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JADE: Developing AI-based models to create optimized adaptive investment policies that balance environmental impacts and economic growth

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Abstract
This paper explores the development of an AI-based model designed to create adaptive investment policies that balance environmental impacts and economic growth. The hypothesis is that for any given interconnected system of industrial producers and populations, and a relative weighting of economic growth and environmental impacts, there exists an optimal solution for economic transfers that will maximize the overall utility. The model simulates three case studies: smartphone manufacturing, gasoline production, and wind turbine deployment, considering their environmental impacts on affected populations, especially vulnerable communities disproportionately harmed by pollution. In addition to addressing specific local impacts, the model accounts for global environmental issues, such as greenhouse gas emissions. Machine learning algorithms are used to optimize a payment structure known as JADE (Joint Adaptive Dividends for the Environment) that requires polluters to invest in supporting the communities they affect. The results indicate that targeted investments through this adaptive framework can enhance long-term economic growth while promoting environmental sustainability. Specifically, the findings reveal that the AI-optimized JADE payments significantly improve aggregate utility across all three scenarios, demonstrating 37-64% improvement over the status quo. This work highlights the potential of AI-driven policy models to address critical challenges resolving competing environmental and financial interests.

Keywords
Environmental engineering, Pollution control, Machine learning, Greenhouse Gas Emissions, Environmental justice, Quantitative policy, Optimization, Lifecycle analysis, Remediation, Environmental impact

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Introduction

One need not travel far almost anywhere in the world to see the disparate impacts of pollution from modern industry. While some neighborhoods are green and idyllic, others choke in the shadow of smokestacks or are maligned with tainted water and soils. And it is often poor or marginalized communities that are harmed by hazardous waste, resource extraction, and other land uses from which they often do not benefit (1). It is natural as societies develop in wealth and capabilities that interest in pollution remedy for disadvantaged populations will grow, but actual implementation is notoriously difficult. This concept is sometimes referred to as environmental justice in the scholarship, acknowledging that the term resists a straightforward definition, as it can be used as a descriptive, a normative, or a political term (2).

The modern environmental movement traces its roots back to the conservation movements of the early twentieth century (3), with the foundations of case law beginning in the 1970s (4). And at first glance, fostering fair ecological outcomes seems simple: if a land use is degrading the environment for a poor community, then that land use should cease. The offending factory should be shut down. The landfill should be closed. The power plant should be turned off. But this simple solution will doubtless lead to unintended consequences. What if the factory is providing essential jobs for the impacted community? If the landfill is closed, will the trash just not be diverted to a different vulnerable community? What if the land use in question is a wind farm that reduces air pollution and global greenhouse gas emissions? How should populations with different needs and disadvantages be considered? (5) And what about impacted customers at the other side of the supply chain who depend on the goods or services being produced?

The next variation on the remedy for the environmental disparities is: "the polluters should pay the impacted populations." And again, questions and unintended consequences arise. What is the right amount of compensation? Too little and it won't make a difference; too much and companies will cease to operate. Should the companies bear this financial responsibility, or should their customers? Should these funds transferred be spent on remediation to improve the health and living conditions of populations, or should they be spent to reduce future pollution? If there are multiple vulnerable affected populations, how should these funds be allocated?

It's not surprising that problem of managing the utility functions for all these interconnected parties is so complex that it exceeds human capacity. Current approaches to fair environmental solutions struggle to manage these multiple dimensions (6), and despite decades of efforts, policies in place have not achieved measurable results (4). Fortunately, the tools of machine learning and AI are well-suited for just such tasks. The JADE (Joint Adaptive Dividends for the Environment) framework was envisioned as a means of using

AI to tackle the challenge of balancing environmental impacts with economic growth.

The hypothesis is that for any given interconnected system of industrial producers and populations, and a relative weighting of economic growth and environmental impacts, there exists an optimal solution for economic transfers that will maximize the overall utility. This paper will describe the approach to create a machine learning model to simulate these systems, and then employ the model over thousands of iterations to test the hypothesis that optimal solutions do exist.

Methods

Conceptual framework

As the JADE framework is intended to find the optimal solution for an industrial system of production and impacted populations, the system boundary will be defined as a single supply chain that can encompass everything from resource extraction (e.g. mining, oil drilling) to transportation, to the end user customers of the products, and even to the end-of-life disposition of the products. Importantly, populations outside of the supply chain but which still are impacted by the system will also be included inside the boundary. In practical terms, inputs on environmental impact areas identified by local or national regulators could help resolve the system boundary (7). Finally, a special module for "the world" will be included in the boundary to represent impacts (positive or negative) that the industrial system might have on the global environment (e.g. greenhouse gas emissions). Ever since Hurricane Katrina, climate impacts and local pollution have been considered inextricably linked (8), and will therefore be part of the JADE framework as well. Figure 1 illustrates an example system boundary.

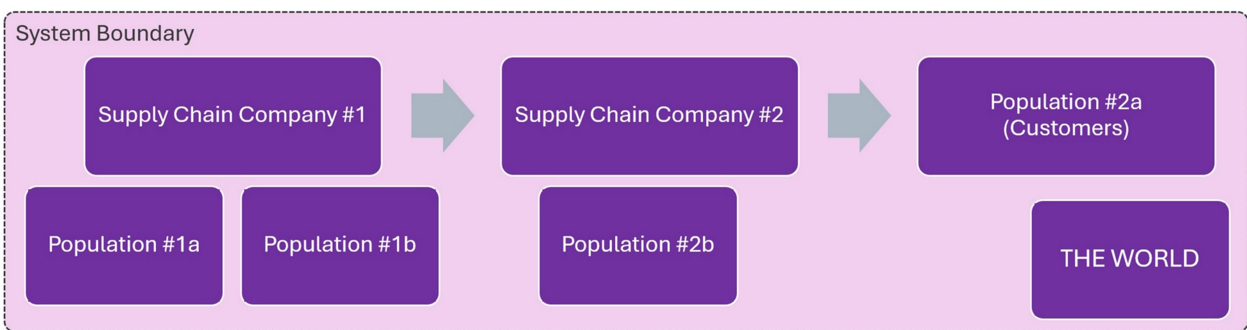


Figure 1. Diagram of general system boundary and the modeled entities of a system. The grouping and numbering of the populations with the supply chain companies indicates which populations are impacted by which companies. Population #2a is the special case, representing the population that is the customer of the product or energy being produced, and also potentially impacted itself. The World is included to represent global impacts, such as greenhouse gas emissions.

For purposes of this initial work, it will be assumed that the number of entities modeled within the system boundary is sufficient to derive meaningful conclusions. In order to test the hypothesis that machine learning would be a useful tool to optimize balanced outcomes, three real-world contemporary scenarios were modeled; the manufacture of smartphones, such as Apple or Samsung devices; the extraction and refining of crude oil to on-road gasoline; the manufacture and deployment of utility-scale wind turbines for power generation. For each of these scenarios, Table 1 shows how the supply chain companies and impacted populations are mapped within the system boundary of the JADE framework.

