Assessing Water Dependency Risks in the Mining Sector: Application of the Nature Risk Profile Methodology designed by S&P Global in collaboration with UNEP-WCMC

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# Introduction

In a collaborative effort, S&P Global and UNEP-WCMC co-developed the Nature Risk Profile methodology, a tool that gauges companies' dependencies and impacts on a plethora of ecosystem services. The objective is to derive an effective measure of nature's physical and transition risk. This assists both companies and investors in driving positive change and aligning with the Nature Positive 2030 agenda.

Of the 21 distinct ecosystem services considered, this project specifically implemented the methodology for the ground and surface water ecosystem services*[[1]](#footnote-1)*, focusing on three major mining entities: BHP Group, Freeport McMoran, and Glencore. The mining industry, with its significant dependence on water, is very sensitive to physical climate risks, especially in scenarios where the global average temperature exceeds the limits set by the Paris Agreement. For instance, Trucost reports that approximately one-fifth of all mines studied are in regions experiencing extreme water stress, consuming over 80% of the available water. The highest risk exposure is seen in iron ore mines, with 30% of them facing water stress, predominantly in Chile, Peru, and China. According to this study, mines in these regions are more vulnerable to disruptions during extended drought periods[[2]](#footnote-2).

The three mining companies for which I computed the water dependency scores[[3]](#footnote-3) operate a diverse array of global assets. Their operations span a range from sugar refining, biofuel production, oil extraction, to power generation, steel manufacturing and more. Consequently, the degree of dependency on water services varies extensively, contingent on both the type of asset and its geographical location.

This document outlines the scope and findings of my work, structured as follows:

* **Summary of Methodology**: This section offers a detailed overview of the Nature Risk Profile methodology's implementation, with a focus on the assumptions made and key steps involved in score computation.
* **Final** **Results & Insight to an Investment Portfolio Manager**: This section presents a summary of the results, illustrating the water dependency score risk at the asset, asset group, and company levels. It concludes by offering recommendations to portfolio managers.
* **Limitations & Suggestions for Improvement**: A critical evaluation of the work pinpointing areas that could benefit from further refinement or enhancement.

# Summary of Methodology

I implemented the dependency score methodology at multiple levels: asset-specific, asset group, and encompassing the entire company. The process can be divided into three primary stages:

* Calculation of the Reliance Resilience and Dependency Score for individual ecosystem services (both ground and surface water) on an asset-specific basis.
* Computation of Reliance, Resilience, and Dependency scores at the asset type level.
* Generation of a Composite Score for the asset type level.
* Evaluation of the overall dependency score at the company-wide scale.

In the following sections, I will delve into each of these steps in more details.

## Reliance, Resilience and Dependency Score Asset Level

In order to compute the **Reliance Score**, the Materiality of the Dependency needed to be assessed first. This involved several steps:

1. *Asset Categorization and Materiality Assessment*: Companies possess a variety of assets, such as sugar refineries, biofuel plants, coal mines, power plants, and more. Each of these asset types has a unique materiality of dependency. The Encore dataset provides materiality ratings for each process. For this stage, two datasets are essential:i) assets, detailing the types and specifics of company assets; and ii) materiality, containing the materiality ratings.The goal is to align each materiality process with its corresponding asset type.

2. *Merging and Score Assignment*: After the initial mapping, this data can be integrated with the assets dataset. As a result, every asset will be associated with a specific rating score, ranging from 0 to 1.

For the calculation of the Reliance Score, it is typically derived from the geometric mean of the product of materiality and an adjustment factor known as the "relevance score". However, for the provisioning services of interest, namely ground and surface water, the methodology specifies that this adjustment is not required. Furthermore, since the geometric mean of 'n' at the asset level is the root of 1 (owing to only one score component per ecosystem service), the reliance score at the asset level directly equates to the materiality score.

