Challenges and opportunities when assessing exposure of financial investments to ecosystem regime shifts

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Credit Statement

André P. Silva (APS) led the conceptualisation of the proposed idea and led the manuscript writing. Nielja Knecht (NK) & Romi Lotcheris (RL) led the manuscript section on early warning signals for regime shift detection. APS and RL also designed the manuscript figure. Romain Thomas (RT) led the section on using the Regime Shifts DataBase for identification of regime shifts. Beatrice Crona (BC) was responsible for gathering funding (to cover APS) through the Mistra FinBio project and tailoring the paper to an interdisciplinary audience. Juan Carlos Rocha (JCR) led the section on feedbacks amplifying the risk of regime shifts, supervised the validity of the proposed idea and gathered funding to cover NK, RL and RT through FORMAS projects.

Running title

Exposure of financial investments to ecosystem regime shifts

Abstract

Financial investments will be affected by ecological regime shifts through the loss of natural resources underpinning dependencies of most economic sectors. We suggest one possible pathway to link industry and products to the likelihood of ecological regime shifts. The challenges and opportunities are discussed at each step, including datasets, methods and metrics. To this end, we identify recent large-scale, state-of-the-art literature that can link land-based company activities to regime shifts. The estimation of investment exposure to regime shifts is possible, but higher resolution in company trade data as well as spatially-explicit datasets of commodity production are needed to improve estimations. This will require coordinated effort from the scientific community, businesses, and the policy sector.

Introduction

The financial sector contributes to global environmental degradation, adding risk to its investments [1]. When tipping points (i.e. a specific threshold) are crossed, environmental regime shifts can be triggered leading to large, abrupt, and persistent changes in the structure and function of ecosystems. Regime shifts are characterised by a gradual or sudden transition from one configuration to another, and can have significant ecological and socioeconomic consequences [2]. These shifts can occur over a few years or decades, changing the types of natural resources or ecological services (such as carbon storage) produced by ecosystems. Once a regime shift has occurred, it can be difficult or impossible to reverse in the lifespan of humans [3], or reversible at very high cost.

Ecological regime shifts can thus lead to dramatically reduced monetary value of sectors with high dependencies on particular ecosystems [4]. New estimations point out that 75% of all corporate loan exposures in the euro area have strong dependency on at least one ecosystem service [5]. As an example, human-driven disturbance of the Amazon rainforest may lead to lower rainfall affecting the rain fed agriculture in South America as well as hydropower, leading to loss of revenue [6,7]. There are also indications consistent with a potential regime shift in the Amazon rainforest [8]. This can lead to loss of carbon storage contributing to further destabilise Earth's climate [9,10]. Finally, as parts of the Earth system can interact between each other this can lead to cascading-effects[1] [11,12], with the financial sector potentially facing exposure from multiple origins. On a regional scale, feedbacks (i.e. two-way causal interaction) between systems can put financial actors at risk as well. For example, coastal hypoxia and eutrophication are regime shifts driven by over enrichment of nutrients. Agricultural activities that use too much fertiliser, or urban settlements and industrial activities with inappropriate waste water management can lead to hypoxic events. These in turn feed back human well being by decreasing fishing productivity, tourism revenues or increasing risk of human diseases [13,14]. In other ecological systems, some coral reefs, critical for the tourism industry, may have surpassed the tipping point of mass high temperature bleaching in the 1980s [15]. Thus, regime shifts have the potential to trigger indirect impacts such as general economic slowdowns due to more systemic effects of environmental events, such as disruptions of resource supply and infrastructure from droughts or floods, or through pandemics caused by land-use change driving emergence of zoonotic disease, like COVID-19 [16–18].

Early detection of regime shifts has been restricted by the lack of high resolution spatially explicit time series-data, limited methods (e.g. for noise and rate induce transitions) and noise in environmental data [19,20]. However, recent advances in combining early-warning signal[1] detection and machine learning applied on remotely-sensed data are promising advances [21–23].

Overall, our aim is to find ways of connecting financial portfolios[1] to regime shifts highlighting financial risks on investments in dependencies that can be affected by ecosystem change. To that end, we need to find ways to identify investments that might lead to regime shifts. We focus on reviewing the most recent updates (i.e. datasets, methods and analytical approaches) in several steps linking industries to areas prone to ecological regime shifts and identifying current challenges (i.e. obstacles to accurate regime shift detection).

