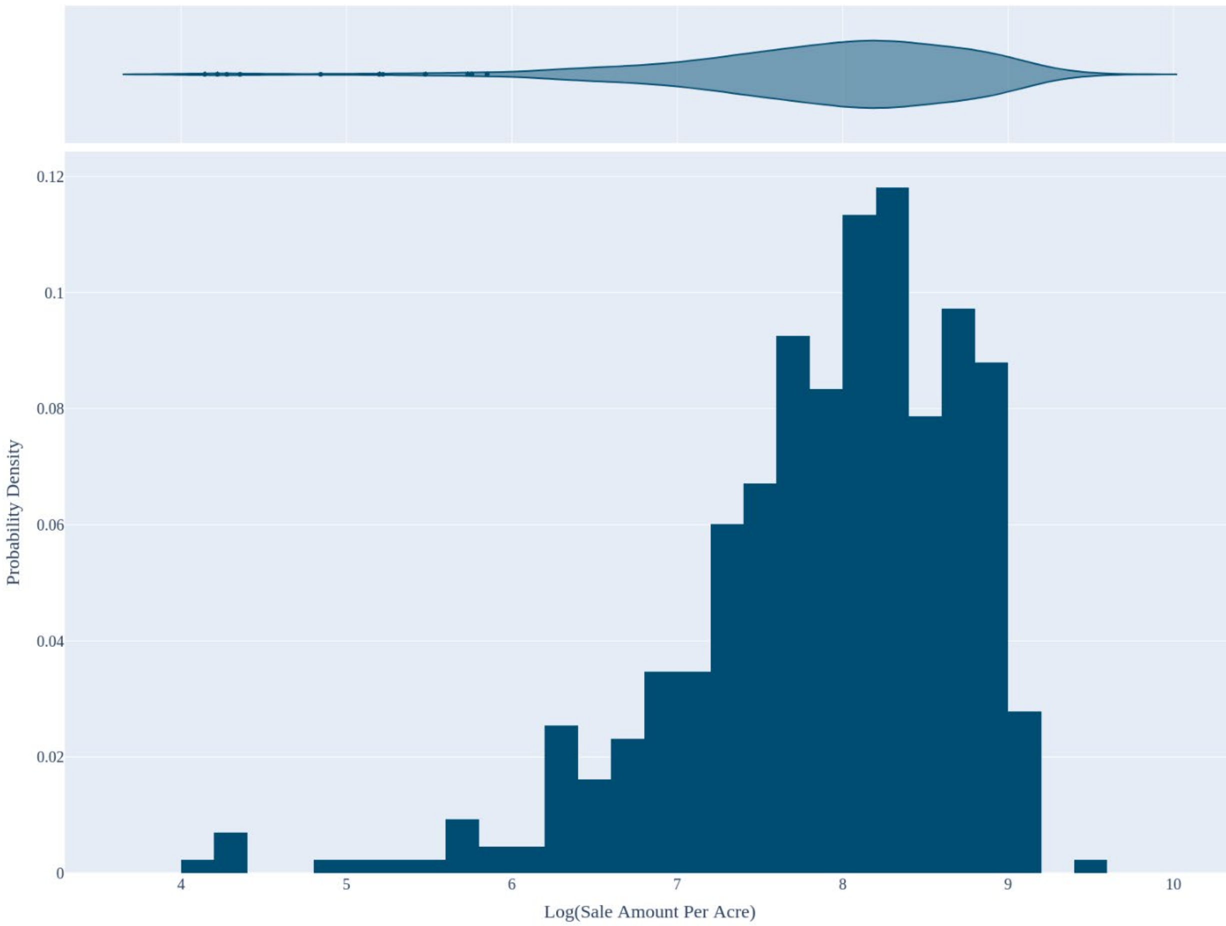

Figure C-1. Distribution of log-transformed sale amount per acre (skewness = -1.265).

Appendix D Pairwise Correlation of Nitrogen Loading Versus Phosphorus Loading.

