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Fast tracking tool selection for sustainability decisions

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Abstract

Non-technical Summary. In decision-making, especially for sustainability, choosing the right assessment tools is crucial but challenging due to the abundance of options. A new method is introduced to streamline this process, aiding policymakers and managers. This method involves four phases: scoping, cataloging, selection, and validation, combining data analysis with stakeholder engagement. Using the food system as an example, the approach demonstrates how practitioners can select tools effectively based on input variables and desired outcomes to address sustainability risks. This method can be applied across various sectors, offering a systematic way to enhance decision-making and manage sustainability effectively.
Technical Summary. Decision making frequently entails the selection and application of assessment tools. For sustainability decisions there are a plethora of tools available for environmental assessment, yet no established and clear approach to determine which tools are appropriate and resource efficient for application. Here we present an extensive inventory of tools and a novel taxonomic method which enables efficient, effective tool selection to improve decision making for policymakers and managers. The tool selection methodology follows four main phases based on the divergence-convergence logic; a scoping phase, cataloging phase, selection phase and validation phase. This approach combines elements of data-driven analysis with participatory techniques for stakeholder engagement to achieve buy-in and to ensure efficient management of progress and agile course correction when needed. It builds on the current limited range and scope of approaches to tool selection, and is flexible and Artificial Intelligence-ready in order to facilitate more rapid integration and uptake. Using the food system as a case study, we demonstrate how practitioners can use available input variables and desired output metrics to select the most appropriate tools to manage sustainability risks, with the approach having wide applicability to other sectors.
Social Media Summary. New method simplifies tool selection for sustainable decisions, aiding policymakers & managers. #Sustainability #DecisionMaking

1. Introduction

The global community faces a multitude of difficult decisions across all sectors of society. These decisions involve balancing different factors, for example how to provide more nutrient dense food to tackle the growing double-burden of obesity and micronutrient deficiency with the need to protect and restore our environmental capital (WEF, 2021), or how to make effective use of the outstanding benefits offered by artificial intelligence (AI) whilst avoiding a collapse of our political, financial and healthcare systems (Kelly et al., 2019; Willcocks, 2020). Difficult decisions, such as these, need to be based on evidence in order to be robust and effective. However, making these decisions from scratch is time consuming and complicated. Hence in several fields, assessment tools, which are methodologies developed to evaluate complex situations, and used to identify, quantify, and assess the potential benefits, consequences or risks associated with specific policies, practices, actions, or systems, and to accelerate and ease intervention plans, are used to aid the decision-making process. In the environmental and sustainability fields, numerous assessment tools have been developed to answer questions posed about specific situations, including for example Life Cycle Assessment (LCA) (Chaplin-Kramer et al., 2017), which is used extensively across sectors to evaluate the environmental impact of projects, plans, and products, and Multi-Criteria Assessments (Chaudhary et al., 2017), that enable analysis of a diverse range of socioeconomic and environmental factors by government, statutory bodies, industry, and NGOs.

Yet simply having access to tools does not overcome the initial problem in decision making – specifically which tool to use. As the number of tools increases, often with overlapping functionality, many incorporating sophisticated modeling and simulation capabilities, and increasingly with AI functionality (Konya & Nematzadeh, 2024), selecting the best tool for the job becomes ever more challenging. Environmental managers and policymakers, in particular, do not have the time or necessarily the expertise to explore the intricacies of many tools. Without a clear process for identifying tools there is open scope for inappropriate tool usage, effort duplication, wasted resources, and bad decisions. The importance and effectiveness of good decision making is well accepted in areas such as medicine with EBM (Evidence-Based Medicine) (Sackett et al., 1996) or business with EBMgt (Evidence-Based Management) (Rousseau, 2012). However, while evidence- and tool-based decision making as a concept is widely used in the sustainability field there is not yet an established approach for the rapid identification of the most effective and efficient tools to use in specific scenarios, despite the fact that climatic and environmental change has been identified as the most severe risks to our global society in terms of likelihood and impact (WEF, 2021). This leaves the practitioner facing a potentially subjective and uninformed choice on which tool, from the plethora available to them, best suits their need. In this perspective we develop a novel taxonomic framework for facilitating tool selection and effective decision making for policy and management in the sustainability arena. We demonstrate the utility of our framework by using food production as a case study although our approach can be applied widely.

