



Financial Materiality

*Criticality of Accounting for
Nature Risk in Financial Decision-Making.*

01 Introduction

Traditional financial models have historically treated the natural world as a perpetual, cost-free externality. A growing consensus among leading economic institutions now recognises that the degradation of nature and the loss of biodiversity represent a new frontier of systemic risk, with profound implications for corporate performance and investment returns. For fiduciaries, nature-related risk is rapidly moving from a peripheral "non-financial" concern to a core, financially material factor that demands rigorous quantification and active management.

This whitepaper presents a data-driven case study developed to demonstrate nature data is material when it comes to pricing in financial risks. It moves beyond generic, high-level environmental scoring to provide a granular, actionable framework for investment decision-making. The central thesis is that financially material nature risk is most accurately identified at the intersection of two critical dimensions: a company's operational dependency on specific ecosystem services and the verifiable integrity of the ecosystems at its precise asset locations. This approach combining dependencies and geospatial risk transforms an abstract concept into a quantifiable risk variable.



02 NatureAlpha Data

NatureAlpha provides comprehensive data solutions designed to quantify nature-related risks and opportunities for investors and financial decision-makers. NatureAlpha integrates diverse datasets including geospatial company data, corporate policy assessments, and various nature impact and dependency metrics. Additionally, the platform systematically measures companies' dependencies on ecosystem services, highlighting how reliant business operations are on natural capital such as freshwater availability, pollination, and climate regulation.

For the case of combining core thematic areas essential to understanding nature-related financial risk:

Table 1. Three themes identified in the NatureAlpha data, along with a description of the theme and the relevant variables.

Theme	Description	Geospatial Data	Key Dependencies
Water	Assesses company risk exposure related to water scarcity, pollution, and regulatory risks tied to freshwater use.	Water stress basins, drought indices, watershed vulnerability, river basin health	Freshwater availability, water regulation, and water quality
Ecosystem	Evaluates risks related to ecosystem integrity, including habitat loss and the degradation of natural protections against environmental hazards.	Ecosystem integrity index; overall ecosystem health	Flood and storm protection, water regulation, disease control
Biodiversity	Measures corporate impact on biodiversity, focusing on species loss and habitat fragmentation.	Biodiversity intactness index; biodiversity remaining	Climate regulation, soil quality, maintenance of nursery habitats

The financial materiality of nature risk emerges at the intersection of these two pillars: geospatially specific information and key dependencies. A high dependency on an ecosystem service becomes a significant financial risk only when the company's operations are located in a region where that specific service is degraded or under threat. For instance, a beverage bottling company (high water dependency) faces a far greater material risk if its plant is located in a basin flagged for severe water scarcity than if it is located in a water-abundant region. This integrated analysis pinpoints these "hotspots" of risk, transforming a generic environmental issue into a specific, measurable, and financially relevant variable. This leap in analytical precision is fundamental, as it demonstrates that nature risk is not homogenous across a sector or even within a single company. The true risk is hyper-local, and only by analysing a company's geographic footprint can investors accurately assess their exposure.

03 Nature Risk Portfolio Approaches

Screened Portfolio

As investors increasingly recognise the materiality of nature-related risks, one common and intuitive strategy is **portfolio screening**. This method involves setting clear, rules-based criteria to either include or exclude securities based on their performance against specific metrics. It is a transparent approach that allows for a direct reduction of exposure to undesired risks.

To explore the implications of this strategy, we applied a screening methodology to the **MSCI World index**, a universe of approximately 1,409 securities (as of Q4 2024). Our process was as follows:

- 1. Define the Risk Metric:** We analysed each company based on our "Ecosystem Interaction Risk" metric. A company is flagged as high-risk only if it meets two conditions simultaneously: it has significant operational dependencies on ecosystem services and its assets are located in areas with high geospatial ecosystem risk.
- 2. Establish a Threshold:** We set a threshold to isolate the companies with the most significant exposure. This identified approximately 300 companies (~20% of the index) as the "High Risk" cohort, with the remaining firms forming the "Low Risk" cohort (as illustrated in **Figure 1**).