I did not calculate the reliance score for the following facility category as I assume they have no relation with water risk: 'Instn Address', 'Company Headquarters'

To calculate the **Dependency Score** at the asset level, I needed to also compute the Resilience Score. The Resilience Score leverages the water risk framework from the World Resource Institute (WRI), known as Aqueduct.

Few Important Assumptions that I made are as follow:

1. *Significance of Resilience & Chosen Risk Indicator*: the framework identifies water risk through 13 distinct indicators, covering Physical Quantity (e.g., baseline water stress), Physical Quality (e.g., untreated wastewater), and Regulatory and Reputational aspects (e.g., unimproved drinking water). These indicators are combined to produce a comprehensive water risk score using various weightings. I opted for the aggregate, sector-specific weighting, as it aptly captures both the tangible physical and regulatory risks impacting service provision. Moreover, the Task-force on Nature Financial Disclosure emphasizes both these physical and transition risks. Hence, the overall water risk was chosen as the representative measure for ecosystem resilience.

2. *Regionalization of Resilience Score*: In risk assessment, it's imperative to pinpoint potential high risks. Thus, when aggregating at the country level, I've chosen to take the maximum risk value. This approach adeptly captures heightened tail risk while simultaneously preserving variation across sectors.

The Calculation Step were as follow:

1. Mapping: The initial step involved aligning asset process definitions with the sector classifications provided by WRI. Further, the aggregate risk variable at the sector level was mapped to the sector names as delineated by WRI.

2. Scaling: Scores derived from this dataset span a range from 0 to 5. To tailor these scores for this analysis, the Min-Max Normalization technique was employed. This method upholds the inherent relationships between data points, ensuring the resultant scaled values fall within the [0, 1] range.

3. Resilience Score Regionalized: The resulting normalized resilience score will then get aggregated at the country level by taking the maximum of value for every sector.

4. Merging Resilience Score: The resulting regionalized resilience score was then attributed to the corresponding asset level.

5. Dependency Score: The final Dependency Score is obtained by multiplying the resilience by the previously computed materiality. It's worth noting that due to a score component of 1 for each type, the geometric mean of the multiplication mirrors the multiplication result itself.

## Reliance, Resilience and Dependency Score Asset Type Level

To calculate all scores for each asset group, I did the following:

1. Separating Dataset: I begin by splitting the resulting asset level dataset into two distinct subsets: one focused on groundwater services and the other on surface water services. Each subset contains values for both materiality (which corresponds to reliance) and resilience at the asset level.
2. Score Calculation: in each dataset, we multiply the resilience and reliance scores. While performing this multiplication, the geometric mean is applied, and the results are aggregated by both company ISIN and asset process levels.

## Composite Score

Businesses that heavily rely on a few ecosystem services are at greater risk than those with diversified dependencies. This is akin to putting "all one's eggs in a single basket." If a critical service fails or is compromised, it can have significant repercussions for a business. Conversely, businesses that spread out their dependencies across multiple ecosystem services have a safety net, as the failure of one service might be mitigated by the others.

To quantify this relationship, The Nature Risk Methodology uses a logarithmic function. Logarithms inherently capture the concept of diminishing returns — the initial dependencies introduce substantial risk, but each additional dependency contributes progressively less to the overall risk.

The measure, the "Ecosystem Service Dependency Score," ranges between 0 (no risk) and 1 (maximum risk). This score is derived from the combined dependency values of different services. A logarithmic transformation ensures that a high dependency on fewer services results in a score closer to 1, indicating higher risk.

During aggregation I added 1 to ensure that:

1. The logarithmic transformation can be applied even when the sum of dependencies is zero (as the logarithm of zero is undefined).

2. The transformation is always in the positive domain, reflecting increasing risk as the dependency score increases.

## Dependency Score Company-wide Scale

To aggregate the composite score at the company level, I wanted to determine the appropriate weight for each sub-asset group. The reason for this weighting is to account for the varying impact each process has on ground and surface water services. The Universe dataset provides financial metrics such as turnover and water consumption at the sector level, which can be leveraged to assess the intensity of impact each sector has on these ecosystem services. The granularity of the GICS sector name allows it to be mapped back to asset group processes. Therefore, the following steps were performed to compute the aggregate score:

1. **Mapping Process to GICS Name**: Create a new column to map each asset process to its corresponding GICS name.

