DNB Working Paper
No 857/April 2026

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EUROSYSTEEM

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April 2026

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April 9, 2026

Abstract

This paper presents a top-down stress testing framework for estimating the financial (stability) impact of nature degradation. The methodology links the three components of the NGFS conceptual framework on nature-related risks: nature, the economy, and the financial sector. In the first step, a shock on nature, e.g. water scarcity, is calibrated based on the macroeconomic impact of proxy scenarios of nature degradation. We then estimate the impact of this shock on nature on companies. For this, we modify the Merton model (Merton, Robert C. 1974) to account for the vulnerability of companies to nature. The resulting higher probabilities of default are the main driver of credit and market risk losses for banks and insurers respectively. While the framework we introduce is general and can be applied to multi-dimensional nature shocks and joint climate-nature shocks, in quantification we focus on water as a sub-category of nature. The results show that the financial-stability implications of nature-related disruptions can be quantified in a coherent manner. Losses are allocated according to sectoral, geographical and ecosystem-service vulnerabilities. The framework delivers granular indicators – from sectoral production impacts to market revaluations and prudential ratios – supporting a wide set of analytical and supervisory applications.

Key Words: nature degradation, ecosystem services, biodiversity loss, dependence score, financial stability, risk, credit risk, market risk, Merton model
JEL Classification: G21 ; G28 ; Q57

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[*] The views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank or of the Eurosystem. We are grateful to Daniel Dimitrov, David-Jan Jansen, Robert Vermeulen, and Maurice Bun. All remaining errors are our own.

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1. Introduction

Nature-related risks could have significant macroeconomic and financial stability implications. The central banking community now widely recognizes that nature-related risks could pose a threat to financial stability. In 2022, the NGFS concluded that ‘nature-related risks, including those associated with biodiversity loss, could have significant macroeconomic implications, and that failure to account for, mitigate, and adapt to these implications is a source of risks relevant for financial stability’ (NGFS, 2022). In the same spirit, central banks and supervisory authorities have been increasingly performing risk assessments related to nature degradation and voicing supervisory expectations on the management of nature-related risks (ECB, 2020; DNB, 2023; FSB, 2024).

This recognition followed the publication of seminal work that documented the increasing degradation of nature over the past decades and the importance of nature to our economies and human prosperity. Such was the 2019 publication of the Global Assessment Report of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services, which outlined the worldwide degradation of nature (IPBES, 2019). Other research shows that we now breach most of the planetary boundaries within which humans are known to prosper (Crona et al., 2025). Crossing these boundaries increases the risk of generating large-scale abrupt or irreversible environmental changes. In Europe, research by the European Environmental Agency shows that biodiversity is declining across terrestrial, freshwater and marine ecosystems due to persistent pressures driven by unsustainable production and consumption patterns (EEA, 2025). More than 80% of protected habitats are in a poor or bad state, while only 37% of Europe's surface water bodies had a good or high ecological status in 2021. The 2021 Dasgupta report, which presented a global review of the economics of biodiversity, concludes that our entire economy is dependent on nature given that humanity is embedded in nature (Dasgupta, 2021).

Nature-related financial risks can be categorized into physical risks and transition risks. Physical risks stem from the degradation of nature and the loss of the services that nature offers us. Transition risks stem from a misalignment of economic actors with actions aimed at protecting, restoring, and/or reducing negative impacts on nature (NGFS, 2023a). Due to the multi-dimensionality of nature and availability of nature data, the ways that nature is defined sometimes differ. Traditionally, risk assessments depict nature through the services that it offers us, the so-called ecosystem services. These are services such as water purification and the provision of raw materials. The extent to which nature can provide these ecosystem services depends on its biodiversity, i.e. the variability among living organisms. At the same time, many indexes that rate the degree to which nature is degraded are defined at a higher nature category level – such as water and soil – that differs from the ecosystem service level. This complicates the analysis of nature-related financial risks.

Literature on nature-related financial risks has been proliferating since 2020. Research has focused on different aspects of nature-related financial risks: on nature scenarios that can be used for economic and financial stability risk assessments (Oxford-NGFS, 2023), on the repercussions on nature degradation for price stability (Maurin, et al. 2022, Bats et al. 2025), on the pricing of nature-related risks in financial markets (Giglio et al., 2025), and on the economic and financial stability impact of nature degradation. Herein we focus on the latter category of the financial stability impact of nature degradation, given that this paper intends to contribute to that literature.

The financial risk repercussions of nature degradation were initially assessed through “exposure-based” assessments, which find significant dependencies of financial institutions (FIs) assets on ecosystem services. The first and most widely-used assessments have traditionally been “exposure-based” assessments, which highlighted the significant dependencies of the assets of FIs – based on the economic sectors to which they belong – on certain ecosystem services (ES). The DNB study Indebted to Nature, which was the first to analyze such dependencies, relied purely on the ENCORE database to identify the direct dependencies of FIs’ exposures to ES and their direct impact on ES (van Toor et al., 2020). The second dependency study, from Banque de France, brought in scope also indirect dependencies, i.e. dependencies throughout the supply chain, through using input-output tables that proxy supply chains together with ENCORE (Svartzman et al., 2021). Other studies have largely relied on this methodology to estimate the dependencies of FIs on nature in different geographic areas (Calice et al., 2021; World Bank and Bank Negara Malaysia, 2022; Martínez-Jaramillo and Montañez-Enríquez, 2021. Boldrini et al., 2023; Hadji-Lazaro et al., 2024). All these studies found significant dependencies of FIs’ assets on nature.

More recently, there have been attempts to move from exposure-based to risk-based assessments that combine dependency to nature with also initial estimates of the shock on nature, the extent of nature degradation, and/or the risk profile of FIs’ assets. Since 2023, researchers have applied exploratory methodologies in trying to estimate nature-related financial risks (Prodani et al. 2023; Boldrini et al., 2023; Ranger & Oliver, 2024). The first study that tried to make the full link from a shock on nature to economic impact and ultimately financial sector impact provided insights on the workings of nature and economy models. The study highlighted how such macroeconomic assessments are difficult to undertake given that nature-to-economy models are not well connected to stress testing models used to test the resilience of FIs’ to shocks. (Prodani et al., 2023) In addition, these equilibrium macro models make generous assumptions about the substitutability of factors of production and supply chains, which calls into question the reliability of these results in cases of tail events on nature. Similar findings were highlighted by the NGFS from a largely theoretical review of a wide range of nature-to-economy models (NGFS, 2023b).

Currently, there is no well-established and widely used methodology for translating a shock on nature into a financial stability impact. To at least temporarily bypass the limitations of nature-to-economy models until they better reflect tail or stress scenarios, this paper builds on the methodology proposed in Gallet et al.(2024) to estimate an (micro)economic and then financial sector impact of nature (or ES) shocks using a structural financial model, namely the Merton model. That methodology reflects how the balance sheet of a company, and therefore its probability of default, is affected by a shock on an ES and the agent’s vulnerability to that ES. The vulnerability is a function of the agent’s dependence on an ES and the extent of degradation of that ES. Gallet et al (2024) was agnostic as regards the magnitude of the shock on ES and therefore produced results that could be read only in relative terms, i.e. how much more one FI is affected compared to another FI that lends to companies active in different sectors and with supply chains in different countries. This paper brings the field further, as it calibrates the shock on ES based on proxy macro scenarios and therefore makes it possible to conclude on the materiality of impact on the financial sector. These proxy scenarios are used to approximate the macroeconomic impact of nature degradation scenarios in the absence of well-established nature degradation scenarios and models that translate these into macro-financial impacts. (NGFS, 2023b)

This paper aims to close this gap by (i) proposing a top-down stress testing framework that intuitively explains the channels through which a shock on nature, sometimes in combination with climate change, can affect the stability of financial institutions and (ii) applying this framework to water as a sub-category of nature. In doing so, it links the three blocks of the NGFS conceptual framework for nature related risks: nature, the economy, and the financial sector. The starting point for this framework is to calibrate a shock on nature (specifically water) based on the macroeconomic impact of proxy nature scenarios These scenarios are used to derive a proxy macroeconomic impact that will serve as input for the rest of the analysis. These proxy scenarios point to a magnitude of around 10% GDP loss at the EU level. This figure is intended solely as an order-of-magnitude benchmark to test the framework and should not be viewed as a scientifically validated scenario. This exogenous macroeconomic impact at the EU level is then expressed as a function of vulnerability to nature (in our case study water service depletion). This concept of vulnerability to nature, first introduced in Gallet et al (2024), is a function of dependence on nature – used in previous studies – and extent of degradation of nature. The vulnerability of companies to nature is defined at country- economic sector level, given the lack of company-level data. In other words, the more dependent a company - as proxied by the country-sector pair to which it belongs - is on nature and the more degraded that nature is, the larger the losses that the company will suffer in case there is a shock on nature. Our methodological choice of deducing a uniform underlying shock on nature based on a fixed EU-wide macroeconomic impact allows us to spread the losses among companies (and countries) in a way that fully reflects their vulnerability to nature. This vulnerability is the driver of the losses that a company will incur in case of a shock on nature and subsequently the depletion of its equity. Through modifying the Merton model to consider a company's vulnerability to nature, we translate the calibrated shock on nature into an increase in a company's probability of default. The resulting increases in companies' probabilities of default subsequently drive banks' credit risk and insurers' market risk.

This study makes four key contributions to the literature on nature-related financial risks. First, it links all three components of the NGFS framework – nature, the economy, and the financial sector –, which are needed to translate nature shocks into financial losses. The paper calibrates a nature shock based on the macroeconomic impact of proxy nature (degradation) scenarios. This nature shock is used to estimate a microeconomic impact on companies, financial market losses, and regulatory capital depletions for financial institutions. The framework also allows us to produce sectoral scores of vulnerabilities to nature for different countries, and therefore also sectoral production losses due to a shock on nature for different countries. Second, it improves the definition of vulnerability to nature introduced in Gallet et al (2024), which is the driver of nature-related losses. The concept of vulnerability of a firm to nature degradation is necessary to arrive at a risk, i.e. financial loss, estimation. The improvement to the concept of vulnerability is done by proposing an alternative way of measuring the dependence of governments and the financial sector on nature, for which traditionally the ENCORE database has been used. As these sectors are only indirectly linked to nature, the direct dependency of these sectors on nature as found in ENCORE is very low. The newly proposed methodology for estimating their dependence on nature offers an alternative to ENCORE, which results in higher dependencies of governments and the financial sector on nature. Third, the paper introduces a novel way for incorporating a firm's vulnerability to nature in a traditional risk assessment model – the Merton model – to reflect how a loss due to a shock on nature affects companies, namely through a reduction in the equity in companies' balance sheet. Fourth, this paper expands the scope and methodology of the financial sector analysis conducted in Gallet et al (2024) to include the debt and equity holdings of insurers, pension funds, and banks.[1] Lastly, the paper makes a start in analytically expressing how joint climate and nature shocks would impact the companies' financial position and therefore also the regulatory capital impact of FIs that finance them.

The results suggest that vulnerability to nature drives substantial heterogeneity in losses among countries and financial institutions. We find that for an aggregate loss of 10% of production imposed at the EU level in line with the proxy external scenarios of nature degradation, EU countries experience widely differing production losses for the same shock on water, reflecting their very different vulnerability. For instance, production losses per country range from -6.3 % for Finland to -14.6 % for the Netherlands. At the EU level, the combined market value of debt and equity holdings as reported in SHS-S declines by approximately 5% (EUR 500 billion). For Dutch banks, common equity tier 1 (CET1) ratio depletion due to credit risk associated with loans reported in AnaCredit and debt holdings reported in SHS-S ranges from –5.4% to –14.4% when accounting for a joint impact of losses and increases in risk weighted assets (RWA) (or –0.2% to –11.3% when excluding the RWA impact). For Dutch insurers, valuation losses on debt and equity holdings – considering spread movements only and excluding the risk-free rate shift – range from -0.6% to -50.4% reduction in the solvency capital (SCR) ratio.

The remainder of the paper is structured as follows. Section 2 describes the data sources used, including how this shape our categorization of water-related variables. Section 3 introduces the three proxy scenarios of nature degradation that are used to calibrate the macroeconomic impact of nature shocks (section 3.1), presents the proposed methodology for calibrating a nature shock based on the macroeconomic impact of the proxy scenarios (section 3.2), estimates the microeconomic impact of the nature shock (section 3.3), and translates this microeconomic impact to financial market losses (section 3.4) and regulatory capital depletions of banks and insurers (section 3.5). Section 4 extends this methodology to joint climate and nature shocks and multi-dimensional nature shocks. Section 5 presents the production losses per EU country (section 0), the financial market losses per EU country – i.e. the losses of FIs' asset value of debt and equity holdings – (section 5.2), and the regulatory capital depletions of banks' credit risk-related exposures and insurers' market risk related exposures (section 5.3).

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[1] Gallet et al. (2024) considered only banks' lending to non-households as reported in AnaCredit.

2. Data

This analysis combines publicly available data on the degradation of nature and dependence on nature, sector-level accounting information, macroeconomic indicators, and regulatory disclosures, together with confidential supervisory data on banks' and insurers' securities and loan exposures. These datasets are integrated to quantify the vulnerability of economic sectors to nature at the EU level and to assess the financial and prudential implications of nature-related shocks for Dutch FIs.