2. Current status of research in sustainability tools and the need for a new approach

2.1 Status of research in sustainability tools

Research to date in sustainability tools covers four key spheres: reviews of tools and their application to case studies; comparative studies of specific tools; integration of tools into computational models; and frameworks on how to integrate different tools. There are also a diverse range of factors that can influence the way tools are currently selected.

A diverse scientific and institutional literature exists that reviews tools and their application to case studies. In sustainability, these tools are used to evaluate the environmental consequences of products, services, projects, policies and other anthropogenic activities. They tell us whether our actions, in effect, have consequences for the environment. They encompass established systematic examinations, such as LCA or ecological footprint analysis (Loiseau et al., 2012), and also emerging approaches like socio-environmental assessments (Szewrański & Kazak, 2020) and ecosystem services valuation (Costanza, 2020). This literature offers critical insights into each methodology, their applicability across different contexts, and their effectiveness for assessing environmental impacts (Supplementary Information 1).

Some studies compare specific tools and their strengths and weaknesses (Allesch & Brunner, 2014; Andersson et al., 2016; EuropeanCommission, 2010; Finnveden & Moberg, 2005; Hauschild & Olsen, 2018; Lehtinen et al., 2011; Windsor et al., 2018). These studies critically evaluate the risks and uncertainties associated with specific tools, and some advise on the most appropriate contexts to apply them. For example, Grout et al. (Grout et al., 2018) compared eight different tools for assessing the environmental impacts of agricultural systems. They selected Health Impact Assessment (HIA) for New Zealand's dairy sector as it was the only tool that covered environmental, health, social, and economic aspects, and that was designed to assess the impacts of a proposed policy. The problem with this approach is that it makes use of the selected tool relatively inflexible – in this case HIA is not appropriate for analyzing alternative scenarios – meaning new tools have to be selected.

Efforts have also been made to integrate sustainability tools together in various ways. These include conducting post-hoc analyses of results from different tools, combining results and modifying the underlying methodology, or incorporating additional indicators to enhance an analysis. Computational predictive tools and models are becoming increasingly important in tool integration. For example, the MIT Integrated Global System Modelling (IGSM) Framework (Reilly et al., 2013), the Integrated Model to Assess the Global Environment (IMAGE) (Teillard et al., 2016), GCAM v5.1 Model (Calvin et al., 2019), E3ME-FTT-GENIE (Mercure et al., 2018), and SEAMLESS (van Ittersum et al., 2008). Each is designed to explore potential development pathways and provide a set of scenarios showing the time-dependent evolution of environmental, human and ecosystem health indicators, and other socio-economic parameters. These models can however suffer from imbalances between the dimensions they consider, and may not always scale well. For example there is still uncertainty as to whether SEAMLESS can effectively be upscaled beyond its test case and whether it can cope with the environmental externalities of farming systems assessed with large bio-economic farm models (Grout et al., 2018; van Ittersum et al., 2008).

Frameworks have been developed to integrate different tools, with prominent examples including the Life Cycle Sustainability Assessment (LCSA) (UNEP/SETAC, 2011) and Environmental Impact Assessment (EIA) (de Ridder et al., 2007; EuropeanCommission, 2014, September, 4). For LCSA, while there are case studies of application, the framework is not widely used as it still requires further scientific work on method integration and on harmonization of procedures in presenting and interpreting the results. EIA was implemented by the European Commission with a corresponding Directive 2011/92/EU.

The selection of appropriate tools can be influenced by a range of factors, including the topic or issue to be investigated, the scope and complexity of the project or activity under consideration, the relevant environmental indicators to be considered, legal and regulatory requirements, the need or otherwise to consider stakeholder and public involvement, availability and quality of data, technical expertise required, and the cost of the tools and specialist databases (Hemming et al., 2022; Wong-Parodi et al., 2020). For example, in industry, the use of Environmental, Social, Governance (ESG) assessment tools is gaining traction, primarily driven by regulatory reporting requirements in the financial sector (Baratta et al., 2023); in food production applications, LCA is widely deployed for product and supply-chain assessment where process input and output data are readily available; and at the global level tools such as the IPCC models are more appropriate for assessing and intervening on climate, biodiversity and disease spread issues (Rocklöv et al., 2023).