Table 1. The systems modeled for this paper. This table maps the companies and populations to the system diagram in Figure 1. The populations represent the people directly impacted by pollution impacts of the supply chain, and Population #2a is also the customers of the product.

Case	Company #1	Population #1a	Population #1b	Company #2	Population #2a	Population #2b
Smartphones	Metals mining for batteries and components	Near mines	Manufacture of semiconductors and finished Smartphones	Phone producer and its subcontractors	Smartphone customers worldwide	Impacted by e-waste disposal
On-road Gasoline	Crude oil extraction	Near oil wells	Affected by transportation and storage	Oil refining and marketing	Retail gasoline customers	Near oil refinery
Wind Turbines	Metals mining and turbine manufacture	Near mines	Near turbine factories	Power production and marketing	Retail electric customers	Near wind farm

For reasons of simplicity, the system boundary in this paper was limited to two supply chain companies and four affected populations. There seems no reason to think why the framework could not be extended to cover many more companies and populations, and longer supply chains.

Jade settlements

As the name JADE (Joint Adaptive Dividends for the Environment) suggests, the framework is intended to specify specific payments (aka dividends) which are paid by the entities within the system that either benefit from the supply chain or cause pollution impacts. These dividends are paid on a regular basis into a pool, and then dispersed for the benefit of those populations impacted by the activity.

There are two broad dispositions for the JADE settlements. 1] Funds that are allocated to remediate current impacts, such as cleaning up chemical spills, relocating affected populations, medical care and treatments; and 2] Funds that are allocated to reduce future pollution, such as installation of air emissions filters or scrubbers, training for safe handling of chemicals, repair or replacement of leaking product tanks. Evidence shows that efforts to reduce future pollution in conjunction with remediation of current impacts are the most effective in advancing environmental stewardship (9).

It is evident that it becomes a complex task to determine simultaneously the magnitude of the JADE settlement required, exactly how much should be collected and dispersed to each party, and the disposition for current vs future remediation. This is why the problem lends itself well to a machine learning algorithm to assist with optimizing. Figure 2 is an illustration of the indicative JADE settlement for the smartphone scenario.

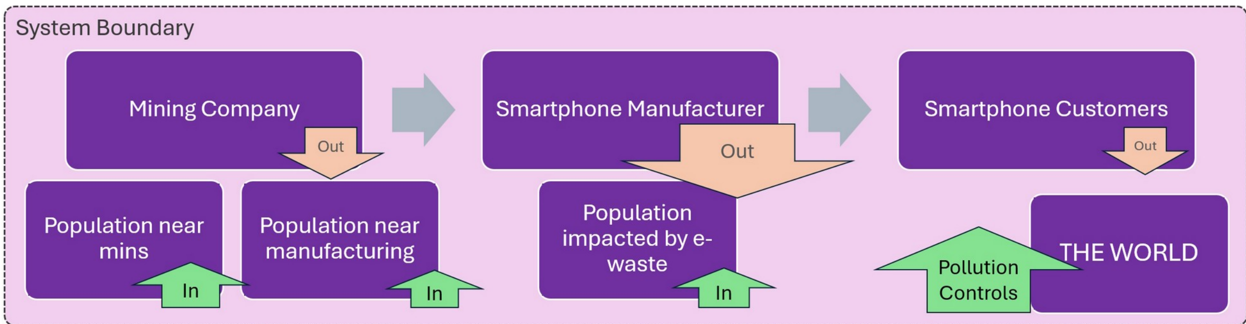


Figure 2. Example of a solution for the optimal flow of JADE settlements within a particular system boundary, with the size of the arrow proportional to the amount of payment. The orange arrows indicate payments into the JADE pool from companies or populations which benefit from the system. The green arrows represent the flow of funds from the JADE pool to populations impacted by the activity. The arrow for "Pollution Controls," indicates that some of the settlements will be used to mitigate future pollution rather than remediate existing impacts.

The diagram illustrates an optimal solution for the entities within the system boundary, where all of the companies in the supply chain, as well as the smartphone customers, provide JADE payments. The largest amount of payments go towards controls to mitigate future pollution, with additional payments directly to all of the affected populations for remediation, health, and safety improvements.

The model

The model for the JADE framework was built in Microsoft Excel and comprises several modules and activities, including Pollution, Companies, Populations and Utility, Simulation Inputs, Simulation Runs, and Machine Learning.

Pollution

Tracking pollution is at the core of any analysis of environmental impacts, starting at the local level. Strong evidence suggests that pollution follows poverty (10), and also to a non-random relation between environmental hazards and social disadvantage (11). The pollution categories used in the JADE framework are intentionally the same as those used for detailed lifecycle analysis (LCA) and are described by ISO 14040:2006/Amd 1:2020 (12). Table 2 lists the pollution impact categories used.

Table 2. The pollution impact categories used in the JADE model and indication of their scope. Impacts with "Local" scope will be assumed to only impact the populations associated with the companies (see Figure 1).

Category	Units	Scope	Category	Units	Scope
Photochemical oxidant (Ozone) or smog formation	kg ethylene-eq	Local	Abiotic and biotic resource depletion	kg Sb-eq	Global
Acidification	kg SO_2-eq	Local	Global warming	kg CO_2-eq	Global
Eutrophication	kg PO_4-eq	Local	Ozone depletion	kg CFC-11 eq	Global
Human toxicity	kg 1,4-DCB-eq	Local			
Ecotoxicity	kg 1,4-DCB-eq	Local			

The quantified pollution impacts across all these categories for each of the supply chain companies in Table 1 are listed in Appendix A. These impacts have been derived from ISO 14040 analysis in published supply chain sustainability impact papers (13-15). Each of these papers provides category impact on a unit basis, i.e. per smartphone produced, km of miles driven from gasoline, and kWh of wind power produced. The impacts studied were normalized to a population size of one million households, approximately 2.5 million people based on recent US census data. Average annual consumption values were used for per-household smartphone purchases, miles driven, and consumption of wind power to derive the following (16-19).

Table 3. Consumption rates for supply chain products are normalized to a size of one million households. The table shows unit rates per household and total consumption on an annual basis.

Annual Consumption	Smartphones	Distance driven in cars	Wind power
Unit consumption per household	1.74 phones	40,225 km	1,079 kWh
Total consumption 1M households	1,740,000 phones	$4.02 * 10^{10}$ km	1,079 GWh

Under the JADE framework, a supply chain company will have “responsibility” for both local and global pollution impacts, which will be additive,

$$Net\ Impacts = (Local\ Impacts) + (World\ Impacts) \quad \text{(eq. 1)}$$

Note also that impacts can be beneficial as well as harmful. For example, the release of contaminated mine tailings would be a harmful local impact of minerals extraction. The reduction of greenhouse gas emissions from the deployment of wind turbines is a beneficial global impact (by reducing other carbon-intensive generation). This pollution data could be collected though the existing pollution regulation infrastructure, private or nonprofit efforts, purpose-fit GIS-based initiatives (20), or even novel crowdsourced methods (21), before being tabulated per ISO 14040.