2.1 Nature data

Nature-related information is sourced from the ENCORE and ND-GAIN databases, which provide information on ES dependencies and the state of nature, respectively. ENCORE version 3 quantifies the direct dependence of 86 GICS-classified production processes[2] on 21 ecosystem services, translating these into sector-level dependency scores encompassing five scales, from very low to very high.

To capture dependencies embedded in global value chains, the ENCORE direct-dependency scores are supplemented with multiregional input–output (MRIO) data. EXIOBASE 3, one such MRIO database described in Stadler et al. (2018), is used to derive indirect dependencies for sectors whose exposure to nature arises through upstream suppliers rather than direct production processes[3].

Conceptually, nature can be defined in multiple ways. In financial analysis, ecosystem services have become the dominant lens due to the widespread use of ENCORE. However, indicators describing the state of nature—such as the degree of ecosystem degradation or resilience—are typically available only at a more aggregated level[4]. This mismatch requires consistent mapping across datasets. As this study assesses financial stability impacts of water-related shocks, we reconcile ENCORE's detailed water-related ES (e.g., flow regulation, water purification, rain-pattern stabilization) with ND-GAIN's broader water vulnerability indicator, which we use to approximate the extent of degradation of water.

When there are no direct matches between the ES categories of ENCORE and the nature categories of ND-GAIN, principal component analysis (PCA) can harmonize the level of detail. PCA applied to ENCORE's sector-level dependency scores groups ecosystem services that show similar dependency patterns across sectors. These clusters can be treated as single underlying dependencies and linked to common indicators of ecosystem condition.

The analysis yields three stable clusters (Figure 1), each dominated by one service – Water Supply, Biomass Provision, and Education & Research – that can be directly aligned with indicators of nature's state or degradation. This confirms that Water Supply can serve as a representative category for all water-related ecosystem services. Therefore, in the remainder of the paper,

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[2] ENCORE maps the production processes to economic sectors using the Global Industry Classification Standard (GICS) classification. The GICS is then mapped to the NACE classification. This process is the same as that followed in the EDSI paper.

[3] Other MRIO frameworks – such as FIGARO (OECD), GLORIA (Lenzen et al., 2023) or WIOD (Timmer et al., 2015) – should similarly be employed as benchmarks.

[4] Such indices include the ND-GAIN, the WWF risk filter or the ESI (Earth System Impact) for instance.

ENCORE's Water Supply cluster is mapped to ND-GAIN's water vulnerability indicator to estimate the financial stability implications of water-related shocks.

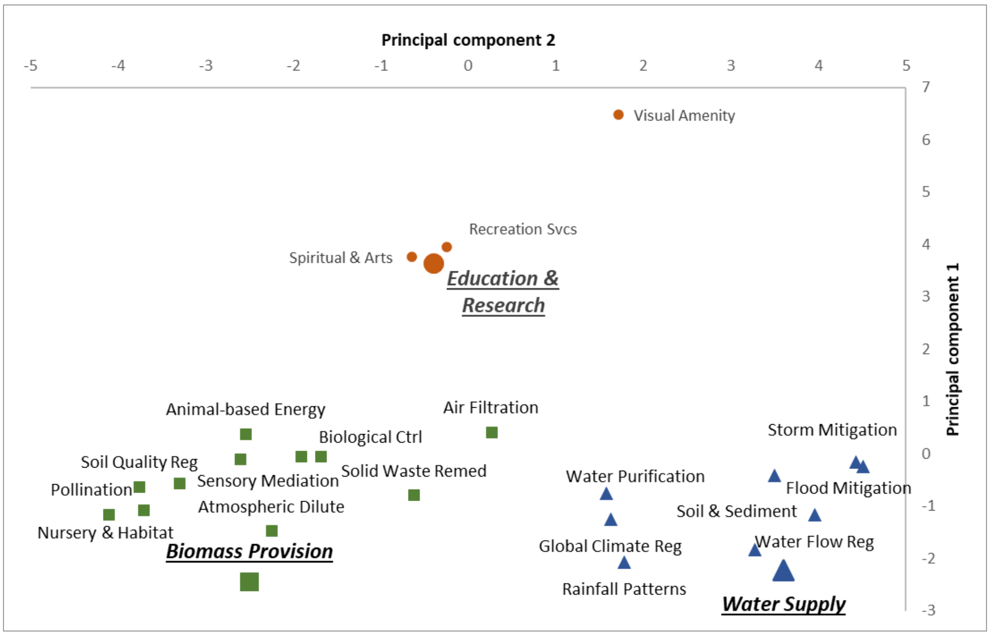

Figure 1: PCA analysis with 3-means clustering of ENCORE ecosystem services

2.2 Financial and regulatory data

This analysis relies on data from COREP reporting of Dutch banks, which is also publicly disclosed in Pillar 3 reports. It also relies on Solvency II reporting of Dutch insurers. Additional publicly available sources are used to assign sector-level financial parameters, including stock-price volatility, return on assets (ROA), and debt ratios.

Loan level data for euro area banks' exposures to NFCs, governments, and financial institutions (excluding households) is retrieved from AnaCredit. Security level data on debt and equity holdings of banks, insurers, and pension funds is retrieved from the euro area SHS-S database. These datasets enable us to quantify exposures to nature-related risks across both loan and securities portfolios.

The analysis is done at two different geographical levels. At the EU level, we estimate (i) sectoral and aggregate production losses per country and (ii) market valuation losses for each country, consisting of an aggregation of valuation losses for a country's banks', insurers', and pension funds' debt and equity holdings. At the level of the Netherlands, the analysis is extended to assess the regulatory capital impact for individual Dutch banks and insurers.

3. Methodology

3.1 Using proxy scenarios to approximate the macroeconomic impact of a shock on nature

Nature-related scenarios form the basis for stress-testing the financial sector against the economic consequences of nature shocks. In principle, these scenarios translate biophysical changes into macroeconomic outcomes. However, nature-to-economy modelling remains subject to significant methodological challenges, sector-specific complexities, and data limitations (NGFS, 2023b, Prodani et al, 2023). For this study, we therefore take the macroeconomic outputs of nature scenarios as given.

To partially address the substantial uncertainty surrounding the macroeconomic impacts of nature degradation, we build on three complementary proxy scenarios for quantifying “severe but plausible” nature-related shocks. Each scenario generates an estimate of the aggregate production loss associated with a significant deterioration of nature. This loss is subsequently allocated at the micro level and propagated through the financial system—following the steps detailed in Section 3.2 to 3.5.2—to assess the resulting implications for financial stability.

The three proxy scenarios are based off existing data on the historical variation of global production and existing literature on the economic impact of nature degradation scenarios. (see Appendix A for an in-depth description of these proxy scenarios) The first such scenario is based off the historical variation of global production and assumes that water supply depletion is the origin of projected production losses. The second such scenario is based off a tool developed by the EDHEC Climate Institute that provides insights on how climate-driven temperature changes, which are intrinsically linked to disruptions in the water cycle, affect gross regional product. The third such scenario is based off an existing methodology for assessing long-run environmental stress as outlined in the seminal report The Limits to Growth (Meadows et al., 1972).

The results of these scenarios indicate that simple modelling approaches or benchmarks can provide workable proxy scenarios for estimating productivity losses from nature degradation. It is important to note that scenario design and calibration are not the focus of this paper. Instead, the analysis concentrates on the transmission channels once an aggregate production loss is defined. In line with the results produced from these scenarios, we use a **10% aggregated production loss at the EU level as a working assumption for this analysis**. The information about this loss—whether past or future—is assumed to be incorporated instantaneously by markets and creditors at the onset of the shock. As a result, the financial shock is modelled as immediate, even though the underlying nature shock unfolds over time. In the next step, this production loss will be used to calibrate the shock on water and then allocate production losses across companies using their vulnerability to water-supply deterioration.

3.2 Calibrating the shock on nature

Although technical, this calibration step is one core methodological contribution. It serves as the interface between biophysical shocks—typically derived from exogenous models or inputs—and their transmission to the real economy, enabling a clear separation between the two. This section shows how, based on the proxy scenarios described above (see also Appendix A: The three proxy scenarios of nature degradation), nature-related shocks are calibrated and then used to estimate microeconomic impacts (Section 3.3) and financial sector impacts (Sections 3.4 and 3.5).

3.2.1 Nature-related risk

To do so, we need to define nature-related risk at a macroeconomic level. Similarly to the definition of risk in Svartzman et al. (2021), we define risk as a function of hazard, i.e. a shock on nature, exposure to nature, and vulnerability to nature (Hadji-Lazaro et al., 2024):

$$Risk = Hazard * Exposure * Vulnerability \tag{1}$$

A critical step in the analysis is determining what economic or financial variable the nature-vulnerability metric should be applied to. The choice matters: applying vulnerability to production volumes yields different outcomes than applying it to asset valuations (as done in Gallet et al 2024), probabilities of default, or measures of ecological variation such as Mean Species Abundance (as done in Boldrini et al. 2023).

Vulnerability to nature is a central concept of this paper, initially introduced in Gallet et al (2024), being the primary determinant of the economic and financial losses companies suffer. This vulnerability is a function of dependence on nature and the extent of nature degradation. Therefore, vulnerability to nature should be applied to the same quantity to which the dependence to nature is applied. By the definition of the ENCORE dependency scores, these scores are intended to represent each economic activity's potential dependencies on nature.[5] We then consider that these raw dependency scores, and similarly the vulnerability index derived from it, must be applied to production only. This leads us to define nature-related risk at the *macroeconomic* level as the variation of production (P), expressed as the product of a shock/hazard, exposure and vulnerability to nature[6]:

$$dP = \alpha * P * Vuln^{production} \tag{2}$$

With:

- dP, production variation, i.e. nature-related risk;
- α, exogenous hazard representing the shock itself;
- P, the usual production, unaffected by the hazard, i.e. the *exposure;*
- Vuln, the vulnerability of production to nature, driven by dependence on nature and the extent of nature degradation, as defined in section 3.3.

The relative production loss for a company(i) can be estimated per ES or nature category as defined in section 2.1. Rearranging equation (2) relative production loss of a specific company (i) can be expressed as follows:

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[5] https://encorenature.org/en/data-and-methodology/materiality

[6] This representation is aligned with the theoretical representation of nature-related risk -as a function of a shock/hazard on nature, exposure to nature, and sensitivity to nature - in Svartzman et al. (2021).

$$\left(\frac{dP}{P}\right)_{ES,i} = \alpha_{ES} * Vuln_{ES,i}^{production} \quad (3)$$

With $\left(\frac{dP}{P}\right)_{ES,i}$, relative production variation of company (i) due to a shock on and vulnerability to the ES. From equation *(3)* it becomes clear that to calibrate the shock on nature we need the production loss and vulnerability of production to nature. As the production loss is retrieved from the proxy scenarios outlined in section 3.1, in the rest of this section we focus on defining the vulnerability index.

3.2.2 Vulnerability to nature

Gallet et al (2024) introduced the concept of Vulnerability to nature as a means of moving from "exposure analyses", based solely on dependence on nature, to "risk analyses" that could provide an estimate of financial losses and regulatory capital depletion. Vulnerability was there, and is here as well, defined as a function of dependency on nature and the extent of nature degradation. In this way, the vulnerability of a company on nature is a result of the extent to which operations depend on nature but also the extent to which nature is well-functioning or degraded. As an example, if we consider the shock of global water quality deterioration, for a company the risk is higher the more dependent it is on this water quality and on the extent to which the water quality is already degraded along the production chain.

Dependency refers here to the dependency score of an economic sector on nature. This dependency includes direct and indirect dependencies. Direct dependencies represent the direct dependence of a sector on nature, based only on the registered activity of the company's headquarters. This approach captures the full dependence of an upstream sector on nature—such as a farm relying on pollination—but it overlooks much of the supply chain for downstream companies, like a car retailer that depends on multiple upstream sectors. The direct dependencies for all sectors except government and financial sector are retrieved from the ENCORE database. For the dependency scores of the government and financial sectors we doubted the realism of the scores defined in ENCORE and therefore propose an alternative methodology in Appendix B. For more information on how the vulnerability index and its two components, namely the dependency index and nature degradation index, are built, please refer to Gallet et al. section 3.2.2 (2024).

The key question is how to estimate a company's overall vulnerability to nature, combining its direct exposure to nature – linked to its primary activity in its home country – and its indirect exposure through the supply chain. Garel et al. (2025) compute a weighted dependency score for 26,595 listed firms based on sectoral revenue data from the private database Refinitiv. To preserve simplicity and bypass data availability issues, our approach weighs direct and indirect vulnerabilities by the share of each firm's production that is subject to the relevant type of exposure. This yields an upstream production ratio that reflects, at a macroeconomic level, the proportion of inputs sourced from other sectors and countries (equation 4). Throughout the remainder of the report, company (i) will often be represented by an approximation of their sector and country (s, c). The notation (i) therefore refers to (s_i, c_i) which denotes the simplified sector–country pair to which it belongs. This simplification is applied to streamline the presentation of equations and to adapt with the structure of the underlying databases.

To compute this share of direct and indirect production, we rely on the EXIOBASE input–output tables.

$$UpR_i = \frac{\sum_{(s_j,c_j)\neq(s_i,c_i)}^{all\ sector/cntry} Z_{(s_i,c_i),(s_j,c_j)}}{X_{s_i,c_i}} := \frac{\sum_{j\neq i}^{all\ sector/cntry} Z_{i,j}}{X_i} \tag{4}$$

with

- UpR_i , upstream production Ratio of the company (i) proxied at (s_i, c_i) level;
- $Z_{i,j}$, intermediate inputs from sector/country j used by sector/country i (upstream for i, downstream for j);
- X_i , total output of sector/country i; and
- $j\neq i$ ensure that we exclude cases where emitter and receiver of the economic flow are the same, meaning that the subcontractor is within the same country/sector and is therefore facing the same direct dependency.