To link portfolios to regime-shifts we highlight four major steps (figure 1). First, we suggest understanding which industries and products the portfolio is associated with (i.e. product scoping). Then we suggest the identification of where companies act (i.e. company activity) to associate them with particular ecosystems (i.e. ecosystem identification). Finally, once company activity in particular ecosystems is established we suggest databases and warning signals to estimate the risk of regime-shifts and possible feedbacks1 (i.e. regime shift detection).

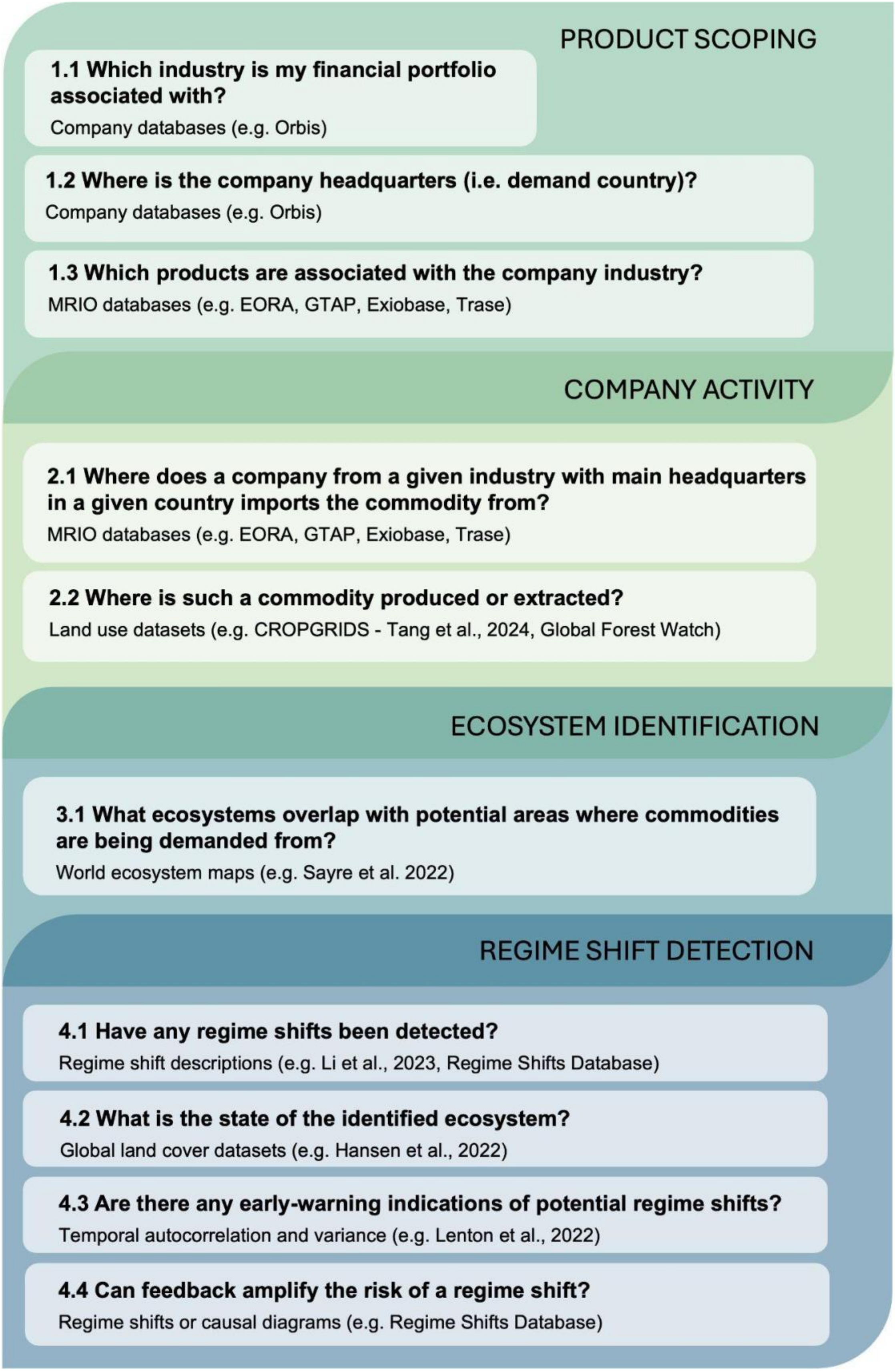

Figure 1: Conceptual diagram representing steps to identify financial exposure to regime shifts including the questions, databases and metrics.

