Socially responsible investing and multinationals' pollution

Evidence from global remote sensing data*

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October 30, 2024

Abstract. This paper investigates the impact of Socially Responsible Investment (SRI) capital on the polluting practices of industrial Multinational Enterprises (MNEs) across all their facilities. We leverage the inverse relation between local pollution and high-frequency satellite-based measurements of local vegetation health through the normalized difference vegetation index (NDVI). Our empirical analysis encompasses a comprehensive dataset of 911 parent companies and 52,806 establishments worldwide. We estimate how the within-cell panel variation in NDVI relates to changes in SRI ownership and document an overall positive association between SRI ownership of a company and the NDVI around the company's establishments. However, this improvement is limited to facilities located within OECD countries. We observe no relation between SRI and NDVI in non-OECD countries. These heterogeneous findings underscore the importance of considering the global nature of MNEs when evaluating sustainability efforts.

JEL Classification: F23, G23, O33, Q56, Q58

UN SDGs: 13, 15, 17

Keywords: Socially Responsible Investment (SRI), Normalized Difference Vegetation Index (NDVI), Multinational Enterprises (MNEs), Plant-Level Pollution, Institutional Investors.

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*Financial support from the Fundação para a Ciência e Tecnologia (UID/ECO/00124/2013 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209), POR Norte (Social Sciences DataLab, Project 22209), and 2022.01187.PTDC is gratefully acknowledged. We thank Pedro Matos, Lakshmi Naaraayanan, Daniel Streitz, Hannes Wagner, seminar participants at Durham University, CEPR Women in Economics Seminar Series (Finance), Lund University, EIEF (Rome), Vienna School of Finance and NOVA SBE and participants of the 3rd Conference in Sustainable Finance, University of Luxembourg, Exeter Sustainable Finance (ESF) Conference for comments and suggestions.

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1. Introduction

This paper introduces a novel methodology to assess the impact of socially responsible investing (SRI) on pollution generated by multinational enterprises at the establishment level worldwide. Although we are concerned about multinationals' polluting activities globally, reliable data on companies' activities and pollution in many regions are lacking. To address this challenge, we propose utilizing satellite data, specifically the normalized difference vegetation index (NDVI), which measures vegetation health and appears to react to pollution. The healthier and denser the vegetation, the higher its NDVI value. We aim to determine whether SRI capital leads to significant improvements in vegetation quality surrounding multinationals production facilities, as an indicator of pollution by the production facility. Understanding the effectiveness of SRI in reducing corporate pollution is crucial, given the increasing influx of funds into this sector (Dyck et al., 2019; Gantchev et al., 2022; Heath et al., 2023; Naaraayanan et al., 2020). Furthermore, a recent survey by Stroebel and Wurgler (2021) indicates that pressure from institutional investors is perceived as the most potent force for change among firms in the economy.

Multinationals are significant contributors to pollution both domestically and internationally (Tanaka et al., 2022; Levinson, 2009). According to the Environmental Protection Agency (EPA), the manufacturing sector, dominated by multinationals, generates around 60% of the hazardous waste in the U.S. This sector also significantly contributes to water pollution, responsible for substantial chemical waste, air pollution[1], and soil contamination, releasing heavy metals and toxic chemicals. Their pervasive environmental impact underscores the importance of examining their pollution patterns.

Whether the response to SRI is homogeneous across all facilities of a multinational is an open empirical question. On one hand, companies behave differently depending on environmental regulations and countries' bargaining power (Ben-David et al., 2021; Yang et al., 2022). Wealthier countries tend to have stricter environmental regulations and monitoring requirements, suggesting that SRI may be more effective in these countries. On the other hand, if multinationals pollute more in places with less stringent environmental regulations or weaker bargaining power, the greatest potential for reducing pollution may lie in facilities located in these areas. The environment being a global public good,

[1] Levinson (2009) finds that U.S. manufacturing firms, including multinationals, are responsible for about 20% of global sulfur dioxide (SO_2) emissions, 15% of nitrogen oxides (NO_x) emissions, and 12% of carbon dioxide (CO_2) emissions.

assessing whether SRI is successful requires knowing how it affects multinationals' pollution across all their facilities. Analyzing pollution at the facility level thus allows for a more precise assessment of the environmental impact and effectiveness of SRI initiatives. Facility-level data provides granular insights into how specific locations are managed and how local environmental regulations influence corporate behavior. This level of analysis is an essential step to be able to develop targeted strategies to mitigate pollution where it is most severe.

Our key assumption is that changes in vegetation health as captured by the NDVI react to local industrial pollution.[2] This assumption finds support in the recent environmental science literature which outlines that pollution interferes with chlorophyll production, reducing the NDVI values. This reduction has been documented for various types of vegetation and for all major families of pollutants.[3] While encouraging, these studies tend to have smaller geographical scopes and more controlled environments than our study. Going further, to ensure the validity of our hypothesis at our scale of interest, we examine the responsiveness of the NDVI to releases from the universe of industrial facilities that report to the US EPA.[4] We find a statistically significant negative correlation between the NDVI in the and the *on-site* toxic chemicals released by facilities present in each cell. Additionally, we examine how vegetation health reacts to environmental accidents – toxic chemical spills made available by the U.S. Coast Guard's National Response Center (NRC) since 2006. Our findings indicate a significant and prolonged negative effect on vegetation, with NDVI values showing a marked decline for up to four months post-accident and only slowly recovering. Overall, both approaches empirically support the assumption that changes in NDVI are reliable signals for changes in local pollution levels.

Besides its reactivity to local pollution, the NDVI has several key advantages to answer our research question. Firstly, the data are available globally, including in regions of the world where no other

[2] While we have compelling reasons to make this assumption, as detailed later in this paper, it is crucial to distinguish between using changes and levels. We do not claim that NDVI is an appropriate measure of pollution levels. Our assumption is that all other factors being equal (such as vegetation type, agro-climatic zone, or the presence of industrial facilities), a significant increase in local pollution will, on average, result in a decrease in average NDVI. A significant correlation between changes in both measures is sufficient to validate our assumption.

[3] Appendix A-1 presents a summary of the NDVI's diverse applications and its suitability for assessing industrial pollution's impact in our context. For further details, see Rai (2016), Sheng et al. (2023), Lim et al. (2004), Dean et al. (2024), Amer et al. (2017), Clevers et al. (2004), Garty (2001), Li et al. (2021a), Sridhar et al. (2007), Zhang et al. (2022) and Resende Vieira and Christofaro (2024).

[4] The NDVI data and the unit of observation for this test match those of our main analysis, namely the MODIS data in a bi-weekly panel of 0.1° x 0.1° cells starting in 2006 and ending in 2021.

data (self-reported or estimated) are available. Secondly, remotely sensed data are immune to the sort of selection into reporting or monitoring, manipulation of the reporting, or manipulation of actual pollution level in days where firms know they are monitored (as evidenced by studies such as Zou (2021) in the context of local governments) – which plague virtually all non-satellite data. Third, the spatial granularity of the NDVI data allow us to dis-aggregate it at the facility level. While the focus on these local variation does not allow to capture the full spectrum of firms' pollution, e.g. ignoring pollution from transportation, this focus is of high policy relevance: Currie et al. (2015) report that they are only able to detect significant impacts of toxic air emissions on air quality within 1 mile of the emitting facilities. Finally, leveraging the NDVI does not limit us to CO_2 emissions, an essential contribution to the literature given the multi-spectral nature of pollution, and concerns that focusing on one type of pollutant only twists firms incentives into pollution substitution (Gibson, 2019).

To study the link between SRI and firms polluting behavior, we combine the NDVI measures with three main sources of data covering 52,806 facilities in 13,651 cells within 124 countries between 2006 and 2021. First, we exploit geo-localized facility-level data indicating, for each facility owned by a US multinational, what is their parent company. Second, we match the information on the parent company of each facility with the ownership structure of these parent companies. Last, we make use of the time-varying list PRI signatories to measure shareholder engagement with ESG principles. Our measure of SRI ownership is the proportion of a company's shares owned by institutions that are signatories of the PRI, the largest global ESG initiative in the asset management industry. Equipped with these data, we estimate how facility-level pollution responds to changes in the relative intensity of SRI ownership in a bi-weekly (16 days) panel of cells at a resolution of $0.1^\circ \times 0.1^\circ$ (approximately 11 by 11 kilometers at the equator).

Our baseline empirical approach exploits two dimensions of variation in exposure to SRI capital: time, and the relationship between each facility and its parent company. Consider two facilities, producing at a given point in time in two neighboring cells, but belonging to different parent companies. Based on our combined data on ownership structures, we identify changes in SRI prevalence in the funds of a company, over time and across the parent companies of these two facilities. The structure of the data allows us to partial out any local time-varying shocks affecting both facilities, and to account for any time-invariant differences in the level of pollution or ESG commitments of both the facilities and their parent companies. We are also able to partial out any change in the NDVI due to seasonality or specific weather conditions in a given locality and month. Our analysis basically exploits within-cell variation in SRI ownership. This controls for investors' selection based on companies intrinsic characteristics, including their environmental impact, and helps support causal interpretation of the effect of SRI ownership on firms' behavior. The only selection left is if SRI investors select companies with improving prospects.

We find a significant improvement in the NDVI in cells with higher levels of SRI, suggesting that firms owned by institutions committed to sustainability significantly decrease their average pollution across their global operations. Importantly, this result holds when focusing on cells with only one facility to avoid aggregation issues at the cell level. We also make sure that this result is independent from weather shocks or the general level of economic activities through a battery of time-varying controls at the cell level. In particular, we control for temperature, rainfall, local nighttime light emissions (a proxy of local economic activity Pinkovskiy and i Martin (2016)), buildings and population.

To discern any composition effects, we also specifically examine global firms, defined as those with at least one facility outside the Organisation for Economic Co-operation and Development (OECD) countries. When considering only cells with global firms, we still observe better vegetation health around facilities with SRI ownership.

In the final part of the paper, we explore heterogeneous effects and find that global firms tend to pollute more in non-OECD countries and regions with lenient environmental regulations. This disparity underscores the importance of considering regional differences in environmental impact and emphasizes the need for global monitoring of any sustainability effort.