Using the above definition, we estimate the total vulnerability of production of a company (as approximated by its country and sector pair) to a particular ES shock:

$$Vuln_{ES,i}^{Production} = UpR_i * Vuln_{ES,i}^{indirect\ production} + (1 - UpR_i) * Vuln_{ES,i}^{direct\ production} \tag{5}$$

With:

- $Vuln_{ES,i}^{indirect\ production}$, the indirect vulnerability of company i's production to ecosystem ES;
- $Vuln_{ES,i}^{direct\ production}$, the direct vulnerability of company i's production to ecosystem ES.

This study adopts the maximum granularity of GICS used in EXIOBASE. In practice, this means that the NACE level 4 taxonomy is used, except in cases when EXIOBASE has less sectoral granularity and shifts to NACE level 3 or 2.

The vulnerability term $\mathrm{Vuln}_{ES,i}^{\mathrm{production}}$can also be defined as $\mathrm{Vuln}_{ES,i}^{\mathrm{ENCORE}}$, as the raw ENCORE dependency scores are applied to production.

Having defined the vulnerability of production to nature, we can derive the aggregate shock across all companies that must be consistent with the production shock imposed by the scenario. The scenario-consistent production loss for the EU area is then given by:

$$\left(\frac{dP}{P}\right)_{ES,EU\,area} = \frac{\sum_{i\in EU} \alpha_{ES} * Vuln_{ES,i}^{prod.} * X_i}{\sum_{i\in EU} X_i} \tag{6}$$

Inverting this expression yields the shock α_{ES}, which is common to all sectors in the calibration area:

$$\alpha_{ES} = \left(\frac{dP}{P}\right)_{ES,EU\,area} * \frac{\sum_{i\in EU} X_i}{\sum_{i\in EU} Vuln_{ES,i}^{prod.} * X_i} \tag{7}$$

That is, the shock α_{ES} can be expressed as the ratio between the total production loss in the area $\left(\frac{dP}{P}\right)_{ES,\text{area}}$ (here a 10% decline in the EU area according to the proxy scenarios of Section 3.1) and the weighted average vulnerability of companies (i). Note that the vulnerability of production is used to calibrate the shock based on a scenario of declining production. Therefore, $\frac{dP}{P}$ and α_{ES} are negative numbers.

This shock on nature – calibrated from the macroeconomic scenarios of section 3.1 - will be the input for estimating the microeconomic, i.e. company-specific, impact of section 3.3, which will then feed into the financial market impact section 3.4 and regulatory capital ratio impact section 3.5.

3.3 The microeconomic impact of a shock on nature

This section presents the second core technical contribution, which builds on a Merton-type framework to link firms' production vulnerability to the previously calibrated nature-related shock and its implications for distance to default. While this formalism was introduced in Gallet et al. (2024), the present approach refines the transmission from production losses to changes in firms' asset and equity values, enabling a more consistent assessment of microeconomic impacts on default probabilities.

In Merton R.C. (1974), the one-year Distance To Default (DTD) is defined as:

$$DTD_i = \frac{ln\left(\frac{A_0}{D_0}\right)+\left(\mu-\frac{\sigma^2}{2}\right)}{\sigma} \tag{8}$$

with

- DTD_i, distance to default before the shock, i.e. at t=0 of company (i), for a debt of maturity T=1 year;
- A_0, company's asset value before the shock;
- D_0, company's debt value before the shock;
- μ, the instantaneous expected rate of return on the company per unit of time;
- σ_A, asset volatility, considered as constant; and

Gallet et al (2024) shows how, through several derivations, the distance to default of company i (DTD_{i}) decreases due to a shock on nature in a way that is proportional to the company's vulnerability to nature[7]:

$$DTD_i^{Loss \propto_{ES}} = DTD_i - \frac{\propto_{ES} * Vuln_{ES,i}^{Assets}}{\sigma_i} \tag{9}$$

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[7] For the derivation of equation 9, please refer to the derivation of equation 6 used in Gallet et al (2024).

with

- $DTD_i^{Loss \propto_{ES}}$, the DTD diminished by aa shock on a specific ES;
- α_{ES} : the shock on an ES (in our case water supply), derived in section 3.2 based on the proxy scenarios of nature degradation;
- σ_i : volatility of asset value (see Appendix E: Quantitative finance tools for how this is defined from the volatility of equity)[8]; and
- $Vuln_{ES,i}^{Assets}$ or $Vuln_{ES,s_i,c_i}^{Assets}$, the vulnerability of a company (i)'s assets value to a shock in a specific ecosystem service (ES), later defined at granularity sector (s_i) and country (c_i).

The company-level nature-related vulnerability used in this section differs from the **vulnerability of production** defined earlier in Section 3.2.2, due to the fact the Merton model is based on asset value. In analogy with the macroeconomic formulation (equation 3), we define microeconomic nature-related risk as follows.

$$\frac{dA}{A}_{ES,i} = \alpha_{ES} * Vuln_{ES,i}^{Assets} \qquad (10)$$

To compute the updated distance-to-default as defined in equation 9, we must now express the vulnerability of a company to a shock on nature, denoted $\mathrm{Vuln}_{ES,i}^{\mathrm{Assets}}$, in terms of the vulnerability of production $\mathrm{Vuln}_{ES,i}^{\mathrm{production}}$ (equation 3 and 5). As a starting point, we assume that the microeconomic analogue of macro-level production (P) is the company's revenue. Using the return-on-revenue ratio (RoR), return at company level can therefore be written as:

$$Return_i = RoR_i * P_i \qquad (11)$$

Assuming that RoR remains constant during the shock, the variation in return is:

$$dReturn_i = RoR_i * dP_i \qquad (12)$$

If market participants expect this reduction in return to persist, the reduction directly affects the company's valuation. This can be thought of as a negative future dividend. Using a discounted-cash-flow (DCF) approach and assuming debt remains constant, the change in equity value can be expressed as below.

$$dE_i = \sum_{t=1}^{\infty} \frac{RoR_i * dP_i}{(1+r)^t} = RoR_i * dP_i * \frac{1+r}{r} \qquad (13)$$

With:

- dE_i, the change in equity value (EUR);
- RoR_i, the return on revenue (assumed constant);

---

[8] While in this paper we use only sectoral proxies, an entity-level quantification or at least a quantification at the country-sector pair would be preferable.

- dP_i, the variation in production (and thus revenue).

The discount rate $r$can be interpreted as the company's long-term cost of equity (CoE), which in equilibrium approximates its long-run return on equity (RoE). In a mature, competitive market, RoE converges to CoE: if RoE exceeds CoE, new entrants erode excess returns; if RoE falls below CoE, companies exit the market. CoE is therefore a more stable long-term parameter than short-term RoE and will be used as the discounting rate for this valuation.

Assuming no change in debt during the year, the variation of asset value is equal to the variation of equity value for company i. In this way, we can express the variation of asset value as in the below equation.

$$dA_i = RoR_i * dP_i * \frac{1+CoE_i}{CoE_i} \qquad (14)$$

At the same time, the Return On Revenue, RoR_i can be re-written as:

$$RoR_i = \frac{Return}{Production} = \frac{RoA_i * A_i}{P_i} \qquad (15)$$

From the above we get the below expression, which shows that the ratio between the relative variation of production due to an ES shock and relative variation of asset value due to the same shock is $\left(RoA_i * \frac{1+CoE_i}{CoE_i}\right)$.

$$\frac{dA_i}{A_i} = \frac{dP_i}{P_i} * RoA_i * \frac{1+CoE_i}{CoE_i} \qquad (16)$$

Combining equation *(3)*, *(9) and (16)*, we can express the vulnerability of assets for a company as below (equation 17). Given the lack of company specific supply chain data, we approximate the vulnerability of assets to an ES by the dimensions of s (sector) and c (country). The vulnerability of assets now considers the return and cost structure of each company, as approximated by averaged sectoral values[9].

$$Vuln_{ES,i}^{Assets} = RoA_i * \frac{1+CoE_i}{CoE_i} * Vuln_{ES,i}^{Production} \qquad (17)$$[10]

Lastly, computing $\Delta DTD_i = -\frac{\propto_{ES} * Vuln_{ES,i}^{Assets}}{\sigma_i}$ together with the previous probability of default of the company gives us the increase (ΔPD_i)[11].

---

[9] The sectoral breakdown (s) used is that of NACE sector lvl2 for data granularity constrain.

[10] Vulnerability of assets value was not applied in Gallet et al. (2024), where the vulnerability of production was used as a proxy for asset vulnerability (see Appendix F: Modification of the EDSI Formulation).

[11] $PD_i^0 = \Phi(-DTD_i^0)$ and then $\Delta PD_i = \Phi(\Phi^{-1}(PD_i^0) + \Delta DTD_i) - PD_i^0$, with Φ the standard normal cumulative distribution function (CDF).

Figure 2 summarizes the framework used to estimate changes in a company's probability of default, i.e. ΔPD_i. Building on this analytical foundation, we then examine the resulting financial and prudential implications, using PDs and their variations as the key driver across quantitative financial and prudential impact in sections 3.4 and 3.5.

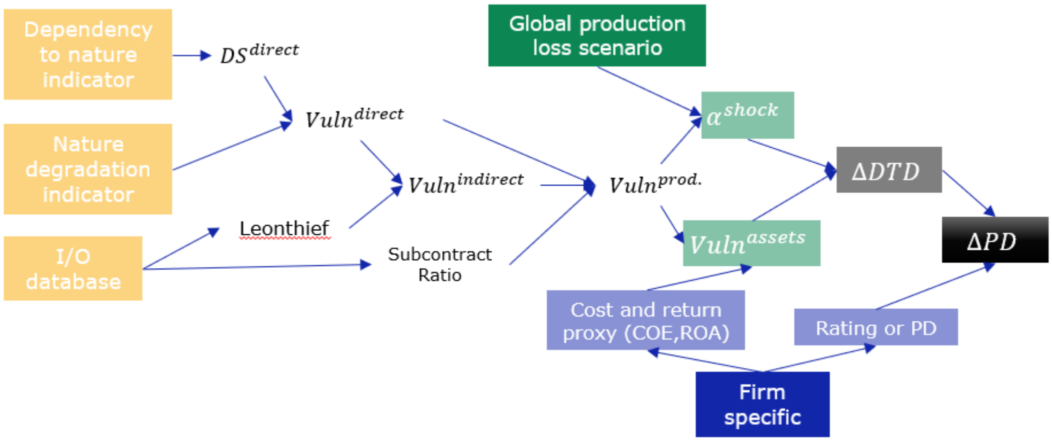

Figure 2: Building blocks to reach PD variation

3.4 The financial market impact of a shock on nature

In this section we estimate the impact of a shock on nature on financial markets, specifically on the market value of the debt and equity holdings of financial institutions (FIs). For this, we use the new DTD (PD) due to the ES shock that is calibrated based on proxy macroeconomic scenarios and the vulnerability of the companies' assets to that ES shock. This new PD drives the loss in the value of FIs' debt and equity holdings.

3.4.1 Bond price variation

In this section we estimate how much the market value of a bond falls when the issuing entity's probability of default increases due to a shock on nature and the entity's vulnerability to it. To start, we define the price of a risky bond emitted by company (i) (B_i^{risk}) with a coupon and recovery rate as follows (Schurman, 2020; Wang, 2025; Duffie and Singleton 2003).

$$B_i^{risk} = 1 + (c^* - r - PD.LGD) * \frac{1-e^{-(r+PD).T}}{r+PD} \tag{18}$$

with

- B_i^{risk}, price of a risky, meaning defaultable, bond;
- c^* , the coupon in % of the nominal value;
- r , discounting rate assumed constant to reflect a simplified scenario with no impact on the risk-free rate curve, allowing us to isolate the effect of PD variations. In a more

realistic stress-test setting, shifts in the RFR curve could be incorporated straightforwardly;

- PD , the 1 year risk neutral probability of default[12] considered constant over the bond maturity T for simplicity;
- LGD, the Loss Given Default is the share of the nominal exposure lost upon default, estimated as a function of changes in PD, following the model proposed by Frye and Jacobs (2012) (see Gallet et al. (2024) Appendix 7.2);
- T , the bond maturity.

The general variation of the bond price in percentage can then be simply calculated based on ΔPD_i , derived from ΔDTD_i variation.

3.4.2 Equity price variation

In this section we estimate how much the market value of equity falls when the issuing entity's probability of default increases due to a shock on nature and the entity's vulnerability to it. Using the Black–Scholes expression of equity expectancy price as a call option, the value at time $t = 0$ and for 1 year in line with the supervisory convention of using a one-year probability of default:

$$E_i^0 = A_i^0\, N(DTD_i^0) - D_i\, e^{-r}\, N(DTD_i^0 - \sigma_i) \tag{19}$$

With:

- E_i^0, the company's equity value at $t = 0$;
- A_i^0 , the company's asset value at $t = 0$;
- D_i , the company's face value of debt (assumed fixed over one year).