Managers may select tools in a variety of ways; they may re-use a tool they are already familiar with, they may ask colleagues for advice or they may make use of some of the reviews or comparative studies described above. Their approach to tool selection will depend on their experience level, available time, and financial resources but, with so many tools available, this can be a daunting task. Problematically, there are many pitfalls to tool selection – ranging from negligence in not investing the required time or resources to research appropriate tools, to more nuanced and complex factors. These include overlooking context-specific factors or ignoring the dynamic nature of environmental systems, such as failing to adequately consider biodiversity dependencies in industrial and agricultural practices (van der Werf et al., 2020), or failing to consider social dimensions in assessments (Pollok et al., 2021). Certain well-established tools, such as LCA and ecological footprinting (Mancini et al., 2016), may become the default choice for a sector, even when more suitable tools may exist. For example, LCA, while excellent for assessing impact of a production system on the environment, is typically unsuited for the reverse, in considering impacts of the environment on the production system (Hauschild & Olsen, 2018). As our understanding of the interconnectedness of complex systems grows, the deficiencies of these tools become more apparent. Furthermore, in many instances there is a preference for quantitative data, but this may overlook important qualitative socio-economic nuances, stakeholder preferences, and other less tangible considerations. Perhaps the biggest pitfall in tool selection relates to lack of knowledge and lack of capability in a given organization. Organizations may only be aware of the tools that are either prescribed by regulators or are a standard in their industry – there is no robust classification of the tools or a comprehensive overview of what types of issues they can assess – the gap that we address with our research program.

2.2 The need for a new approach to tool selection

Various frameworks and guidelines do exist to assist practitioners in selecting suitable tools in some contexts. These include the ISO 14001 standard for environmental management systems, which offers a broad framework that, while not specifying particular tools, focuses on incorporating environmental considerations into organizational decision-making. Sustainability Assessment Frameworks like the Comprehensive Assessment System for Built Environment Efficiency (CASBEE) (bin Hishammuddin et al., 2019), provide a suite of tools for assessing sustainability and making informed decisions based on specific criteria. LCA, although a tool itself, is also a framework offering a structured approach for assessing environmental impacts throughout a product's lifecycle that can incorporate other tools to provide a more holistic perspective. Guidelines from environmental agencies and international organizations, such as the United Nations Environment Programme (UNEP) and the European Environment Agency (EEA), provide additional resources and recommendations for tool selection tailored to specific needs.

However, despite these frameworks and guidelines, and the diverse research on tools, their strengths, weaknesses, and integrations, there is not yet an effective tool selection process or database with global applicability across a wide range of sectors. A large number of studies use sustainability tools (see Supplementary Material 1), but they lack comprehensive explanation regarding the rationale behind tool selection, weakening confidence that these are the most appropriate tools to address the requirements of the intended decision making process (Viola & Marinelli, 2016). Where studies do provide rationale on selection, it is typically limited to the specificities of that study, and so lacks the flexibility to adapt to different input or output data, which could lead to decision making errors if implemented elsewhere. Furthermore, current studies frequently do not include an approach to effectively manage practitioner engagement during the development and subsequent roll-out of the tool, which is imperative for tools designed for use by practitioners (Ness et al., 2007). A robust rationale, flexible application, and method for stakeholder engagement are critical requirements for a tool selection process to have broad applicability in making difficult decisions (Alrøe et al., 2016; Cucurachi et al., 2019; Onat et al., 2017).

The consequences of using inadequate environmental assessment can be severe, ranging from environmental degradation and loss of biodiversity to social unrest and economic losses, underscoring the need for thorough, context-sensitive environmental assessments (Morgan, 2012). Where large infrastructure projects, like dams, roads, or mining operations, have been planned in ecologically sensitive areas, the use of EIAs is commonplace, but they may fail to fully account for biodiversity loss, habitat fragmentation, increased poaching or illegal logging, among other problems. For example, the controversial development of the Belo Monte dam in Brazil, where the construction and 60% river flow reduction caused by the dam operations destroyed the livelihoods of 20,000 people – and a more robust quantification of potential negative impacts following a correspondingly robust tool selection process may have helped to sway political stakeholders to implement further mitigation measures (Kraljevic et al., 2013). Similarly, agricultural development projects that rely on simplified environmental assessments may overlook the cumulative impacts on watersheds and water resources, leading to unsustainable water use, degradation of water quality, and conflicts among water users. This was seen in the Aral Sea disaster, where implementation of irrigation schemes using tools that did not adequately consider the downstream effects on water availability for other users or ecosystems (Micklin, 2007).