Supply chain companies

In any complex supply chain, such as petrochemicals production, there are dozens or hundreds of companies involved. Mining companies would be examples of supply chain companies modeled in JADE, and the framework will provide an estimate for their significant level of environmental impact (22). The working JADE model for this paper is constructed as a high level, hence all the companies involved in each sector were conflated and modeled as a single entity. In a real-world implementation of JADE, each mining company and resource (copper, cobalt, gold, tantalum, lithium, etc.) would be tracked individually, to ensure that companies decreasing their pollution can be rewarded with reduced payment obligations. The supply chain companies are modeled with the input parameters shown in Table 4 which quantify both the financials of the company and the profitability of its products.

Table 4. The parameters used to model the companies in the supply chain for the product or energy output.

Parameter	Description
Pollution produced in each category	A numbered range for each impact in Table 2 denoted in the units shown for that impact. Appendix A lists the pollution impacts for each company in each of the three scenarios.
Profits	Total yearly profits of the company ($M/year)
Production function based on profits	Sensitivity of quantity of product produced as a function of profits

The Company module for JADE (supplementary file) uses a simple economic model to forecast how the supply-demand equilibrium for the product will change with financial burdens imposed by the JADE framework. This will be modeled similar to a tax payment in conventional economics, where the supply-demand line shifts to the left with the added cost, resulting in a new equilibrium at a higher price and lower demand. For example, in a scenario where a given company is required to pay $10 per smartphone sold for JADE settlements, the market will settle at a new point with fewer units sold. A linear function is used to show how the quantity of products or energy *Q(J)* sold will change when JADE is implemented, $Q(J)=Q_0\cdot(1+\frac{J}{P})$ (eq. 2), where Q_0 is the maximum production, *P* represents the corporate profits, and *J* is the total Net JADE payment from the company (negative *J* implies a net outflow). This function models the reduction in products produced and sold as JADE payments increase, which will reduce customer utility (see Populations and Utility). Figure 3 shows this relationship visually.

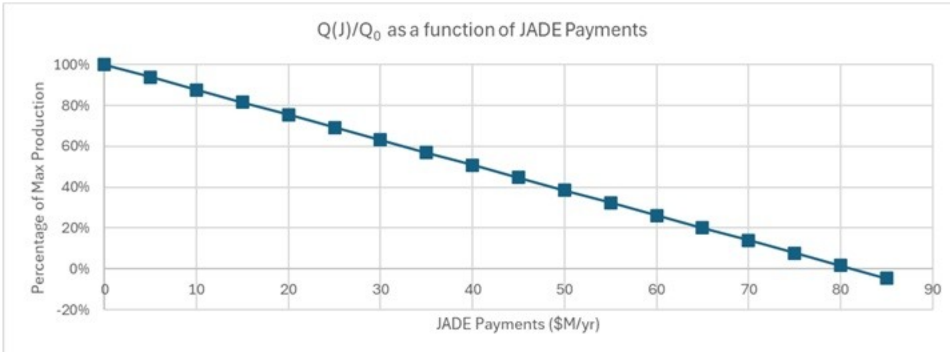


Figure 3. The relation of product produced by a supply chain company as a function of JADE payments required. In this example, company profits are \$81M per year. When the JADE payments reach \$81M per year, the company effectively exits the market, demonstrating one of the boundries of the framework.

The change in *Q(J)* from applying a JADE settlement (as shown in Figure 3) will also impact the net profit of each company, as shown in equation 3.

$$Net\ Profits = (Base\ Profits) + (Change \text{ in } Profits\ consumption \text{ or } demand) + (Net\ JADE\ Payments)$$
(eq. 3)

The overall profitability of the companies in the supply chain will one of the factors considered in the JADE optimization. If the companies cannot retain some degree of profitability, the solution will not be implemented. Note that the simple economic model used in this paper is intended to provide a projection for how the supply chain companies and customers would respond to JADE payments being imposed. In a real-world implementation the modeling would not be needed, as the actual market data would be recorded.

Populations and utility

Maximizing the health, well-being, and economic livelihood of populations is core to the premise of the JADE model. The model tracks a "utility" function for each impacted population over the course of the simulation timeframe, which is a concept borrowed from economics and will be defined as quantitative score for the average individual well-being and satisfaction of population members. This population utility score will be used as an input to the function to score overall outcomes. For each population, their utility is the sum of the following components, which track environmental impacts (good or bad) and economic changes, as shown by equation 4.

$$Net\ Utility = (Local\ Waste\ Impacts) + (Local\ Environmental\ Benefits) + (Economic\ Development) + (Net\ JADE\ Payments) \quad \text{(eq. 4)}$$

Table 5 lists the inputs used to model the populations impacted by land use and industry in JADE. The consumption utility function is a measure of the sensitivity of utility to the quantity of product consumed and the total cost of the product.

Table 5. The parameters used to model the populations within the system boundary.

Parameter	Description
Gross population	Millions of people
Wealth	Measure of the population's purchasing power available for the product ($M/yr)
Economic development	Measure of the total jobs and economic benefit of the modeled land use ($B)
Consumption utility function	Sensitivity of utility to quantity of product consumed and total cost of product

The local waste impacts used are the sum of those in the local category in Table 2. The reduction in a population's utility function from environmental hazards is the means to model impacts to health and well-being, such as higher incidences of cardiovascular disease and asthma, as well as infant mortality from air pollution (23) and degradation of access to clean water (24). It is also possible that the supply chain companies could cause environmental benefits, for example if cleaner power sources were used to replace outdated polluting sources. Finally, the economic development from the supply chain is considered, along with any JADE payments that might be the population's responsibility.

As shown in Table 1, Population #2a is a special "customer" population, meaning that they are the primary purchaser of the products or energy produced by the land use or industry. For this population, the JADE model quantifies the utility, a measure of the benefit or satisfaction derived from these purchases. This consumption utility, denoted as *U(Q,C),* is added as an additional component in the *Net Utility* calculation in eq.4. *U(Q,C)* is a function of both the quantity of consumption *Q* and the unit cost of each product *C* and will be modeled to follows a classic exponential demand function (25) as modeled by eq.5,

$$U(Q,C) = a \cdot \ln(Q) - b \cdot (C - J) \quad \text{(eq.5).}$$

where *a* represents the marginal utility from consuming more quantity, *b* is the negative impact of increasing cost, and *J* is net JADE payments from the population (negative means adding to cost). Figure 4 shows this relationship visually.