We denote the post-shock equity value as E_i^{Loss}. Equation (9) links the pre-shock and post-shock asset values, $A_i^0$and A_i^{Loss}respectively. Using the logarithmic identity $d\ln(x) = dx/x$, we obtain the following.

$$A_i^{Loss} = A_i^0\, e^{Vuln_{ES,i}^{Assets} * \alpha_{ES}} = A_i^0\, e^{CLS_i} \tag{20}$$

With CLS_i, the Company-Level Shock, taking into account the cost and return structure of the company as represented by a sector-country pair. Note that CLS_i is negative due to α_{ES}. CLS_i can then be derived from the above equation and equation (16).

$$CLS_i = RoA_i * \frac{1+CoE_i}{CoE_i} * Vuln_{ES,i}^{Production} * \alpha_{ES} \tag{21}$$

Then

$$E_i^{Loss} = A_i^0 e^{CLS_i}\, N\left(DTD_i^{Loss}\right) - D_i e^{-r} N\left(DTD_i^{Loss} - \sigma_i\right) \tag{22}$$

---

[12] Risk-neutral PDs can be derived from historical PDs, e.g. from ratings-based PD tables. Refer to Appendix E: Quantitative finance tools for more details.

The term e^{FLS_i} represents the one-year depletion of asset value and can be used as an indicator to compare the magnitude of the shock as perceived by company (i). Since the parameter $\propto_{ES}$ is identical for all companies in the comparison set, it does not influence the relative assessment.

At that point, we do not have information on the assets (A) and debt (D) of companies but through equation (8) we can link the ratio of asset-to-debt with the distance-to-default before and after the shock.

$$\frac{A_i^0}{D_i} = e^{\sigma_i * DTD_i^0 - \left(r - \frac{\sigma^2}{2}\right)} \text{ and } \frac{A_i * e^{-FLS_i}}{D_i} = e^{\sigma_i * DTD_i^{Loss} - \left(r - \frac{\sigma^2}{2}\right)} \tag{23}$$

Combining (19) (22) and (23), the relative variation of equity price is given through the equation below, in which the unknown assets and debt terms cancels out.

$$\frac{\Delta E_i}{E_i} = \frac{e^{\sigma_i * DTD_i^{Loss} - \left(r - \frac{\sigma_i^2}{2}\right)} * N\left(DTD_i^{Loss}\right) - e^{-r} * N\left(DTD_i^{Loss} - \sigma_i\right)}{e^{\sigma_i * DTD_i^0 - \left(r - \frac{\sigma_i^2}{2}\right)} * N\left(DTD_i^0\right) - e^{-r} * N\left(DTD_i^0 - \sigma_i\right)} - 1 \tag{24}$$

As for bond price variations, r—the firm’s expected risk-neutral return—is assumed to be fixed, but it could in principle be included as a scenario parameter.

Since the probability of default (PD) is directly linked to the distance-to-default, it can be derived from rating-based correspondence tables. Once a rating or PD is mapped into a risk-neutral PD, the corresponding change in the equity price becomes fully computable. The only additional input needed is the asset-return volatility σ_i, obtained by converting the observed stock-price volatility into its asset-value equivalent (see Appendix E: Quantitative finance tools).

3.5 The regulatory capital ratio impact of a shock on nature

In this section we estimate the impact of a shock on nature on the prudential capital ratios of Dutch banks and insurers.

3.5.1 Banks’ CET1 impact due to credit risk

We estimate the impact on banks’ Common Equity Tier 1 (CET1) ratios using the regulatory formulas outlined in the Capital Requirements Regulation (CRR)[13] for credit-risk RWAs and expected losses (EL). For simplicity, we assume all bond holdings sit in the banking book and therefore generate credit-risk capital charges only. While this is largely the case for most banks, some bonds may in practice be held in the trading book.

The depletion in the CET1 ratio arises through two channels: higher losses that directly reduce CET1 capital and higher risk-weighted assets (RWAs). The higher PDs that result from a shock on nature are the driver of both the losses and the RWAs. For the estimation of risk-weighted assets, we use the same exposure, change in PD and change in LGD as in the EL estimation. While this is

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[13] See https://eur-lex.europa.eu/eli/reg/2013/575/oj/eng and the latest amendments introduced in https://eur-lex.europa.eu/eli/reg/2024/1623/oj/eng.

not customary, it follows the reasoning that the impacts of nature degradation could be long-term. For more details, please refer to Gallet et al (2024) section 3.3.

The CET1-ratio impact can be expressed as follows.

$$\Delta CET1_{ratio} = \frac{CET1 - \Delta EL}{RWA + \Delta RWA} - CET1_{ratio} \tag{25}$$

With:

- ΔEL, the change in expected loss amounts, which if larger directly reduce CET1 capital;
- ΔRWA, the increase in RWA resulting from the deterioration in credit quality (primarily through higher PDs entering the internal ratings based (IRB) formulas).
- CET1 ratio, the bank's initial CET1 ratio prior to the shock.

CRR prescribes different regulatory formulas for estimating the RWA of different exposure classes. The exposures in scope of our analysis are loans to and bond holdings of governments, FIs, central banks, and corporates[14]. We therefore use the risk weight (RW) formula of Article 153 CRR. We exclude equity holdings from the analysis given their negligible magnitude in Dutch banks' balance sheets, as retrieved from SHS. Loans to households are also excluded from the analysis due to data limitations.

The RWA for these exposure classes is estimated using the formula below.

$$RWA = 12.5 * EV * LGD * f(\text{PD}, M) \tag{26}$$

With:

- EV, Exposure value
- LGD, loss given default
- PD, probability of default

The function $f(\text{PD}, M)$captures the capital requirement per unit of exposure, adjusted for maturity effective maturity M (in years):

$$f(PD, M) = \left[N\left(\frac{1}{\sqrt{1-R}} N^{-1}(PD) + \sqrt{\frac{R}{1-R}} N^{-1}(0{,}999) \right) - PD \right] * \frac{1 + (M - 2{,}5)b}{1 - 1{,}5b} \tag{27}$$

With:

- $N(\cdot)$, cumulative standard normal distribution
- $N^{-1}(\cdot)$, inverse of the cumulative standard normal distribution

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[14] We make the simplifying assumption that corporate exposures belong to Article 153 CRR and not to the NFC category that falls under the retail exposure class.

- R, asset correlation (a function of PD)
- b, maturity-adjustment coefficient
- Parameters b and R, defined as:

$$\begin{cases} b = \left(0{,}11852 - 0{,}05478 * ln(PD)\right)^2 \\ R = 0{,}24 * \left(1 - \dfrac{1 - e^{-50*PD}}{1 - e^{-50}}\right) + 0{,}12 * \dfrac{1 - e^{-50.PD}}{1 - e^{-50}} \end{cases}$$

The variation of RWA is simply the difference in RWA before and after the shock. Expected loss amounts are estimate in line with Article 158 CRR formulas below.

$$EL = PD * LGD * EV \tag{28}$$

Changes in expected losses before and after the shock are captured by re-estimating this formula with updated PDs and – where relevant – adjusted LGDs based on a model linking PD and LGD (Frye and Jacobs, 2012).

Credit protection and guarantees are not considered in the modelling. In addition, PD estimates are subject to the regulatory floor of 0.03% in line with Article 160 CRR. Maturity adjustments are made in line with Article 162 CRR.

3.5.2 Insurers' SCR impact due to market risk

For insurers, the Solvency Capital Requirement (SCR) is a prudential requirement stipulated in the Solvency II Directive[15]. Similarly to the bank analysis, changes in SCR can be approximated by revaluing asset portfolios following PD-driven adjustments in market prices, as previously described. For simplicity, the assessment focuses solely on the asset side, given the scarcity and limited granularity of supervisory data on insurers' liabilities. Nonetheless, it remains possible to approximate the liability impact through the loss-absorption capacity of technical provisions, following the approach outlined in Sydow et al. (2024), which provides a pragmatic way to capture how liabilities partially offset asset-side losses under shock scenarios. According to this paper, we can define asset price variation per insurer as

$$\Delta A_{ins\ j} = \sum_k^{bonds\ of\ j} \Delta B_{j,k} + \sum_l^{equities\ of\ j} \Delta E_{j,l} \tag{29}$$

With:

- $\Delta A_{ins\ j}$, the variation of asset market value of the insurance (j);
- $\Delta B_{\ j,k}$, the total variation of market value of all bonds owned by insurance (j) based line by line (k) on PD variation (see Section 3.4.1); and
- $\Delta E_{j,l}$, the total variation of market value of all equity shares owned by insurance (j) based line by line (l) on PD variation (see Section 3.4.2).

Using this framework, we can express the variation of SCR ratio as follows.

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[15] Solvency II is established in Directive 2009/138/EC, as amended by Directive 2014/51/EU (Omnibus II), and supplemented by Commission Delegated Regulation (EU) 2015/35 and subsequent amendments.

$$\Delta SCR_{ratio} = \frac{EOF - \Delta EOF}{SCR + \Delta SCR} - SCR_{ratio} \tag{30}$$

With:

- EOF, Eligible Own Funds as defined under the Solvency II regulation.
- ΔEOF, the share of the lost attributed to shareholders.
- $\Delta SCR = 0$ according to the fact that at first order, the SCR is recalculated annually based on regulatory requirements, and short-term changes in asset quality do not modify the SCR value itself.

Defining now ΔL , the variation of liability including loss absorption capacity, Sydow et al. (2024) introduce the following expression as a proxy for changes in the SCR ratio:

$$\begin{cases} \Delta SCR_{ratio} = \dfrac{-\Delta EOF}{SCR} = \dfrac{-\Delta A + \Delta L}{SCR} = \dfrac{-\Delta A + (1-\theta) * \Delta A}{SCR} \\ \theta = \dfrac{SCR_{Market}^{Net}}{\Delta A_{Market}^{s2}} \end{cases}$$

Lastly, the variation in the SCR ratio can be estimated by linking changes in the market value of assets with prudential data reported under the Solvency II framework. ΔA comes from the previous estimation of the impact of PD variation and other parameters $SCR_{Market}^{S2,Net}$, SCR and , ΔA_{Market}^{s2} come from Solvency 2 reporting templates[16].

The proposed framework allows us to generate a plausible proxy for changes in key risk parameters under a simple nature shock scenario. In the next section, we extend the approach to more complex scenarios, including multiple ES disruptions alongside potential climate or transition-related shocks.

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[16] $SCR_{Market}^{S2,Net}$ reporting code S25.01.01.01 C0030R0010 and SCR reporting code S25.01.01.01 C0030R0100,
ΔA_{Market}^{s2} decomposed in $\Delta A_{type\ 1}^{s2} + \Delta A_{type\ 2}^{s2} + \Delta A_{bonds\&loans}^{s2}$ reporting codes S26.01.01.01 columns (C0040-C0020) for rows (R0210+R0250+R0410)

4. Extension of the methodology to joint climate and nature risks

The methodology outlined in section 3 considers shocks individually, i.e. a shock in a single ES. Herein, we extend the framework to a scenario where multiple ES depletions occur simultaneously, sometimes in combination with climate physical risks and transition risks.

4.1 Multi-shock definition and consequences

In the case of multiple shocks, we can express the general relative variation in production for a specific sector- country pair (i) as the weighted sum of these shocks (m) and their associated sector-country vulnerabilities.

$$\left(\frac{dP}{P}\right)_i = \sum\nolimits_m^{multi-shocks} Vuln_{m,i}^{prod} * \alpha_m \tag{31}$$

Where “multi-shocks” is the list of type of shocks. However, as shown earlier, this relationship can likewise be expressed in terms of asset-value variations using the asset’s vulnerability. To define a multi-shock, we consider four building blocks of risk sources. The first block represents ES-related physical-risk shocks. The second block represents transition shocks. Here we focus on ES-related transition shocks, which would target companies exerting high pressure on nature, but the same would hold for climate-related transition shocks. For ES-related transition shocks, the methodology would be the same as for the physical ES-related transition shocks, but the ENCORE *impact* score would be used instead of the ENCORE dependency scores. The third block captures climate-related physical shocks and includes natural hazards linked to global warming that are not covered by the ES definition. The fourth block represents cross-amplification among shocks, which reflects the non-linearity of real systems and is capture by the term X_{ampli}. X_{ampli} is general here and capture inter ecosystem dynamics and feedback loops.

The impact of a combination of the above shocks at company asset-value level would analytically be expressed in this framework such as:

$$\left(\frac{dA}{A}\right)_i = \sum_p^{ES} Vuln_{p,i}^{Asset,Depend} * \alpha_p + \sum_t^{Laws} Vuln_{t,i}^{Asset,Impact} * \alpha_t + \sum_n^{Climat} Vuln_{n,i}^{Asset,Depend} * \alpha_n + Xampli$$

In a non-linear framework, there is no principled basis for allocating $Xampli$ exclusively to any single shock dimension. For simplicity, we therefore assume that $Xampli$ is generated proportionally by the underlying and standalone shocks. Under this assumption, the expression can be reformulated by introducing δ, an additive shock component that reflects the contribution of $Xampli$.

$$\left(\frac{dA}{A}\right)_i = (1+\delta) * \left(\sum_p^{ES} Vuln_{p,i}^{Asset,Depend} * \alpha_p + \sum_t^{Laws} Vuln_{t,i}^{Asset,Impact} * \alpha_t + \sum_n^{Climat} Vuln_{n,i}^{Asset,Depend} * \alpha_n\right)$$

We then define an overall shock parameter coming from the multi-dimensional nature-climate scenario as follows:

$$\alpha_{multi} = (1+\delta) * \left(\sum_{p}^{ES} \alpha_p + \sum_{t}^{Laws} \alpha_t + \sum_{n}^{Climat} \alpha_n \right)$$

With:

- α_{multi} , the overall shock parameter coming from the multi-dimensional exogenous scenario that includes climate, nature-related physical risks, transition risks and cross-amplification;
- δ, the cross-amplification term expressed as a percentage of the sum of all sub shocks and
- $\alpha_x, x \in \{p, t, n\}$, individual shock calibrated by running several versions of the global scenario, each time isolating one category (i.e., deactivating the others) giving each time a $shock$ per sub-category (x).