Analysing the resulting portfolios reveals distinct characteristics that are a direct consequence of this screening approach.



Figure 1. Data from all MSCI World securities depicted and their geospatial risk on the x-axis and ecosystem dependencies on the y-axis. High and low nature risk are defined by setting an upper threshold, if both thresholds are reached the security is categorised in the high-risk group (marked in red).

This screening exercise demonstrates a clear and straightforward method for reducing exposure to a specific nature-related risk. However, it also highlights an important outcome: the resulting portfolio has a fundamentally different risk and return profile from the benchmark due to significant sector deviations. For investors seeking to manage nature risk while maintaining broad market exposure, this trade-off is a critical consideration.

- **Inherent Sector Tilts:** The "High Risk" portfolio has a significantly different sector composition from the parent index. It is heavily weighted towards sectors like *Materials, Energy, Utilities, and Consumer Staples*, whose business models are often more directly intertwined with natural resources. Conversely, the "Low Risk" portfolio is dominated by sectors such as *Information Technology and Financials* (Figure 2 top).
- **Global Distribution of Risk:** An assessment of the geographic location of company assets shows that ecosystem interaction risk is a global phenomenon. High-risk facilities are not confined to a vastly differently oriented geographical space, both are distributed worldwide, including throughout developed markets (Figure 2 bottom).