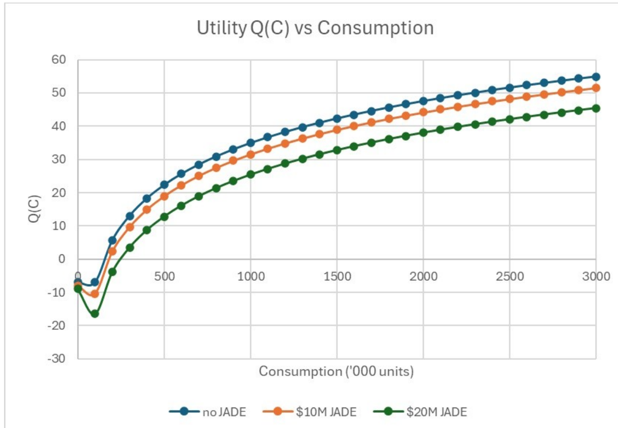


Figure 4. For the Smartphone scenario, the figure shows the relationship between customer population utility, the consumption of the product, and the magnitude of JADE payments applied to the product. The blue line is the base utility function for the population based on consumption of phones, assuming a total cost of $70M per year across the population. The orange and green lines illustrate the lower utility for the customers if JADE payments are $10M and $20M per year, respectively.

The JADE settlements (and investments from those settlements) therefore become the driver of dynamic changes to the JADE model. When JADE payments are introduced into the system, these economic models will find a new equilibrium and determine how utility has changed. Through these interconnected utility functions for impacted populations and the population of customers, the JADE model will be able to discern and help roll back what some researchers call the "pollution inequity"—specifically that minority communities have been shown to bear 56-63% more pollution relative to their share of consumption (26). The JADE framework will be able to solve for optimal points where costs and benefits of the supply chain are fairly allocated.

Simulation inputs

There are a number of key inputs which represent the operative parameters for the JADE framework—that is, parameters which determine to what magnitude JADE is implemented, which entities should bear responsibility for making JADE payments, and what should be the disposition of those payments (Table 6). The first of these – JADE implementation - is the most important, which determines the percentage of pollution impacts that the JADE payments are intended to remedy; i.e. the overall level of JADE settlements that will be collected. The other parameters determine which parties will bear responsibility and whether the settlements will used for current or future remediation. The Base Value is the starting parameter setting prior to running optimization. The JADE Use Switch Year is explained later in the manuscript.

Table 6. The six key parameters within the JADE framework which will be optimized by machine learning.

Inputs	Base Value and [Sensitivity Values]	Description
JADE Implementation	50% [0%-200%]	Percentage of pollution impacts which JADE payments are intended to remedy; a value of 100% means that JADE payments are considered to match the full pollution impacts; increasing the number will increase impact of program but add to costs; could even be higher than 100%
JADE Responsibility	50% [25%, 75%] Supply Chain; 50% [75%, 25%] Population	Determines whether the cost of JADE should be borne by the companies in the supply chain or by the populations which benefit from the supply chain economic impacts and utility
JADE Allocation	50% [25%, 75%] by Profit; 50% [75%, 25%] by Pollution	Determines whether the allocation JADE responsibility for companies in the supply chain should be weighted by the relative profits on the companies or by their relative pollution impacts
JADE Uses	50% [0%, 100%] Pollution, 50% [100%, 0%] Restitution	Determined whether the JADE payments should be applied towards reducing future pollution or restitution assisting populations and remediating pollution; model allows for a switch of allocations between two periods, Phase 1 and Phase 2
JADE Use Switch Year	Year 11 [5, 15]	Indicates which year of the model (between 1 and 20) that the JADE Uses should switch strategies from Phase 1 to Phase 2

There are other inputs which are important to the functioning of the JADE model shown in Table 7 which are fixed and will not be modified as part of the optimization.

Table 7. Additional parameters for JADE framework. These parameters are fixed for all scenarios and will not be changed with machine learning.

Inputs	Value	Notes
Years of JADE framework simulation	20	A reasonable horizon to consider for long-term policy planning
Discount rate	5% per year	The discount rate is applied to cash flows and environmental impacts, to provide a weighting for near-term results vs those in the future; similar to a financial discounted cash flow analysis, where a factor of 1/(1+Discount Rate) is applied for each successive year past the scenario start year when computing aggregate impacts
Percentage of pollution fixed	25%	For any polluting activity modeled, represents a baseline amount of pollution generated from background activity (climate control, administration, maintenance, etc.) even if activity is running at a curtailed rate
Population allocation of JADE impacts	33% Economic development, 33% Population, 33% Wealth	For JADE costs incurred by a population, determines the blend of weighting factors used to allocate a relative share of each population's contribution; in this model version the decision was to weigh economic development, gross population size, and population purchasing power (wealth) evenly; this parameter could be revisited or even optimized with machine learning later

These parameters could be tuned for some macro-level inputs to the analysis. For example, if the focus was on shorter-term solutions, stakeholders might choose a 10-year simulation timeframe and a higher discount rate, such as 12%. The higher discount rate would steer the model towards prioritizing nearer-term pollution reductions by increasingly discounting future reductions.

Simulation run

The JADE model is structured to project outcomes into the future, with whatever time horizon is provided in the inputs (in our case, 20 years). The model determines a state each year of the simulation, considers the pollution and economic impacts, and then evolves the state to the next year. The framework is intended to anticipate how the entities within the system boundary would react and change over that forecast period. For example, as investments are made in pollution reduction, the impacts within the system will decrease and population utility will increase. If JADE payments are excessive, then companies would stop producing products. The model contains a parameter to allow for a switch of strategy (defined by the parameters) once during the course of the time horizon. This is to anticipate the likelihood that the optimal strategy might evolve once JADE is implemented. For purposes of simplicity, only one change event was considered, though there is no reason with more computational power available that the framework could not be optimized even further to allow even more switch events.

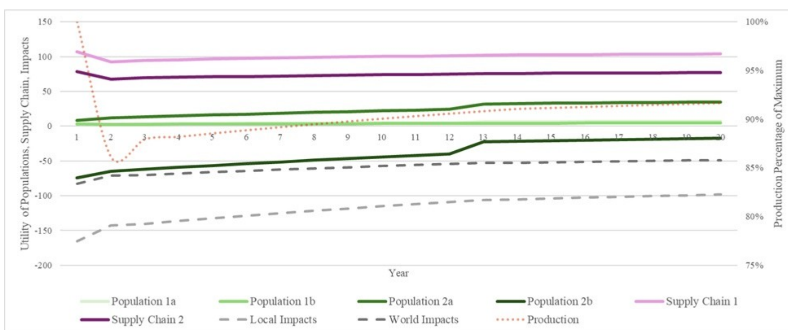


Figure 5. Chart showing the impact of JADE settlements on the utility function for populations, companies, and the environment across a 20-year simulation for the wind turbine case. The JADE settlements decrease the overall pollution from mining and increase the populations' utility. The amount of greenhouse gas reductions is maintained at a high level.