To which industries and products is my investment associated?

In a first step, we suggest identifying the industry each company in the financial portfolio belongs to (see figure 1, product scoping). Industry classification is provided by international codes such as the International Standard Industrial Classification (ISIC) and Statistical Classification of Economic Activities in the European Community (NACE). Databases like Orbis (bvdinfo.com) offer such classification codes for companies (see table 1, step 1). The country where the company has its headquarters can be extracted from the databases with company information as this will serve as the importing country in trade databases such as Multi-Region Input-Output (MRIO) tables in the next step. MRIO tracks the flow of goods and services between industries in different sectors of the economy across world regions or countries, providing insights into the economic relationships and dependencies among them. Databases on the global economy (e.g. Exiobase, GTAP and EORA) are available though country coverage varies [24]. Recently, MRIOs database with higher spatial and sectoral resolution have been developed [25,26].

How to connect company activity to land-use and ecosystems?

The number of datasets with company activity data is growing quickly, recently 145 asset databases have been recorded across several sectors [23]. However, spatial and temporal resolution, spatial coverage, inconsistent formatting and incomplete ownership data are still limitations [27]. Detailed spatially-explicit datasets on commodity extraction have been restricted only to a few economic sectors and to broad spatial resolutions [23,24]. For agriculture, a recent update of a global spatial dataset to finer spatial resolution (approximately at 5.6km resolution) for 173 crops and for the year 2020 is promising [28]. These datasets can be linked with products identified in the Exiobase [25] and company activity data (see table 1, step 2) but examples of such linkage are sparse. For instance, Maus et al. [26] provide mining data that was used in connection with Exiobase [27] but this type of approach is yet unfeasible for financial portfolios diversified across multiple economic sectors. The new spatially explicit multiregional input-output (SMRIO) models [28], though with the same limitations of update frequency, and spatial-temporal resolution as the MRIO tables in which they are based on, are a way to allocate consumption into spatial grid cells through relationship matrices between land-use type, land-use intensity and input-output tables. Then the potential locations of resource extraction can be combined with global ecosystem mapping [29] allowing to identify potential ecosystems where a company belonging to a certain industry might operate (see ecosystem identification in figure 1). It will remain, however, a guess unless companies engage and contribute spatially explicit data of their outsourcing (e.g. trase, trase.earth).

Which regime shifts have already been identified?

Once ecosystems associated with the company's industry are identified, the past occurrence of regime shifts in those ecosystems can be explored (figure 1) in the Regime Shifts Database [30]. The database is the one of the most complete global databases of regime-shifts, documenting over 30 different types of regime shifts and >3500 case studies; including the causes of different regime shifts, their impacts on ecosystem services and human well-being, as well as potential managerial options. Another recent databases are the Chinese thresholds database with 110 case studies from China [31], the thresholds database with ~300 cases [31], the Global Ocean Oxygen Network which documents ~400 cases of coastal hypoxia [14], the forest die-off database with >1000 cases [32], the bush encroachment database with >400 cases [33]. Companies can use these databases to identify the types of regime shifts they are exposed to by looking at the types of ecosystems or land uses under which their activities develop (table 1, step 4). They can also identify if their production processes or supply chains impact ecosystems or are affected by consequences of regime shifts. In the case that no regime shifts have yet been detected it is suggested to look at predictors of future regime shifts.

How to predict regime shift risks?