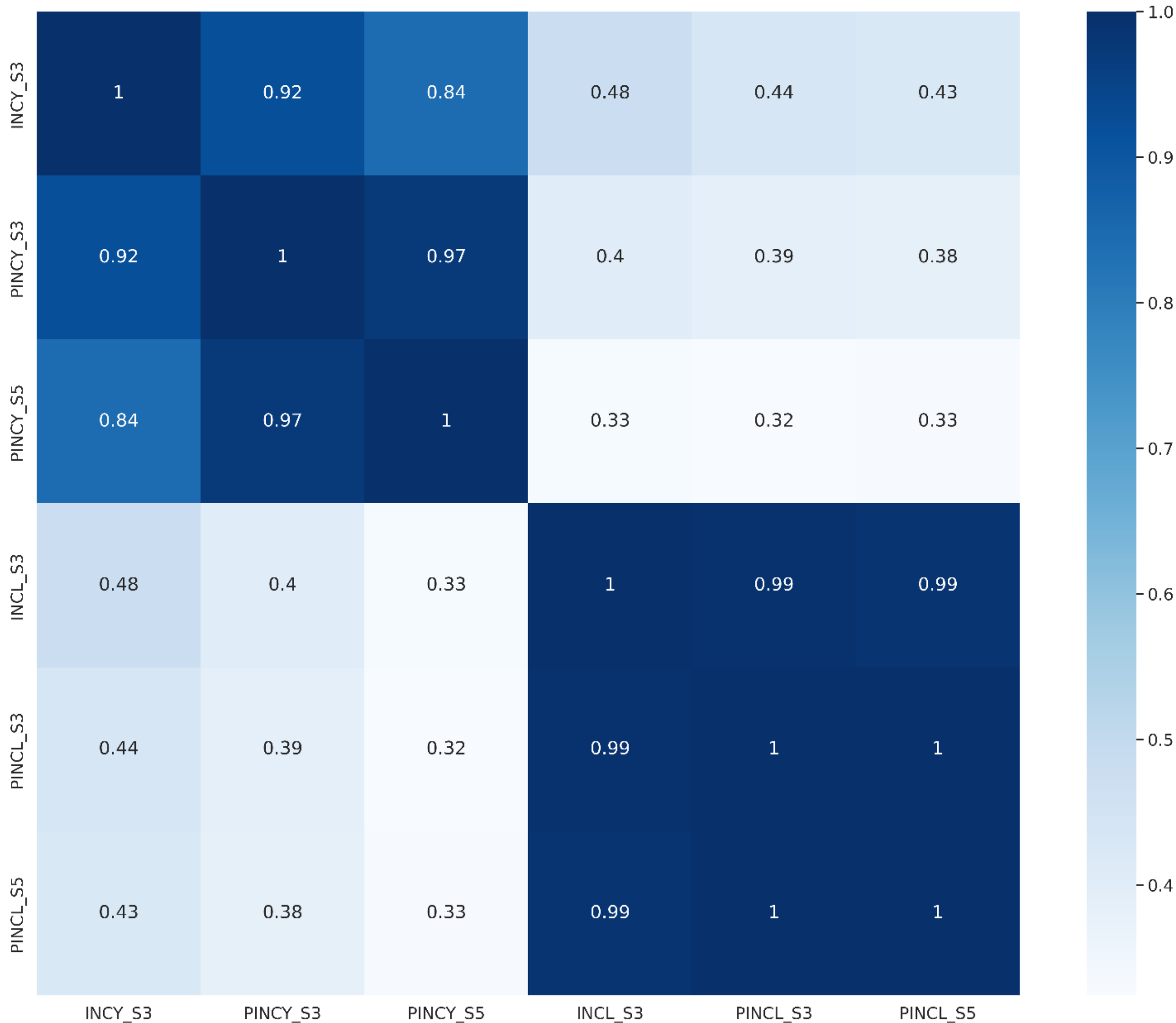

Figure D-1. Pairwise correlation of nitrogen loading versus phosphorus loading. Notation description is as follows: INCY_S3 (nitrogen loading from fertilizer), PINCY_S3 (phosphorus loading from fertilizer), PINCY_S5 (phosphorus loading from agriculture land), INCL_S3 (absolute phosphorus loading from fertilizer), PINCL_S3 (absolute phosphorus loading from fertilizer), PINCL_S5 (absolute phosphorus loading from agriculture land).