During each 20-year run, utility functions are calculated for each of the four populations based on their health and safety, environmental burdens, and economic impacts. The profits of the two modeled companies serve as the utility function for the supply chain. The local and global environmental impacts form the utility functions for the local and global environment (where pollution is negative utility). Figure 5 provides a visualization of these utility functions for the optimized wind turbine case.

Simulation outputs

The parameter which is maximized in the JADE model is called the JADE Score, which is a combination of population utility, company profits, and environmental impacts within the system boundary.

Table 8. The outputs of utility, profits, and environmental impacts for the smartphone scenario in the optimized case.

Output	Base Case Value	Notes
Utility for Population 1a	-271	Impact of minerals mining
Utility for Population 1b	-110	Significant economic activity
Utility for Population 2a	553	High utility of smartphone customers
Utility for Population 2b	-25	Impacts of e-waste disposal
Total Utility	**146**	**Combined utility of populations**
Profits for Supply Chain 1	218	Lower margins on mining
Profits for Supply Chain 2	973	Significant smartphone profits
Total Profits	**1191**	**Combined profits of companies**
Environmental Impacts, Local	-559	Sum of local pollution, toxicity
Environmental Impacts, World	-151	Mostly driven by greenhouse gas emissions
Total Environmental Impacts	**-710**	**Combined supply chain impacts**
TOTAL JADE SCORE	**627**	**Sum of Total Utility, Total Profits, Toal Environmental Impacts**

The JADE Score is determined by adding the values in each of these categories across the years of the simulation time frame, with future cash flows and impacts discounted according to the input discount rate. These discounted sums are then weighted and all added together to form a single JADE Score, which is then optimized with the machine learning engine. Table 8 proves an example buildup of the JADE Score for the Smartphone scenario. The units are relative to the JADE scoring system and normalized to be comparative. Environmental impacts of the supply chain affect both the utility of the populations, considering human health and well-being, and are also tracked on their own in the Environmental Impacts category. Note that the 20-year total for impacted populations often shows negative utility, as the early years will contribute negative amounts from the starting conditions, and it may take years for cleanup to occur and overall utility to turn positive.

The key outputs then of the JADE model are the six input parameters from Table 6 that derive the optimal JADE Score. These parameters will define the JADE settlements that produce optimally balanced outcomes.

Sensitivity analysis

A simple sensitivity analysis was performed, demonstrating how the JADE Score varies with each of the input parameters in Table 4, including the sensitivities. In Figure 6, each of the inputs was toggled between its base, low and high cases, while the JADE implementation parameter was adjusted from 0 to 200% in 10% increments.

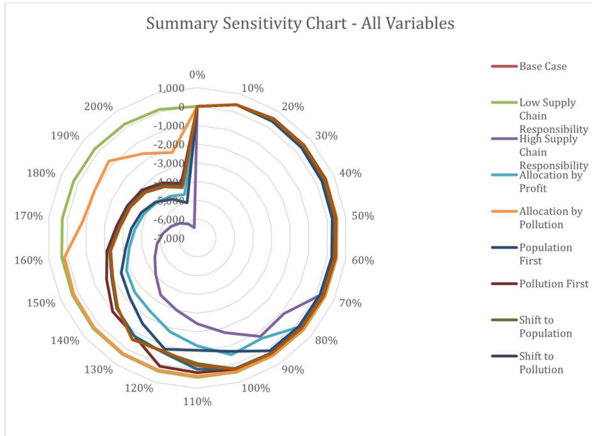


Figure 6. A spider chart illustrating the sensitivity of the JADE model outcomes to the input parameters for the smartphone case. The percentages on the circumference show for each parameter what fraction of the base input is used. The radius of the diagram is in relative units and shows the overall output "score" attributed to that input, representing the utility to the populations.

Statistical analysis and logic

This paper presents a simulation model designed to explore the complex interplay between competing interests. It is important to note that, unlike experimental studies, this work does not involve direct measurements or empirical data with associated error bars. Therefore, traditional statistical analyses focused on quantifying uncertainty in experimental results are not applicable. Instead, the analysis relies on the logical structure of the model, the relationships defined between variables, and the iterative optimization process driven by machine learning to identify potential solutions and assess the relative impact of different policy parameters within the simulated system.

The spider chart is useful for illustrating the complex interplay between the different inputs. The intent is to illustrate the usefulness of using a machine learning approach to optimize the JADE Score across six independent inputs, rather than manual iterative techniques.

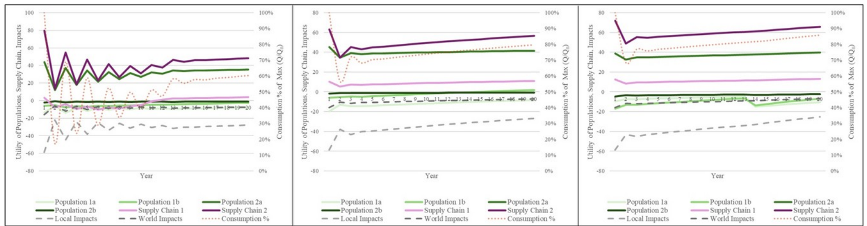
Machine Learning

The premise of the JADE framework is as the name suggests: "Joint Adaptive Dividends for the Environment." The intent of JADE is to be able to "adapt" to the input conditions and solve for the package of dividends that provides the most optimally balanced utility. Given the complexity of the model and the large number of degrees of freedom from six independent inputs, there may be innumerable potential solutions.

A question to address is whether this optimization could be achieved with conventional calculus minima/maxima formulations. While simple maxima/minima problems with few variables can be solved analytically using partial derivatives, the JADE model contains six independent input parameters (Table 6) that interact through complex equations governing production responses (eq.1), population utility functions (eq.4), and environmental impact calculations. These relationships create a non-convex solution space where gradient descent methods would likely converge to local optima rather than the global maximum. The option to switch strategies mid-simulation adds additional complexity, especially if multiple strategy switches were employed—turning the utility function into a piecewise function with an indeterminate number of pieces. Machine learning becomes essential for efficiently exploring billions of potential parameter combinations while balancing competing objectives: corporate profits, population utility metrics, and environmental impacts across a discounted time series. The TensorFlow implementation enables adaptive exploration of this high-dimensional space through stochastic sampling and iterative refinement, capabilities beyond the reach of calculus techniques, especially given the model's discrete strategy-switching parameters.

Indeed, the TensorFlow machine learning platform is ideally suited to optimize complex models such as JADE (27). The Excel add-in PyXLL was used to connect the TensorFlow libraries running in Python with the JADE model developed in Excel (supplementary file).

