Future Industrial Pollutant Data for Higher Fidelity Atmospheric Chemistry Modeling

Jake Stevens

Climastry - CarbonCAD

Hello, {name}

For as long as engineers have been engineering, they have been constrained by:

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Sustainability-Linked Debt, a Data Driver

Figure 1.1 A step-up and step-down SLB structure

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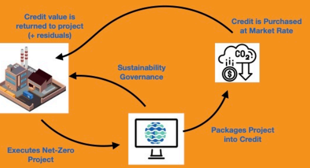
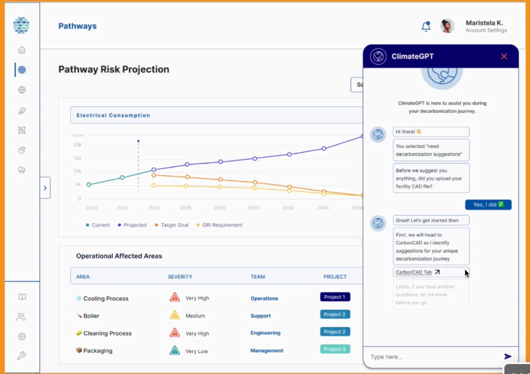
CarbonCAD



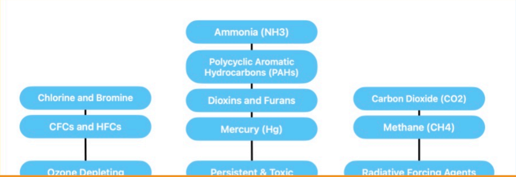
CarbonCAD enables engineers responsible for manufacturing process optimization to master the complexities of sustainable finance.

This technology creates a virtual model that illustrates the cause-and-effect relationships between activities and their emissions, which can then be used to support investment decisions in projects aimed at reducing emissions.



Manufacturing's Externalities

The manufacturing sector is econometrically rich with data.



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Piece-Rate Emissions Factors (PREF)

$$GHG_{ML} = \beta_0 + \beta_1 PREF_1 + \beta_2 PREF_2 + \cdots + \beta_n PREF_n + \varepsilon \quad (6)$$

where;

GHG_{ML} = GHG Emissions from Manufacturing Line

$PREF_n$ = Peicerate emissions factors associated with each of the n manufacturing processes

β_0= intercept, the baseline level of emissions when all PREFs are equal to zero

$\beta_1, \beta_2, \ldots, \beta_n$ = Regression coefficients, representing change in GHG_{ML} associated with one-unit increase in each PREF, holding all other PREFs constant

ε = Error, representing random variation not explained by PREFs

$$\mathrm{PREF} = \sum X_p (EF_p = RV_i) + X_{p \ldots n} \quad (5)$$

where;

PREF = Piecerate emissions factor for single process

X_p = Production output at a given product production quality

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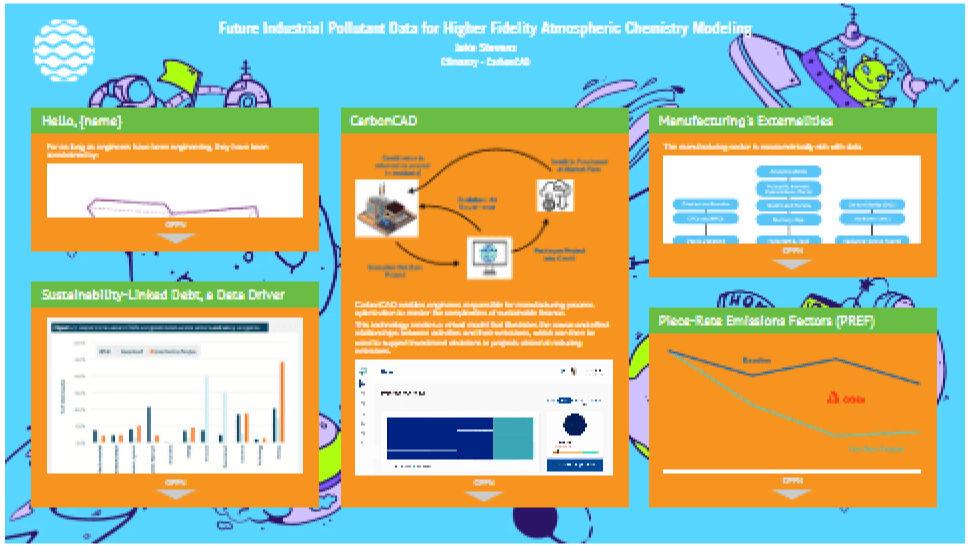