The proximity of an ecosystem to a regime shift can be assessed by detecting meaningful changes in key system properties over time and space. This requires identifying important observable variables in the system. In a forest, this could be indicators of primary productivity or species abundance , for coastal systems, these could be measuresof algal growth and oxygen concentrations. Early Warning Signals (EWS) are indicators that a system is losing resilience and might be approaching a regime shift [32]. They are mainly based on the theory of Critical Slowing Down1 (CSD) which suggests that a system will show signs of slower recovery prior to ashift [32]. There is a wide range of both temporal and spatial EWS to detect resilience loss, that vary from simple statistical properties to complex model- or network-based indicators [33,34]. Temporal methods are more widely applied, but spatial methods can be useful for specific systems such as drylands[17,35]. The two most widely applied metrics are autocorrelation at lag-1 (AR (1)) and the variance (see example in Table 1 step 4). If both of these increase significantly over time, the system takes more time to recover from disturbances [36]. These two indicators have shown resilience loss in, amongst others, tropical forests, coastal environments, and lake ecosystems [34,35]. Generally, there is no single best EWS. Methodological choices should be adapted to the properties and characteristics of the studied system [36] (but see guidelines [36–38]). A rigorous assessment whether the case meets the theoretical assumptions for applying EWS is also crucial [39,40]. It is important to consider that EWS methods can fail, not all types of regime shifts can be detected using CSD[41] not all detected increases in AR (1) and variance result in a catastrophic shift [43,44]. The spatial and temporal scale at which to measure indicators of resilience loss should also be considered. This depends on the scales of both the system and the regime shift of interest [41]. Time series need to be long enough, and at a high enough frequency to detect relevant signals, with a resolution high enough to capture important variability (the characteristic time scale of the system). For example, systems operating at slower time- and larger spatial scales (e.g. forests) generally require longer, spatially coarser datasets, while smaller systems operating at faster time scales (e.g. phytoplankton) require higher frequency and spatial resolution datasets [45]. Data sources which can represent system state variables often include remotely sensed satellite data or reanalysis products[1] [46]. Data users should consider that satellite products might have high levels of noise in time series data, or have temporal and spatial gaps depending on satellite and cloud coverage. Reanalysis data[1] are spatially and temporally consistent, but may not always capture the natural ecosystem variability required to assess certain regime shifts [47].

How to account for uncertainties and feedbacks amplifying the risk of regime shifts?

The current datasets on the location of companies, their ownership structure or money flows (endowments) are both incomplete and behind paywalls, making it very difficult to track exposure and attribute responsibilities (but see [18,48]). Higher transparency from industry and governments is needed to correctly attribute risk and responsibilities in particular to account for multiple associations of the same company to several ecosystems (i.e. teleconnections). In addition, the current assessments of proximity to tipping points do not have ground truth, their accuracy or uncertainty is an open area of research [22,23]. Feedback mechanisms can amplify the risk of regime shifts. One way to visualise causation is through causal diagrams[1] representing a socio-ecological system (see table 1, step 4) by its parts and relationships, proposing how these interact to bring about a phenomenon [49]. The Regime Shifts Database provides a collection of causal diagrams that qualitatively assess the diverse ways regime shifts can occur. It can also be used to identify relevant observables at the scale of business operations, though fine grain data and problems of attribution remain challenging. There exist methods for feedback quantification [50], however they often rely on large scale and computationally expensive models that run scenarios with the feedback on and off to capture its impact on the overall dynamics of the system. These experiments are typically not available to companies without scientific advice and large computational facilities.

Table 1 - Proposed steps including proposed metrics, methods, databases. An example is given on what information could be extracted for the proposed steps applied to a company, like Red Bull GmbH, acting within the manufacture of beverages sector with headquarters in Austria and based on their use of one specific product (sugar cane, sugar beet). Complete company exposure would have to be calculated based on all products used by the company.