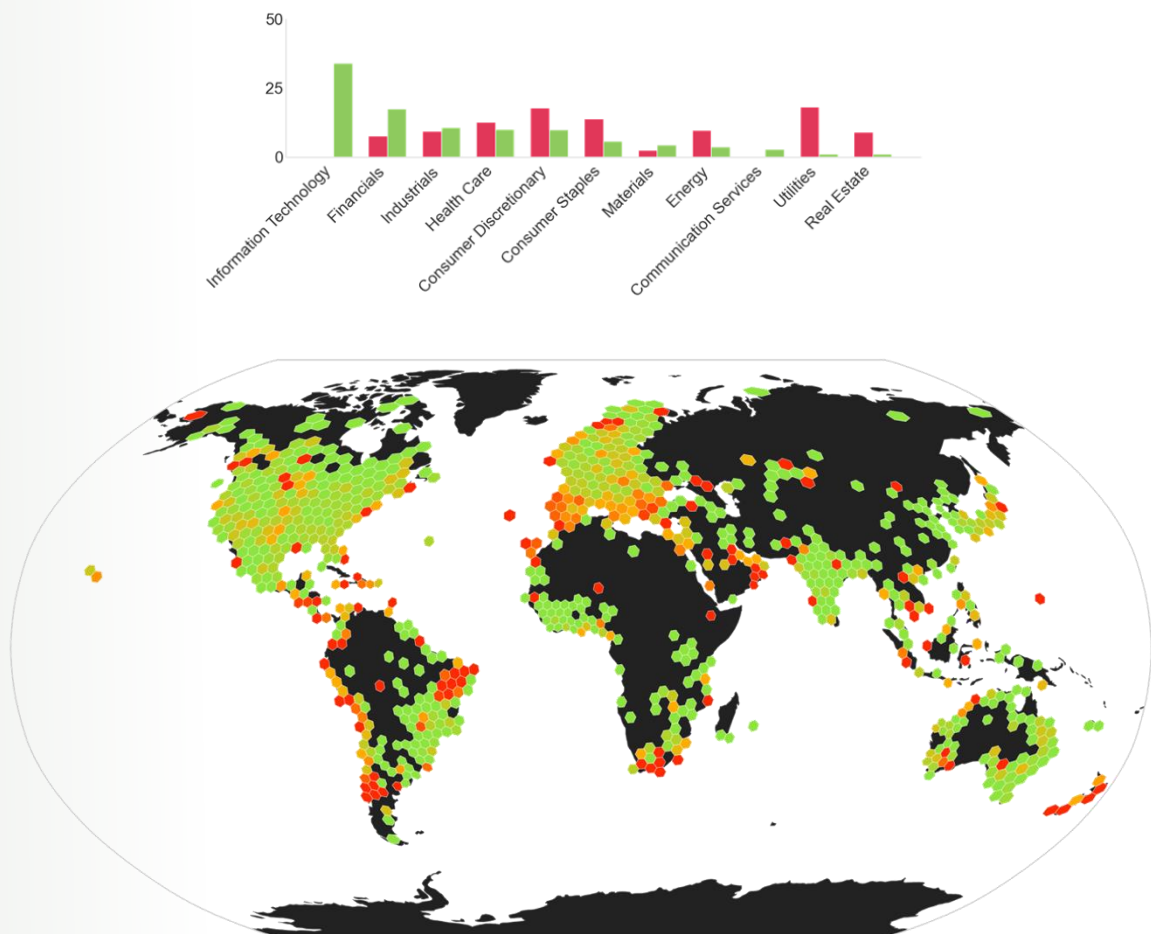


Figure 2. Top panel shows the percentage of securities based on their primary sector, it contrasts the low-risk group in green and the high-risk group in red. Bottom panels visualises the company locations for the high- and low-risk groups the if multiple securities have assets located in the same hexagon the green-red colour gradient shows the proportion of high- or low-risk security assets in that area.

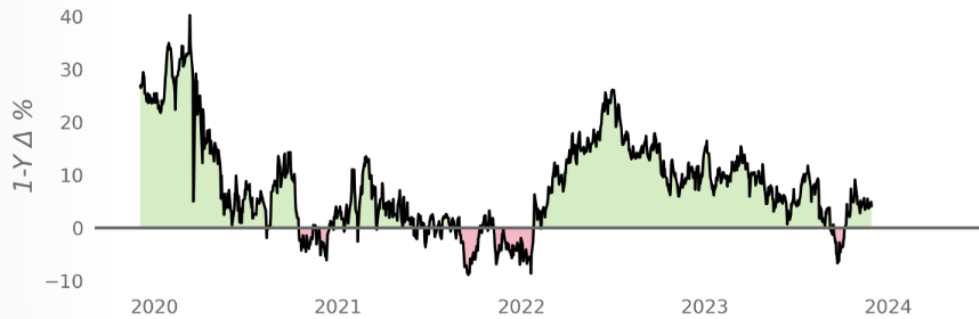


Figure 3. Difference in historic financial performance between the high- and low-risk groups over a rolling 1 year time window. Overall, the low-risk portfolio outperforms the low-risk portfolio in this 2020-2025 period.

Once groups with high and low risk are defined based on ecosystem interaction, their historical stock market performance can be compared. This is achieved by gathering daily closing security prices for all 1409 constituents, categorising them into high and low-risk groups, and calculating annual returns. The original weights from the MSCI World portfolio are used to determine the relative importance of each constituent.

To compare the relative performance of the two risk groups, we subtract the high-risk returns from the low-risk returns. Positive returns indicate that the low-risk group outperforms the high-risk group. This calculation uses a rolling one-year window, answering the question: what would have been the percentage profit if one had invested in the low-risk portfolio compared to the high-risk portfolio?

Screening approaches have their place in the investment landscape but may be inadequate for sophisticated portfolio management. They focus on eliminating one type of risk (nature) while affecting the properties of the portfolio. More conventional portfolio risks they simultaneously create (high tracking error, sector concentration). Risk management is often not about elimination; it is about the intelligent balancing of multiple, often competing, objectives. This limitation of simple screening creates a clear need for a more advanced, multi-objective solution.

Screened Portfolio

To overcome the limitations of simplistic screening, we turn to optimisation-based portfolios. This provides a way to more carefully control for portfolio characteristics while eliminating nature-related risk. This framework is designed to address the challenge faced by institutional investors: how to systematically reduce exposure to financially material nature-related risks while simultaneously maintaining fidelity to a benchmark's core financial characteristics.

The core of the methodology is a multi-objective function that seeks to find the ideal portfolio composition by balancing three critical, and sometimes competing, goals: minimising nature risk, controlling for sector deviations, and minimising tracking error relative to the financial benchmark. This approach is explicitly designed to create an investable product that aligns with the practical constraints and objectives of modern portfolio management. The implementation of this complex optimisation is powered by [OR-Tools](#) library (published by Google), which includes scalable performant optimisation logic. It should be noted that this approach can be extended or simplified based on the parameters of interest.