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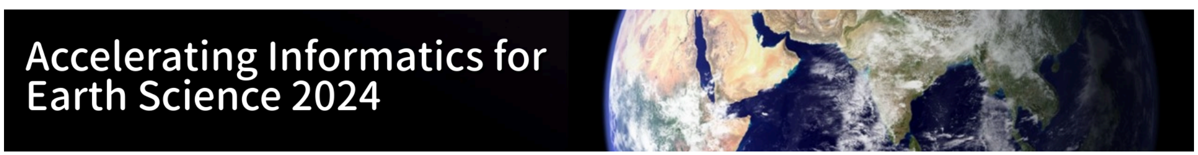
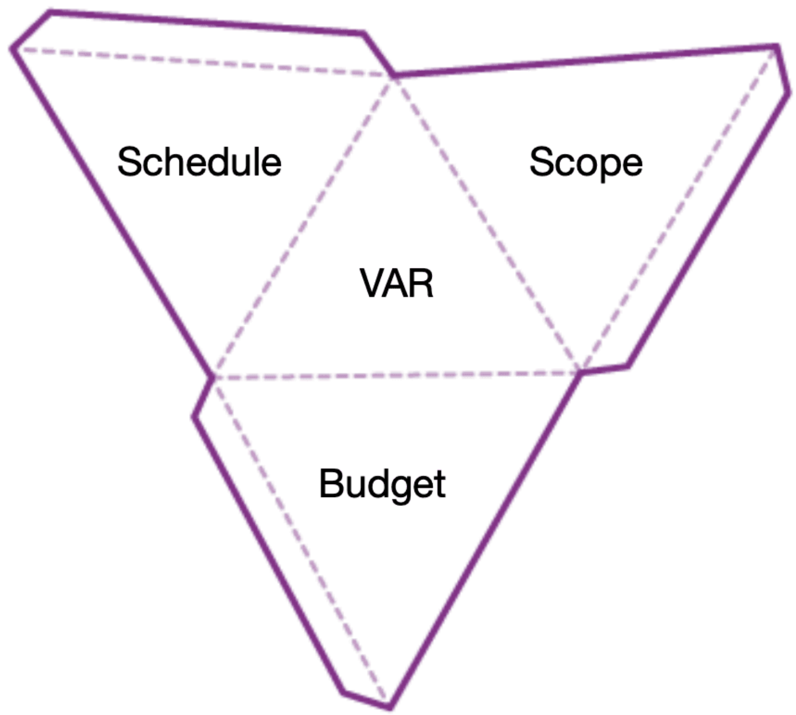


HELLO, {NAME}

For as long as engineers have been engineering, they have been constrained by:



Where, [VAR] now equals any number of sustainabilty-linked key performance indicators (KPIs) that impact the cost of capital.

Engineers improve this data quality by accurately creating externality models of production systems to then measure change against them.

There is value in that change and becuase of new financial mechaisms and markets, there are also increasingly commonplace efforts to audit and improve this data quality (CFTC (https://www.cftc.gov/PressRoom/PressReleases/8723-23)).

Through these efforts, manufacturer project plans are iteratively planned to achieve externatility abatement. It is through this work that we believe there is opportunity to refine estimates of future industrial pollutants for more representative earth science models.

Due to the particular diversity of externalities in the manufacturing sector, we believe the greatest clarity can be brought to the least understood atmospheric reactions due to their concentrations and rarity in production or disclosure.

SUSTAINABILITY-LINKED DEBT, A DATA DRIVER

Figure 1.5 Corporate issuance of SLBs and green bonds across sectors and rating categories

SOURCE: Bloomberg

Figure 1.1 A step-up and step-down SLB structure

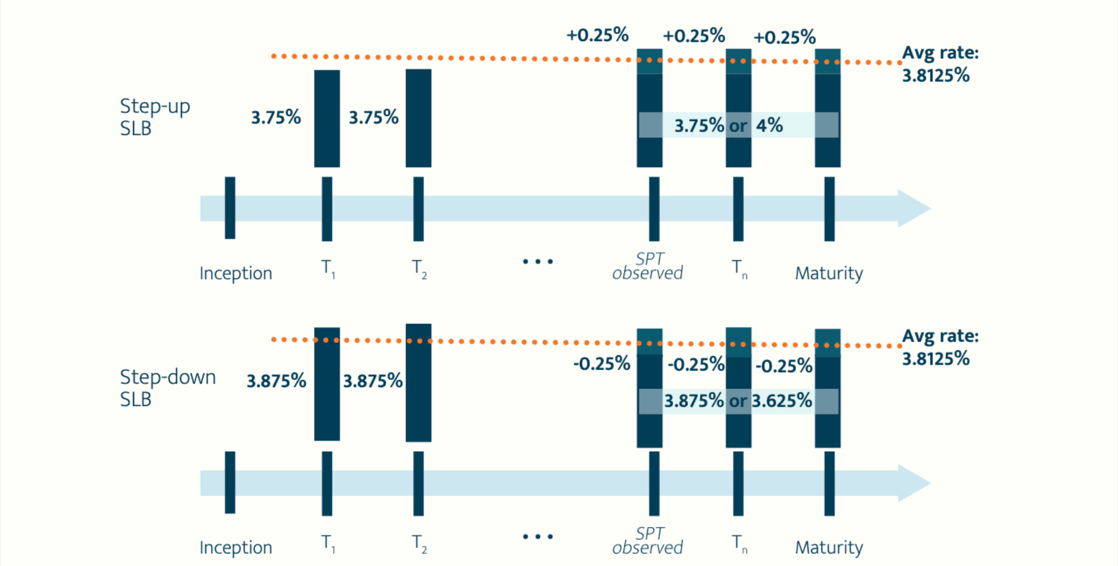


Figure 2.1 Embedded options structure of a step-up SLB: (left) the coupon level in the step or no-step up case, (right) the expected SLB coupon/the probability weighted average of the step and no-step up coupon levels.