Given the current lack of an effective tool selection process we aimed to develop a solution. Since it is at the heart of human needs and draws from nature, we used the global food production system as a sustainability case study, working with the UK Centre for Environment, Fisheries and Aquaculture Science (Cefas). Cefas are working with governments, academia, and NGOs to maximize the social, economic and environmental sustainability of food production, collectively under the banner of One Health.

Cefas are spearheading their efforts via their 'One Food' project (Cefas, 2024, April 17). This aims to develop a groundbreaking system that places hazard profiling and management at the heart of environmentally, economically, and socially sustainable food system design. The project will develop a systems-based approach to comprehensively map terrestrial and aquatic food sectors and scenarios and their potential to interrupt safe and sustainable supply chains. A comprehensive mitigation plan will be developed by analysis of supply chain options for hazard control. The project aims to visualize and realize the benefits of this approach via calculation of the impact on key indicators associated with the Global Burden of Animal Disease (GBAD), Global Burden of Crop Loss (GBCL) (Rushton et al., 2018), biodiversity, and climate efficiency.

A core component of the One Food project is the development of the Risk Tool (Cefas, 2023, September 7). The tool aims to generate an understanding of the multiplicity of hazards across food sectors, allowing users to identify priorities for mitigation, explore trade-offs between different hazards and food sectors, and understand the possible outcomes of mitigation interventions. The tool

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requires the selection of a robust environmental impact assessment method to provide it with information on the environmental implications of food production. The environmental challenges associated with food systems will vary according to country-specific geographical and socio-economic circumstances, meaning wide variations between applications. Consequently, the selected method needs to be adaptable to a multitude of circumstances and sectors. It, much like broader initiatives, thus requires an effective and widely applicable tool selection methodology.

3. A methodology for fast tracking tool selection

Here we provide a novel methodology for flexible and efficient identification and transparent selection of tools to support sector-level analysis and decision making by policymakers and managers, ensuring a holistic approach to assessment. The intention is to encourage thought and promote a default practice in which organizations proactively review and make a measured decision on what tool they intend to use before initiating an action. This can apply to interventions including addressing anthropogenic impacts on the environment, biodiversity, resource availability, and threats and risks to food production systems.

Our methodology improves on previous frameworks by enabling fast track high-quality decision making in food production systems, and meeting current needs for a system with robust rationale, flexible application, and a method for stakeholder engagement. We illustrate the approach with the case study of the One Food project.

The methodology (Figure 1) consists of four main phases based on the divergence-convergence logic (Kerr et al., 2013). Firstly, identifying the focus area, objectives, and frame of reference for the industry or regulatory body. Secondly, cataloging the tools used in industry, policy, and academia. Thirdly, selecting a suite of tools, and finally, validation. This approach combines elements of data-driven analysis with participatory techniques for stakeholder engagement to achieve buy-in and to ensure efficient management of progress and agile course correction when needed. In our case study we established an interdisciplinary team of researchers and users with experience in industry and policy advice.

3.1 Scoping

The first step of the methodology is to establish specific objectives and a shared understanding of what is in and out of scope and thus narrow down potential tools. This 'scoping' phase is critically important and is the first point of failure in a tool selection process. If the practitioner fails to conceive the system boundaries correctly and the relevant inputs, outputs, risks and hazards, the tool selection may miss key dimensions – leading to failures, as described in 2.2 (Kraljevic et al., 2013; Micklin, 2007). Further scope refinement takes place by capturing key stakeholder requirements, corresponding to different decision scenarios, which are amalgamated into a single set of requirements. In the case of the One Food project, this included specific environmental issues and risk categories, and national priorities for reduction of food waste/loss based on the economic benefits and consequences to the environment and identifying least harmful food production methods as targets for new policies. Typically, this scoping process is iterative between the research and stakeholder team members, leading to a detailed outline of the overall study program.