Our paper contributes to the growing literature on the real effects of sustainable investments of institutional investors on firms' sustainability practices and pollution behaviors. The existing literature presents mixed evidence. For example, Heath et al. (2023) show that while SRI funds tend to select firms with higher environmental and social metrics, an increase in SRI ownership does not necessarily lead to significant changes in firm behavior. Gantchev et al. (2022) show how divestments by E&S-conscious investors prompt policy enhancements. Flammer (2021) uncovers a negative correlation between green bond issuance and CO_2 emissions, suggesting that capital allocation can indeed yield tangible environmental benefits. Recent theoretical work highlights that market discipline's effectiveness in promoting environmental responsibility depends on investors' impact on firm cost of capital and valuations (Broccardo et al., 2022; Berk and van Binsbergen, 2021; Heinkel et al., 2001). De Angelis et al. (2023) presents a dynamic model where green investors drive emissions reductions based on asset share, climate sensitivity, and anticipated regulations. They conclude that the impact of green investors remains limited given their current wealth share and practices. Oehmke and Opp (2024) argue that impact requires social responsible fund's mandate to permit the fund to trade-off financial performance against reductions in social costs. Moreover, engagement and governance is found to be more effective than exit in reducing pollution and improving economic outcomes (Akey and Appel, 2021). Naaraayanan et al. (2020) study the real effects of environmental activist investing using plant-level data for the US. They find that targeted firms reduce their toxic releases, greenhouse gas emissions, and cancer-causing pollution by exploiting the Boardroom Accountability Project (BAP) in a difference-in-differences specification to estimate the effectiveness of climate-focused engagements. Their study suggests that engagements are an effective tool for long-term shareholders to address climate change risks.

We extend the literature on the real effects of green investments by providing evidence on the impact of SRI capital on multinational firms' polluting activities both domestically and internationally, and by monitoring pollution at the facility level using objective data, beyond subjective measures or US-centric data.[5] Previous studies, such as Dyck et al. (2019), Ben-David et al. (2021) and Dai et al. (2021), have explored the global implications of institutional ownership on environmental performance but often rely on aggregated data. Our approach leverages detailed, facility-level pollution data to provide a more granular perspective on how firms manage pollution across various facilities and regulatory environments. This global perspective highlights the strategic allocation of pollution reduction efforts in highly monitored countries, demonstrating the complex dynamics of environmental responsibility in multinational firms.

[5]Despite increased voluntary carbon emissions disclosures, significant underreporting persists (Bolton and Kacperczyk, 2021; Klaaßen and Stoll, 2021). Our findings underscore the global challenge of accurately measuring emissions, with implications for environmental responsibility and policy effectiveness. See for example: Glencore's emissions baseline understated by at least 24% - ACCR, source. Additionally, a report by the Boston Consulting Group underscores that over nine out of ten companies globally fail to comprehensively measure their total greenhouse gas emissions (source), corroborated by Climate Trace revealing oil and gas facilities under-report emissions by three times (source).

Our work allows to highlight the potential of alternatives to CO2 emissions data. Emissions data, although vital in assessing a companies' contribution to global warming, represents just one facet of companies' environmental impacts. Other forms of pollution, such as chemical waste, water contamination, and habitat destruction, wield significant influence over a company's overall environmental footprint. Vegetation serves as a crucial host of biodiversity, and this connection is underscored by its importance in the growing literature in the field of biodiversity (Giglio et al., 2023; Garel et al., 2024). As the NDVI will detect any changes in vegetation patterns, it will provide insights into an overall ecosystem health. In contrast, a narrow focus on emissions data risks to inadvertently neglect these aspects. Missing these aspects may have concerning environmental consequences given the established ability of firms to re-optimize pollution activities spatially or across pollutants (Gibson, 2019; Tanaka et al., 2022; Bartram et al., 2022).

Finally, we also propose a methodological contribution by outlying the potential of using satellite-based data to monitor how an external shock changes pollution levels. The use of satellite data holds great promises, in particular to analyze places with limited monitoring (Donaldson and Storeygard, 2016), or in case of concerns of data manipulation (Zou, 2021). Our work outlines the potential of these data. We are, to the best of our knowledge, the first to document the significant association between the NDVI and firms local pollution behavior throughout the US. This positive association opens an avenue to levy the NDVI to monitor local pollution in a variety of settings and research questions.

2. Data

We combine data on establishments' location and ownership with satellite-based measures of vegetation health in a panel of fine-grained cells at annual or bi-weekly (16 days) frequency since 2006. Our baseline analysis rests on a panel of cells at a resolution of $0.1°\times0.1°$ (approximately 11 by 11 kilometers at the equator). This approach ensures both high spatial resolution and efficient analysis as we calculate averages across the cells. Key variables for our final analysis are, for each cell, the number of US-owned establishments, the institutional ownership of these establishments on a quarterly basis, and the NDVI value on a bi-weekly basis.

2.1 US public multinationals facilities

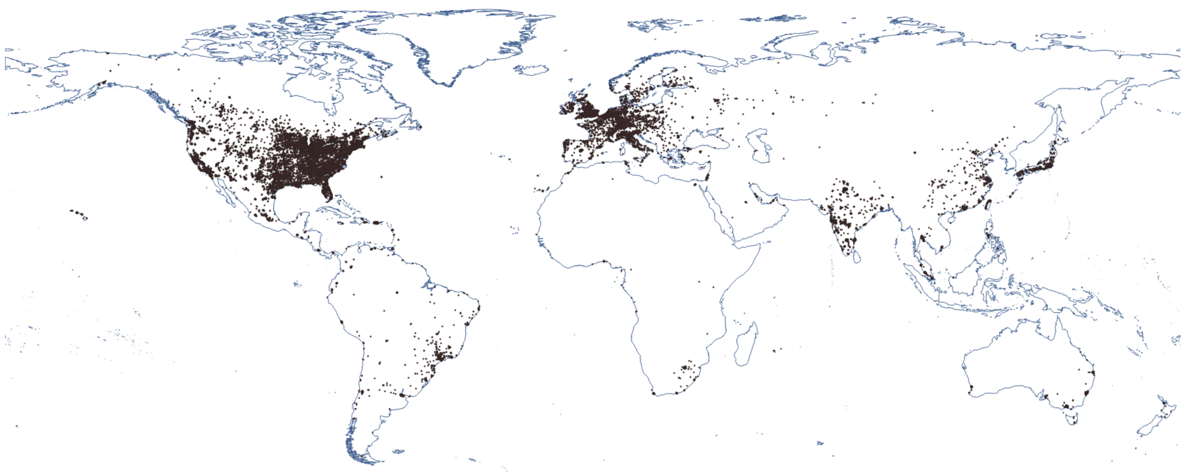
We obtain information on the international establishments of public US multinationals from Dun & Bradstreet (D&B) WorldBase. To the best of our knowledge, D&B is the only database that records in a coherent format the global network of establishments of multinational companies. This provides a distinct advantage over other databases like Orbis, which excels in providing detailed corporate linkage and ownership structures but traditionally focuses more on company-level (and subsidiaries) rather than facility-level data. This unique dataset, however, is cross-sectional: our analysis validity hinges on the persistence of multinationals' network of establishments.[6]

We restrict our sample to companies in SIC codes 01 to 39 , given their well-documented status as significant contributors to pollution and in line with Hartzmark and Shue (2022)'s argument that impact is more likely to occur in polluting firms. These SIC codes correspond to Agriculture, Forestry and Fishing (01-09), Mining (10-14), Construction (15-17), and Manufacturing (20-39). Studies by the U.S. EPA indicate that these industries account for about 22% of greenhouse gas emissions, 30% of total toxic air pollutants, and the majority of toxic pollutants released into land and water. By scrutinizing these polluting entities, we can offer insights into the concept of impact elasticity, shedding light on the effectiveness of SRI capital in catalyzing meaningful environmental change within this crucial and "brown" sector.

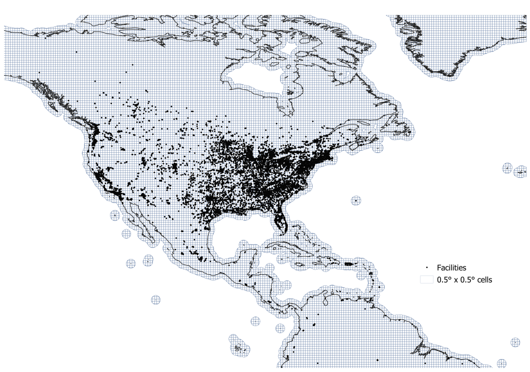
The initial D&B data contain 57,961 establishments across 124 countries, all of which can be traced back to 985 parent companies. Crucially for the purpose of this study, the D&B data allows us to precisely locate all establishments and therefore match them to the satellite data. While latitude and longitude are already provided for US establishments, we recover geo-coordinates from street addresses using ArcGIS World Geocoding Service for the remaining facilities. We drop 572 establishments with missing or insufficient address information. Panel (a) in Figure 1 plots the location of the facilities on the world map.

[6]The cross-sectional nature of the network data, observed as of December 2023, may bias our estimates if multinationals redefine their networks in response to SRI capital, such as outsourcing the most polluting parts of their production processes. If this were to happen, our coefficient of interest would suffer from an upward bias. The pattern of our results reduces our concern that this behavior is particularly widespread. As long as networks do not restructure in response to SRI, the main consequence of the cross-sectional nature of the network data would be to render our analysis less precise.

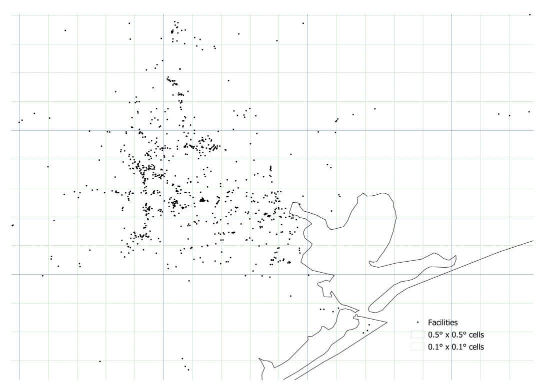
Figure 1: Plants owned and operated by US manufacturing multinational companies. Panel (a) shows the international establishments of public US multinationals with in SIC codes 01 to 39 we obtained from D&B WorldBase. Panel (b) shows the overlay of these facilities in North America with a grid of 0.5×0.5 degrees cells, the level of the widely used PRIO-Grid cells. Panel (c) zooms on the surrounding of Houston and adds the grid of cells of 0.1×0.1 degrees (our baseline level of analysis).



