

RESEARCH ARTICLE



# Life Cycle Assessment of Iridium Production: Environmental Impact Analysis Based on Brightway2

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### **Abstract**

This study aimed to quantify the comprehensive environmental footprint of primary iridium production, a critical yet exceptionally scarce metal, to inform more sustainable practices in its supply chain. The research method employed a cradle-to-gate Life Cycle Assessment (LCA) using the Brightway2 framework, establishing a detailed inventory model for iridium production. The environmental impacts for the functional unit of 1 kg of refined iridium were evaluated using multiple impact assessment methods. Furthermore, sensitivity analysis and Monte Carlo simulations were conducted to assess parameter uncertainties. The results conclude that iridium production imposes a substantial environmental burden, particularly on climate change, with a Global Warming Potential (GWP100) of 12,009 kg CO<sub>2</sub>-equivalent per kilogram. Significant impacts were also identified in the categories of ecotoxicity and human health. This study provides the first robust, probabilistic LCA of iridium, thereby offering crucial insights and a data-driven reference for producers and technology industries to mitigate

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**Keywords**: iridium production, life cycle assessment, environmental impact, carbon footprint, ecotoxicity, sensitivity analysis.

## 1 Introduction

Iridium, a platinum group metal, is irreplaceable in catalysts, aerospace technology, and electronic devices due to its excellent corrosion resistance and high melting point [1]. Crucially, it serves as a critical anode catalyst in proton exchange membrane (PEM) electrolyzers for green hydrogen production, positioning it at the forefront of the clean energy transition. With the development of clean energy technologies, the demand for iridium continues to grow. However, iridium is extremely scarce in the Earth's crust [2], and its mining and processing are complex, energy-intensive, and generate various harmful emissions, potentially burdening the environment. Understanding the environmental impacts of its production process is therefore critical, not only for mitigating its footprint but also for ensuring the sustainability of the hydrogen economy it enables.

## Citation

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Life Cycle Assessment (LCA) is a robust method for quantifying the environmental impacts of a product or process throughout its entire life cycle, from raw material extraction to waste disposal, by assessing resource consumption and environmental emissions [3]. The Brightway2 framework, a Python-based open-source LCA modeling tool [4], was used in this study to conduct a comprehensive life cycle assessment of iridium production. The study identifies the primary sources of environmental impact and evaluates the robustness of the results through sensitivity and uncertainty analyses, providing essential data for a holistic evaluation of clean energy technologies.

#### 2 Materials and Methods

This section provides an overview of the data and methods used for conducting iridium production lifecycle assessment.

### 2.1 Database and Software

Brightway2 Framework: An open-source Python LCA modeling framework, LCA was performed using the Brightway2 platform, which provides a comprehensive set of tools for life cycle modeling and impact assessment.

Database: This study utilized the "biosphere3" database, which contains environmental data required for LCA of various activities, including industrial processes such as iridium production.

#### 2.2 Functional Unit and System Boundaries

Functional Unit: Production of 1 kg of iridium metal. System Boundary: This study covers the entire production life cycle of iridium, from ore mining to the final production stage. The goal of this life cycle assessment is to evaluate the environmental impacts associated with producing 1 kg of iridium [5]. The system boundary adopts a "cradle-to-gate" approach, encompassing raw material extraction, processing, and iridium production. Downstream use and end-of-life phases were excluded, with the focus placed on production-related impacts. The analysis was conducted using the Brightway2 framework, with data sourced from the FORWAST technosphere database and the Biosphere3 environmental flow database [6].

## 2.3 Impact Assessment Methods

Life Cycle Impact Assessment (LCIA): A comprehensive set of impact methods was used to capture a wide range of environmental impacts. Global

Warming Potential (GWP): This impact category was assessed using the IPCC 2021 method [7], with three different time horizons (GWP100, GWP20, and GWP500), expressed in kilograms of CO<sub>2</sub> equivalent. Ecosystem Quality, Ecotoxicity, Toxicity: Human toxicity, including carcinogenic and non-carcinogenic effects, was evaluated using the ReCiPe 2016 v1.03, endpoint (H) method [8]. LCA formula in Brightway framework:

$$h = CBA^{-1}f \tag{1}$$

the environmental impacts per process:

$$h_{\text{process}} = CB \operatorname{diag}(A^{-1}f)$$
 (2)

where A is Technology matrix, B is Intervention matrix, C is Characterization matrix and f is Final demand vector [9].