We can now define the asset-value variation of a multi-dimensional nature-climate nature scenario for a company as follows.

$$\left(\frac{dA}{A}\right)_{multi\ ,i} = \alpha_{multi} * Vuln_i^{multi\ scenario} \tag{32}$$

With:

$$Vuln_i^{multi\ scenario} = \frac{(1+\delta)}{\alpha_{multi}} * \left(\sum_{p}^{ES} Vuln_{p,i}^{Asset,Depend} . \alpha_p + \sum_{t}^{Laws} Vuln_{t,i}^{Asset,Impact} . \alpha_t + \sum_{n}^{Climat} Vuln_{n,i}^{Asset,Depend} . \alpha_n \right)$$

Values of company-specific vulnerability of assets and α_x for a x-dimensional shock can then be used to infer changes in probabilities of default (PDs), enabling an assessment of the financial and prudential implications of multi-dimensional nature–climate scenarios.

4.2 Applying the framework to a combined climate and water scenario

As a use case of the previous general description of a multi-shock, we consider a framework comprising three distinct shocks:

- An ecosystem-based water-supply shock, derived from an exogenous model, which on its own results in an aggregated production loss of 3% at world level.
- A climate-condition shock, also sourced from an exogenous model, associated with an aggregated production loss of 5% at world level too.
- In addition, we employ a model—either the same as above or an alternative one—capable of evaluating the combined effect of both shocks simultaneously. In this illustrative example, the joint scenario results in an aggregate production loss of 10%.

The first step is to calibrate both unique shocks according to scenarios:

- A 3% production loss from water supply degradation alone:

$$\alpha_{Water} = \frac{3\%}{Vuln^{Prod.}_{Water,world}} = 3\% * \frac{\sum\sum X_{s,c}}{\sum\sum Vuln^{Prod.}_{Water,s,c} * X_{s,c}}$$

  With $X_{s,c}$, production of sector (s) and country (c) from input/output table and then $\sum\sum X_{s,c}$ being the total production across sectors and countries in the considered area, here the world.

- A 5% production loss if the scenario on climate physical risk is run alone :

$$\alpha_{Climat} = \frac{5\%}{Vuln^{Prod.}_{Climat,world}} = 5\% * \frac{\sum\sum X_{s,c}}{\sum\sum Vuln^{Prod.}_{Climat,s,c} * X_{s,c}}$$

- Using the global shock and its associated production loss estimated at the world level, we can then express the resulting macroeconomic impact as below:

$$\left(\frac{dP}{P}\right)_{World} = (1+\delta) * Vuln^{Prod.}_{Water,world} * \alpha_{Water} + (1+\delta) * Vuln^{Prod.}_{Climat,world} * \alpha_{Climat}$$

  meaning the 10% production loss for combined effects, implying cross amplification of $\delta = 25\%$ $(10\% = (1+\delta) * 3\% + (1+\delta) * 5\%)$

Each company, represented at the sector–country level (s,c), is thus subject to a variation of Distance To Default (see equation$DTDiLoss \propto ES$⍰ $= DTD_i - \frac{\propto_{ES} * Vuln^{Assets}_{ES,i}}{\sigma_i}$ (9):

$$DTD_{s,c} = DTD^{before\ shock}_{s,c} - \frac{Vuln^{asset}_{global,s,c} * \alpha_{global}}{\sigma_{s,c}}$$

With:

$$\begin{cases} Vuln^{asset}_{global,s,c} = \dfrac{\dfrac{3\%}{\sum\sum Vuln^{Prod.}_{Water,s,c} * X_{s,c}} * Vuln^{asset}_{Water,s,c} + \dfrac{5\%}{\sum\sum Vuln^{Prod.}_{Climat,s,c} * X_{s,c}} * Vuln^{asset}_{Climat,s,c}}{\dfrac{3\%}{\sum\sum Vuln^{Prod.}_{Water,s,c} * X_{s,c}} + \dfrac{5\%}{\sum\sum Vuln^{Prod.}_{Climat,s,c} * X_{s,c}}} \\ \alpha_{global} = \mathbf{1,25} * \sum\sum X_{s,c} * \left(\dfrac{3\%}{\sum\sum Vuln^{Prod.}_{Water,s,c} * X_{s,c}} + \dfrac{5\%}{\sum\sum Vuln^{Prod.}_{Climat,s,c} * X_{s,c}}\right) \end{cases}$$

The estimated impact on company-level distance to default declines would then translate into changes in default probabilities through the Merton framework. These higher default risks would then trigger a repricing of outstanding bonds and equities and would also erode the prudential ratios of banks and insurers that hold these instruments or provide credit to the affected companies.

5. Results

This section presents the impact of a shock on water supply – as defined in section 3.1 and calibrated based on a 10% EU-level production loss – on (i) sectoral production at EU level (section 5.1), (ii) the market value of bond and equity holdings of EU financial institutions (section 5.2), and (iii) prudential capital ratios of Dutch banks and insurers (section 5.3). It is important to recall that, in the absence of a fully developed nature-related (water) degradation scenario, the shock is assumed to be identical across EU countries, with only vulnerability and exposure differing.

5.1 Production losses at EU country level

The first step of the methodology consists in allocating the aggregate production losses from the EU scenario to country–sector pairs. The scenario imposes a 10% reduction in total EU supply production, including upstream supply-chain effects. Production is measured using EXIOBASE gross output data, amounting to €173.3 trillion in the world (€23.3 trillion in the EU), of which the Netherlands accounts for approximately 0.9%. Figure 3 presents the resulting losses, expressed as a percentage of baseline production, across major EU countries and sectors. The allocation of losses is driven by sectoral vulnerability to “water supply” as defined in section 3.1. This vulnerability reflects dependence on water supply, supply-chain structures, and the fragility of water supply. For example, the Dutch Agriculture, Forestry and Fishing sector experiences a 20.0% reduction – the largest across all sector-country combinations – indicating a high level of production at risk due to a shock in water supply.

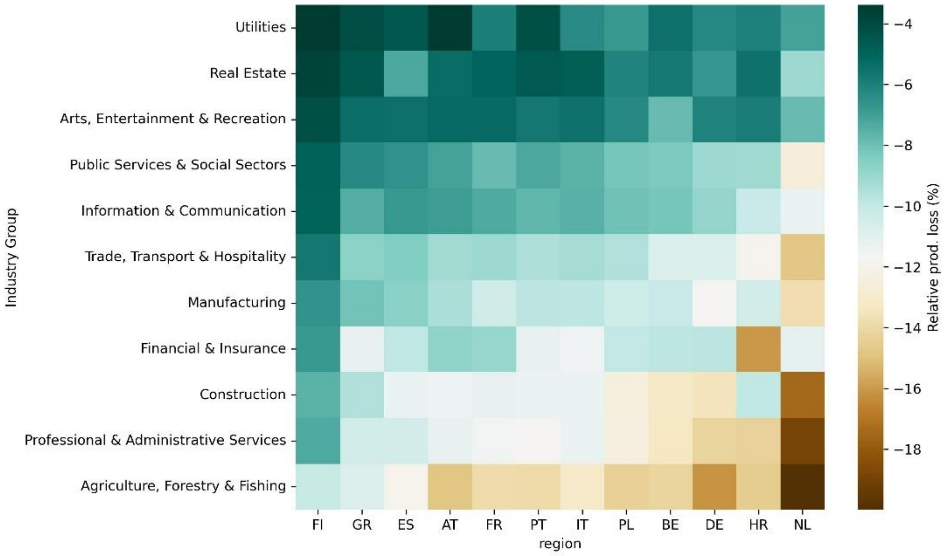

Figure 3 : Relative production losses by sectors and countries

While the largest absolute losses naturally occur in countries with the highest levels of production – such as Germany, with €747 billion (11.2% of its total output), and France, with €427 billion (9.3%) – the Netherlands stands out with a substantially higher relative loss of 14.6% of its gross production. The position of the Netherlands primarily reflects its higher vulnerability to water compared to other countries, as captured by the ND-GAIN water indicator. A large share of the impact is driven by domestic exposure, especially in upstream sectors. The choice of indicator therefore matters and must be checked to ensure that it captures well the phenomenon being quantified. In this case study, the selected indicator was chosen due to its global geographical coverage. Other more granular indicators of nature degradation could be better suited depending on the scope of the analysis.

5.2 Financial market losses at EU country level

This section presents the results obtained following the methodology of section 3.4 to estimate market value losses of EU FIs' bond and equity holdings due to a shock on water supply. EU banks experience higher market value losses of their debt and equity holdings compared to insurers and pension funds, reflecting their higher investments in these securities. (Figure 4)

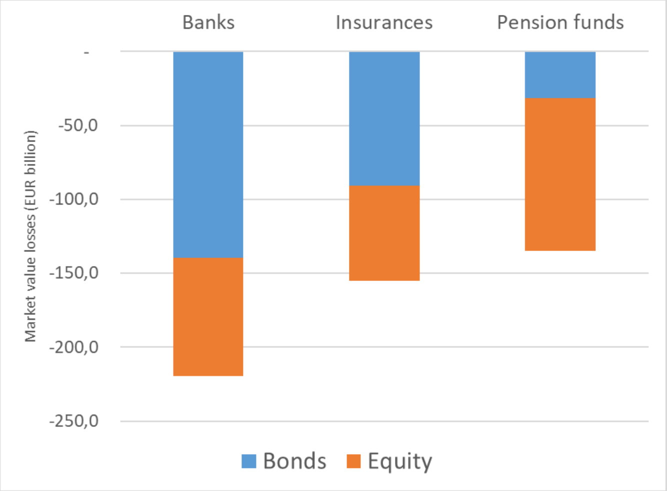

Figure 4: EU-level market value losses for a water supply shock based off a 10% aggregated production loss at EU level

The relative impact, i.e. the impact as a percentage of the value of debt and equity holdings, per country – as represented by the aggregated impact on debt and equity holdings of a country's FIs – across sectors is heterogeneous (Figure 5). As an example, the impact on a country's FIs' debt and equity holdings in the construction sector ranges from a 2.2% market value loss to a 33.7% market value loss. The wide variability in impact reflects differences in both physical vulnerability – driven by dependence on water supply and the degradation of water supply – and financial vulnerability, where initial probabilities of default shape the non-linear response of security values.

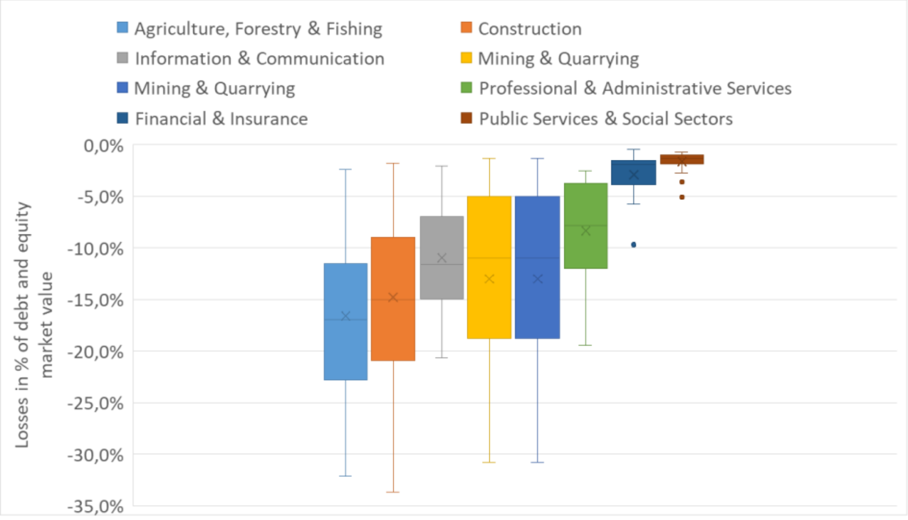

Figure 5: Country distribution of market value losses for a water supply shock based off a 10% aggregated production loss at EU level

The highest absolute impact is on the "financial and insurance" sector, i.e. the FIs' holdings of other FIs' debt and equity. (Figure 6) This reflects the large portion that other FIs' debt and equity holdings make up in FIs' balance sheets. The relative impact on the "financial and insurance" sector is limited, however, given the comparatively low initial probabilities of default (good quality ratings) in this sector. The same holds true for the public services sector.