3.2 Creating a catalog of tools

A landscape of potential tools is then created through a rapid, but comprehensive, literature scan conducted in a systematic and transparent way. This can include using academic search engines, such as Google Scholar and Web of Science, via appropriate search terms. Many tools have also been developed outside of academia in multilateral organizations and are deployed more often by industry and policymakers. Thus, institutional and industrial reports and databases can complement the scientific literature (i.e. the gray literature) – examples from our case study include the FAO, MSC (Marine Stewardship Council), Seafish and Mowi (Supplementary Data 1). The broad scope of the One Food project resulted in an extremely large number of hits, and therefore to decide on our search terms, we used pilot searches to give us a broad range of articles from which to launch our literature review. In addition to desk-based literature review, we conducted qualitative research through discussion with our panel of experts to gain additional data outside of the main searches. For the literature review, we applied the principle of diminishing returns, which provided confidence that we identified the majority of reported tools from different sets of literature, and documented the progress with a discovery curve analogous to species recovery curves used for assessing survey completeness (Colwell & Coddington, 1994). The output of this activity undertaken as part of this study is provided as supplementary data to this article (Supplementary Data 1), and serves as a comprehensive database for future tool selection activities, subject to periodic review and update.

Next, the identified tools are grouped into categories and organized in a structured way; a 'taxonomy'. The literature presents various categorizations of environmental and broader sustainability assessment methods, for example, based on indicators or indices suites for specific sectors, product-related groupings, procedural *vs* analytical approaches, or whether it is a framework with integrated tools (de Ridder et al., 2007; Finnveden & Moberg, 2005; Loiseau et al., 2012). By combining these approaches, we used the underlying characteristics and applications of the tools and clustered them into groups for the taxonomy. The taxonomy is a tool itself that enables the industrial sector to identify the input metrics it has available (Figure 2), and from this identify the tools that could be integrated to build a more complete analysis approach with greater relevance to the sector (Figure 3). In policymaking by government or regulatory bodies, the taxonomy could provide a method for more efficient use of economic resources and to improve policy complementarity. By using the taxonomy to identify desired output metrics (Figure 2), this can allow the practitioner to select the most efficient possible range of tools that can deliver these outputs, helping minimize investments of time and economic resources.

The taxonomy consists of four layers, or 'tiers'. Tier 1 subdivides the tools into 'scope models', focused on an assessment over a specific spatial, economic, or population scale, and 'flow models', evaluating input and output flows within pre-defined system boundaries, where any spatial, population, or economic focus is secondary. Tier 2 encompasses six subcategories. Spatial models focus on assessing a system in space; they estimate the impact of activities and interventions within the defined spatial boundaries and provide a zonation structure for management. Economic models focus on assessing the yield or weighing up the costs and benefits of a certain production system or approach. Population models focus on a given population of a species and