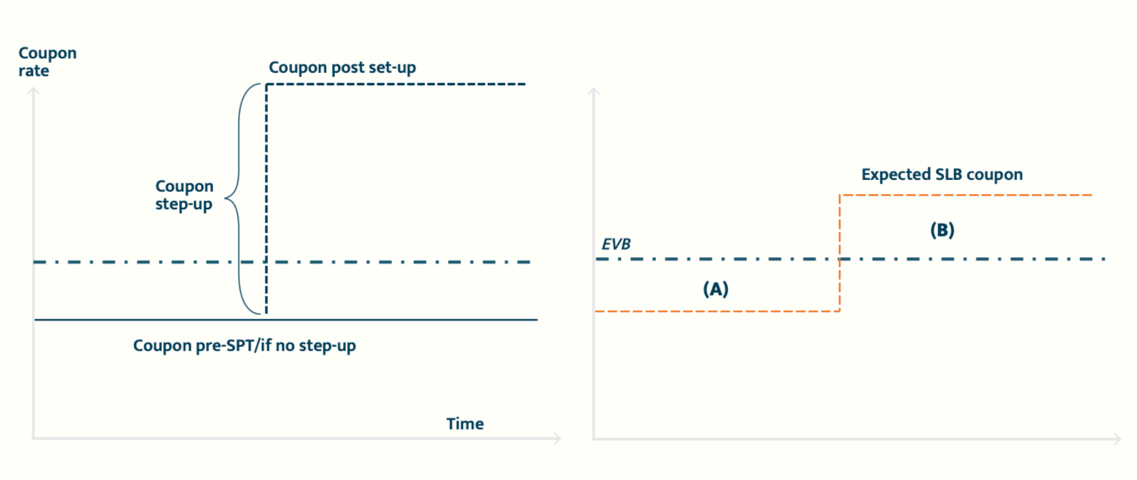
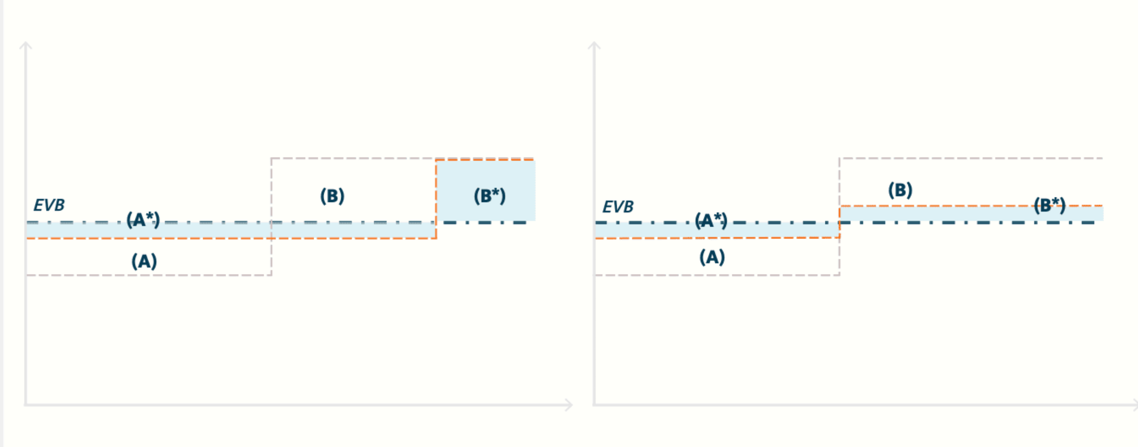


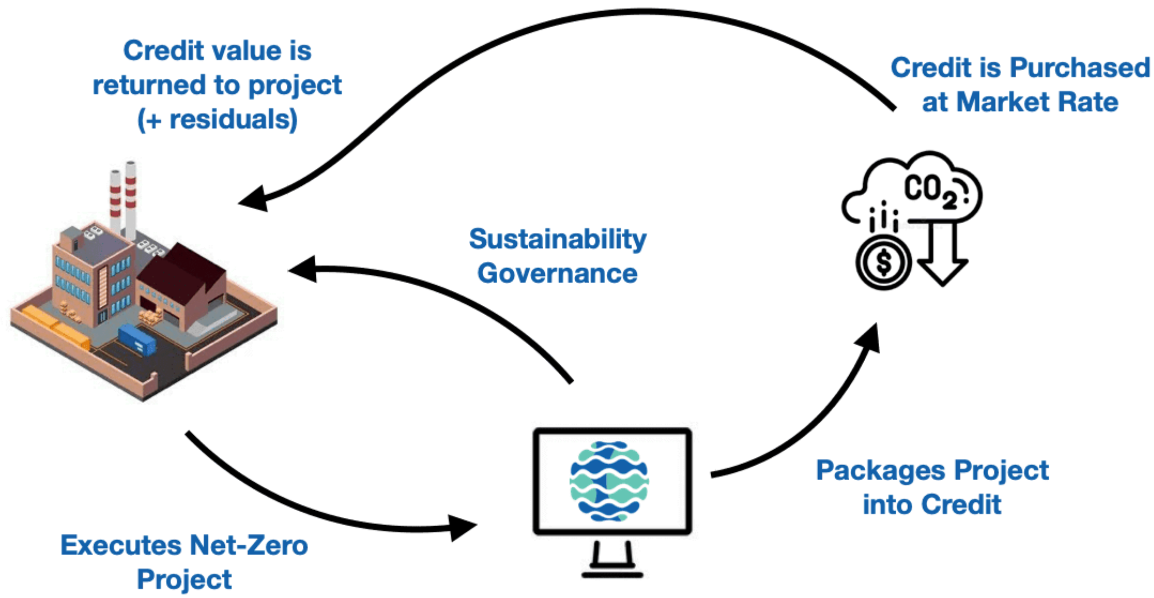
Figure 2.2 (left) An SLB with a late step-up date: as the economic value accruing to the investor, (B) along the x-axis decreases, the option premium must also decrease, (A) => (A*), and the SLB fixed coupon moves closer to the EVB coupon. (right) An SLB with a lower coupon step-up than the baseline, B decreases along the y-axis to B*, lowering the option premium from (A) to (A*)