The optimisation works to solve a single, integrated objective function. This means we find slightly adjust the weights of each of the portfolio constituents to find the set of companies that find the lowest penalty score given the 3 requirements:

1. Keeping the sector exposure the same between the MSCI World benchmark portfolio.
2. Maintaining a tracking error within the specified limits (in our case 200 bps)
3. Eliminating Nature Risk from our portfolio, in the example below we reduce ecosystem interaction risk.

$$\text{Minimise } Z = Z_{\text{Nature}} + Z_{\text{Sector}} + \lambda_{TE} \times TE$$

Z_{Nature} represents the cumulative nature-related penalties across companies included in the fund, aiming to reduce exposure to companies with high nature risk.

Z_{Sector} adds penalties for deviations in sector representation, helping ensure that the fund's sector weights stay consistent with the target benchmark.

$\lambda_{TE} \times TE$ is a term that penalises the tracking error (TE), where λ_{TE} is a weight controlling the importance of minimising TE . Tracking error reflects how closely the fund's performance follows that of the benchmark, with lower values indicating closer alignment.

When we run this optimisation on the same set of MSCI World securities, results show that the optimised portfolio successfully achieved its primary objectives. Compared to the MSCI World benchmark, the NatureAlpha Optimised Portfolio delivered:

- No apparent deviation in returns average of **3-4% higher annual returns** over the analysis period. (see Figure 4)
- Similar sector exposure (sum of sector exposure difference of <2%)
- A **11% reduction in the aggregate ecosystem risk score**, a direct measure of the portfolio's exposure to companies with high-risk dependencies and geospatial footprints.



Figure 4. Contrasting the returns of the benchmark MSCI World portfolio with the optimised portfolio. The top panel shows the normalised portfolio value on a daily basis. The green line (optimised portfolio) edges out the grey line (MSCI World) and accumulates higher returns seen in the divergence of the two lines. The bottom plot, which is aligned to the top plot on the time axis, reinforces this point. This plot shows the % returns the investor would have one year after investing in the optimised portfolio, compared to the benchmark. Positive values indicate you would be better off investing in the optimised portfolio.

Crucially, this outperformance was not achieved by taking on excessive active risk. The optimisation constraints proved effective, holding the portfolio's ex-post **tracking error to 190 basis points (1.9%)** and keeping the **sum of the deviation of sector weights to just 2%** relative to the benchmark. This is an example of delivering a portfolio which adapts to a new risk factor, without fundamentally altering the portfolio's core characteristics. The combination of lower nature risk and similar or higher financial returns represents a "double dividend" for investors, suggesting that nature risk is not just a risk to be mitigated but a market inefficiency that can be exploited for alpha.

04 Factor Analysis

Assessing Contribution Of Nature Risk To Financial Performance

Demonstrating outperformance is a necessary but insufficient condition for validating investment strategies. Whether the observed alpha is genuine or merely a by-product of other known factors requires further testing. As with most components believed to drive financial market performance, establishing a causal relationship with correlational evidence remains challenging. To increase confidence in the relevance of nature-related variables for financial materiality, Factor Analysis can be employed. For example, did the portfolio outperform simply because the optimization process inadvertently created a tilt towards larger companies or away from energy stocks during a period when that was a winning trade? Answering this question and establishing the unique contribution of nature-related risk metrics necessitates statistical analyses.

To validate our portfolio construction methodology, we conducted a multi-factor regression analysis on both the original benchmark portfolio and the final optimised portfolio. This statistical examination allows us to understand which factors drive returns and to measure the impact of our optimisation process. The results reveal that while the model is statistically significant for both portfolios, its explanatory power is higher in the Optimised portfolio, demonstrating a more robust and predictable relationship between the selected factors and asset performance.

Our Analytical Approach: Factor-Based Panel Regression

To identify which company characteristics are the primary drivers of investment performance, we employ a standard financial analysis technique known as a multi-factor model. The general approach begins by gathering two distinct types of data: the monthly investment returns for every company in our universe and a set of corresponding company-specific properties, or "factors," such as market capitalisation, annual revenue, and our proprietary ecosystem interaction metrics.