(a) The global network of US-owned plants



(b) North America with 0.5°×0.5°cells



(c) Houston with 0.5°×0.5°and 0.1°×0.1°cells

2.2 SRI Institutional Ownership

We obtain institutional ownership information at the parent-company level and at a quarterly frequency from the FactSet Ownership database (Ferreira and Matos, 2008). Our measure of SRI ownership is the proportion of a company's shares owned by institutions that are signatories of the Principles for Responsible Investment (PRI). The PRI is the largest global ESG initiative in the asset management industry to date. Signatories commit to incorporating ESG issues into investment analysis and decision-making, being active owners, seeking appropriate disclosure on ESG issues, promoting acceptance and implementation of the Principles, working together to enhance effectiveness, and reporting on their activities and progress.[7] These principles help align investment practices with broader societal objectives and improve long-term returns for beneficiaries. Becoming a signatory involves paying an annual fee and committing to annual reporting on responsible investment activities, including a climate transparency report modeled on the Task Force on Climate-related Disclosures (TCFD). PRI assesses signatories' compliance, and those not meeting minimum requirements may be delisted after a two-year period. Since its inception, PRI has grown significantly, with 5,020 signatories representing about $121 trillion in assets under management as of September 2022. The majority of signatories are investment managers (76%), followed by asset owners (14%) and service providers (10%), with Europe holding more than half of the signatories and North America being the second largest region. We obtain the list of signatories (name and joining date) from the PRI website and hand-matched it to FactSet based on the institution's name.

Panel A of Table 1 provides information on the final sample of multinationals. Out of the initial 985 parent companies in D&B we are able to match manually by name 911 companies to FactSet and a total of 52,806 facilities. 4,353 facilities are located in non-OECD countries. The average company has 58 facilities (median is 18) and 493 companies have at least one facility in a non-OECD country.

As the unit of analysis is the cell, for cells with more than one establishment, we consider the average SRI ownership across the establishments. The distribution of the number of facilities per cell is highly

[7]Principle 1: We will incorporate ESG issues into investment analysis and decision-making processes. Principle 2: We will be active owners and incorporate ESG issues into our ownership policies and practices. Principle 3: We will seek appropriate disclosure on ESG issues by the entities in which we invest. Principle 4: We will promote acceptance and implementation of the Principles within the investment industry. Principle 5: We will work together to enhance our effectiveness in implementing the Principles. Principle 6: We will each report on our activities and progress towards implementing the Principles.

skewed, as reported in panel B of Table 1. The median cell-date observation concerns a cell with one establishment, while there is a small number of cells with a high concentration of establishments. The average number of facilities in a cell is 3.74. SRI ownership at cell-level is 9% on average. To allow firms some time to adjust to the inflow of SRI, we use a moving average over the previous year. This approach captures the sustained impact of SRI over time, providing a more comprehensive understanding of its influence on firms' pollution behaviors. We define "SRI ownership" as the average share of SRI capital among the owners of each establishment's parent company over the previous year.

2.3 Vegetation Health

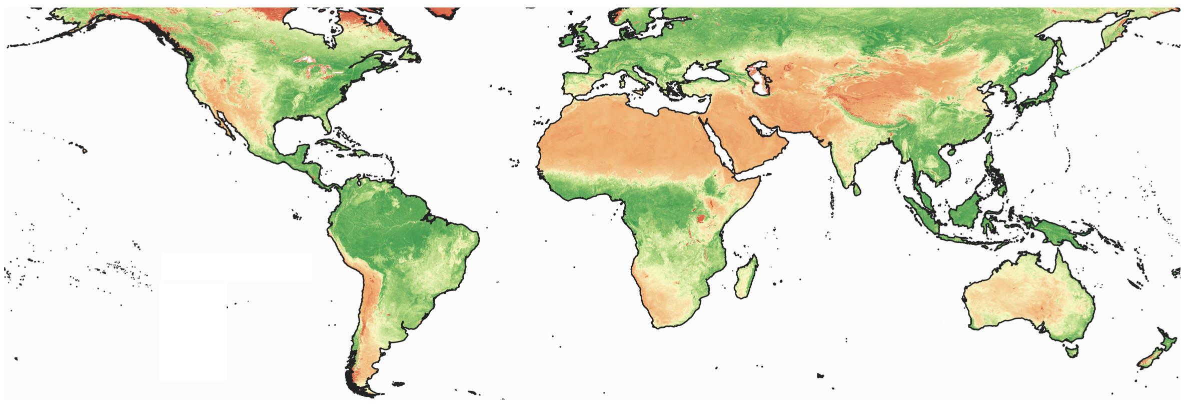
To assess the impact of SRI capital on companies' local pollution, we analyze changes in local vegetation health to reflect variations in pollution levels. We levy the most widely used satellite-based vegetation health index, the normalized difference vegetation index (NDVI) from the NASA MODIS database (Didan, 2015; Alix-Garcia et al., 2015; Asher and Novosad, 2020).[8] The NDVI measures the "greenness" of vegetation based on the reflectance signatures of leafy vegetation.

The NDVI values range between -1 and 1, where negative values correspond to water and snow, values close to zero primarily come from rocks, bare soil or buildings, and higher positive values indicate vegetation, from sparse vegetation (0.1 - 0.5) to dense green vegetation (0.6 and above). The NDVI varies both in space (across cells), and in time (across seasons within a given cell), as appears in Figure 2.

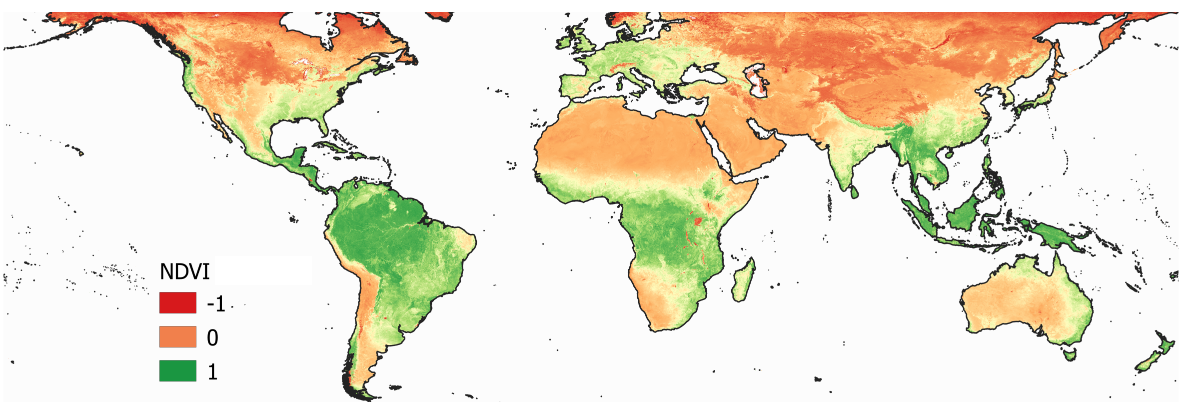
A lot of the time-series variation of the NDVI within a given cell is due to weather, and in particular to seasons. Our empirical analysis will therefore always include cell×month fixed effects to account for cell-specific seasonal variation in the NDVI and will absorb any time invariant heterogeneity in local vegetation and land usage. We also always control for possible variability in the NDVI due to weather conditions by including measures based on monthly rainfall and temperature from Climatic Research Unit of the University of East Anglia (CRU, Harris et al. (2020)). The CRU provides both sources of data with a uniform treatment at a $0.5°\times 0.5°$ resolution (Dell et al., 2014). We consider the average

[8]Source: https://lpdaac.usgs.gov/products/mod13c2v006/, recoding the average NDVI every 16 days at a resolution of 0.05°.

Figure 2: Worldwide NDVI in June and December . Panel (a) shows the variation in the range of NDVI values as of June 9, 2000. Panel (b) shows the variation in the range of NDVI values six months later, as of December 2, 2000.



(a) NDVI in June 9



(b) NDVI in December 2

temperature and the total precipitation recorded in the cell each month as well as their square. Additionally, we introduce agroclimatic zone-by-year fixed effects, which capture variation across different climatic regions and account for year-specific factors affecting agricultural productivity and vegetation growth. This may be important because agroclimatic zones experience distinct environmental conditions, and their year-over-year fluctuations may influence NDVI patterns in ways that are not purely seasonal but are related to broader climatic changes or agricultural practices. Agroclimatic zones are defined based on the Köppen-Geiger climate classification system, as published by the World Bank.[9] These controls allow us to more accurately isolate the effect of our variables of interest by accounting for both spatial and temporal heterogeneity.

In addition to weather related variables, we also control for the cell-level characteristics like the number of facilities in the cell as their clustering varies. We also account for the average of calibrated nighttime light emissions, as compiled by Li et al. (2020) who harmonized the records from the DMSP (1992–2013) and the VIIRS (2012–2018).[10] Nighttime light emissions provide insights into yearly local economic activities by reflecting changes at the household, state, and company levels (Henderson et al., 2012; Pinkovskiy and i Martin, 2016; Angrist et al., 2021). Alternatively, we also measure the buildings and population present in each cell through the Global Human Settlements by the European Union.[11] Finally, to capture global time trends in vegetation, our regression specifications will include year×month fixed effects, which could correlate with global trends in companies' emissions and environmental policies. These controls are essential for reducing omitted variable bias and isolating the true effects of the variables under investigation.

2.4 Dataset

Our final data set encompasses 13,651 cells with at least one facility owned by a US multinational as well as information at quarterly frequency about their ownership structure and the average NDVI at bi-weekly frequency. The sample starts in 2006 to cover a few years before the beginning of the growth

[9] As represented in Appendix Figure A-2. Retrived from https://datacatalog.worldbank.org/search/dataset/0042325 on the 31/05/2024.