Step	**Question**	**Metrics**	**Potential Database/Datasets**	Terrestrial **Example**	**Marine Example**
1. Product scoping	Which industry is my financial portfolio associated with?	1. International Standard Industrial Classification (ISIC); 2. Statistical Classification of Economic Activities in the European Community (NACE)	Orbis (bvdinfo.com); Statista (statista.com/companies/search)	Red Bull GmbH ISIC: 1104 NACE Rev2: 11.07 Sector: Manufacture of Beverages	Findus France SAS ISIC: 102 NACE Rev2: 10.20 Sector: Manufacture of Fish Products
	Where is the company headquarters (i.e. demand country)?	Importing country name		Austria	France
	Which products are associated with the company industry?	Product type	MRIO databases (e.g. EORA, GTAP, Exiobase, Trase)	E.g. Sugar cane, sugar beet (Exiobase - use table)	E.g. Fishing, operating of fish hatcheries and fish farms (Exiobase - use table)
2. Company activity	Where does a company from a given industry with main headquarters in a given country imports the commodity from?	Exporting country name		E.g. The sector of manufacture of beverages in Austria uses sugar cane, sugar beet from European countries (AT; CZ; DE; DK; HU) and India (IN) (Exiobase - use table).	E.g. The sector of manufacture of fish products in France uses fishing from 31 countries with most fish being imported from Spain (ES), France (FR) and Japan (JP) (Exiobase - use table).

	Where is such a commodity produced/ extracted?	Geographical distribution of commodity production		Tang et al. [28]; Becker-Resh et al.[51]; Maus et al. [52], Global Fishing Watch (https://globalfishingwatch.org) /Global Forest Watch (globalforestwatch.org/map/);	E.g. Sugar crops in India occur mostly in the North, South-West and South-East [28]	E.g. Fishing pressure in the Spanish and French exclusive economic zone (EEZ) is mostly concentrated around the Atlantic coast (Global Fishing Watch)
3. Ecosystem Identification	What ecosystems overlap with potential areas where commodities are being demanded from?	Geographical distribution of ecosystems		World ecosystem maps [29]	E.g. Sugar crops in India overlap with subtropical and tropical dry croplands ecosystems [29].	E.g. Fishing pressure in the Spanish and French EEZ overlap with Celtic-Biscay Shelf, Iberian Coastal, and Mediterranean Sea marine ecosystems (data.marine.copernicus.eu)
4. Regime shift detection	Have any regime shifts been detected?	Regime shift descriptions		Regime shift databases [30,53]	E.g. Regime shifts have not been detected in terrestrial environments in India [30]	E.g. Case studies in the bay of Biscay report regime-shifts due to hypoxia and fisheries collapse [30].
	What is the state of the identified ecosystem?	Terrestrial	Land cover percentage	Global land cover [54]	E.g. The regions are mostly classified as cropland and built-up area (percentage not calculated for this exercise)	Not Applicable
			Functional integrity	Mohamed et al. [55]	E.g. The regions display one of the lowest functional integrity values worldwide (approx. below 0.3)	Not Applicable
		Marine	Sea-surface temperature change	Nasa Earth data (wvs.earthdata.nasa.gov) European Space Agency (earth.esa.int)	Not Applicable	E.g. The EEZs have seen sea surface temperature anomalies with temperature increase above average and increased frequency of heat waves (wvs.earthdata.nasa.gov)

			Chlorophyll a change	Nasa Earth data (https://wvs.earthdata.nasa.gov) European Space Agency (earth.esa.int) Copernicus Marine Service (data.marine.copernicus.eu)		E.g. The EEZs have also recorded an increase in global chlorophyll a (data.marine.copernicus.eu)
	Are there any early-warning indications of potential regime shifts?	Terrestrial and Marine	Temporal autocorrelation at Lag-1 (AR(1)) Variance over time	Lenton et al. 2022 [45]; Rocha et al. [22]	E.g. Southern-India displays areas with some of the highest AR (1) found globally suggesting low resilience in particular for dry deciduous forests where the sugar crops can co-occur [45]	E.g. The identified EEZs show symptoms of resilience loss according to more than one EWS. The EEZs belong to the Temperate Northern Atlantic marine realm showing loss of resilience in approx 35% of its area [20].
	Can feedback amplify the risk of regime shift?	Causal diagrams		Regime shift database [30]	E.g. Regime shifts have not been detected in terrestrial environments in India	E.g. Potential link between sea warming and decrease at weigh age for fish species is discussed. Potential link between deepening of the winter mixed layer depth and increased chlorophyll concentration is also suggested. Further causal analysis needed (case studies in [30]).