We then apply a **regressions approach** to this panel data. This analysis determines the statistical relationship between the factors (the inputs) and the monthly returns (the output). The "weighted" aspect of the regression is crucial, as it ensures that companies with a larger allocation in the portfolio have a proportionately greater impact on the results, mirroring the mechanics of real-world portfolio returns. The outcome of this regression reveals which factors have a statistically significant relationship with performance and allows us to measure the strength of those relationships.

In this particular case study, used **market capitalisation, revenue, sector (materiality),** and **ecosystem interaction risk** as factors that can modify returns in the time period of interest. There are a number of observations that result from this Factor Analysis.

- The overall explained variance of the MSCI World returns is **low**. This is expected because we are analysing a large number of securities with even more independent factors that influence returns. Yet the variables together do reliably explain a part of the overall returns ($F_{4,1351636} = 211.6, p < .001$)
- Overall effects of market capitalisation explain the most revenue over the selected time period. This suggests that larger companies with a higher market capitalisation outperformed companies with a lower market capitalisation.
- The ecosystem interaction effect can be attributed by an effect separate from the other factors in this model, suggesting management of this risk does in this case lead to higher returns.

Table 2. Factor analysis results. The coefficient is the weight or 'importance' of that variable in the prediction of returns. The p-value is a statistical metric of confidence, the lower the value the more certain the result is not observed merely by chance. In statistics a p-value below 0.05 is typically considered significant if all comparisons are defined properly. We observe that ecosystem interaction, our nature risk metric, has a significant effect on the prediction of market returns in this case study.

Factor Analysis Nature Data

Factor	MSCI World		Optimised Portfolio	
	Coefficient	P-value	Coefficient	P-value
Market Cap	16.85	<.001	27.419	< .001
Annual Revenue	0.73	0.253	2.228	0.026
Sector Materiality	2.27	0.043	-0.772	0.44
Ecosystem Interaction	3.11	0.018	6.179	<.001

05 Summary

The critical takeaway from our analysis is that nature-related risks and dependencies are financially material, directly impacting investment returns in ways that can no longer be ignored. We have demonstrated how investors can leverage sophisticated, high-quality nature data to gain a more comprehensive understanding of these risks and opportunities within their portfolios.

This whitepaper has presented a specific example of how this can be achieved. By focusing on the interaction between a company's operational dependencies on ecosystem services and its proximity to high-risk ecosystems, we developed a novel "ecosystem interaction" risk metric. Using this metric, we constructed an optimised portfolio that successfully reduced nature-related risk while achieving a 3-4% higher annual return compared to the MSCI World benchmark, all while maintaining a low tracking error and minimal sector deviation.

However, this is just one illustration of a much broader principle. The methodology we have outlined is highly adaptable and can be tailored to fit various investment strategies and risk appetites. For instance:

- **Diverse Nature Metrics:** While we focused on an ecosystem-based metric, investors could similarly integrate data on water stress, biodiversity loss, or other nature-related themes, depending on their specific concerns and objectives.
- **Customisable Risk Tolerance:** The optimisation process can be calibrated to different levels of risk tolerance. Investors with a higher risk appetite could allow for a greater tracking error to pursue even more significant nature-related alpha, while more conservative investors can prioritise keeping the portfolio closely aligned with the benchmark.
- **Broad Applicability:** This approach is not limited to a single index or portfolio. It can be applied to any diversified portfolio, allowing for a consistent and data-driven approach to managing nature-related financial risks across different investment products.

The financial landscape is evolving, and the integration of nature-related data is becoming an essential component of sound investment analysis. As the quality and resolution of nature data continue to improve, so too will the precision and power of these insights. The question is no longer *if* nature should be integrated into investment decisions, but *how*. We have offered one effective method, and we encourage the investment community to explore the vast potential of high-quality nature data in building more resilient and sustainable portfolios.



AI-driven Geospatial Analytics

Analyses and whitepaper by **Dr. Jasper Hajonides**
Based on work with **Dr. Laura Segafredo** and
discussions with **Charles Low**

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