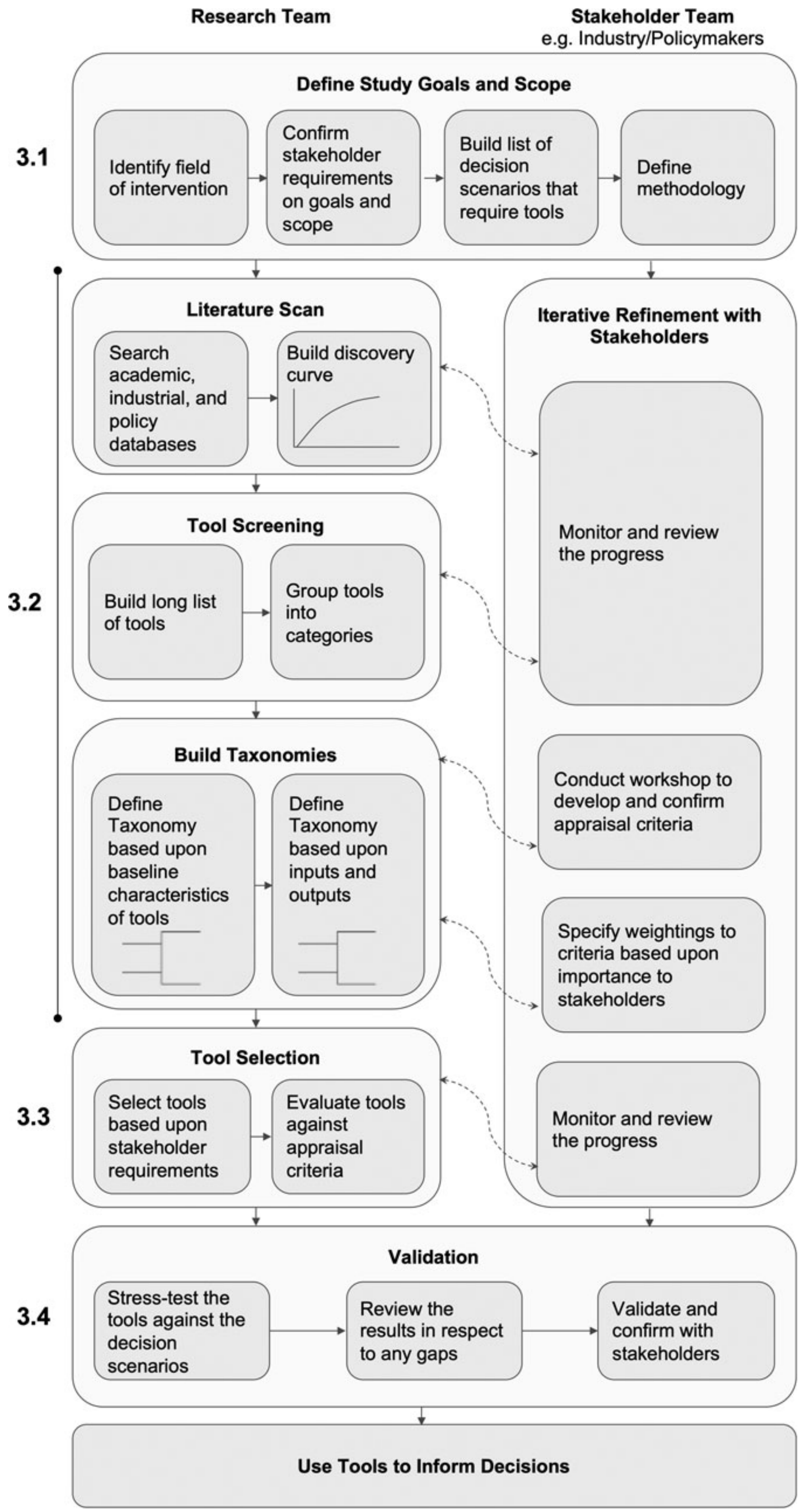

Figure 1. Methodology for fast-tracking tool selection. The numbers on the left hand side refer to the steps outlined in section 3 of the manuscript.

are used to evaluate risks from a set of activities in order to inform population management. Hazard assessments focus on hazards, which are sources or situations with potential to cause harm to the environment, ecosystems and humans; these tools look at individual or multiple hazards associated with a defined production system or activity. Environmental systems approaches are categorized as ‘a system that is based on the natural environment and includes biotic and abiotic components which interact’ (Park