[10] Source:https://figshare.com/articles/dataset/Harmonization_of_DMSP_and_VIIRS_nighttime_light_data_from_1992-2018_at_the_global_scale/9828827/5.

[11] Retrieved from: https://ghsl.jrc.ec.europa.eu/download.php The data records population and buildings every 5 years; we interpolate them into yearly control variables.

in SRI investment and ends in 2021.

Table 1: Summary Statistics of multinationals Facilities Network and Cell-level Panel

Descriptive statistics on international establishments of public US multinationals from Dun & Bradstreet (D&B) WorldBase. Our sample consists of industrial multinationals with SIC codes 01 to 39, representing Agriculture, Forestry and Fishing (01-09), Mining (10-14), Construction (15-17), and Manufacturing (20-39).

	N	Mean	Std	Min	p10	p25	p50	p75	p90	Max
A. MNEs facilities network										
Nr Facilities	52,806									
(outside OECD)	4,353									
Nr Parents	911									
(with facilities outside OECD)	493									
Facilities per parent	911	57.96	115.22	1.00	3.00	6.00	18.00	58.00	140.00	982.00
B. Cell-level panel										
Nr Cells	13,651									
Nr DB Facilities in cell	4,756,407	3.74	8.86	1.00	1.00	1.00	1.00	3.00	8.00	485.00
Average NDVI	4,756,407	0.50	0.20	-0.18	0.23	0.38	0.52	0.66	0.75	0.95
Average SRI ownership	4,756,407	0.09	0.08	0.00	0.01	0.02	0.06	0.16	0.21	0.53
Average Institutional ownership	4,756,407	0.79	0.16	0.00	0.59	0.72	0.81	0.89	0.97	1.00

3. Validation

The contribution of this paper hinges on the idea that vegetation health reacts to variations in firms' pollution. Previous research has consistently shown that the NDVI decreases as pollution increases across all major pollutant categories: atmospheric, soil, and water pollution. This establishes the NDVI as a reliable indicator of industrial plant-level pollution, providing a unique perspective on environmental impact (Amer et al. (2017); Clevers et al. (2004); Garty (2001); Sridhar et al. (2007)).

The NDVI's sensitivity to pollutants is well-documented. Atmospheric pollutants induce oxidative stress in plants, damaging cellular components and negatively impacting plant health, thus reducing the NDVI values (Lim et al. (2004)). Soil contamination, especially from heavy metals, is associated with a reduction in NDVI (Dean et al. (2024)). Additionally, water pollution affects vegetation's nutrient uptake, influencing the NDVI values (Resende Vieira and Christofaro (2024)). The NDVI may also improve if pollution decreases: recent studies, such as that by Li et al. (2023), demonstrate significant improvements in the NDVI during the COVID-19 pandemic in India.

The utilization of vegetation health, quantified through the NDVI, as a means to evaluate changes in pollution levels at the facility level thus holds great promise. However, the above-mentioned studies, and those reviewed in greater detail in Appendix A-1, tend to focus on a smaller geographical scope and a more controlled environment than our study. In the remainder of this section, we establish the reliability and responsiveness of the NDVI to local pollution at the scale relevant for our subsequent analysis through two complementary validation exercises. We assess the responsiveness of the NDVI first to Toxic Releases and second to environmental incidents.

To ensure the robustness of our approach, we first assess US facilities, examining the responsiveness of the NDVI to emission releases from industrial facilities that report to the US EPA. This test, which matches the scale of our main analysis, aims to determine the correlation between the amount of toxic chemicals released *on-site* by production facilities and the NDVI in their proximity. We consider several models that include high-dimensional fixed effects and control for local weather conditions, as well as various levels of geographic resolution. This step is intended to provide compelling evidence that the establishments we observe can plausibly move the needle among all establishments within the $0.1° \times 0.1°$ cells we analyze, demonstrating that the cells where pollution happens are also the cells where our observed effects are concentrated.

Additionally, we examine how vegetation health reacts to environmental accidents. We analyze data on 3,698 toxic chemical spills made available by the U.S. Coast Guard's National Response Center (NRC) since 2006. This analysis serves two main purposes: first, to further validate the relationship between NDVI and pollution, and second, to determine whether and how vegetation recovers after an accident. This step is intended to empirically support our assumption that changes in NDVI are reliable signals for changes in local pollution levels, and to underscore the spatial precision and relevance of our measurements.

3.1 NDVI reaction to firms' toxic releases (TRI)

We first empirically test the relationship between the NDVI and firms' toxic releases, using plant-level data from the Toxic Release Inventory (TRI) collected by the US Environmental Protection Agency (EPA). The TRI database reports total toxic chemical releases at plant-chemical level at annual frequency for facilities in the US. Importantly, the data contains the precise location (geographic coordinates) of each facility, which allows us to merge emissions with satellite-based measures of the NDVI in its proximity. The sample starts in 2006 and ends in 2021 in order to mirror the time coverage of our analysis of SRI. The level of analysis is the $0.1°\times0.1°$ (11km $\times$ 11km) grid cell where a facility is located. We define the dependent variable to be the average NDVI within the cell. Cell-level emissions are then computed as the sum of reported releases across the facilities within a cell. The TRI's nationwide coverage across all U.S. states encompasses various of agro-climatic zones, making it well-suited for our validation purposes, especially as we intend to use the NDVI globally.

The TRI data are the most comprehensive information available on facility-level releases of toxic chemicals. Facilities are required to publicly disclose the amount of chemicals released to the environment, both on-site or transferred to off-site locations, covering over 600 toxic chemicals. Prior research has relied on the TRI to measure industrial pollution and assess corporate environmental impact (Andrikogiannopoulou et al., 2023; Currie et al., 2015; Gibson, 2019; Li et al., 2021b; Naaraayanan et al., 2020; Xu and Kim, 2021). Despite being self-reported, the quality of TRI data is high, and prior research suggests that reporting biases in the TRI program are minimal. For our validation exercise, any measurement error due to potential misreporting would likely result in attenuation bias, making it less likely for us to observe a significant relationship between TRI releases and NDVI. However, another source of measurement error arises from the TRI reporting requirements, which mandate that facilities report releases only if their use of a chemical surpasses a specific threshold[12]. This threshold creates potential artificial discontinuities in the reported release and the number of reporting facilities to which vegetation is not expected to respond. The TRI data provide limited information to determine if a facility stopped

[12] see https://www.epa.gov/toxics-release-inventory-tri-program/basics-tri-reporting for more information on the TRI reporting criteria.

reporting because it fell below the reporting threshold. To mitigate this issue, we restrict our analysis to facilities that have been reporting consistently for at least nine consecutive years. After imposing this restriction we are left with 40% of the cell-year observations in the unrestricted sample. Table 2 provides summary statistics of the restricted sample used for the validation analysis.

The final dataset comprises 5,027 unique cells, containing a total of 7,696 distinct reporting facilities. In 75% of the cell - year observations there is exactly one facility per cell. The last row reports the fraction of total releases that are disposed of on-site. Since we expect local vegetation to only respond to local emissions, this exercise would be futile if companies only disposed of their toxic wastes far from the facility. This is however not the case as the average is 74% and the median is 100%.

Table 2: TRI Sample Summary Statistics. The table provides summary statistics for the TRI sample used for the validation analysis. The unit of observation is the cell. The sample contains all the cells that are matched with a TRI reporting facility in at least one year between 2006 and 2021. The table reports the distribution of the number of facilities per cell at a given point in time, of the yearly average NDVI, of the cell-level total toxic releases and of the fraction of onsite releases over the total releases. Notice that the fraction of onsite releases is not defined for cell-time observations with reported zero total releases.

	N	mean	std	min	p10	p25	p50	p75	p90	max
Nr Cells	5027									
Nr TRI Facilities per cell	67092	1.41	0.93	1.00	1.00	1.00	1.00	1.00	2.00	14.00
Average NDVI	67092	0.51	0.13	0.04	0.34	0.43	0.53	0.62	0.67	0.84
Total Release (1,000 pounds)	67092	587.83	12673.40	0.00	0.00	0.03	4.75	55.84	467.13	1124384.89
Onsite Release (%)	57685	0.74	0.39	0.00	0.01	0.48	1.00	1.00	1.00	1.00

We estimate the response of the NDVI to changes in toxic releases reported to TRI from the following model

$$NDVI_{i,t} = \beta_1 \text{Tot.release}_{i,y} + \beta_2' \text{Weather}_{i,t-1} + \beta_3' \text{Cell}_{i,t-1} + \gamma_{y \times m} + \delta_{i \times m} + \alpha_{\text{Agroclimatic} \times y} + \varepsilon_{i,t} \quad (1)$$

Our coefficient of interest, α_1, captures the relationship between changes in firms' pollution and vegetation health. To identify this effect, the model controls for location-specific seasonality in NDVI, as well as time-invariant differences in land use and vegetation type, by including cell-by-month fixed effects ($\delta_{i\times month}$). To account for weather-driven variation in NDVI, we include controls for average temperature and total precipitation in the prior month, both in level and squared terms. Additionally, we control for cell-level characteristics such as the number of facilities in each cell, calibrated nighttime light emissions (a proxy for local economic activity), and the presence of buildings and population within each cell. Year-month fixed effects ($\gamma_{year\times month}$) are also included to capture time trends in both the dependent and independent variables.

Moreover, agroclimatic zone-by-year fixed effects ($\alpha_{\text{Agroclimatic}\times y}$) are incorporated to account for variations in vegetation health arising from differences in climate across zones, as well as year-over-year changes in environmental conditions that may impact vegetation. To ensure robustness, we progressively introduce increasingly restrictive sets of fixed effects in the analysis, starting with the least demanding and tightening them step by step.

Table 3 documents a robust negative relationship between toxic releases and vegetation health. In Column (1), the impact of total toxic releases is examined, and we observe a statistically significant negative coefficient of -0.005 for total releases. This indicates that increased pollution leads to a decline in NDVI. Moving to the bi-weekly sample in Column (2), the magnitude of the effect becomes -0.002. This coefficient is stable to the inclusion of year-specific fixed effects at the level of agroclimatic zones in Column (3). These results confirm that pollution has a substantial negative effect on vegetation health.