Sustainability-linked debt is typically structured such that the interest rate or other financial terms are tied to the company's sustainability performance. The effectiveness of sustainability-linked debt, however, is contingent on the ability to measure and verify a company's (or Special Purpose Vehicles') sustainability performance indicators, including its carbon emissions. This paper will explore the potential relevance of piece rate emissions factors for sustainability-linked debt related emissions disclosures in the manufacturing sector as it relates to financing decarbonization efforts, including using asset-backed carbon credits. The paper will also examine the challenges associated with measuring and verifying sustainability performance.

Visualizations: AFII Sustainable Bonds Primer (https://anthropocenefii.org/resources/sustainability-linked-bond-handbook)

CARBONCAD



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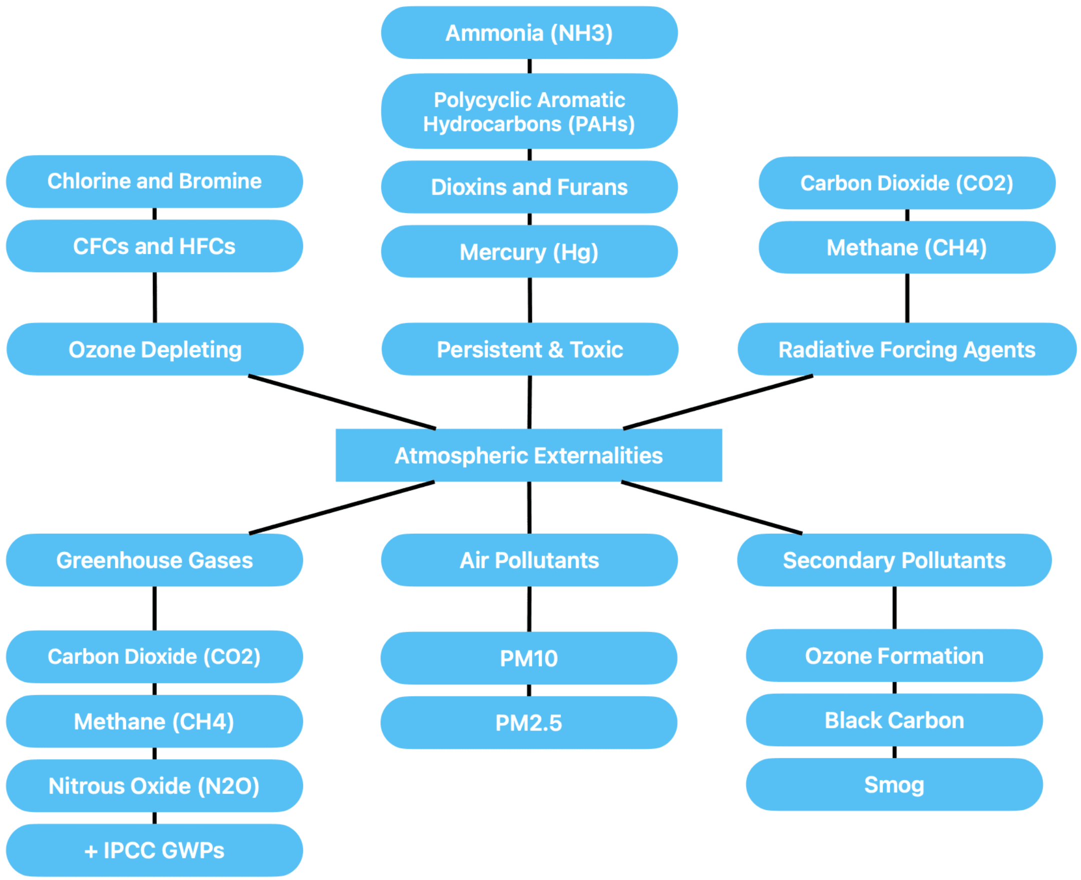
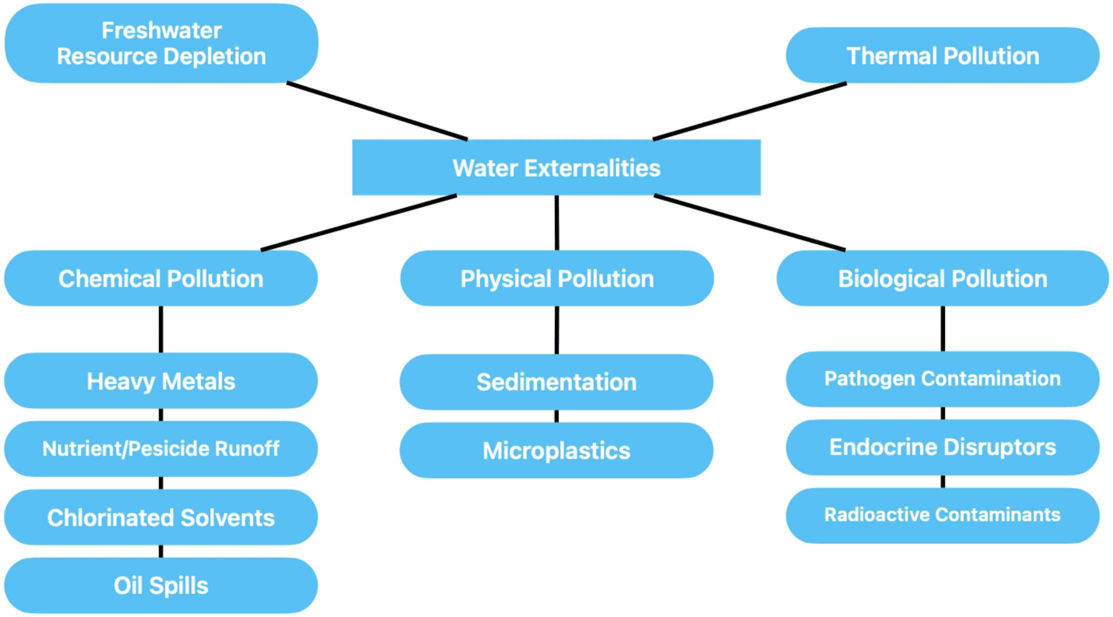
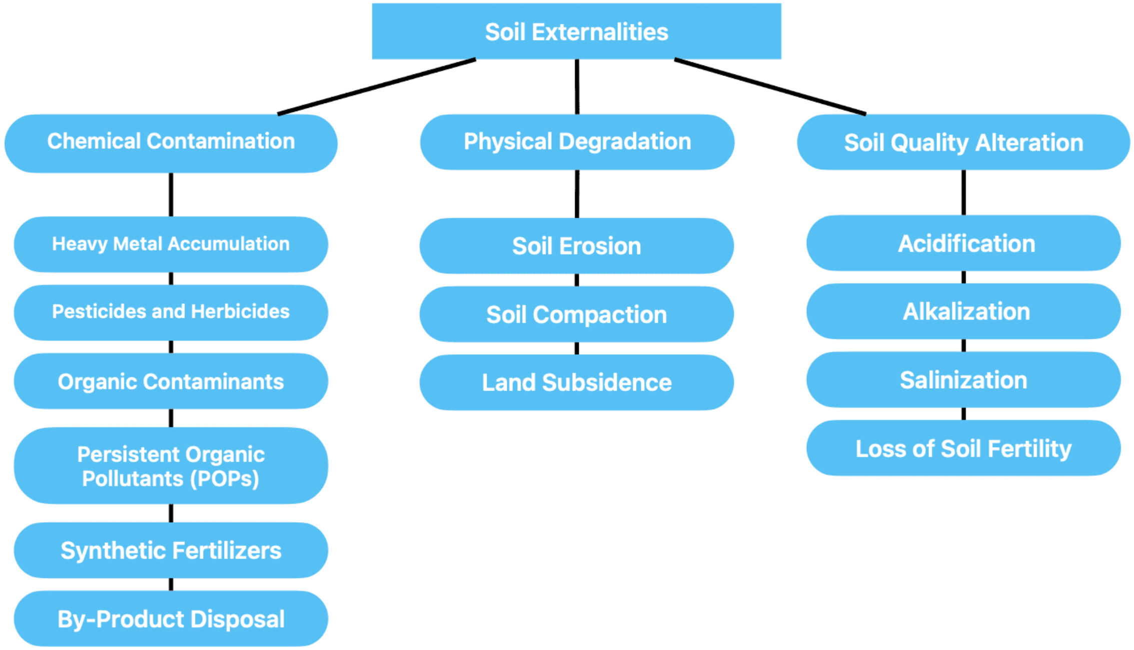
[VIDEO] https://res.cloudinary.com/amuze-interactive/video/upload/q_auto/v1717624438/tomandjerry/F3-4E-57-47-D3-2E-08-03-8C-D1-1D-05-97-C6-D9-8C/Video/Updated_Product_Demo_-_ClimateGPT_ondaow.mp4