The optimization process leverages a hybrid computational approach, combining a machine learning model with an Excel-based simulation. The system takes six input variables (x1, x2, x3, x4, x5, and x6), each constrained within specific ranges, and uses them to drive calculations in the preconfigured Excel workbook. The workbook computes an output (the JADE Score) based on these inputs, which serves as the objective function to be maximized. A TensorFlow-based neural network model with six input features and a single output is initialized and trained iteratively. Initial training uses a small dataset of manually specified inputs and their corresponding outputs. Subsequently, the model is refined in an optimization loop where candidate inputs are generated randomly within their allowable ranges, evaluated by the workbook, and appended to the training dataset. The neural network is retrained at each iteration to improve its predictive capability. The system tracks the best-performing input combination across iterations, ensuring that the optimization adheres to the constraints and maximizes the workbook's output. This approach is similar to the use of machine learning algorithms in other domains with multiple uncertain parameters, such as structural engineering (28). This process integrates stochastic sampling, machine learning, and deterministic spreadsheet calculations to efficiently explore the input space and identify optimal configurations (Figure 7).



JADE Implementation	59%	58%	109%
JADE Responsibility – company / populations	51%	24%	76%
JADE Allocation – profit / pollution	91%	15%	25%
JADE Uses Phase 1 – pollution / restitution	3%	43%	23%
JADE Uses Phase 2 – pollution / restitution	27%	50%	75%
JADE Uses Switch Year	3	4	14

Figure 7. The time series utility chart for the smartphone scenario is shown for three iterations of the optimization, based on the six input parameters from Table 6. The chart tracks the utility of each population and company, the pollution impacts, and the product consumption percentage, for each year of the 20-year scenario. The script JADE_opt.py (supplementary file) tests the input parameters in different combinations and builds its training dataset to optimize the overall total utility of the system.

Number of iterations

The script JADE_opt.py (supplementary file) was run for each of the use cases to find the JADE parameters that would optimize utility. The open question was how many iterations would be required to converge on an optimal solution, though the expectation from machine learning literature on similarly-sized parameter spaces was that a large number of simulations would be required (29). It was decided to run JADE_opt.py using 100, 500, 1000, 5000, and 10000 iterations. Using the equipment at hand, which was a Microsoft Surface Laptop 2 with an Intel Core i5-8250U 1.6 GHz, the time required for a given run was approximately 20 minutes per 1000 iterations. Using cloud computing resources easily available today, run times of 500x faster or more could reasonably be achieved.

Normalization

The quantitative methods in JADE model fundamentally rely on a normalization methodology, comparing pollution impacts, economic interests, and population utility on the same scale, in the formation of a "JADE Score" to be optimized. In this paper, all inputs are normalized on a scale of one million US households. Per-household averages were used to determine the total number of smartphones, miles of driving, or kilowatt-hours of electricity consumed. The pollution LCA impacts recorded from literature under the ISO 14040 standard on a unit consumption basis, scaled to determine total impact for one million households. The economic inputs were estimated from averages for supply chain costs and household wealth. The population utility inputs do not have an associated SI unit and are presented on a relative JADE Score scale. The JADE model is designed to be able to be replicated easily across different populations, for any supply chain where ISO 14040 LCA impacts are available.

Results

Optimal JADE score

The data collected was first analyzed to determine whether the hypothesis was correct, that an optimally balanced solution could be determined with this machine learning method. The following data in Table 9 was collected, showing the maximum JADE Score for all three scenarios using 100, 500, 1,000, 5,000, and 10,000 iterations. The table demonstrates the effect of increasing the number of iteractions, and any benefit in the optimization of the final solution. The cells highlighted in purple are the maximum score realized, while the orange cells highlight cases where the increase in iterations decreased the score compared to the prior best run. The input parameters which resulted in the optimal JADE score (all in the 10,000 iterations row) are provided in Table 10.

Table 9. A determination of the convergence of the machine learning model.

Iterations	Time to Run	Smartphone	Gasoline	Wind Turbines
1 (Base Case)	0 min	417	-387	-855
100	2-3 min	594	-352	1228
500	8-15 min	607	-340	1197
1,000	16-27 min	617	-356	1212
5,000	75-150 min	623	-341	1239
10,000	150-300 min	627	-338	1246

In all scenarios, the use of 10,000 iterations produced the optimal utility. It can also be seen from the orange cells each increment did not always produce a benefit. This can all be attributed to the stochastic nature of the machine learning algorithm, that randomness in the inputs can make an imperfect correlation of iterations to maximum outputs. It is expected that increasing the numbers of runs past 10,000 would, with diminishing returns, provide minor optimization to the JADE Score, though that could be a topic for further study. The amount of computing time to progress beyond 10,000 iterations was prohibitive with the modest computing power available. These results suitably confirm the original hypothesis, that the machine learning approach is be an effective tool to optimize this complex environmental and economic model. In all cases, the machine learning provided significant benefit over the base case, and the optimal outcomes were discovered when the highest number of machine learning iterations were employed.

Optimal solutions

Table 10 lists the inputs which derive the optimized solutions. The machine learning algorithm implemented to optimize the JADE model was able to converge on solutions for each of the scenarios.

Table 10. The optimized values for the six key input parameters. The JADE base case scenario (described in Table 6) used 50% for the parameter in each of the first four rows of this table, and a JADE Use Switch Year of 11.

Iterations	Smartphone	Gasoline	Wind Turbines
JADE Implementation	27%	32%	30%
JADE Responsibility	15% company 85% populations	61% company 39% populations	30% company 70% populations
JADE Allocation	97% profit 3% pollution	92% profit 8% pollution	97% profit 3% pollution
JADE Uses	97%/30% pollution 3%/70% restitution	88%/19% pollution 12%/81% restitution	99%/72% pollution 1%/28% restitution
JADE Use Switch Year	12	13	20
Status Quo (do-nothing) Score	395	-936	911
Base Case JADE Score	417	-387	-855
Optimized JADE Score	627	-338	1246
Improvement vs Status Quo	59%	64%	37%
Improvement vs Base Case	50%	13%	246%

The conclusion is that in all cases the highest JADE Scores are realized using the optimized JADE outputs, with improvements of 37-64% over the status quo, and also that this solution is always superior to the base (non-optimized JADE) case.

Jade settlements for optimal solution

The scholarship for environmental justice uses concepts like distribution, recognition, capabilities, and procedures to label the dimensions of environmental justice (1). The JADE settlement framework takes a more pragmatic approach and focuses on optimal utility. Ultimately, the key functionality of JADE is to generate a package of structured payments between the parties in the system boundary that will provide the means to implement a remedy for environmental harms, balancing economic growth and utility to impacted populations. The JADE framework provides a prioritization for investment in remediation efforts based on criteria of the size the impacted population and the level of pollution. This will help counter some of the bias in current cleanup efforts where priority is often given to the easiest and cheapest cleanup projects, or those near the wealthiest communities (30). For the scenarios studied here, Table 11 summarizes the JADE settlement payments.

Table 11. The proposed magnitude of the JADE settlements for three scenarios, all in units of millions of dollars annually. Negative numbers mean the entity will distribute funds to the JADE pool, and positive numbers means the entity will receive funds.