To put these results in perspective, we can look at how NDVI varies in a given cell over time. Vegetation health varies widely throughout years and seasons and this within cell variation maybe a more accurate reference point than comparing the NDVI values of the Amazon and the Alaska. The within cell NDVI has a standard deviation of 0.073, meaning that a one standard deviation change in toxic releases affects the NDVI by 3% of the within cell standard deviation of the NDVI. Another way to think about this is that a one standard deviation increase in toxic releases, which is equivalent to approximately 8.13 tons of toxic releases, corresponds to a reduction of 0.002 units in NDVI. This environmental damage is comparable to the annual CO_2 emissions of roughly 1.77 passenger vehicles or the emissions generated by producing 8.9 MWh of electricity, which corresponds to the electricity use of an average U.S. household for about nine months.

Columns (4) through (6) differentiate between on-site and off-site releases to distinguish local pollution by the facilities from the facilities overall activity. On-site toxic emissions are the emissions the NDVI should react exclusively to, as they occur within the cell where we measure the NDVI. Off-site releases may be managed in dedicated spaces or facilities outside the facility's cell. We confirm that only on-site total releases decrease vegetation health.

When considering the impact of pollution reduction on NDVI values, it is crucial to address concerns about potential asymmetry: significant increases in pollution may lead to a decrease in NDVI, but a decrease in pollution may not necessarily result in a corresponding increase in NDVI. Such asymmetry could challenge our assessment of the pollution-reduction effects of SRI initiatives. Column (5) analyzes a subsample of cells where toxic releases have decreased over time—that is, releases in year t are lower than in year $t-1$ for all years in the dataset. The results show a positive and significant association between NDVI and reductions in toxic releases, indicating that vegetation health has improved in cells where pollution has decreased. This reinforces the conclusion that reductions in industrial pollution are linked to better vegetation health.

Finally, in Column (6), we restrict the sample to cells containing only one facility, allowing us to attribute the observed effects to a single one source of pollution, without the potential confounding influence of clustered facilities. The results in this subsample confirm our previous findings.

The adverse effects of industrial pollution on vegetation are consistent across various sample specifications and not dependent on spatial clustering of facilities. We repeat the battery of tests presented in Table 3 for the larger cells of 0.5×0.5 degrees, corresponding to the widely used PRIO-Grid cells. We also repeat that test for a smaller cell size of 0.05×0.05 degrees as the smaller the cell, the higher the likelihood that we observe only one plant in each cell. We present the results in Appendix Tables A-4 and A-2 Both exercises confirm the findings from Table 3.

Table 3: NDVI reaction to toxic releases

The table presents the results of OLS estimations with standardized variables. The dependent variable is the Normalized Difference Vegetation Index (NDVI), the explanatory variables come from the Toxic Release Inventory (TRI) database. All columns include weather controls (average temperature and its square, total precipitation and its square) as well as economic controls (nighttime light emissions, buildings in the cell and total population of the cell). Appendix Table A-3 shows the complete specification. * significant at 10%; ** at 5%; *** at 1%. Standard errors are clustered at the cell level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.			—— NDVI ——			
Sample		all cells			TRI down	1 plant/cell
Tot. releases	-0.005***	-0.002**	-0.002**			
	(0.001)	(0.001)	(0.001)			
Tot. on-site releases				-0.002***	-0.003*	-0.004***
				(0.001)	(0.002)	(0.001)
Tot. off-site releases				0.001	0.001	0.001
				(0.001)	(0.001)	(0.002)
Cell FE	Yes	No	No	No	No	No
Cell X month FE	No	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year X agroclimatic FE	No	No	Yes	Yes	Yes	Yes
Frequency	Yearly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly
Observations	98029	2255922	2255922	2255922	1740272	380813
Adjusted R^2	0.98	0.91	0.91	0.91	0.91	0.91

3.2 The NDVI and Environmental Accidents

In this section, we examine how vegetation health reacts to industrial accidents. This test allows us both to further validate the relationship between the NDVI and pollution, and to establish whether and when vegetation recovers after an accident. To gather data on toxic chemical spill incidents, we utilize the U.S. Coast Guard's National Response Center (NRC) database. This database compiles first-hand reports of oil, chemical, radiological, biological, or etiological discharges into the environment across the United States. Reports include details such as the incident's time, location, responsible party, pollution medium, and any evacuations, injuries, or fatalities as long as they led to at least one evacuation. Between 2006 to 2022 the data records a total of 3,698 incidents.

Figure 3 shows the location of each spill and highlights in red the larger incidents, which are those we are interested in. In order to isolate large incidents, we group the universe of recorded events into deciles based on the number of evacuations the event led to, and we use the highest-severity ranked decile. Our final sample of incidents comprises 351 incidents with a minimum of 210 evacuations.[13]

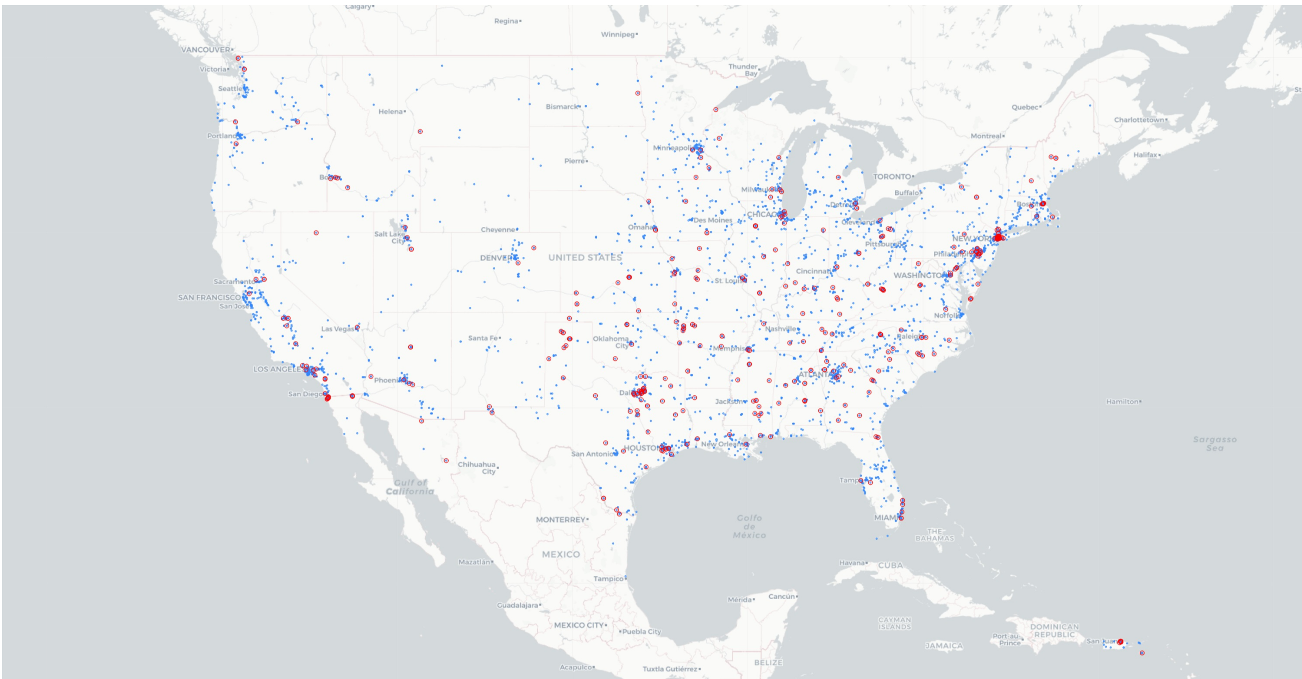


Figure 3: Spatial distribution of toxic chemical spills. The map shows the spatial distribution of toxic chemical spills across the United States over the period 2006 to 2022, based on data from the U.S. Coast Guard's National Response Center (NRC). Each blue dot corresponds to a spill with at least one evacuation. Events that resulted in more than 210 evacuations (90th percentile) are highlighted with a red circle.

To conduct the empirical analysis, we employ a stacked regression approach similar to Tian et al. (2023). We run the following dynamic regression to estimate the month-by-month treatment effects in the months prior to and after the accidents:

$$\text{High NDVI}_{i,e,t} = \sum_{k=-7}^{7} (\beta_k \cdot D_{i,k,t} \cdot \text{treated}_{i,e}) + \mu_{e,i} + \mu_{e,t} + X'_{i,e,t-1} \cdot \delta + \epsilon_{i,e,t} \tag{2}$$

where High $\text{NDVI}_{i,e,t}$ is a binary variable taking the value of one when the NDVI of the cell i, cohort e, at time t is above the cell's typical monthly average (computed outside of the months following the

[13] This is a significantly larger number of events than the 24 events of interest in the ongoing work of Tian et al. (2023) whose selection criteria is that each event led to over 900 evacuations.

incident).[14] $D_{i,k,t}$ is a dummy indicating the time since the event. $\text{treated}_{i,e}$ is a dummy for cells with a spill, zero for control cells. $\mu_{e,i}$ and $\mu_{e,t}$ are fixed effects for cohort-cell and cohort-time, respectively. $X_{i,e,t-1}$ is a vector of control variables. $\epsilon_{i,e,t}$ is the error term. We use a monthly frequency, assigning event time $k = 0$ to the NDVI measurements within $[0, 32)$ days since the event, $k = 1$ for $[32, 62)$ days, consequentially over a window of -7 to $+7$ months. The control group consists of the cells neighboring the incident, up to 1 degrees away: we have a buffer of 9 cells around each cell where an event has taken place. The coefficients β_k capture the likelihood of abnormally low NDVI values in treated cells compared to control cells within the cohort. The primary objective of this analysis is to determine whether abnormally low NDVI values are more likely to occur around the time of toxic spills. This analysis also allows us to assess both the duration of the toxic spill's negative impact on vegetation health and the spatial extent of the affected area surrounding each incident.[15]

[14] As we only include cells in the sample just before and just after the event took place, we want to single out whether the NDVI values of that cell differ from that cell's usual NDVI values. This approach mirrors the standard ways to measure abnormal returns.