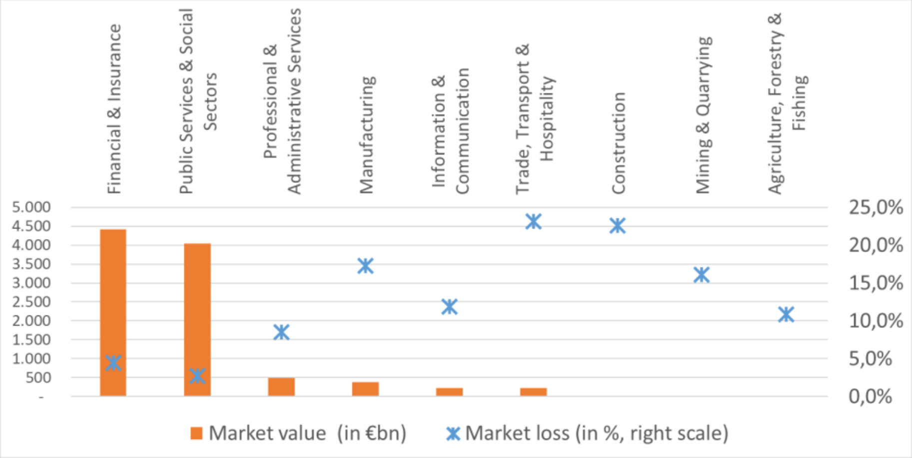

Figure 6: Market value losses of EU FI's bond and equity holdings per sector for a water supply shock based off a 10% aggregated production loss at EU level

Lastly, it is worth highlighting that the sector "professional and administrative services" currently aggregates both the headquarter activities and a residual "other sectors" category that captures meanly misclassified assets. (Figure 6) In practice, most of these exposures would need to be reallocated to the sectors that correspond to the real economic activities of the issuing companies.

5.3 Regulatory capital impact at financial institution level for the Netherlands

5.3.1 Banks' CET1 impact due to credit risk

This section presents the results derived using the methodology outlined in Section 3.5.1. The results present two options, (i) a CET1 ratio depletion due to only the credit-related losses channel that impacts the numerator of the CET1 ratio and (ii) a CET1 ratio depletion due to those same credit-related losses and an increase in RWA that impacts the denominator of the CET1 ratio.[17]company. The estimated CET1 ratio depletions are due to non-household loans (i.e. loans to corporates, governments, and financial institutions) reported in AnaCredit and debt holdings reported in SHS[18][19]. (Figure 7) As expected, the median CET1 ratio depletion decreases from around 19% to around 16% when considering only the credit-losses channel and to around 12% when considering the credit losses and higher RWA in conjunction. We also notice that the impact is primarily driven by loans rather than bond holdings, reflecting in part the much larger share of loans (80%) in the exposures in scope and potentially also the different starting PDs of these exposure classes.

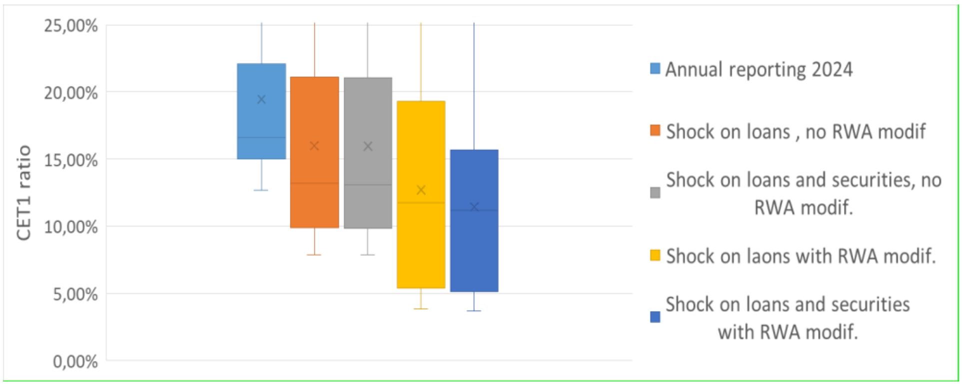

Figure 7: The distribution of CET1 ratios across Dutch banks (%) for a water supply shock based off a 10% aggregated production loss at EU level

5.3.2 Insurers' SCR impact due to market risk

This section presents the results derived using the methodology outlined in Section 3.5.2. The exposures in scope are the debt and equity holdings of Dutch insurers, as reported in SHS.

The impact on Dutch insurers' SCR ratios is heterogeneous, reflecting their different mix of debt and equity holdings and their different sectoral exposures. (Figure 8) The median SCR ratio decreases from around 185% to around 165%. While such a decrease is significant, Dutch insurers currently operate with substantial capital buffers and do not breach the 100% SCR requirement.

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[17] Please refer to Gallet et al (2024) for more information on the assumptions underlying these options.

[18] The national version of SHS-S, prior to European aggregation, was used in order to preserve individual bank granularity.

[19] Direct equity holdings are excluded from the analysis given their negligible share of Dutch banks' balance sheets and inability to see through collective investment funds.

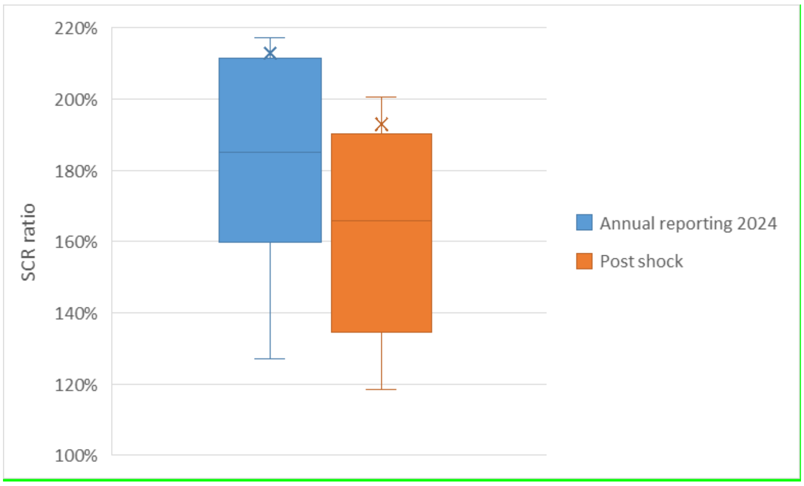

Figure 8: Distribution of Dutch insurers' SCR ratios variation due to market value losses for bonds and equity holdings, resulting from a water supply shock based off a 10% aggregated production loss at EU level

It is worth noting that the above results are based on a simplified scenario that only considers the credit spread, i.e. the idiosyncratic default probability, of the affected company due to a shock in water supply. Broader portfolio-level and insurer-specific effects are not incorporated: the proxy model provides an estimation of the potential impact of nature-related shocks on insurers' solvency but does not account for diversification or dynamic feedback effects and may therefore over- or underestimate actual outcomes. In addition, macro-financial dynamics—such as potential movements in risk-free interest rates and fiscal, monetary, or prudential policy responses to supply-driven inflation—are not modelled. While these channels fall outside the scope of the present analysis, the framework could be extended to incorporate them.

As part of the sensitivity analysis, we re-estimated the results using alternative magnitudes of the aggregated EU-level production loss. Sector-level production losses scale proportionally with the size of the EU-level shock. By contrast, the impacts on financial markets and prudential ratios are non-linear and somewhat dampened. For example, halving the aggregated EU-level production loss to 5% leads to an impact on prudential metrics of around 45% of the effect obtained under the initial 10% shock. Even though, in this case, the deviation from linearity is minimal and the relationship is almost proportional for the water-supply shock, this does not necessarily hold for other ES specifications or different asset-portfolio compositions.

6. Conclusion

This study introduces a structural and supervisory-oriented methodology for tracing how nature-related production losses propagate into financial and prudential outcomes. The objective is not to generate environmental scenarios, which require specialized biophysical and macroeconomic models[20]. Instead, the contribution of this work lies in demonstrating how an externally defined production shock can be transmitted through sectors, companies and financial institutions using a transparent and policy-relevant modelling chain.

The results show that the financial-stability implications of nature-related disruptions can be quantified in a coherent manner. Losses are allocated according to sectoral, geographical and ecosystem-service vulnerabilities, and the framework builds on established supervisory tools. The approach is consistent with recent academic developments, including Giglio et al. (2025), and can accommodate a variety of physical and transition nature and climate-related drivers. It delivers granular indicators – from production impacts to market revaluations and prudential ratios – supporting a wide set of analytical and supervisory applications.

At the same time, the methodology relies on an exogenous scenario and does not yet incorporate macro-financial feedback, such as shifts in interest-rate curves, that would arise from a system-wide supply shock. In this paper, only the idiosyncratic PD component is modelled. In practice, a supply-driven inflationary shock could prompt monetary-policy tightening, raising interbank rates and increasing the overall price of risk. Capturing such dynamics would require a two-dimensional shock – affecting both credit spreads and the interest-rate curve – which is beyond the current scope. The framework could in the future incorporate such scenarios.

Granular company-level data would make the results more actionable. Company-level granularity in this paper remains limited. The analysis relies on simplified supply-chain assumptions and recognizes the limitations of current nature-degradation indices. Expanding the analysis to nature indicators that account for the interconnectedness of ecosystems —such as the Earth System Impact index of Crona et al. (2023)—would help strengthen robustness and realism.

A key, non-trivial next step is the development of a fully integrated stress-testing scenario for nature-related risks that combines climate impacts, ecosystem-service disruptions and transition dynamics, together with regional production shocks and resulting macroeconomic trajectories. Once such a scenario is available, the framework can allocate losses across sectors and jurisdictions, adjust credit-risk and market-valuation parameters, and assess resulting prudential implications.

Overall, this work provides an important building block for nature-related financial-stability assessments. While progress in environmental scenario design and supply-chain data is still needed, the framework is already operational and can support ongoing supervisory analysis and indicator development.

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[20] Such modelling frameworks, e.g. the IMAGE–GLOBIO–MAGNET framework, are currently under further development in the literature.

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Appendix A: The three proxy scenarios of nature degradation

This appendix explains the three proxy scenarios built to approximate the impact of a water-related shock on production.

A.1 Tail scenario based off the historical variation of global production

This scenario assumes that water supply depletion is the origin of projected production losses, statistically similar to how COVID-19 triggered production losses in recent history. The production shock acknowledgment is modeled as a short-term stochastic event calibrated on past series. While the modeled shock is short-term by construction, we assume that market participants, investors, and all financial actors would interpret this production loss as persistent or non-recoverable over the medium term. When losses are seen as permanent—such as irreversible pollution, long-term climate impacts, or the mental shift from acute to chronic damage—the physical risk may evolve gradually, but the recognition of that risk can be abrupt. That sudden acknowledgment is the case we describe here. It is important to note that we do not model the long-term physical effects of the shock itself, but rather the immediate market anticipation of a lasting impact.

To identify the most suitable approach for modeling production shocks, several commonly used methods were tested: a purely descriptive model, ARIMA (widely applied for time-series forecasting), the Geometric Brownian Motion (GBM) often used in financial mathematics, and the Ornstein-Uhlenbeck (OU) process, which captures mean-reverting dynamics. Model performance was assessed using the Bayesian Information Criterion (BIC) and residual normality tests to ensure robustness and statistical validity. Based on these criteria, the OU process emerged as the most appropriate choice, offering a better fit and realistic representation of short-term stochastic shocks with mean reversion (consistent with global GDP variation). (see Appendix C:).

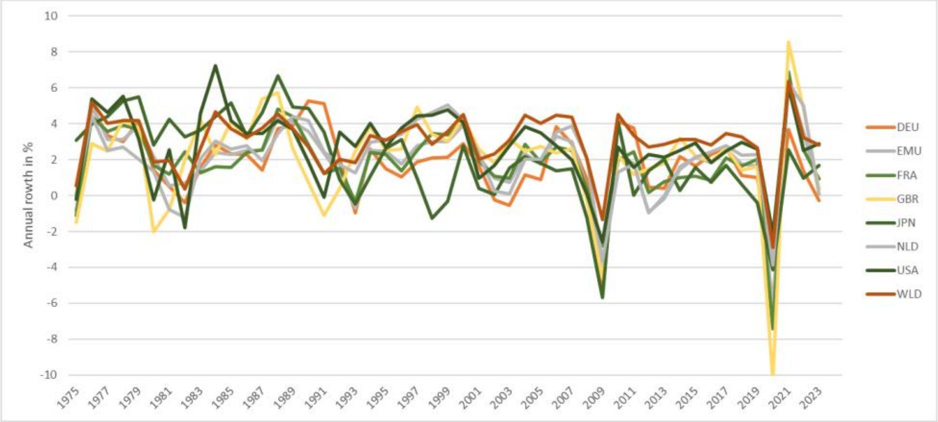

Figure 9:GDP growth (yearly %) - Netherlands, France, US, United Kingdom, Germany

Looking at historical data from the World Bank[21], annual GDP growth has been on a declining trend for more than 50 years, driven by multiple factors such as energy constraints, demographic changes, technological and resource limitations, and potentially nature degradation. Assuming that GDP variation is a good proxy for production variation at the aggregated level, we calibrate

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[21] https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG

the OU process and obtain a volatility estimate of about 3.0%. Using a tail-risk approach consistent with the Solvency II Directive[22], we adopt a 99.5th-percentile one-year shock down, corresponding to a 1-in-200-year event under normal distribution (the equivalent of a -2.6-sigma shock).. This produces an annual production shock of around 7.8%, where the covid produced a shock of -6% for the European Monetary Union. While this is a simplified approach, it provides a useful first reference point for stress-testing extreme nature-related shocks.