Entity	Description	Average payment Phase One ($M)	Average payment Phase Two ($M)	Payment as a % of profits/wealth
Smartphone Supply Chain		12 years	8 years	
Company #1	Metals mining for components	-0.40	-0.30	-3.3%
Population #1a	Near mines	-1.23	2.42	+1.1%
Population #1b	Near manufacturing	-5.72	-1.89	-2.1%
Company #2	Manufacturer and subcontractors	-1.51	-1.15	-2.8%
Population#2a	Smartphone customers worldwide	-1.75	-1.33	-1.3%
Population #2b	Impacted by e-waste disposal	-1.02	-0.59	-0.8%
Pollution	Investments in pollution reduction	11.63	2.84	42% overall reduction
On-road Gasoline		13 years	7 years	
Company #1	Oil extraction	-13.3	-10.6	-20.0%
Population #1a	Near oil wells	-1.2	0.0	-3.9%
Population #1b	Affected by transportation and storage	-2.1	-1.5	-1.9%
Company #2	Oil refining and marketing	-12.0	-9.6	-24.4%
Population#2a	Retail gasoline customers	-5.4	1.6	-1.2%
Population #2b	Near oil refinery	-0.4	13.8	4.6%
Pollution	Investments in pollution reduction	34.6	6.3	38% overall reduction
Wind Turbines		20 years	0 years	
Company #1	Metals mining and turbine manufacture	-0.5	N/A (no second phase)	-7.2%
Population #1a	Near mines	0.5	N/A	2.5%
Population #1b	Near turbine factories	0.4	N/A	0.2%
Company #2	Power production and marketing	-2.4	N/A	-4.7%
Population#2a	Retail electric customers	-7.6	N/A	-4.3%
Population #2b	Near wind farm	0.1	N/A	0%
Pollution	Investments in pollution reduction	9.5	N/A	46% overall reduction

Discussion

Core assumptions

Certain assumptions are required to accept that the outputs of the JADE model are not overly simplified, overlooking the complexity and variability of real-world data and scenarios. This paper is intentionally developed at a simple "proof of concept" level. The JADE model could be optimized even further with more degrees of freedom in the inputs. The model was optimized around six key parameters (Table 6), but there seems to be no reason to believe that additional inputs could be included to add granularity and accuracy to the results. This paper was limited to using the computing power of a single laptop, but a far more robust system could be used to solve models of significantly more granularity faster with larger computing resources.

Another objection might be the model's reliance on historical data, not accounting for future changes in environmental policies or economic conditions. Again, this is a function of the early stage of development for this model. In a real-world implementation in the future, the JADE certification could accommodate changes to policy or economics in real time.

This paper does also not consider the potential resistance from industries or the socio-political challenges in implementing such a framework. The underlying assumption is that JADE payments can effectively balance economic growth and environmental impacts in a way that will satisfy these parties. This paper attempts to implement a supply-and-demand model that anticipates the utility and decision making for companies and populations, but it is likely that this will need to be refined in later versions.

Ethical standards - principles of JADE payments

This section begins by responding to an expected line of criticism: JADE is about polluters “paying off” those impacted by their pollution or effectively “buying out” of their responsibilities. This is emphatically not the case or the intent of JADE—an ethical approach is at the core of the initiative. The framework is intended to drive utility where pollution in place is remediated, health and safety of populations are improved, and future pollution is decreased. Experience has shown that these results can be achieved with targeted attention and investment (31). While some theories of environmental justice advocate for a dismantling of capitalism (32), JADE works toward a more pragmatic approach. The JADE framework is intended as a balanced and practical adaptation of certain Principles of Environmental Justice ensconced at a historic conference in 1991 (33), embraced and updated with enabling technology.

Comparison with Carbon Credits

The question arises as to how JADE settlements are distince from carbon credits or offsets. After all, mechanisms for applying a cost to CO_2 emissions share some of the same mechanics as JADE – payments are collected from emitters and then used to fund pollution reductions elsewhere (34). However, these frameworks are fundamentally different in both scope and purpose. While carbon credits and offsets focus narrowly on greenhouse gas emissions, JADE settlements are designed to address a much broader array of environmental harms. Specifically, JADE comprehensively models and assigns responsibility for multiple pollutants, including those impacting air, land, and water, such as toxic air emissions, contaminated soils, and polluted waterways—not just CO_2. The JADE framework uses AI to optimize payments from all parties that benefit from or contribute to pollution within a supply chain, distributing funds to both remediate current harms and invest in future pollution reduction, with a focus on advancing environmental justice while maintaining economic growth. Importantly, JADE is not mutually exclusive with carbon cost regimes; it can operate alongside carbon credits or taxes, supplementing them by filling critical gaps—such as addressing non-carbon pollutants and local environmental inequities—that traditional carbon markets often overlook.

Limitations

The paper does not consider certain factors influencing the independent variables such as 1] Inflation. The model does not consider the impact of inflation during the 20-year simulated runs. 2] Regional Differences. Given that supply chains can extend across continents, regional differences in environmental regulations are likely to be material. 3] Technological Advancements. The model assumes that all of the pollution reductions would be the results of JADE investments, whereas in reality there is likely to be a baseline level of improvement occurring alongside the progression of technology. Future versions of the JADE model could address all these factors.

Practical implementation

In the examples shown, what would the proposed JADE settlements look like in real-word terms? As shown in Table 11**,** for the Gasoline production scenario the optimally balanced utility (normalized to one million households) is realized when the oil drilling corporations pay \$13 million per year, the refiner pays \$12 million per year, and the gasoline customers base pays \$5 million per year. For thirteen years, these funds are invested 88% towards future pollution reduction and 12% towards cleanup of current pollution, and then for the next seven years those ratios are changed to 19% and 81% respectively.

Different frameworks could be imagined to achieve this outcome. In a voluntary model, the oil company would seek the JADE certification for its products, and a certifying body or agency would examine the supply chains and impacted populations with the methodology in this paper. The specified amounts of JADE payments would be collected from the gasoline producer and its suppliers, or added to the cost of fuel, and pooled to form the JADE fund. Subsequently, these funds would be used to construct programs of pollution control and cleanup for the impacted populations. By implementing this full beneficial cycle, the oil company would be able to use the JADE logo to communicate its commitment to fairness and environmental stewardship.

On the other hand, JADE could also be implemented as a government-mandated program. For example, the government could require that all on-road gasoline sold in a particular country be JADE certified. The same government could oversee the collection of JADE payments and the administration of programs for pollution cleanup and prevention.

Either as a voluntary certification or a government-mandated program, the JADE framework would help get past structural problems which have hindered implementation and enforcement of existing environmental regulations. A large study done in Chicago found that punitive actions for violations were only implemented 50% of the time in benefit of minority communities (35). The JADE framework provides objective, transparent standards for enforcement of standards which will not be subject to discretionary application.