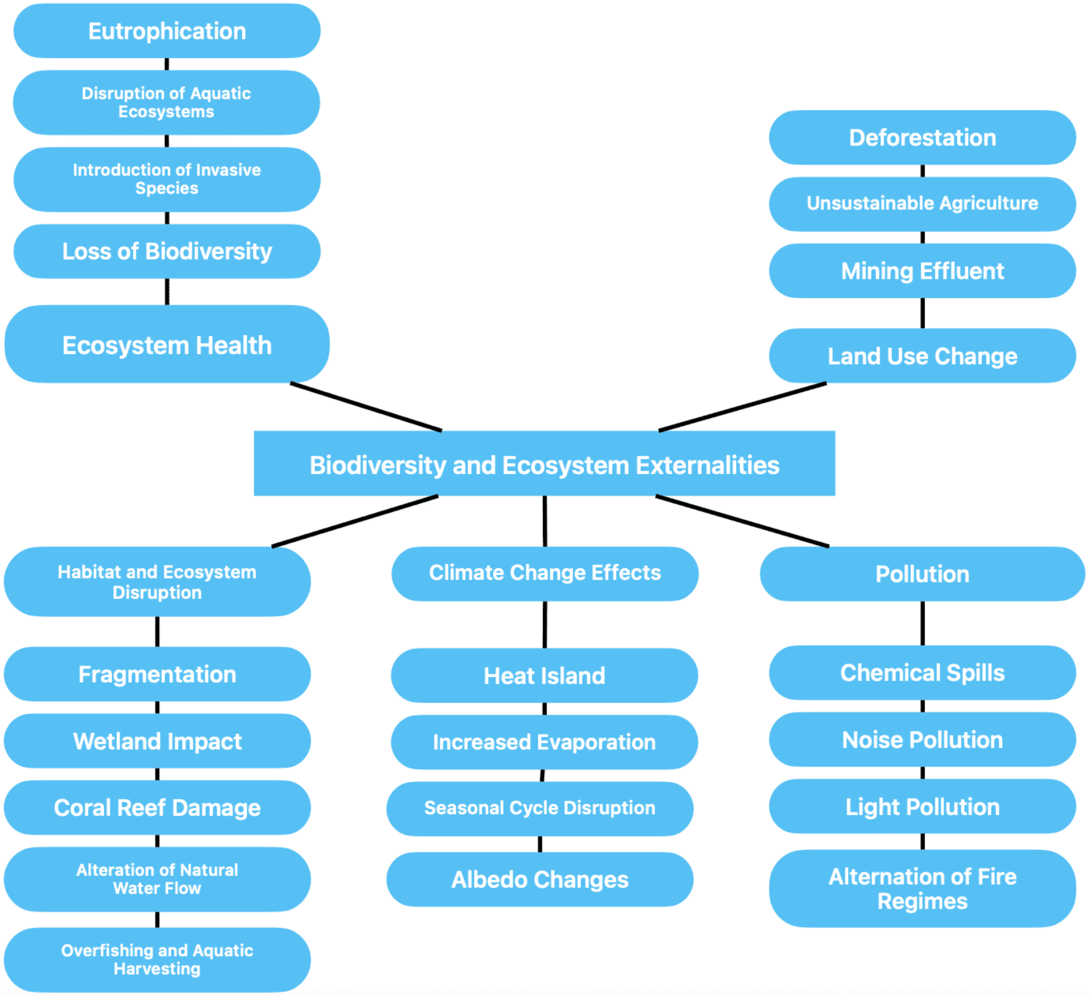
MANUFACTURING'S EXTERNALITIES

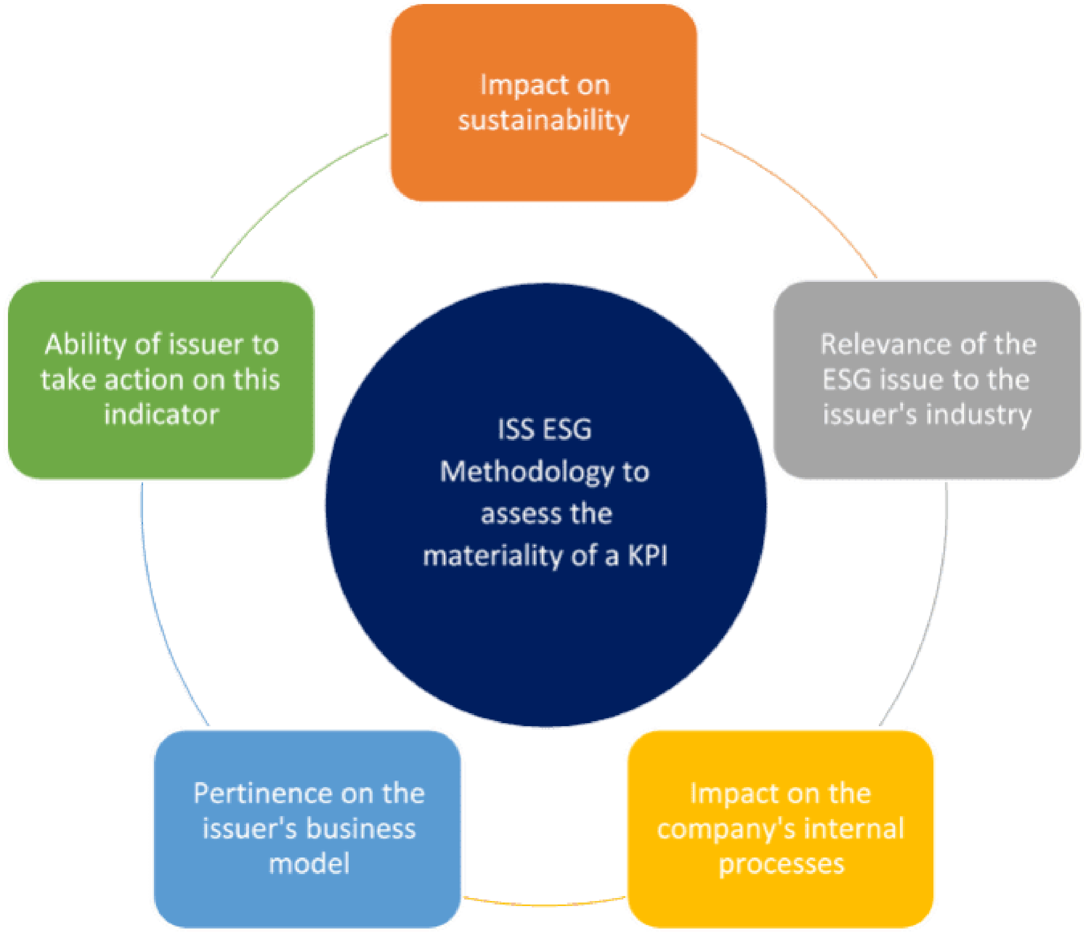
The manufacturing sector is econometrically rich with data.