[15] Our approach rests on the idea that for each accident, we want to take as control cells the cells exposed to similar forces as the cell where the accident took place. However, the immediate neighboring cell of an accident might suffer from negative spillovers of the accident, and the probability to observe of such negative spillovers should decrease as we go away from the cell (up until 100km).

Table 4: NDVI Reaction to Environmental Accidents

The table presents the results of one stacked regression approach similar to Tian et al. (2023), estimating the month-by-month treatment effects before and after the accidents on high NDVI, for the cell where the incident took place up until its 9th ranked neighbor (the 10th ranked neighbor is the omitted category). Each column shows the estimated impact of the spill on the probability to observe an abnormally low NDVI in a different (set of) cell(s). The first column shows the coefficients for the central cell, where the incident happened. The second column shows the coefficients for the immediate neighbors of that central cell, the thrid columns shows coefficient for the second layer of enighbors, etc. The accidents come from the U.S. Coast Guard's National Response Center (NRC) database, including first-hand reports of toxic chemical spills from 2006 to 2022. All columns include weather controls. The analysis focuses on major toxic chemical spills defined as the top 10% in terms of evacuations. * significant at 10%; ** at 5%; *** at 1%. Standard errors are clustered at the cohort-cell level and reported in parentheses.

Dependent variable	——— High NDVI ———									
	Neighboring Cells rank									
Day intervals	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
-192	0.011	0.003	0.004	0.005	-0.001	0.000	-0.002	-0.002	-0.004	0.001
	(0.018)	(0.012)	(0.011)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.004)	(0.003)
-160	-0.017	-0.006	-0.004	0.003	-0.001	-0.000	-0.004	-0.001	-0.004	-0.004
	(0.020)	(0.013)	(0.012)	(0.010)	(0.008)	(0.008)	(0.007)	(0.005)	(0.005)	(0.003)
-128	-0.020	-0.020	-0.018	-0.021**	-0.018**	-0.013*	-0.009	-0.003	-0.005	-0.002
	(0.020)	(0.013)	(0.012)	(0.010)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)
-96	-0.018	-0.033**	-0.035***	-0.024**	-0.015*	-0.007	-0.004	-0.001	-0.001	0.000
	(0.022)	(0.014)	(0.012)	(0.010)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)
-64	0.003	-0.013	-0.015	-0.011	-0.006	-0.004	0.001	0.005	0.009*	0.001
	(0.021)	(0.014)	(0.012)	(0.011)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)
-32	-0.010	-0.017	-0.025**	-0.019*	-0.011	-0.010	-0.010	-0.008	-0.001	-0.001
	(0.021)	(0.014)	(0.012)	(0.010)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)
0	-0.046**	-0.045***	-0.037***	-0.029***	-0.019**	-0.015*	-0.014*	-0.007	-0.005	-0.001
	(0.022)	(0.015)	(0.012)	(0.010)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)
32	-0.031	-0.035**	-0.030**	-0.030***	-0.025***	-0.019**	-0.020***	-0.016***	-0.012**	-0.005
	(0.022)	(0.015)	(0.013)	(0.011)	(0.010)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)
64	-0.020	-0.021	-0.020*	-0.015	-0.011	-0.009	-0.009	-0.006	-0.007	0.000
	(0.021)	(0.014)	(0.012)	(0.011)	(0.009)	(0.009)	(0.007)	(0.006)	(0.005)	(0.003)
96	-0.045**	-0.030**	-0.025**	-0.015	-0.019*	-0.011	-0.008	-0.008	-0.005	0.001
	(0.021)	(0.015)	(0.012)	(0.011)	(0.010)	(0.009)	(0.008)	(0.006)	(0.005)	(0.003)
128	-0.038*	-0.028**	-0.027**	-0.017*	-0.010	-0.008	-0.007	-0.004	-0.005	-0.001
	(0.020)	(0.014)	(0.012)	(0.010)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)
160	-0.025	-0.027*	-0.025**	-0.014	-0.011	-0.010	-0.008	-0.010	-0.004	-0.002
	(0.021)	(0.014)	(0.012)	(0.010)	(0.009)	(0.009)	(0.007)	(0.006)	(0.005)	(0.003)
192	-0.001	0.003	-0.005	-0.007	-0.012	-0.006	-0.010	-0.003	-0.003	-0.003
	(0.021)	(0.013)	(0.012)	(0.010)	(0.009)	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)

The results presented in the table highlight the dynamic treatment effects of toxic spills on vegetation health. In the pre-accident period, from day -192 to day -32, the coefficients fluctuate around zero and show minimal statistical significance, indicating no significant difference in NDVI values between treated (spill-affected) and control cells before the event. For instance, at day -192, the coefficient for the central cell is 0.011, and at day -128, it is -0.020, neither of which is statistically significant. This finding is consistent with the expectation that vegetation health should not be impacted by a pollution event that has not yet occurred.

However, at the time of the spill (day 0), there is a sharp and statistically significant decline in NDVI values for the cell where the spill took place, with the coefficient for day 0 being -0.046, significant at the 5% level. This substantial reduction in vegetation health persists in the following period, with a coefficient of -0.031 at day 31, although less precise. These results demonstrate a sharp and immediate decline in vegetation health following the toxic spill. In the post-spill period, from day 64 to day 192, the NDVI values in treated cells remain lower than in control cells up until 160 days after the incident, reflecting a sustained negative impact that gradually fades away.

Additionally, the analysis reveals the spatial pattern in the impact, with the negative effects of the spill decreasing monotonically as the distance from the spill site increases. The coefficients for neighboring cells farther from the spill tend to show smaller negative effects or lack statistical significance, indicating that the environmental impact of the spill is more concentrated near its source. For example, at day 0, the impact is strongest close to the spill (-0.046) and diminishes as the distance from the source increases but remains significant up until neighbors of rank six. A month after the event, the negative effect appears to have spread spatially with a probability to observe an abnormal NDVI up until the neighboring cells of rank eight. This spatial analysis underscores both the localized nature of the environmental damage caused by toxic spills, how this local impact spreads spatially, and how after some time all cells appear to return to their standard NDVI values.

These findings, complemented by the established correlation between the NDVI and TRI, underscore the efficacy of the NDVI in gauging pollution changes and ecological impacts. Having demonstrating the NDVI's responsiveness to both chronic toxic releases and acute environmental accidents, we can turn to our main analysis.

4. Multinationals' Global Pollution and SRI Capital

4.1 The average effect of SRI ownership

To estimate the effect of SRI ownership on local vegetation health, we use the following specification:

$$\text{NDVI}_{i,t} = \beta_1(\text{SRI IO}_{i,t-1}) + \beta_2'\text{Weather}_{i,t} + \beta_3'\text{IO}_{i,t-1} + \beta_4'\text{Cell}_{i,t-1} + \delta_{i\times m} + \alpha_{\text{Agroclimatic}\times y} + \gamma_{y\times m} + \varepsilon_{i,t}$$

where $\text{NDVI}_{i,t}$ is the average NDVI in cell i at time t. $SRI\ IO_{i,t-1}$ represents the geometric mean of the SRI ownership of establishments in cell i, calculated over a rolling window of the prior four quarters from time t. As explained in Section 2., as the unit of analysis is the cell, we consider the average SRI ownership across the establishments present in each cell and time, and define SRI ownership as the average share of SRI capital among the owners of each establishment's parent company over the previous year. We consider a moving average over the previous year to render the idea that SRI owners are more likely to have an impact if there is ownership stability. For ease of interpretation, we standardize all variables.

In order to isolate differences in SRI ownership from differences in overall institutional ownership, we explicitly control for the average institutional ownership in the same window ($IO_{i,t-1}$) as SRI ownership. As in model (1), we include weather controls ($\text{Weather}_{i,t}$), cell-level characteristics such as the number of facilities in each cell, calibrated nighttime light emissions (a proxy for local economic activity), and the presence of buildings and population within each cell. $\gamma_{y\times m}$ are year-month fixed effects, and $\delta_{i\times m}$ are cell-month fixed effects agroclimatic zone-by-year fixed effects ($\alpha_{\text{Agroclimatic}\times y}$) are incorporated to account for variations in vegetation health arising from differences in climate across zones. We cluster standard errors at the cell level.

With this equation, we estimate how the within-cell panel variation in the NDVI relates to changes in SRI ownership. Besides local seasonality, the cell-month fixed effects absorb any time-invariant characteristics of establishments in the cell, including time-invariant parent company characteristics as long as the network is constant. This set of fixed effects is important to partial out the fact that SRI investors tilt their portfolios towards companies in greener industries. In parallel, the year-month fixed effects are a highly flexible way to account for any global evolutions over time of things like global weather conditions, a financial crisis, or the average expansion of SRI. The agroclimatic zone-by-year fixed effects account for differential patterns of exposure to global warming or plants specificness across these zones.

The estimation results are presented in Table 5, with varying levels of fixed effects and sample specifications across the columns. In Columns 1 to 3, we progressively tighten the fixed effects, moving from year fixed effects to year-month and agroclimatic-year fixed effects. To address concerns over aggregation at the cell level which might not be picked up by the controls for nighttime light emission and buildings, we also examine cells containing only one plant in Column 4 to account for concerns that firms clustering bias our results. Finally, we restrict the sample to global firms as we are interested in whether these firms react differently to SRI. We define a global firm as a firm with at least one facility outside an OECD country.

The results consistently show a positive and statistically significant relationship between SRI ownership and NDVI across all specifications, indicating that SRI ownership is associated with improved vegetation health. Specifically, the coefficients on SRI ownership range from 0.032 to 0.036 in the full sample (Columns 1-3), with slightly lower values observed in the restricted samples, such as 0.031 in the single-plant sample (Column 4) and 0.021 in the sample of global firms (Column 5). These findings suggest that SRI ownership has a positive environmental impact, benefiting local vegetation health, and the effect remains robust across different firm types and geographical contexts.