JADE Certification

While the focus of this paper is on a technical effort to develop a framework to measure environmental impacts across populations, and score methods to mitigate those impacts, JADE also lends itself to a certification program. One can envision a program for evaluating the environmental impacts of a manufactured product (such as a smartphone) or an energy source (such as refined gasoline) while considering the customer utility, profits, and economic development from that product. If the impacts are determined to exceed defined standards, then the JADE model would be used to determine the level of required investments across the supply chains and populations to remedy pollution and deliver a balanced utility. The logo in Figure 8 might serve to certify products that meet the JADE standard.

JADE
Joint Adaptive Dividends
for the Environment

Figure 8. Example of a logo that could be used to label a JADE-certificated product or energy supply.

Public messaging might help to bridge the current disconnect between awareness and support. One study found that only 34% of respondents were aware of lifecycle environmental impacts from everyday products, but 78% endorsed action once it was explained (36).

Perspectives

The JADE framework is open and flexible, and there appears to be no limit to the number or variety of products or energy outputs which could be modeled and optimized for balanced outcomes. Some examples could be air travel and airports, legacy coal power plants, bottled water production, municipal solid waste disposal, electric car manufacturing, livestock farming and meat processing, and data centers for AI computations.

There is no geographical limit to where the JADE framework would not be valuable.

Research has demonstrated environmental impacts from air pollutions on every continent (37). There is an assumption in this paper that the JADE framework can be universally applied across different industries and geographies, though in reality adjustments may need to be made to account for the unique environmental and economic contexts of each region or sector.

Conclusion

The hypothesis was shown to be correct, i.e. that a machine learning platform would be effective for optimizing the solutions for this complex model that balanced environmental and economic utility. It is too large of a task for a human to iterate the model across billions of potential solutions, but within 10,000 runs and a few hours of computing time the machine language engine was able to converge on the optimal solutions for several test cases modeling smartphone manufacture, gasoline production, and wind turbine deployment. The number of current and future supply chain and energy production scenarios that could be optimized for balanced outcomes with this framework is virtually limitless.

The challenge of delivering sustained economic growth and environmental stewardship is complex, but one that can likely be resolved equitably, objectively, and transparently with the application of quantitative reasoning. With tools such as JADE in place, there would no longer be excuses for inaction. JADE is a tool to implement practical and actionable solutions to help impacted communities.

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Supplementary files

Machine Learning Python script

JADE model Excel workbook

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Appendix A – Scenario Parameters

Input parameters to model populations and companies across three production scenarios. Pollution impacts are derived from LCA literature using ISO 14040 methodology (13-15).

		Units	Smartphones	Gasoline	Wind Turbines
SUPPLY CHAIN COMPANY #1					
	Product		Metals	Crude Oil	Metals
	Company Profits	$M/year	18.3	124.6	12.7
	α	N/A	0.0182	0.0500	0.0789
Pollution impacts on Population #1a					
	Photochemical oxidant formation (Ozone) or smog formation	kg ethylene-eq	-0.9	0.0	-21.6
	Acidification	kg SO_2-eq	-0.2	-1.9	-2.1
	Eutrophication	kg PO_4-eq	-1.2	-5.7	-1.0
	Human toxicity	kg 1,4-DCB-eq	-6.9	-0.2	-25.5
	Ecotoxicity	kg 1,4-DCB-eq	-23.5	0.0	-9.7
Pollution impacts on Population #1b					
	Photochemical oxidant formation (Ozone) or smog formation	kg ethylene-eq	-0.8	-0.4	-11.6
	Acidification	kg SO_2-eq	-0.2	-0.5	-1.1
	Eutrophication	kg PO_4-eq	-0.8	-0.7	-0.6
	Human toxicity	Kg 1,4-DCB-eq	-5.2	0.0	-13.7
	Ecotoxicity	kg 1,4-DCB-eq	-17.0	-0.1	-5.2
Pollution impacts on World					
	Abiotic and biotic resource depletion	kg ethylene-eq	-0.000003	-25.7	-0.01
	Global warming	kg CO_2-eq	-0.1	-15.4	0.0
	Ozone depletion	kg Sb-eq	-10.0	-11.7	0.0
SUPPLY CHAIN COMPANY #2					
	Product		Smartphones	Gasoline	Wind Turbines
	Company Profits	$M/year	81.3	94.2	89.5
	α	N/A	0.0061	0.0010	0.0112
Pollution Impact Denominator			100	200	100
Pollution impacts on Population #2a					
	Photochemical oxidant formation (Ozone) or smog formation	kg ethylene-eq	0.0	-1.1	16.2
	Acidification	kg SO_2-eq	0.0	-21.7	0.9
	Eutrophication	kg PO_4-eq	0.0	-20.9	0.2
	Human toxicity	Kg 1,4-DCB-eq	0.0	-0.4	14.3
	Ecotoxicity	kg 1,4-DCB-eq	0.0	-1.8	6.6

		Units	Smartphones	Gasoline	Wind Turbines
Pollution impacts on Population #2b					
	Photochemical oxidant formation (Ozone) or smog formation	kg ethylene-eq	0.0	-34.8	-1.2
	Acidification	kg SO_2-eq	0.0	-24.1	-0.1
	Eutrophication	kg PO_4-eq	0.0	-46.9	-0.1
	Human toxicity	Kg 1,4-DCB-eq	-0.1	-1.5	-2.7
	Ecotoxicity	kg 1,4-DCB-eq	-1.7	-2.7	-0.5
Pollution impacts on World					
	Abiotic and biotic resource depletion	kg ethylene-eq	0.0	-3.3	0.0
	Global warming	kg CO_2-eq	-0.1	-16.0	0.0
	Ozone depletion	kg Sb-eq	-5.7	-10.4	0.0
POPULATION #1A					
	Description		near mines	near oil wells	near mines
	Population	millions	5.0	0.5	5.0
	Wealth	$M/year	20.0	20.0	20.0
	Economic Development	$B	3.65	12.46	25.34
POPULATION #1B					
	Description		factory workers	near transportatio n and storage	near turbine factories
	Population	millions	10.0	1.0	5.0
	Wealth	$M/year	200.0	100.0	200.0
	Economic Development	$B	14.6	7.5	25.3
POPULATION #2A					
	Description		Smartphone customers worldwide	Retail gasoline customers	Retail electric customers
	Population	millions	2.5	10.0	2.5
	Wealth	$M/year	121	257	177
	Economic Development	$B	1.65	2.0	0.18
	Base Cost of Product (C)	$M/year	70	63.96	176.97
	a	N/A	1.0	1.0	1.0
	b	N/A	18.2	18.0	22.9
POPULATION #2B					
	Description		Impacted by e-waste disposal	Near oil refinery	Near wind farm
	Population	millions	1.0	1.0	0.5
	Wealth	$M/year	100.0	100.0	300.0
	Economic Development	$B	0.3	38	2.1