## 2.4 Uncertainty and Sensitivity Analysis

To evaluate the robustness of the LCA results and account for potential variations in input data, two analytical methods were employed:

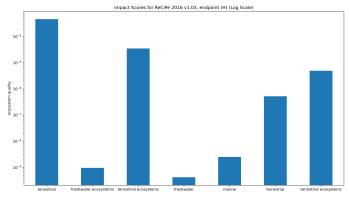
- Sensitivity Analysis: The technosphere matrix inputs were adjusted by  $\pm 10\%$  to observe changes in GWP100. This method identifies the most influential factors in the model by deliberately altering single or a few parameters, quantitatively analyzing their impact on the results. This helps pinpoint priority areas for optimization and assess the model's robustness [10].
- Monte Carlo Simulation: Assuming a log-normal distribution for inputs, 1,000 iterations were performed to analyze the distribution characteristics of GWP100. This method quantifies the uncertainty range of the results by randomly sampling input parameters, yielding the probability distribution, mean, and variance of the results. This provides a basis for assessing the confidence and variability of the results, supporting risk management [11].

#### 3 Results

### 3.1 Impact Assessment Results

This assessment employed the ReCiPe 2016 v1.03, endpoint (H) method within the Brightway2 framework, utilizing logarithmic scale visualization to illustrate the relative magnitudes of the impacts. The life cycle impact assessment results reveal that the production of iridium has a substantial effect

on human health, particularly in areas such as climate change, ozone depletion, and particulate matter formation. In contrast, the impact of iridium production on ecosystem quality is relatively minimal. The comparison of various impacts on ecosystem quality is shown in Figure 1, while Figure 2 presents the comparison of impacts on human health.



**Figure 1.** Comparison of various impacts on ecosystem quality.

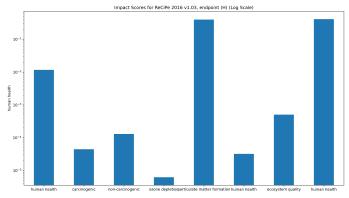


Figure 2. Comparison of various impacts on human health.

For each kilogram of iridium produced, the Global Warming Potential (GWP100) is 12,009 kg CO<sub>2</sub> equivalent. The GWP20 is the highest, indicating that iridium production has the most significant short-term climate impact, with short-term greenhouse gas effects likely contributing more to environmental impacts. The GWP scores across the three time horizons (20 years, 100 years, and 500 years) range from 11,000 to 13,000, demonstrating the relatively high stability of climate change impacts across different time scales. The GWP for 1 kg of iridium production is shown in Figure 3.

## 3.2 Life Cycle Inventory (LCI) Main Flow

The life cycle inventory results provide a comprehensive account of the material and energy flows associated with iridium production. The top

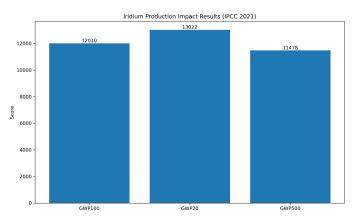


Figure 3. GWP for 1 kg iridium production.

three flows are presented in the form of a horizontal bar chart in Figure 4, which highlights energy inputs (e.g., electricity) and chemical reagents as the primary contributors. Among these, carbon dioxide emissions from fossil fuel combustion are the highest, followed by sulfur dioxide and non-fossil carbon dioxide. These flows highlight the energy-intensive nature of iridium extraction and refining, particularly during the mining and smelting processes. The flows are directly linked to climate change  $(CO_2)$ , acidification  $(SO_2)$ , and air pollution (PM), emphasizing the high-temperature, high-energy characteristics of the smelting and refining stages.

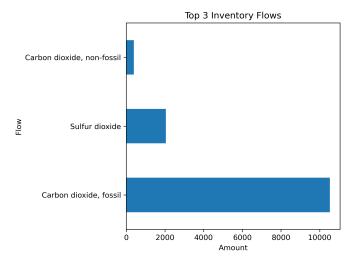


Figure 4. Top3 Inventory Flows.

#### 3.3 Sensitivity Analysis

According to the sensitivity analysis, the Global Warming Potential (GWP, in kg CO<sub>2</sub>-eq) exhibits a negative correlation with the Technosphere Input Factor. As the Technosphere Input Factor increases from 0.9 to 1.1, the GWP decreases from approximately 1,3000 kg CO<sub>2</sub>-eq to about 1,1000 kg CO<sub>2</sub>-eq. This



relationship shows a nearly linear downward trend, indicating that each unit increase in the Technosphere Input Factor leads to a consistent reduction in GWP. The system is particularly sensitive to changes in the Technosphere Input Factor, especially in the lower range (0.9 to 1.0), where the GWP decrease is more pronounced. In the higher range (1.0 to 1.1), the downward trend becomes less steep. This suggests that optimizing the Technosphere Input Factor (e.g., improving resource utilization efficiency or technical inputs) can effectively reduce the system's carbon footprint, although the marginal benefits may diminish as the factor increases. When the technical input is reduced by 10%, the GWP100 increases to approximately 13,400 kg CO<sub>2</sub>-eq, while a 10% increase leads to a reduction to about 10,900 kg CO<sub>2</sub>-eq. These results indicate that the production process is highly sensitive to energy consumption, and improvements in energy efficiency can significantly reduce the carbon footprint. The sensitivity analysis is shown in Figure 5.