2. **Water Intensity Metric**: After I calculated company annual total water abstraction I divided it by company total revenue to generate a water intensity metrics to derive asset process level water usage.

3. **Merging and Weights Definition**: the water intensity value at gics level is then associate at the asset group level. With a normalization logic I created and assigned weights

5. **Calculating Aggregate Score**: The composite score is multiplied by its relative weight at the company level, and the final aggregate score is subsequently determined.

**Key Assumptions**:

1. **Intensity Metric:** To compute the intensity metric, I opt to use 1) *Total Revenue* as it is less subject to accounting adjustments and provides a straightforward representation of a company's operational scale. ii) *total company water abstraction*. Upon examination, it appears that by subtracting "company annual water purchased for cooling" and "company annual water abstraction for its own process" from the "company annual water abstraction and purchase" variable, we can estimate the value for "company annual water abstraction for cooling," which is missing in approximately ~96% of the dataset. Once this estimate is obtained, it will be summed back to "company annual water abstraction for its own process" to derive the total company water abstraction. This total will serve as the numerator in calculating the final water intensity metric. Another issue is that the variable tcabswaterdirectprocess used to compute water intensity metric still contains ~40% of null value. Instead of just taking an average or another simple measure to replace the missing value, it looks at the relationships between the variable with missing data and other variables you have. It uses these relationships to make a more educated guess about what the missing value might be.

2. **Conservative Approach:** In line with my intent to maintain a conservative approach and capture potential tail risk, I adopted a two-step aggregation method when consolidating water intensity values at the GICS Name level. Firstly, I aggregate by year, selecting the maximum values, and then proceed to average these maximums across all years.

# Final Results & Insights To an Investment Portfolio Manager

From the provided visuals and table, it's clear that Freeport-McMoran Company has the highest average asset dependency score for both ground and surface ecosystem services. Additionally, this company boasts assets that consistently show higher average resilience and materiality for both services. Intriguingly, it isn’t so much the variation in materiality scores across companies that captures attention, but the resilience scores. This underscores the importance of geographic location, implying that companies whose assets are situated in areas with lesser water risk exposure have a distinct edge. Yet, differing materiality scores across companies also hint at the impact of asset types on these metrics. Lastly, mining companies with such profiles seem more dependent to surface water services than to ground water services.

A graph with a number of points

Description automatically generated with medium confidence

A screenshot of a computer

Description automatically generatedA screenshot of a computer screen

Description automatically generated

A diagram of a distribution

Description automatically generated

A screenshot of a computer screen

Description automatically generated A screenshot of a computer

Description automatically generated

A chart with different colored squares

Description automatically generated

A table with numbers and text

Description automatically generatedA table of numbers and text

Description automatically generated with medium confidence

The geographic location of assets plays a pivotal role in determining the final dependency score. Presented below are graphics illustrating the count of assets per company by geography. The color schemes for both the bar chart and maps differentiate countries based on their risk level, with more intense colors indicating higher risks.

A graph of a number of countries/regions

Description automatically generated A graph of different states

Description automatically generated

A graph of a number of countries/regions

Description automatically generated

A map of the world

Description automatically generated

A map of the world with red and black colors

Description automatically generated

A map of the world

Description automatically generated

Below is a depiction of the water dependency scores for both ground and surface water, as well as the associated composite score. Freeport appears to be far less diversified in terms of asset type compared to other companies. This lack of diversification could potentially be a key factor explaining the higher risk levels at the company level, as we will explore shortly.