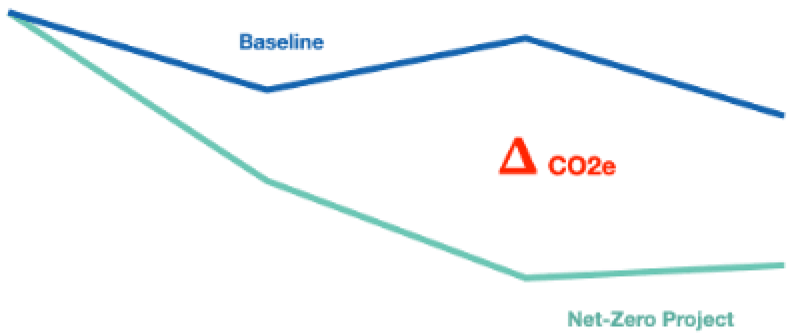

Freshwater
Resource Depletion
Thermal Pollution
Water Externalities
Chemical Pollution
Physical Pollution
Biological Pollution
Heavy Metals
Nutrient/Pesicide Runoff
Chlorinated Solvents
Oil Spills
Sedimentation
Microplastics
Pathogen Contamination
Endocrine Disruptors
Radioactive Contaminants


Soil Externalities
Chemical Contamination
Physical Degradation
Soil Quality Alteration
Heavy Metal Accumulation
Pesticides and Herbicides
Organic Contaminants
Persistent Organic Pollutants (POPs)
Synthetic Fertilizers
By-Product Disposal
Soil Erosion
Soil Compaction
Land Subsidence
Acidification
Alkalization
Salinization
Loss of Soil Fertility


Eutrophication
Disruption of Aquatic Ecosystems
Introduction of Invasive Species
Loss of Biodiversity
Ecosystem Health
Deforestation
Unsustainable Agriculture
Mining Effluent
Land Use Change
Biodiversity and Ecosystem Externalities
Habitat and Ecosystem Disruption
Fragmentation
Wetland Impact
Coral Reef Damage
Alteration of Natural Water Flow
Overfishing and Aquatic Harvesting
Climate Change Effects
Heat Island
Increased Evaporation
Seasonal Cycle Disruption
Albedo Changes
Pollution
Chemical Spills
Noise Pollution
Light Pollution
Alternation of Fire Regimes


Impact on sustainability
Relevance of the ESG issue to the issuer's industry
Impact on the company's internal processes
Pertinence on the issuer's business model
Ability of issuer to take action on this indicator
ISS ESG Methodology to assess the materiality of a KPI

PIECE-RATE EMISSIONS FACTORS (PREF)



$$GHG_{ML} = \beta_0 + \beta_1 PREF_1 + \beta_2 PREF_2 + \cdots + \beta_n PREF_n + \varepsilon \tag{6}$$

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ε = Error, representing random variation not explained by PREFs

$$\mathrm{PREF} = \sum X_p (EF_p = RV_i) + X_{p \ldots n} \tag{5}$$

where;
PREF = Piecerate emissions factor for single process
X_p = Production output at a given product production quality
RV_i = LCA Regression Variable
EF_p = Emissions Factor for Production Variable

Emissions or carbon accounting is the process of estimating and measuring emissions of greenhouse gases (GHGs) such as carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), fluorinated gases, and other environmentally significant equivalents that include forever chemicals [13], markers of biodiversity [14], and other categories actively investigated.

Emissions accounting provides a baseline for setting emissions reduction targets, tracking emissions deviation from a baseline, and identifying effective strategies and projects to reduce emissions. The deviation between the baseline and real emissions value is what is first estimated and then measured for audit by a given facility to generate an emissions credit.

-

Piece Rate Emissions Factors or PREF, are an evolutionary development of process-based emission factors that create a direct link between specific emissions factor regression variables and project externalities that impact the emissions intensity or rate of emissions output. The variables of the regression model used for manufacturing specific PREF can include variables such as energy consumption, raw material inputs, or human inputs; with an acute emphasis on industrial process types such as lathing, milling, and associated work instructions or programmable logic controller (PLC) data.

In the PREF equation, Xp represents the production quantity at a given production quality, including waste streams and their associated impacts. The emissions factor is a coefficient that captures the emissions intensity of the manufacturing process per mapped emissions factor variable identified on the manufacturing line. Piece-rate emissions factors (PREF) set regression analysis (LCA) equal to emissions factor regression variables. Said regression variables are statistically associated with projects that significantly impact their emissions intensity or rate of emissions output.

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Aluminum Lathing Example:

Variables such as cutting speed and feed rate become significant to process optimization.

Table 1: Example PREF table based on a given manufacturer's aluminum lathing processes and associated project-linked regression variables.

$$PREF_{Lathe\ Cell} = \sum X_{Lathe\ Operations}(EF_{Lathe} = RV_{Lathe}) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \varepsilon$$

Process LCA: Lathe (X_n)	α_n	β_n
Cutting Speed (X_1)	50	0.001
Feedstock Rate (X_2)	0.2	0.01
Coolant Type/ Amount (X_3)	0.05	0.05
Cutting Tool Geometry (X_4)	0.2	0.005
Scrap Generation (X_5)	0.05	0.1

In this example, we assume that the emissions factor for lathing aluminum is 0.132 metric tons of CO2 per metric ton of aluminum produced [2], and assuming that the units in the regression equation are consistent with the provided values for the independent variables, we can estimate the variable values as follows:

: Given the provided emissions factor, the intercept would be approximately 0.132 metric tons of CO2-equivalent emissions per unit of production (i.e., per metric ton of aluminum produced). This value assumes that all the other independent variables are held constant at their respective baseline values.