Appendix E Variance Inflation Factor

Table E-I. Variance inflation factor for nitrogen and phosphorus loading

Feature	*Variance Inflation Factor*
Nitrogen loading	22.89
Phosphorus loading	205.71
Phosphorus loading (Agricultural land)	121.08

Table E-II. Variance inflation factor for absolute nitrogen and phosphorus loading

Feature	*Variance Inflation Factor*
Absolute nitrogen loading	130.42
Absolute phosphorus loading	1003.34
Absolute phosphorus loading (Agricultural land)	533.12

Appendix F F-statistics and Corresponding Probabilities

Table F-I The F-statistics and corresponding probabilities

	F-statistic	*Prob(F-statistic)*
Nitrogen loading	4.338	3.34×10^{-9}
Phosphorus loading	4.647	4.35×10^{-10}
Phosphorus loading (Agricultural land)	4.707	2.92×10^{-10}
Absolute nitrogen loading	4.792	1.66×10^{-10}
Absolute phosphorus loading	4.844	1.17×10^{-10}
Absolute phosphorus loading (Agricultural land)	4.858	1.07×10^{-10}

Appendix G Absolute Nitrogen and Phosphorus Loading Hedonic Regression

Table G-I. Hedonic regression results explaining farmland sale amount per acre for absolute nitrogen and phosphorus loading (n=432)

	Nitrogen from fertilizer		Phosphorus from fertilizer		Phosphorus from agriculture land	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
SPARROW						
Absolute nitrogen loading	0.01***	0.001	-	-	-	-
Absolute phosphorus loading	-	-	0.77***	0.001	47.26***	0.003
Environmental Production and Consumption Variables						
Average NCCPI	1.74	0.885	1.17	0.922	-5.63	0.642
Cultivated land % of parcel	3817.34***	0.001	3788.39***	0.001	3967.27***	0.001
Forest area % of parcel	-560.77	0.763	-566.94	0.760	705.90	0.719
Grassland area % of parcel	873.21	0.684	815.81	0.704	1644.46	0.450
Soil organic carbon	0.05	0.379	0.05	0.351	0.03	0.525
Root zone depth	14.81***	0.003	14.73***	0.003	11.70**	0.016
Root zone available water storage	-5.61	0.197	-5.67	0.192	-3.38	0.438
Soil loss tolerance factor	-127.53	0.538	-138.47	0.504	-51.40	0.803
Drought vulnerable	622.81	0.197	602.78	0.211	701.51	0.146
Well drained	936.46	0.298	907.52	0.313	845.04	0.349
Poorly drained	649.10	0.488	623.05	0.505	387.40	0.680
Prime farmland if drained	259.49	0.479	251.09	0.493	306.96	0.402
Not prime farmland	-1472.07**	0.013	-1473.52**	0.013	-1181.89**	0.048
Farmland of local importance	-238.37	0.576	-239.29	0.574	-128.04	0.764
Built Production and Consumption Variables						
Acres	-9.65**	0.020	-9.68**	0.020	-8.15*	0.053
Noncropland area % of parcel	115.50	0.963	62.85	0.980	1065.68	0.678
Developed area % of parcel	374.13	0.945	345.24	0.949	1297.05	0.812
Representative slope	86.55	0.191	89.17	0.193	78.56	0.252
Distance to city	-0.02	0.270	-0.02	0.279	-0.012	0.476
Constant	-726.68	0.737	-599.02	0.782	-1613.30	0.462
R^2	0.189		0.191		0.186	

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