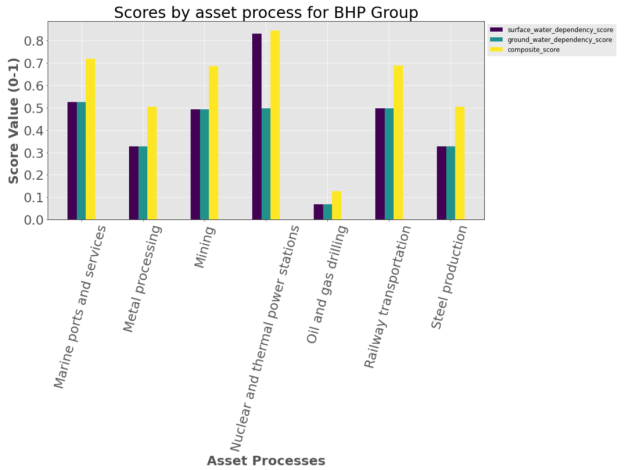
On a separate note, an interesting observation is regarding nuclear and thermal power stations. For these processes, there is a noticeable difference in values for ground and surface water services, where there is a heightened dependency on surface water services.

A graph with different colored bars

Description automatically generated with medium confidence

A graph with text on it

Description automatically generated



The tables below present the composite score, water intensity, derived weights, and the weighted aggregate score at the company level, broken down by sub-asset process. The weight is determined by normalizing the water intensity at the process/GICS level. Consequently, a higher intensity combined with a lesser number of processes (indicating less diversification) results in a larger weight for that process. This, in turn, amplifies the overall risk score of the company, as evidenced by the following image:

A graph with different colored squares

Description automatically generated

**Freeport-McMoRan Inc.**

A screenshot of a computer

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**Glencore plc**

A table with numbers and letters

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**BHP Group**

A table with numbers and letters

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Translating these findings into actionable insights for an investment portfolio manager, here's my assessment:

For the portfolio manager who already has investments, if there's a significant holding in Freeport-McMoran Company, it becomes important to understand the company's pronounced lack of diversification. This is evident especially in terms of asset type. Such limited diversification has, as the findings indicate, heightened its risk, leading it to achieve an unfavorable aggregate score in comparison to its industry peers.

Depending on the size of the investment in Freeport-McMoran, there are two key considerations. Firstly, one might consider initiating a direct engagement with the company. The goal of this engagement would be to encourage Freeport-McMoran to craft and implement a robust resilience plan, especially as TFND transitions out of its beta phase and gains momentum, similar to the trajectory observed with TCFD. Such a plan would aim to address and potentially mitigate the company's elevated risk exposure.

Alternatively, rebalancing the portfolio might be a strategic move. This would involve recalibrating the exposure to Freeport-McMoran, potentially reducing the weight allocated to it. Yet, it's essential to note that for a holistic rebalancing strategy, a similar analysis would be beneficial for other companies within the portfolio. Moreover, while Glencore and BHP Group have achieved better risk scores, it's still prudent to either engage with them or reconsider portfolio exposure, based on individual circumstances. To effectively reweight the portfolio, benchmarking these companies against other industry peers (perhaps using a cohorting mechanism) would be advantageous.

For the portfolio manager seeking potential investments, the recommendations are somewhat parallel. While there may not be an immediate need for engagement with the companies in question, it's crucial to heed the findings related to asset and geographic diversification when considering investments within the mining sector. One could, for instance, consider using the inverse of a company's risk profile to derive investment weights, essentially assigning reduced weight to companies with higher risk scores and vice versa. It's essential to emphasize that any scoring mechanism should be benchmarked against the broader investment universe of interest. If the investment is being considered only within these three companies, then based on current findings, a heavier weight should be assigned to Glencore plc, followed by BHP Group, and lastly, Freeport-McMoran Inc.

# Limitations & Suggestions for Improvement

In reflecting on my work, I'd like to highlight certain limitations within my analysis, as well as propose avenues for potential enhancements.