: The value of would depend on the units used for cutting speed in the regression equation. Assuming that cutting speed is expressed in meters per minute, for example, we might expect the value of to be on the order of 0.001 metric tons of CO2-equivalent emissions per meter per minute of cutting speed. This value assumes that cutting speed has a relatively small effect on GHG emissions compared to the other independent variables.

: Assuming that feed rate is expressed in millimeters per revolution, for example, we might expect the value of to be on the order of 0.01 metric tons of CO2-equivalent emissions per millimeter per revolution of feed rate. This value assumes that feed rate has a moderate effect on GHG emissions compared to the other independent variables.

: The value of would depend on the coding scheme used to represent coolant type (e.g., 0 for dry machining and 1 for wet machining). Assuming a binary coding scheme, we might expect the value of to be on the order of 0.05 metric tons of CO2-equivalent emissions for wet machining (i.e., when coolant is used) compared to dry machining (when coolant is not used). This value assumes that the use of coolant has a relatively large effect on GHG emissions compared to the other independent variables.

: The value of would depend on the coding scheme used to represent cutting tool geometry (e.g., 0 for a sharp tool and 1 for a dull tool). Assuming a binary coding scheme, we might expect the value of to be on the order of 0.005 metric tons of CO2-equivalent emissions for a dull tool compared to a sharp tool. This value assumes that the choice of cutting tool geometry has a relatively small effect on GHG emissions compared to the other independent variables.

: The value of would depend on the units used to measure scrap (i.e., the amount of scrap generated per unit of aluminum produced). Assuming that scrap is measured in metric tons of scrap per metric ton of aluminum produced, for example, we might expect the value of to be on the order of 0.1 metric tons of CO2-equivalent emissions per metric ton of scrap generated. This value assumes that the amount of scrap generated during the lathing process has a relatively large effect on GHG emissions compared to the other independent variables.

Assuming that all the other independent variables are held constant at their respective baseline values, the values for the given variable values would be:

: Assuming that cutting speed is expressed in meters per minute, for example, and the given value for cutting speed is 50 meters per minute, the value of would be approximately 0.001 x 50 = 0.05 metric tons of CO2-equivalent emissions per unit of production (i.e., per metric ton of aluminum produced).

: Assuming that feed rate is expressed in millimeters per revolution, for example, and the given value for feed rate is 0.2 millimeters per revolution, the value of would be approximately 0.01 x 0.2 = 0.002 metric tons of CO2-equivalent emissions per unit of production (i.e., per metric ton of aluminum produced).

: The value of would depend on the coding scheme used to represent coolant type (e.g., 0 for dry machining and 1 for wet machining). Assuming a binary coding scheme and the given value for coolant type is 1 (indicating the use of coolant), the value of would be approximately 0.05 metric tons of CO2-equivalent emissions per unit of production (i.e., per metric ton of aluminum produced) compared to the baseline emissions when coolant is not used.

: The value of would depend on the coding scheme used to represent cutting tool geometry (e.g., 0 for a sharp tool and 1 for a dull tool). Assuming a binary coding scheme and the given value for cutting tool geometry is 0 (indicating the use of a sharp tool), the value of would be equal to the baseline emissions for cutting tool geometry, which is approximately 0.132 metric tons of CO2-equivalent emissions per unit of production (i.e., per metric ton of aluminum produced).

: Assuming that scrap is measured in metric tons of scrap per metric ton of aluminum produced and the given value for scrap is 0.05 metric tons of scrap per metric ton of aluminum produced, the value of would be approximately 0.1 x 0.05 = 0.005 metric tons of CO2-equivalent emissions per unit of production (i.e., per metric ton of aluminum produced).

With the knowledge of how these variables are structured, a practitioner can begin to see how projects can then be linked to the identified variable assumptions or how coded variables can be tracked to live data such as tool life for more robust data. To link LCA regression variables to project sustainability KPIs, the first step is to identify the relevant LCA regression variables for the specific process or product. Then, these variables can be used to develop project disclosure KPIs that track the environmental impact of the project or manufacturing process. For example, if the LCA regression variables show that energy use is a major contributor to the environmental impact of the process, it can associate to the project disclosure KPI for tracking energy consumption and efficiency.

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TRANSCRIPT

ABSTRACT

This poster presents an evaluation of asset-backed carbon credits as a financing mechanism for decarbonization efforts in the manufacturing sector, with a focus on a novel emissions factors approach. A piece-rate emissions factor methodology is proposed to estimate emissions and "link" Life Cycle Analysis (LCA) regression variables to facility projects by leveraging existing sustainability-linked debt performance indicator disclosure requirements. The statistical confidence of existing emissions factor methodology is assessed as it is currently practiced within the manufacturing industry with a discussion emphasis on the impact to the claim integrity related to emissions abatement and sustainability-linked debt for marginalized industry actors. The results suggest that asset-backed carbon credits can be a useful tool for financing decarbonization efforts in manufacturing while minimizing the challenges in determining the value of carbon credits and ensuring positive environmental impact.