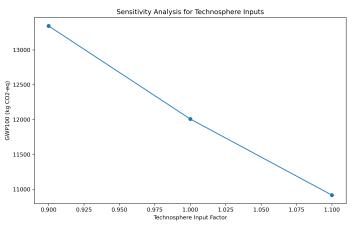
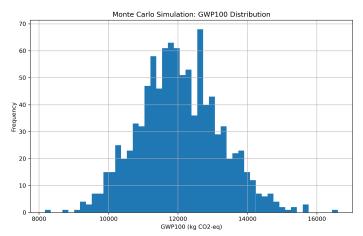


Figure 5. Sensitivity analysis.

#### 3.4 Monte Carlo Uncertainty Analysis

Figure 6 presents the distribution of GWP100 (100-year Global Warming Potential, in kg  $CO_2$ -eq) based on Monte Carlo simulations. The results show that GWP100 values are primarily concentrated within the range of 10,000 to 14,000 kg  $CO_2$ -eq, with the highest frequency occurring around 12,000 to 13,000 kg  $CO_2$ -eq, representing the most likely range of the system's carbon footprint. The distribution exhibits a slight right skew, indicating a lower probability of higher values (>14,000 kg  $CO_2$ -eq); however, some uncertainty remains, and carbon emissions could significantly increase under certain extreme conditions. The overall distribution spans from 8,000 to 16,000 kg  $CO_2$ -eq, highlighting the impact of input parameter uncertainty on the results. This uncertainty may arise

from variability in input data, such as the proportion of electricity sources, smelting energy efficiency, and fluctuations in ore grade, suggesting the need for further analysis of key parameters to enhance the robustness of the assessment.



**Figure 6.** Monte Carlo uncertainty analysis.

#### 4 Discussion

The study results highlight the significant environmental footprint of iridium production, particularly in terms of climate change and toxicity. The high Global Warming Potential (GWP100) reflects the energy-intensive nature of iridium mining and refining processes, which, in many production regions, heavily rely on fossil fuel-based electricity generation. Emissions of heavy metals and chemicals during the refining process contribute to toxicity impacts, underscoring the need for improved waste management and emission control technologies [12].

Compared to previous studies on platinum group metals [13], this analysis provides a more comprehensive assessment by integrating multiple impact categories and uncertainty analysis. Sensitivity analysis confirms that energy inputs are a critical hotspot, suggesting that transitioning to renewable energy sources could significantly reduce GWP. Monte Carlo results indicate moderate variability, further emphasizing the importance of high-quality, site-specific inventory data to minimize uncertainty.

Limitations of this study include reliance on secondary data from FORWAST and Biosphere3, which may not fully capture regional variations in the production process. Additionally, the cradle-to-gate scope excludes downstream impacts from iridium use and disposal, which could be significant in certain applications, such as hydrogen production catalysis [14].

## 5 Conclusion

This life cycle assessment demonstrates that iridium production is a highly environmentally intensive process, characterized by a significant carbon footprint (12,009 kg  $\rm CO_2$ -eq per kg) and substantial contributions to toxicity-related impact categories. The identification of energy consumption and chemical emissions during refining as the primary environmental hotspots provides a clear target for intervention.

The sensitivity and uncertainty analyses further underscore that the magnitude of these impacts is highly dependent on the efficiency of the energy grid and the specific reagents used, highlighting the critical need for more accurate, primary inventory data. To mitigate these impacts, the following actionable steps are recommended:

Technological Optimization: Refineries should prioritize the adoption of direct electrification and hydrogen-based smelting technologies where feasible, coupled with advanced solvent extraction techniques to improve reagent efficiency and recycling within the hydrometallurgical circuit [15].

Renewable Energy Integration: The single most effective lever for reducing the GWP is decarbonizing the energy supply [16]. A strategic shift towards powering mining and refining operations with renewable energy sources is paramount. This could be achieved through power purchase agreements (PPAs) or on-site solar/wind installations [17].

Policy and Certification: Policymakers are encouraged to develop support mechanisms for critical raw materials that internalize their environmental cost [18]. This could include carbon pricing, green public procurement criteria for iridium, and funding for research into low-impact refining technologies. Establishing a sustainability certification scheme for PGMs would create market incentives for greener production [19].

Future research must focus on collecting primary operational data to enhance inventory accuracy, expanding the system boundary to include the use phase and end-of-life recycling potential, and incorporating the assessment of resource depletion to provide a truly comprehensive sustainability evaluation [20]. These findings offer stakeholders a data-driven foundation to fundamentally improve the environmental profile of this critical metal, ensuring its role in a sustainable clean energy future is truly

net-positive.

# **Data Availability Statement**

Data will be made available on request.

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This work was supported without any funding.

#### **Conflicts of Interest**

The authors declare no conflicts of interest.

## **Ethical Approval and Consent to Participate**

Not applicable.

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