A primary constraint of this study is the absence of a forward-looking, scenario-based examination. This is especially pertinent when addressing the dynamics of climate and nature risk evaluations. By examining future water risk profiles of countries under varying scenarios - be it a business-as-usual, a more pessimistic outlook (RCP 8.5), or an optimistic projection (RCP 2.6) - the conclusions drawn from this analysis could experience significant shifts. Given more time, and ideally, the opportunity for interdisciplinary collaboration, my inclination would be to calculate scores across these mentioned scenarios and aggregate them. Such an approach would offer a deeper understanding of which companies truly exhibit the highest resilience to water risk. As Professor Riccardo Rebonato from Edhec Business School aptly points out, scenarios inherently lack associated probabilities. Nonetheless, there may be a need to devise a methodology that aggregates these forward-looking scores into a unified resilience metric[[4]](#footnote-4).

Another limitation stems from the inability to attribute specific geographic coordinates to assets at the country level. In my current analysis, assets are broadly categorized by country, without granular insight into their precise locations. An enhanced approach would involve overlaying the exact asset positions with the World Resource Institute's country-basin geometries. This granular mapping would provide a more accurate assessment, allowing for better precision in understanding asset-specific risks.

# Additional Research Notes

@Results

* When we examine the actual water intensity footprint, it's evident that all three companies are witnessing a decline in their respective intensities. However, with only three to four data points, and considering the inherent uncertainties in these estimates, it might be premature to draw definitive conclusions. Freeport McMoran has the most significant footprint, starting from just over 18,000 m^3/USD$ in 2019 and dropping to around 8,000 m^3/USD$ by 2022 (and biggest reduction!). This is followed by BHP Group, whose intensity began at approximately 8,000 m^3/USD$ and reduced to about 4,000 m^3/USD$ in 2022. Glencore, on the other hand, has the smallest footprint, starting from around 4,000 m^3/USD$ and dwindling to roughly 1,600 m^3/USD$ by 2021. These observations are consistent with the weights we previously assigned. It is important to point out – as show by image below – that intensity has been reduced mainly by a reduction in water abstraction across all three companies (Glencore the most!).

A graph of water intensity

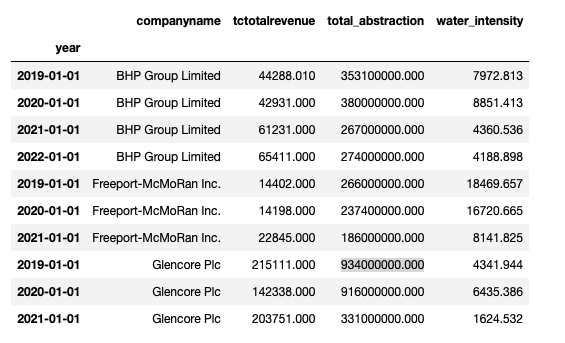
Description automatically generated with medium confidence

A graph of a graph showing the number of different colored lines

Description automatically generated with medium confidence

A graph showing the growth of a company

Description automatically generated with medium confidence



@Limitation

* Furthermore, an additional **limitation** of the analysis worth highlighting is the need to provide separate scores for transition and physical risks, in addition to the aggregate score. By doing so, investors could better discern what poses the most significant threat to their investee companies, whether it's extreme weather events or a lack of policy alignment.

1. As defined by Encore, *Groundwater is water stored underground in aquifers made of permeable rocks, soil, and sand. This water primarily originates from rainfall, snow melts, and flows from natural freshwater resources*. Conversely, *surface water is procured from freshwater resources resulting from accumulated precipitation and natural water sources:* <https://encorenature.org/en/data-and-methodology/services> [↑](#footnote-ref-1)
2. <https://www.spglobal.com/marketintelligence/en/news-insights/blog/climate-related-considerations-in-the-metals-and-mining-sector> [↑](#footnote-ref-2)
3. The Taskforce on Nature-related Financial Disclosure (TFND) defines 'dependencies' as those facets of ecosystem services upon which an organization or entity is reliant for its operations. [↑](#footnote-ref-3)
4. <https://www.ft.com/content/b03691be-19ef-4164-9a74-7592d7c73457> [↑](#footnote-ref-4)