Note: The steps to identify potential exposure of a company in a given industry from a given country to ecosystem regime shifts. This is different from company-specific exposure as two companies from the same industry with headquarters in the same country will have the same exposure. Conversion from ISIC code to NACE code requires conversion tables available in trade databases. Proposed state-variables and early-warning indicators are meant as a starting point and not as the only variables to be used. Apart from querying databases and overlapping spatial datasets, no other analyses are needed in the proposed steps, however the application of early-warning indicators should be always used with scientific consultancy.

Gaps and Future Directions

We are still far from any accurate detection of financial exposure to ecological regime-shifts. A major reason for this is the lack of information of actual location of production sites which forces us to currently rely on various input-output tables and statistics amassed at the level of nations or based on industry averages. Needless to say, estimates of exposure to ecological regime shifts based on such data can, at best, only be rough guesses since neither companies nor third party observers actually know where the input materials for any given product is actually sourced form. Improved supply chain transparency would allow companies to better understand their own supply chains and through this also gain an improved and more reliable assessment of their ecological regime shift exposure.

The Global Reporting Initiative (GRI), the European Sustainability Reporting Standards (ESRS), and the Taskforce on Nature-related Financial Disclosures (TNFD) all represent emerging standards and frameworks for publicly disclosing non-financial information, such as location of individual operating sites and ecosystem dependencies. If adhered to, and if locations of the full range of production sites are actually disclosed, these should greatly improve our collective ability to link production sites to ecosystems and risks of regime shifts.

In addition to company reported data, the connection of economic flows (as a proxy for company activity data as suggested in table 1) need an increased detail in trade databases (e.g. supply from lower administrative areas) to allow accurate correspondence to land-use change. Regarding commodity extraction, in particular of non-agricultural commodities, the efforts by Maus et al. [52] are valuable but don't distinguish between different types of extracted materials (e.g. metals or minerals). Global maps seem to be absent for the extraction of other resources such as fossil fuels, non-metallic minerals like salt, sand, and gemstones/diamonds. We envision a platform similar to the Global Forest Watch (globalforestwatch.org) where extraction of commodities from natural resources could be systematically monitored and assessed.

Only when more detailed data about economic activities meet more accurate information on change on land-use and ecosystem functions, can the exposure of companies and investors to regime-shifts become reliable [48]. Such a development would also allow for the calibration of available early-warning frameworks to local conditions, and standardise frameworks for early-warning signal detection [56,57]. Based on recent technical developments these frameworks could also allow for the incorporation of feedback mechanisms [58].

Conclusion

We reviewed progress on methods connecting different databases on company activity and ownership with methods of regime shift detection. The understanding of how companies' activities are exposed to the risk of regime shifts and impact on the environment remains a key challenge and is an open area for research. We highlighted two outstanding challenges: data transparency and impact attribution. Further progress depends on active collaborations between businesses, government and scientists and will require open data to speed up discovery as well as opportune management actions.

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Glossary

Cascading-effects

Chain reaction where a small initial change triggers a series of subsequent changes, often amplifying the original impact. This can happen due to interconnectedness and feedback loops within the system but does not require a two-way interaction.

Causal diagrams

Visual tools used to represent the cause-and-effect relationships between variables within a system. Typical included components are: Variables - the key elements within the system; Links - represent causal relationships between variables; Loops - a chain of links forming a closed loop.

Critical slowing down

As a system approaches a tipping point, its resilience decreases, and it takes longer to recover from disturbances. This can be seen in the recovery rate after a perturbation.

Early-warning signals

Statistical indicators that can help us anticipate an impending regime shift in an ecosystem. These signals arise as the system approaches a tipping point, where a small change can lead to a sudden and irreversible shift to a new state. Critical slowing down and increased variance are typical early-warning indicators.

Feedbacks

Circular causal relationships, (i.e. a two-way ínteraction) where the output of a system influences its input, leading to either amplification or dampening of change.

Financial portfolio

Collection of investments, typically including a mix of assets (e.g. stocks, bonds, real-estate), held by an individual or an organisation with the purpose to achieve financial goals, such as retirement savings or wealth accumulation.

Reanalysis data

Comprehensive and long-term datasets that combine observational data from multiple sources like remotely sensed data and field data with advanced prediction models.

Footnotes

1 Key terms used in this article are defined in the Glossary.