A.2 EDHEC-CLIRMAP : Combination with Climate production losses

The EDHEC-CLIRMAP[23] (EDHEC-CLimate-Induced Regional MAcroimpacts Projector) propose a web-based tool developed by the EDHEC Climate Institute to visualise how climate-driven temperature changes affect gross regional product (GRP) across time and space. Using macro econometric model, IPCC-aligned scenarios, reference temperature models, and global climate models, it provides spatially explicit projections for 3,672 sub-national regions worldwide.

CLIRMAP builds on an integrated framework linking short-run thermal damages to long-run productivity effects, supported by 50 years of historical data and high-resolution NASA climate simulations.

Under a SSP5–RCP8.5 scenario over 20 years, the model projects average production losses of about –10% in Southern Europe and –5% in Northern Europe. An indicative value of –8% is therefore a reasonable approximation for temperature-driven regional impacts.

While CLIRMAP focuses on temperature, temperature changes are intrinsically linked to disruptions in the water cycle. Temperature-based models thus capture part of the water-related impacts—such as reduced precipitation, lower water availability or drought—but not all. Important dimensions, including water-quality degradation, over-extraction or seasonal flow changes, lie only partly within the scope of temperature-driven models. The figures should therefore be seen as order-of-magnitude indicators, not full estimates of water-related losses.

Given the strong interdependence between temperature and hydrological dynamics, isolating their respective effects is challenging. Nonetheless, for this quantification exercise, an indicative production loss of 8% is considered as a severe but plausible benchmark for a water-related shock, consistent with ranges suggested by regional climate–economic studies.

A.3 Alternative methodology based on long-run system-dynamics modelling: World 3 model (Limit to Growth, Meadow's report)

A complementary methodology for assessing long-run environmental stress comes from the seminal report The Limits to Growth (Meadows et al., 1972). The report used the World3 system-dynamics model to simulate interactions between population, production, natural resources, pollution, and agricultural capacity. The original report examined several global development pathways, including (i) a business-as-usual (BAU) scenario, in which resource depletion and pollution gradually erode industrial output and lead to stagnation around 2020 and

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[22] Directive 2009/138/EC, Article 101(3) and Delegation Regulation 2025/35, Article 37(1).

[23] https://climateinstitute.edhec.edu/data-visualisations/edhec-clirmap

potential collapse thereafter, and (ii)and a stabilized-world (SW) scenario, in which coordinated policy intervention maintains long-run economic and ecological balance.

Recent updates comparing observed 2019 data to four World3 scenarios—BAU, BAU2, SW, and comprehensive technology (CT)—provide additional insights (Nebel, 2024). BAU2 represents a refined business-as-usual trajectory that includes higher natural-resource efficiency and slower pollution accumulation but still lacks structural sustainability reforms. CT assumes accelerated technological progress that delays, but does not fully prevent, environmental-driven constraints on output. SW, by contrast, embeds strong policy measures moderating production and resource use to maintain equilibrium.

Empirical comparison in this paper shows that BAU2 and CT align most closely with real-world data up to 2019, while SW diverges markedly. Because World3 models how environmental degradation—particularly resource stress—translates into declining industrial output, these trajectories offer a valuable macro-systemic lens for constructing stress-test magnitudes. In this report, we use variation in industrial output across the BAU-type scenarios as a proxy for productivity losses induced by environmental degradation, recognizing that system-dynamics models provide orders of magnitude rather than biophysical granular model projections.

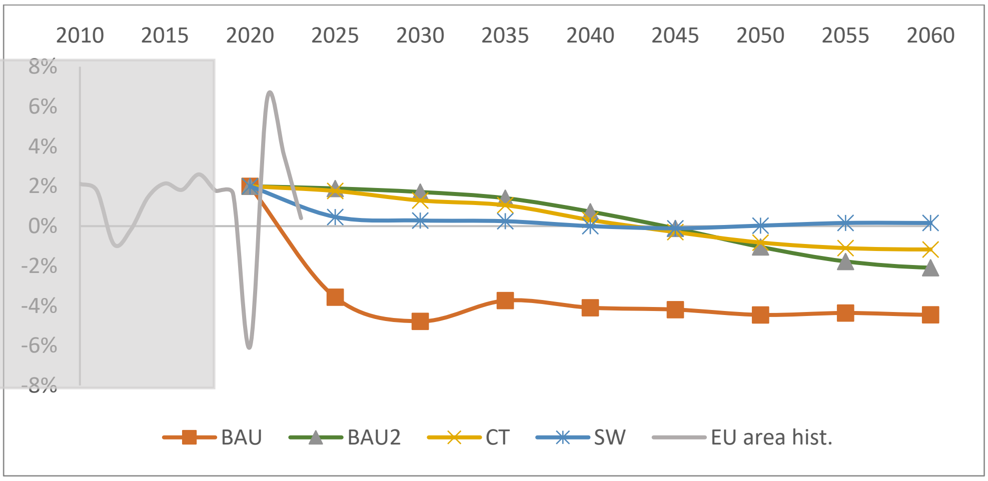

Figure 10:Production paths for 4 scenarios (historical values until 2024)

According to Nebel, the BAU2 pathway suggests that industrial production declines on average by 1,6% between 2040 and 2060. Given a typical five-year financial commitment horizon, this anticipation would translate into an accumulated production loss of around 7,6% over the life of an average loan or bond. The loss could potentially be higher for longer maturities.

By design, system-dynamics models such as World3 generate smoother and slower-moving trends than short-horizon stress-testing approaches. Selecting an appropriate time horizon is therefore essential. In financial markets the horizon reflects the duration of exposures, while in the real economy it reflects the time needed for agents to adjust to structural shocks. A five-year horizon offers a meaningful operational timescale for both dimensions.

As an alternative, we could also have used the scenario from Green Finance Institute. 2024, which applies national and international shocks across multiple ecosystem services—including chronic pressures such as water pollution and scarcity, and acute shocks such as drought. Their analysis shows that services and manufacturing face the largest monetary losses, with the full UK scenario resulting in a GDP declines of around 13% (and around 6% at the global level), offering a relevant order-of-magnitude benchmark for the Netherlands.

Appendix B: Benchmark of Vulnerability/ dependency score for governments and Financial Institutions

For both governments and financial institutions, dependence on ecosystem services—and the resulting vulnerability—is mainly indirect. These sectors do not produce goods themselves, yet their financial performance and credit quality depend on the output of other economic sectors.

While ENCORE provides dependency scores for governments and financial institutions, their systemic role and their weight in national balance sheets justify a complementary approach. The method below refines the assessment by anchoring vulnerabilities in the structure of national production and in the composition of financial-sector balance sheets.

Government Vulnerability

Government vulnerability to a given ecosystem service is estimated using the composition of national production. Each sector's vulnerability contributes proportionally to its share of total output:

$$Vuln_{ES,gov,c}^{Prod} = \frac{\sum_j Vuln_{ES,j,c}^{Prod} X_{j,c}}{\sum_j X_{j,c}}$$

where:

- j : sector of the real economy excluding finance. For conceptual and technical simplification raison.
- $X_{j,c}$: production of real economy sector j (excluding finance) in country c (from MRIO-EXIOBASE).
- $Vuln_{ES,j,c}^{Prod}$: ENCORE-based vulnerability of production to ecosystem ES, in sector j and country c.

This indicator captures supply-chain effects and reflects exposure to ecosystems both domestically and internationally. For the subsequent step—deriving the vulnerability of government assets—we lacked a well-defined accounting analogue to metrics such as the cost of equity or return on assets. We therefore approximated asset-level vulnerability using

$$Vuln_{ES,gov,c}^{asset} = \frac{\sum_j Vuln_{ES,j,c}^{asset} X_{j,c}}{\sum_j X_{j,c}}$$

Financial-Sector Vulnerability

The financial sector's vulnerability depends on the vulnerability and value of the assets it holds. These assets are issued by non-financial corporations (NFCs), governments, and financial institutions themselves.

Because asset values are linked to the equity values of issuers, financial vulnerability can be represented as the weighted average vulnerability of the underlying borrowers and issuers. Vulnerability of finance is then seen as the weighted average by asset values category:

- Holding of NFCs and government assets
- Holding of other financial institutions of other countries
- Holdings of financial institutions inside the same country and so sharing the same vulnerability

$$Vuln^{asset}_{ES,fin,c}.A^{fin,c} \quad = \sum\nolimits_s^{sect} \sum\nolimits_k^{count} Vuln^{asset}_{ES,s,c}\, A^{fin\,c}_{s,k} + \sum\nolimits_{k\neq c}^{count} Vuln^{asset}_{ES,fin,k}\, A^{fin\,c}_{fin,k} + Vuln^{asset}_{ES,fin,c}\, A^{fin\,c}_{fin,k}$$

With terms:

- $A^{fin,c}$: total assets held by financial institutions in country c
- $A^{fin,c}_{s,k}$: assets issued by sector s, country k and held by FI's in country c
- $A^{fin\,c}_{fin,k}$: assets issued by financial sector country k and own by financial sector country c
- $Vuln^{asset}_{ES,fin,k}$: vulnerability of asset values for sector finance in country k

Let's now rewrite that linear expression (one per country c) in matrical form. We first see that $Vuln^{asset}_{ES,fin,c}$ appear both side because a FI in a country own asset from FI's in the same country. The NFC and government terms can each be treated as a single value for every financial sector in country kkk. Moreover, the central term can be rewritten as the product of the financial-sector vulnerability matrix for each country and a square matrix to be derived. So now rewriting for each country c the equation gives:

$$Vuln^{asset}_{ES,fin,c} \quad = \sum_s^{sect} \sum_k^{count} Vuln^{asset}_{ES,s,c} \frac{A^{fin\,c}_{s,k}}{A^{fin,c} - A^{fin\,c}_{fin,k}} + \sum_{k\neq c}^{count} Vuln^{asset}_{ES,fin,k} \frac{A^{fin\,c}_{fin,k}}{A^{fin,c} - A^{fin\,c}_{fin,k}}$$

And then with $[V_c]$, vector column of $Vuln^{asset}_{ES,fin,c}$for all countries c , and

$$[B_c] = \sum_k^{count\ emit} \frac{1}{A^{fin,c} - A^{fin\,c}_{fin,k}} \sum_s^{sect} Vuln^{asset}_{ES,s,c}\, A^{fin\,c}_{s,k}$$

We can define the matrix $\left[C_{c,k}\right]$ in order to get:

$$\sum_{k\neq c}^{count} Vuln_{ES,fin,k}^{asset} \frac{A_{fin,k}^{fin\,c}}{A^{fin,c} - A_{fin,k}^{fin\,c}} = [C_{c,k}].[V_c]$$

Meaning that matrix elements can be written as being:

$$C_{c,k} = \frac{A_{fin,k}^{fin\,c}}{A^{fin,c} - A_{fin,k}^{fin\,c}}$$

With diagonal =0 ($A_{fin,k}^{fin\,c}$=0) Finally rewritten as:

$$[V_c] = [B_c] + [C_{c,k}].[V_k]$$

But of course $[V_c] = [V_k]$ meaning the vulnerability of finance per country is the same if the asset is hold directly by country c or indirectly by country k. We can now use usual resolution solution of linear equations with

$$[V] = [I - C]^{-1}.[B]$$

A complete representation would require FINREP or central-bank datasets. For now, we assume **AnaCredit + SHS provide a representative breakdown** of financial-sector assets of financial institutions.

Mapping NACE Codes to EXIOBASE

Vulnerability is theoretically defined at the **NACE level 4**, but financial datasets often include aggregated NACE codes (levels 1–4). ENCORE provides a correspondence table linking NACE codes to EXIOBASE sectors.

Vulnerability for any NACE code is computed as:

$$Vuln_{ES,NACE,c} = \frac{\sum_{j\in NACE} Vul\, n_{ES,j,c}\, X_{j,c}}{\sum_j X_{j,c}}$$

With:

$X_{j,c}$: national production of EXIOBASE sector *j*

$Vuln_{ES,j,c}$: sectoral vulnerability (production or asset-based)

Assumption:
When one NACE code maps to multiple EXIOBASE processes, we assume a representative company distributes its production across those processes following the national production

structure. This ensures consistency with the broader supply-chain treatment used throughout the analysis.

Results

Let’s compare the total DS and vulnerability score (Total meaning direct and indirect impacts weighted by the subcontracting ratio) for the Finance and Public sectors. One version is derived from the ENCORE DS scores, and the other comes from a recalculation based on the DS values of all other sectors as seen previously.

	Total DS score		Total Vulnerability SCORE	
	ENCORE	Recalculated	ENCORE	Recalculated
FIs excl. Ins and PF	14,0%	21,4%	6,6%	9,3%
Insurance and Pension Funds	16,0%	21,4%	7,2%	9,3%
Public	26,0%	48,1%	11,9%	21,3%

The increase is meaningful—noticeable enough that it warrants consideration, even if it is not transformative. For the purposes of the study, and unless otherwise specified, we rely on the recalculated figures for the financial and public sectors.

Appendix C: Ornstein-Uhlenbeck modelling approaches for fitting historical GDP fluctuations from World Bank data

To gauge the scale of a severe yet plausible production shock, we assessed several modelling approaches—ARIMA, Geometric Brownian Motion and the Ornstein–Uhlenbeck (OU) process—using World Bank GDP growth data. Our objective was to develop a robust projection framework and derive a realistic proxy for an extreme downturn. Based on AIC/BIC criteria, the OU model provided the best fit and is therefore retained for the analysis.