Table 5: SRI Ownership and NDVI

The table presents the results of OLS estimations with standardized variables. The dependent variable is the Normalized Difference Vegetation Index (NDVI), the main explanatory variables is $SRI\ IO_{i,t-1}$ which represents the average SRI ownership of the establishments in cell i in the year prior to time t. Global firms are firms that have at least one facility also outside the OECD. All columns include weather controls : average temperature and its square, total precipitation and its square. * significant at 10%; ** at 5%; *** at 1%. Standard errors are clustered at the cell level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	NDVI				
Split:	Full sample		One plant	Global firm	Full sample
SRI IO	0.036***	0.033***	0.031***	0.021***	0.032***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
IO	-0.002**	-0.002**	-0.001*	-0.001	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature	0.011***	0.011***	0.010***	0.010***	0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rain	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rain Sq	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temperature Sq	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lights	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Builts	-0.000	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population	-0.000	0.000	0.000	-0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.455***	0.445***	0.442***	0.459***	0.440***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Cell-month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No
Year-country FE	No	Yes	Yes	Yes	Yes
Year-Agroclimat FE	No	No	Yes	Yes	Yes
Observations	3703402	3703402	3695303	1828100	3317346
Adjusted r^2	0.90	0.90	0.90	0.90	0.90

4.2 Heterogeneous SRI effects

In this section, we examine whether the effects of SRI ownership on vegetation health vary depending on the geographical location of the facilities. Specifically, we explore how SRI's impact differs between OECD and non-OECD countries. Regulatory environments and bargaining power might influence corporate behavior. At the extreme we may be concerned that SRI may increase pollution exportation (Tanaka et al., 2022), where companies production process greener only closer to where investors are at the expense of other locations and production facilities.

Environmental regulations and the bargaining power of countries significantly affect how companies operate (Ben-David et al., 2021; Yang et al., 2022). Wealthier countries, like members of the OECD, tend to have stricter environmental regulations and more robust monitoring systems, which may enhance the effectiveness of SRI in promoting better environmental practices. On the other hand, if multinational corporations are more prone to pollution in non-OECD countries where environmental regulations are less stringent, the potential for SRI to reduce environmental damage might be greater in these regions. To explore this, we introduce an interaction term $outsideOECD \times SRI\ IO$ to assess the differential impact of SRI ownership between OECD and non-OECD countries.

The results, presented in Table 6, indicate that SRI ownership has a positive and significant average effect on NDVI across all facility types. In OECD countries, a one standard deviation increase in SRI ownership raises NDVI by 0.038, signifying a clear improvement in vegetation health. Levying the quantification we did for Table 3, this increase in NDVI is associated with a reduction of toxic releases by approximately 154.44 tons, equivalent to the CO_2 emissions of 33.57 passenger vehicles or the generation of 169.71 MWh of electricity—comparable to the electricity use of a typical U.S. household for 14 years.

However, when we examine the interaction term for non-OECD countries, we observe the opposite effect. The coefficient on $outsideOECD \times SRI\ IO$ is negative and statistically significant, ranging from -0.024 to -0.043. The overall net effect of SRI ownership across OECD and non-OECD countries is basically zero. The negative coefficient for SRI in non OECD countries almost perfectly offsets the positive baseline effect in all specifications.

Table 6: SRI Ownership and NDVI - Facilities located inside or outside OECD

The table presents the results of OLS estimations with standardized variables. The dependent variable is the Normalized Difference Vegetation Index (NDVI), the main explanatory variables is $SRI\ IO_{i,t-1}$ which represents the average SRI ownership of the establishments in cell i in the prior year. Non-OECD equals one in cells outside the OECD. All columns include weather controls : average temperature and its square, total precipitation and its square. * significant at 10%; ** at 5%; *** at 1%. Standard errors are clustered at the cell level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	——— NDVI ———				
Split:	—— Full sample ——			One plant	Global firm
SRI IO	0.038***	0.035***	0.032***	0.022***	0.033***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
outsideOECD × SRI IO	-0.043***	-0.031***	-0.028***	-0.024**	-0.029***
	(0.005)	(0.010)	(0.010)	(0.012)	(0.010)
IO	-0.002**	-0.002**	-0.001*	-0.001	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature	0.011***	0.011***	0.010***	0.010***	0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rain	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rain Sq	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temperature Sq	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lights	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Builts	-0.000	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population	-0.000	0.000	0.000	-0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.453***	0.445***	0.442***	0.459***	0.440***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Cell-month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No
Year-country FE	No	Yes	No	Yes	Yes
Year-Agroclimat FE	No	No	Yes	Yes	Yes
Observations	3703402	3703402	3695303	1828100	3317346
Adjusted r^2	0.90	0.90	0.90	0.90	0.90

5. Conclusion

This study leverages remote sensing data to investigate the impact of the adoption of SRI principles by institutional investors on the ecological footprint of multinational industrial companies worldwide. By exploiting the inverse relationship between local pollution and high-frequency satellite-based measurements of vegetation health via the NDVI, we uncover the high potential of NDVI as an indicator for variations in local pollution, assessing the net effect of a wide range of pollutants beyond emissions alone. The granularity of NDVI data allows for frequent monitoring and consistent analysis across diverse companies and their global facilities, forming the core of our assessment of SRI practices.

We begin by validating the NDVI's relevance in capturing variations in local pollution. Leveraging USA-wide data, our analysis demonstrates that vegetation health significantly deteriorates in areas with increased toxic releases and improves with reductions in releases. This finding highlights the importance of considering both the scale and concentration of pollution when assessing environmental impact. As an alternative validation exercise, we levy toxic chemical spills and document their significant and prolonged negative effect on vegetation, with NDVI values declining for up to four months post-accident. These results empirically support that changes in NDVI signal changes in local pollution levels. By validating the NDVI's responsiveness to both chronic toxic releases and acute environmental accidents, we confirm its utility as a reliable tool for monitoring pollution

Following this validation, we analyze how NDVI values in each $0.1^\circ \times 0.1^\circ$ cell correlate with average SRI ownership within that cell. Our findings reveal a positive association between ESG or sustainable institutional ownership and pollution reduction, as measured through NDVI. Firms with higher SRI ownership tend to decrease pollution. This relationship is predominantly observed in OECD countries or those with stringent environmental laws. In contrast, in non-OECD locations, where environmental regulations may be less stringent, vegetation quality around facilities does not show any significant reaction to SRI inflows. This heterogeneity suggests a potential strategic behavior of multinationals receiving SRI when deciding where to focus their environmental efforts. These insights also illuminate the concrete environmental impacts driven by sustainable capital, surpassing reliance solely on self-reported emissions data.

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A-1 NDVI: Literature Review, Relevance and Uses.

Below, we provide a comprehensive overview of various applications of the NDVI, and why it is a reliable and appropriate method for assessing impact of industrial pollution in our setting.

Applications of the NDVI for land degradation assessment: The NDVI is primarily used to determine Land Use and Land-Cover Change (LULCC), which refers to human modification of Earth's terrestrial surface. The quantity and quality of vegetation cover play a crucial role in shaping landscapes, affecting provision of environmental services, and influencing ir resilience or degradation (Yengoh et al., 2015). Human activities that lead to land degradation comprise uncontrolled expansion of mineral mining and industrial activities, farming practices that are not sustainable, overgrazing, and extensive air and water pollution by waste materials. The NDVI also has potential to serve as a proxy for desertification, deforestation, vegetation response to fluctuations in rainfall, enhancements in farming techniques, and population movements or displacement (Sommer et al., 2011).

Determinants of the NDVI variation: Spatio-temporal variation in vegetation quality and quantity can be caused by several factors, which are in turn captured by the NDVI. Precipitation, vegetation type, soil type, temperature, and land use type are major driving forces that cause variations in the NDVI over time. Land use, which is most direct reflection of human activities on vegetation health, is in some cases responsible for up to 25% in variation of the NDVI (Zhang et al., 2022). Land use and human-induced factors can negatively impact vegetation health, and thus the NDVI, through several channels such as:

- *Atmospheric Pollutants:* Gas forms (oxidized and reduced forms of carbon and nitrogen) and particulate matter (PM) (PM10 and PM2.5 and toxic heavy metals) can harm vegetation either directly, through toxic effects, or indirectly, by altering soil pH and making toxic metal salts, such as aluminum, more soluble. PM can also have a detrimental mechanical effect by covering leaf surface and blocking stomata, which reduces light penetration and impairs process of photosynthesis, leading to a significant decline in rate of photosynthesis (Gheorghe and Ion, 2011) and (Rai, 2016). For instance, Moraes et al. (2003) find that PM emissions of an industrial complex had adverse impacts on surrounding vegetation. The forest species that were studied suffered visible injuries, reductions in net photosynthesis, growth parameters, adsorbate concentrations, and increased F, N, and S foliar concentrations. A similar study by Alfani et al. (2000) reports high levels of heavy metals and or elements in plant leaves close to major industrial plants.

- *Soil Pollution:* Phenomena such as soil salinity and soil erosion have a harmful impact on vegetation health. Salinity occurs when salt is present in places where it should not be, which can negatively impact quality of water and ability of plants to absorb water and nutrients. Salinity can be caused by human-induced factors such as contamination of soils with salt-rich waste waters and industrial by-products (Louwagie et al., 2011).

- *Water Pollution:* Land use and human activities such as industrial production can also alter quality of water, affecting uptake of nutrients by surrounding vegetation. Mining, for instance, generates discharge wastewater that negatively impacts quality of surface and groundwater, and may pose risks to drinking water supplies and losses of vegetation on land and in aquatic environments. In oil and gas industry, process of extracting shale gas results in generation of significant quantities of wastewater through hydraulic fracturing. This wastewater can have high levels of dissolved solids, such as salts, along with naturally occurring radioactive materials and metals, as well as or chemicals utilized during drilling and well completion.

NDVI vs. air pollution measures Remote sensing measures that capture air quality and pollution have been widely used in environmental studies as well as in economics [16]. However, focusing on impact of industrial activities on air quality only can be limiting. Gibson (2019) and Bi (2017) find that plants in U.S. increase ir level of toxic water emissions by 105% following introduction of Clean Air Act (CAA), which regulates air emissions in particular counties. Similarly, Greenstone (2003) reports that reduction in air pollution might be largely attributed to use of devices such as scrubbers and electrostatic precipitation. These devices effectively remove pollutants from air, but remaining residuals are discharged into water bodies, landfills, or injected into ground. Moreover, re is evidence that the NDVI is highly sensitive to residual atmospheric contamination (Xiao et al., 2003). This essentially means that the NDVI indirectly captures levels of air pollution. For these reasons, we introduce the

[16] See Donaldson and Storeygard (2016) for a survey of literature

NDVI as a measure of industrial pollution since it captures negative externalities of air, water, and ground pollution.

A-2 Tables

Table A-1: Distances in Kilometers at the Equator for Different Degrees of Latitude. These calculations are based on a simplified approximation using the average Earth's circumference at the equator of approximately 40,075 kilometers (24,901 miles). The actual distances at specific latitudes may vary slightly from these estimates. To calculate the distance covered by degrees of latitude, we need to know the approximate circumference of the Earth at the given latitude.

Degrees of Latitude	Distance (in Kilometers)	Data
0.05	5.56	NDVI input data
0.10	16.67	Final dataset
0.5	55.56	CRU input data

Table A-2: NDVI reaction to toxic releases 0.05 cells

The table presents the results of OLS estimations with standardized variables. The dependent variable is the Normalized Difference Vegetation Index (NDVI), the explanatory variables come from the Toxic Release Inventory (TRI) database. All columns include weather controls (average temperature and its square, total precipitation and its square) as well as economic controls (nighttime light emissions, buildings in the cell and total population of the cell). * significant at 10%; ** at 5%; *** at 1%. Standard errors are clustered at the cell level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.			——— NDVI ———			
Sample			all cells		TRI down	1 plant/cell
Tot. releases	-0.003**	-0.001	-0.001			
	(0.002)	(0.001)	(0.001)			
Tot. on-site releases				-0.001*	-0.003**	-0.004***
				(0.001)	(0.001)	(0.001)
Tot. off-site releases				0.000	0.000	-0.001
				(0.000)	(0.000)	(0.001)
Cell FE	Yes	No	No	No	No	No
Cell X month FE	No	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year X agroclimatic FE	No	No	Yes	Yes	Yes	Yes
Frequency	Yearly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly
Observations	163443	3760789	3760789	3760789	2949745	673123
Adjusted R^2	0.98	0.90	0.90	0.90	0.90	0.90

Table A-3: NDVI reaction to toxic releases 0.1 cells - showing control variables

The table presents the results of OLS estimations with standardized variables. The dependent variable is the Normalized Difference Vegetation Index (NDVI), the explanatory variables come from the Toxic Release Inventory (TRI) database. As appears in the table, all columns include weather controls (average temperature and its square, total precipitation and its square) as well as economic controls (nighttime light emissions, buildings in the cell and total population of the cell). * significant at 10%; ** at 5%; *** at 1%. Standard errors are clustered at the cell level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.			—— NDVI ——			
Sample		all cells			TRI down	1 plant/cell
Tot. releases	-0.005***	-0.002**	-0.002**			
	(0.001)	(0.001)	(0.001)			
Tot. on-site releases				-0.002***	-0.003*	-0.004***
				(0.001)	(0.002)	(0.001)
Tot. off-site releases				0.001	0.001	0.001
				(0.001)	(0.001)	(0.002)
rain	0.260***	0.058***	0.058***	0.058***	0.057***	0.051***
	(0.018)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
temperature	0.802***	0.434***	0.434***	0.434***	0.423***	0.384***
	(0.015)	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)
temperature sq.	-0.703***	-0.306***	-0.306***	-0.306***	-0.299***	-0.267***
	(0.017)	(0.004)	(0.004)	(0.004)	(0.004)	(0.008)
rain sq.	-0.140***	-0.028***	-0.028***	-0.028***	-0.027***	-0.024***
	(0.016)	(0.004)	(0.004)	(0.004)	(0.005)	(0.003)
Lights	-0.060***	-0.049***	-0.049***	-0.049***	-0.048***	-0.056***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)
Population	-0.078**	-0.048***	-0.048***	-0.048***	-0.050***	-0.010
	(0.031)	(0.018)	(0.018)	(0.018)	(0.019)	(0.062)
Build	0.149***	0.073***	0.073***	0.073***	0.079***	0.032
	(0.028)	(0.016)	(0.016)	(0.016)	(0.017)	(0.055)
Cell FE	Yes	No	No	No	No	No

Table A-4: NDVI reaction to toxic releases 0.5 cells

The table presents the results of OLS estimations with standardized variables. The dependent variable is the Normalized Difference Vegetation Index (NDVI), the explanatory variables come from the Toxic Release Inventory (TRI) database. All columns include weather controls (average temperature and its square, total precipitation and its square) as well as economic controls (nighttime light emissions, buildings in the cell and total population of the cell). * significant at 10%; ** at 5%; *** at 1%. Standard errors are clustered at the cell level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.			——— NDVI ———			
Sample			all cells		TRI down	1 plant/cell
Tot. releases	-0.012***	-0.006***	-0.006***			
	(0.001)	(0.001)	(0.001)			
Tot. on-site releases				-0.006***	-0.007***	-0.007***
				(0.001)	(0.001)	(0.001)
Tot. off-site releases				0.008	0.018*	0.055
				(0.006)	(0.010)	(0.044)
Cell FE	Yes	No	No	No	No	No
Cell X month FE	No	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year X agroclimatic FE	No	No	Yes	Yes	Yes	Yes
Frequency	Yearly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly	Bi-weekly
Observations	10231	235209	235209	235209	170310	26394
Adjusted R^2	0.99	0.94	0.94	0.94	0.93	0.93

A-3 Figures

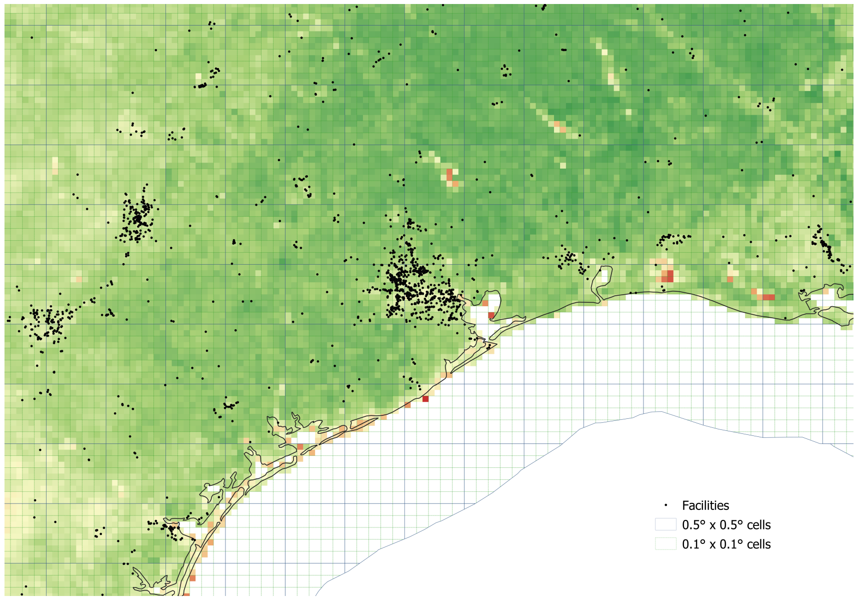

Figure A-1: NDVI and firms in the surroundings of Houston. The map shows the raw NDVI values retrieved from the MODIS data at a resolution of 0.05×0.05 degrees, as of June 9, 2000 in the surrounding of Houston. The map overlays the grid cells of size 0.1×0.1 degrees (our baseline level of analysis), 0.5×0.5 degrees (the level of the widely used PRIO-Grid cells), and the facilities located around.

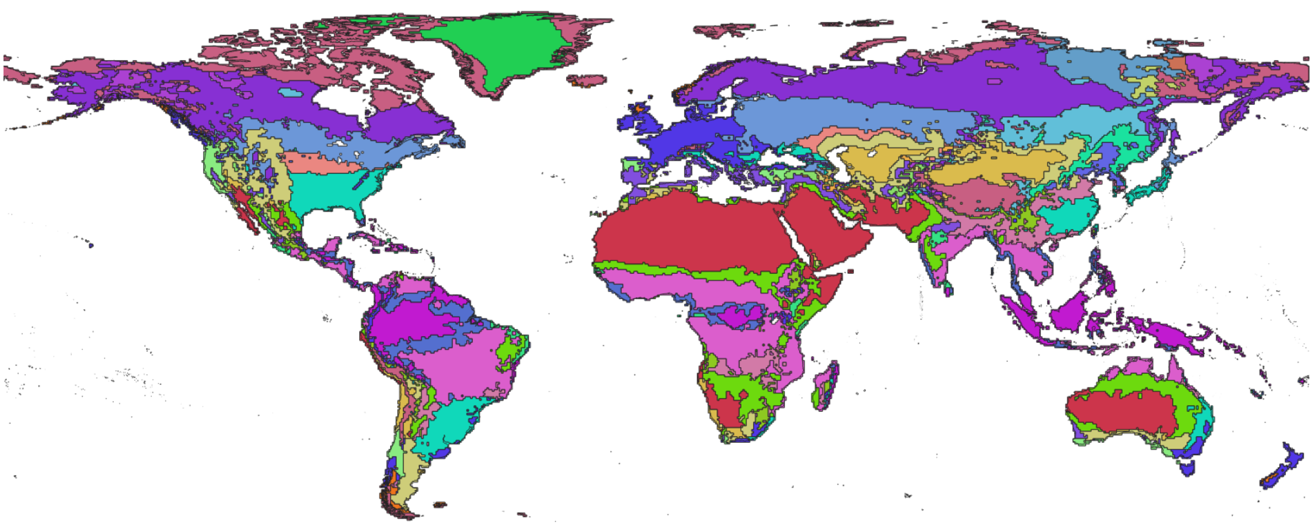

Figure A-2: Agroclimatic zones. The map shows the Köppen-Geiger climate classification system, as published by the World Bank .