The OU process captures GDP dynamics through a mean-reverting stochastic structure: deviations from the long-term equilibrium gradually correct themselves, while short-term shocks introduce volatility around this trend. This balance of persistence, reversion, and controlled randomness makes the OU model particularly suitable for representing macroeconomic cycles.

$$\frac{\Delta Prod_{c,s}}{Prod_{c,s}} = X_t = [\theta(\mu_0 + \nu t - X_t)]dt + \sigma dW_t$$

Where:

- $\frac{\Delta Prod_{c,s}}{Prod_{c,s}} = X_t$ *is the process at time t*
- *θ>0 is the rate of mean reversion*
- *μ is the long-term mean (drift target)*
- *σ is the volatility coefficient*
- *W_t is a standard Wiener process (Brownian motion)*

Since X_t represents the instantaneous change in production at time ttt, it must be integrated over time to obtain the annual accumulated change in production reported in the World Bank database. Integrating both sides from 0 to t:

$$e^{\theta t}X_t - X_0 = \theta\int_0^t e^{\theta s}(\mu_0 + \nu s)ds + \sigma\int_0^t e^{\theta s}dW_s$$

Solving for X_t:

$$X_t = X_0 e^{-\theta t} + \theta e^{-\theta t}\int_0^t e^{\theta s}(\mu_0 + \nu s)ds + \sigma e^{-\theta t}\int_0^t e^{\theta s}dW_s$$

Evaluating the Deterministic Integral $\int_0^t e^{\theta s}(\mu_0 + \nu s)ds$, can be computed as:

$$\mu_0\int_0^t e^{\theta s}ds + \nu\int_0^t s\, e^{\theta s}ds$$

$$= \mu_0\left(\frac{e^{\theta t} - 1}{\theta}\right) + \nu\left(\frac{e^{\theta t}(\theta t - 1) + 1}{\theta^2}\right)$$

Evaluating the Stochastic Integral $(\int_0^t e^{\theta s} dW_s)$, this is an Itô integral, and it cannot be evaluated in the classical sense. However, we can describe its distributional properties starting with mean $E\left[\int_0^t e^{\theta s}\, dW_s\right] = 0$ and variance

$$\mathrm{Var}\left(\int_0^t e^{\theta s}\, dW_s\right) = \int_0^t e^{2\theta s}\, ds = \begin{cases} \dfrac{e^{2\theta t} - 1}{2\theta} & if\ \theta \neq 0 \\ t\ if\ \theta = 0 \end{cases}$$

Therefore, the stochastic integral is normally distributed:

$$\int_0^t e^{\theta s}\, dW_s \sim \mathcal{N}\left(0, \frac{e^{2\theta t} - 1}{2\theta}\right), \quad \text{for } \theta \neq 0$$

For t=1, when we look at annual data:

$$X_1 e^{\theta} = X_0 + \mu\left(e^{\theta} - 1\right) + \nu\left(\frac{e^{\theta}(\theta - 1) + 1}{\theta}\right) + \sigma\sqrt{\frac{e^{2\theta} - 1}{2\theta}}\varepsilon$$

with $\varepsilon \sim \mathcal{N}(0,1)$. The model parameters are estimated using maximum likelihood estimation (MLE), which selects the values that make the observed GDP series most probable under the assumed Ornstein–Uhlenbeck process. This yields the following parameter set:

PARAMETERS	US	WORLD	NL
$\boldsymbol{\theta}$	1.51	1.56	0.99
$\boldsymbol{\mu}$	3.05	5.73	2.84
$\boldsymbol{\nu}$	-0.01	-0.64	-0.01
$\boldsymbol{\sigma}$	3.64	3.00	2.23

Figure 11, using the estimated parameters, we simulated 1,000 back-projections starting from 1960 and extracted the 99.5th percentile trajectory. This high-severity path aligns well with historical outcomes: over the past seven decades, the actual GDP series crossed this extreme envelope only once—during the COVID-19 shock—while other downturns approached it as expected.

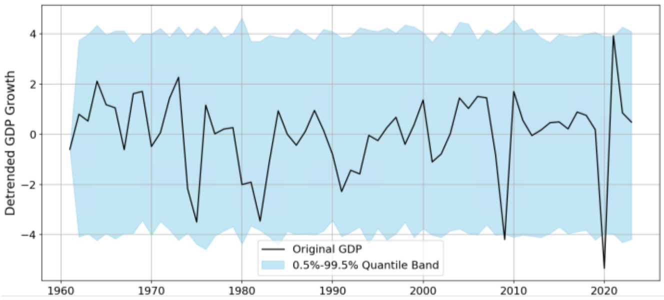

Figure 11:Ornstein-Uhlenbeck simulation of detrended world GDP Growth

Appendix D: Microeconomic foundation confirmation starting from recent literature

This appendix reformulates the theoretical framework underlying nature-related production losses in a more general and mathematically explicit manner. Starting from the structure proposed in Giglio et al. (2025), The Economics of Biodiversity Loss, we reconstruct our model to show that the two approaches are formally equivalent. Although Giglio et al. focus specifically on biodiversity, we demonstrate that their framework naturally extends to our more general formulation, which does not distinguish between individual ecosystem services.

In Giglio et al. (2025), aggregate ecosystem services E arise from multiple ecological functions, each supported by a set of partially substitutable species. Because ecological functions are non-substitutable, aggregate ecosystem services exhibit strongly diminishing returns in species richness.

The paper shows that the expected change in log ecosystem services conditional on biodiversity s follows:

$$\mathbb{E}[d\log\ E \mid s] = \mathcal{F}(s)\ ds.$$

- s= species richness actively supporting ecosystem functions,
- $\mathcal{F}(s)$= *ecosystem fragility*, i.e. the sensitivity of aggregate ecosystem-service production to a marginal decline in biodiversity.

Thus, a common decline ds across ecological functions induces a proportional loss in aggregate ecosystem services. Assume economic production P responds linearly to small changes in ecosystem services:

$$\mathrm{d}\log\ P = \beta\ \mathrm{d}\log\ E.$$

Using the expression above:

$$\mathbb{E}[d\log\ P \mid s] = \beta\ \mathcal{F}(s)\ ds.$$

For a continuous-time, company-level production loss due to biodiversity depletion is assumed having a deterministic trend:

$$\mathbb{E}\left[\frac{dP_i}{P_i} \,\middle|\, s\right] = \mu_{i,\mathrm{BioLoss}}\ dt = \beta_i\ \mathcal{F}_i(s)\ ds$$

Where β_i denotes the production-dependence strength of the relationship with ecosystem-service for company i. To align with the notation used in our paper, let's write:

$$\mu_{i,\mathrm{BioLoss}} = \mathrm{Vuln}_i\ \alpha_{\mathrm{BL}},$$

which implies the mapping allowing for free linear relation γ_i:

$$\mathrm{Vuln}_i = \gamma_i\ \mathcal{F}_i(s)\ and\ \alpha_{\mathrm{BL}} = \frac{\beta_i}{\gamma_i}\frac{ds}{dt}$$

Scaling constants γ_i is arbitrary ($\in \mathbb{R}_+$) and may be chosen in order to get $\frac{\beta_i}{\gamma_i}$ normalised to 1 (so $\gamma_i = \beta_i$). This yields two useful identifications:

- Vulnerability ≡ ecosystem fragility ($\mathcal{F}_i$) X production-dependence strength (β_i)

Vulnerability can be expressed as the product of ecosystem fragility and the strength of production dependence. This matches the metric used here, where vulnerability equals the ND-GAIN Nature Degradation Index multiplied by the ENCORE Dependency Score. The Nature Degradation Index captures ecosystem fragility, while the Dependency Score reflects production-dependence. Both approaches follow the same logic: separating vulnerability into an environmental state component and an economic sensitivity component.

- Biodiversity shock intensity (α_{BL}) ≡ rate of species loss ($\frac{ds}{dt}$)

Although derived differently, both frameworks describe the same mechanism.

Appendix E: Quantitative finance tools

E.1 Volatility equivalency

To apply the Merton model, we require the volatility of the company's asset value. However, only the equity volatility (e.g. as reported in Bloomberg) is directly observable. Fortunately, the Merton framework provides a mapping between the two, given by the following equation

$$\sigma_A = \frac{\sigma_E}{N(DTD)} . \frac{E}{A} = \frac{\sigma_E}{N(DTD)} . (1 - Debt_{ratio})$$

- E : equity price
- A: assets value
- DTD : distance to default
- σ_A: Assets value volatility: the one needed
- σ_E: Equity price volatility: the one we get from stock exchange information (i.e. Bloomberg)
- $Debt_{ratio}$: ratio between face value of the debt and the current value of assets.

$Debt_{ratio}$ (like the equity volatility) should ideally be calibrated at the company level and, where this is not possible, at the sector / country level. However, for reasons of simplification and data availability, it is applied at the sector level only in this study. Sector-level debt ratios used in this study are sourced from www.readyratios.com

E.2 PD real-world versus PD risk neutral

PD risk neutral is the implied PD embedded in price valuation and depend also on the modeling of the price structure. I our case, the Merton base approach gives us (Tedeschi 2018)

$$\mathrm{PD}_{\text{risk-neutral}} = \mathrm{N}\left(\mathrm{N}^{-1}(\mathrm{PD}_{\text{real-world}}) + \rho_{\mathrm{a,m}} \cdot \frac{\mu_{\mathrm{m}} - \mathrm{r_f}}{\sigma_{\mathrm{m}}} \cdot \sqrt{\mathrm{t}} \right)$$

Where:

- $PD_{\text{real-world}}$: Historical default probability available in corresponding table linking ratings and historical probability (S&P or Moody's)
- $N(\cdot)$: Standard normal cumulative distribution function.
- $N^{-1}(\cdot)$: Inverse of the standard normal cumulative distribution (i.e., the z-score).
- $\rho_{a,m}$: Correlation between the obligor's asset returns and market returns, typically estimated via linear regression.
- μ_m: Expected market return.
- r_f: Risk-free interest rate.
- σ_m: Volatility of market returns.
- $\frac{\mu_m - r_f}{\sigma_m}$: Market Sharpe Ratio, representing excess return per unit of risk. Would be considered at NACE sector level for keeping data manageable.
- t: Time horizon (e.g., 1 year).

Interpretation: This formula adjusts the real-world default probability by incorporating market risk aversion. The adjustment depends on:

- How closely the obligor’s assets move with the market (correlation).
- How much excess return the market demands for taking risk (Sharpe Ratio).

A higher correlation between the obligor’s assets and the market, together with a higher Sharpe ratio, increases the risk-neutral probability of default. When the asset–market correlation $\rho_{a,m}$ is high, a larger share of the obligor’s risk becomes systematic, making its asset value more sensitive to market downturns and raising default probabilities under stress—while also increasing default clustering across obligors. Conversely, a lower $\rho_{a,m}$ implies that risk is more idiosyncratic, leading to more independent default events and greater scope for diversification within credit portfolios.

The value of correlation is typically derived via linear regression or from data providers. A key limitation of this method is the possible mismatch between equity and credit market dynamics.

For this study and due to time and manpower limitation constraints we used data available on the web:

- Return and std deviation: https://fourpillarfreedom.com/stock-sector-returns/
- Correlation : https://valuereports.economatica.com/sector-correlations-impact/

Appendix F: Modification of the EDSI Formulation

Recent developments have clarified that the original EDSI formulation was constructed using the vulnerability of production, but in practice was applied as if it reflected the vulnerability of assets. This implied an inconsistency in the depreciation term. While the conceptual description provided in the paper remains valid, Equation (5) must be updated so that the depreciation term explicitly incorporates the *vulnerability of assets*, not the *vulnerability of production*.

The vulnerability of assets, expressed at the sector–country level (s,c), is now defined as follows**:**

$$\mathrm{Vuln}_{\mathrm{ES,s,c}}^{\mathrm{Assets}} = \frac{\mathrm{RoA}_{\mathrm{s,c}}\,(1 + \mathrm{CoE}_{\mathrm{s,c}})}{\mathrm{CoE}_{\mathrm{s,c}}}\,\mathrm{Vuln}_{\mathrm{ES,s,c}}^{\mathrm{Production}}$$

This correction reflects that the financial impact of ecosystem-service degradation on a company (or sector) depends not only on the sensitivity of its production process, but also on the relationship between equity, asset value, and profitability.

Equation (5) of the EDSI paper must therefore be rewritten as:

$$\mathrm{dep}_{\mathrm{i}} = \alpha_{\mathrm{ES}} \cdot \mathrm{Vuln}_{\mathrm{ES,i}}^{\mathrm{Assets}}$$

Which, substituting the new definition, becomes:

$$\mathrm{dep}_{\mathrm{i}} = \alpha_{\mathrm{ES}} \cdot \frac{\mathrm{RoA}_{\mathrm{i}}\,(1 + \mathrm{CoE}_{\mathrm{i}})}{\mathrm{CoE}_{\mathrm{i}}} . \mathrm{Vuln}_{\mathrm{ES,i}}^{\mathrm{Production}}$$

Ideally, the RoA and CoE parameters would be specified at the company level, since the relationship between production processes, cost structures, and asset valuation is intrinsically company-specific. For practical and data-availability reasons, the implementation relies instead on sector–country averages, which serve as an approximation that ensures the feasibility of this study.

It is important to note that during the calibration phase—when calibration is performed on aggregate production losses—the vulnerability of production must be used to derive the shock parameter α. The resulting α is then applied together with asset-level vulnerability in the distance-to-default formulation.

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