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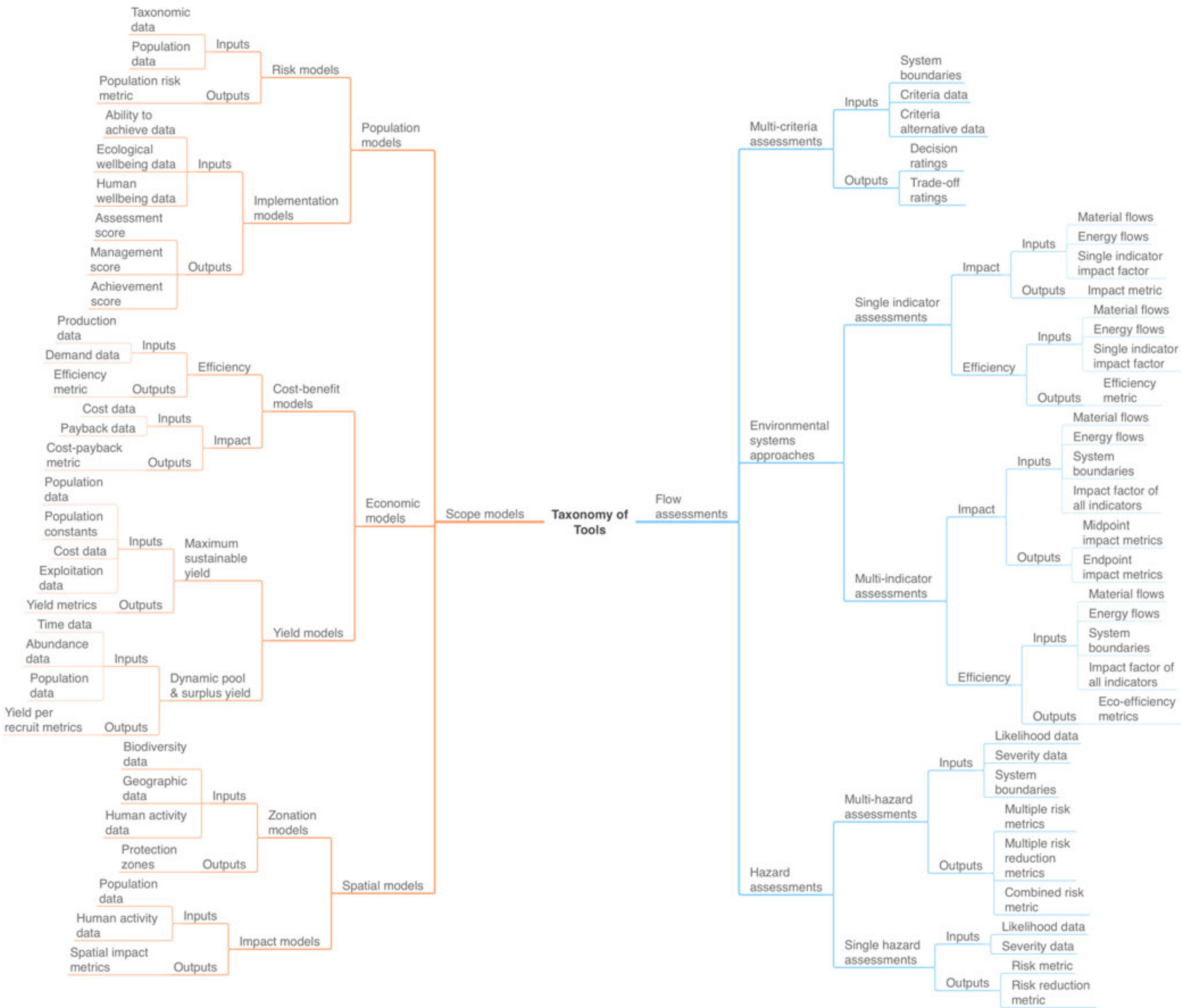

Figure 2. Taxonomy of tools – Inputs and Outputs. The figure shows the taxonomy of tools containing key inputs and outputs at the fourth tier. This would be used by the practitioner to select relevant tool types based upon available input variables and desired output metrics.

& Allaby, 2013); they incorporate life cycle analyses, which typically quantify the environmental impact of a system/product-/service using either a single or multiple indicators, and frameworks integrating additional perspectives, such as economic, and social. Finally, the category of Multi-criteria assessments aims to integrate an interdisciplinary suite of indicators that describe specific aspects of environmental assessment, which are then assessed across a set of criteria to support a specific decision-making process. Further sub-division at Tier 3 groups tools by single/multi-hazard or single/multi-indicator.

A clear definition of the Tier 1 and 2 categories in the taxonomy is fundamental, as these drive the number and type of tools that end up in the final selection by the stakeholder. During the definition process of the taxonomy architecture for the One Food project example, we maintained a focus on a sector-independent character when selecting and defining the levels, as the taxonomy needs to be applicable to a wide range of topics and challenges relevant to the project stakeholders. As the search for the tool landscape was not specifically focused on the food system, we expect the taxonomy to be universally applicable to any type of sector. If the categories are too broad there is a risk that insufficient tools are selected to assess all relevant areas of impact, if categories are too granular this can result in too many overlapping tools, and if a category is missing then an entire tool type or area of impact could be excluded from the final selection. Figure 2 illustrates the taxonomy developed for the One Food project, its substructure based on the tiers and at the lowest level of detail it summarizes the different inputs required by the tools in each category and the main types of the output information and data resulting from the assessments with these tools. Figure 3 shows the taxonomy with its architecture and the different examples of tools within each category; the full list of tools is included in Supplementary Data 1.

3.3 Tool selection

A structured selection process is then used to select a suite of tools for the end user. Any 'no-go' or 'must-have' stakeholder

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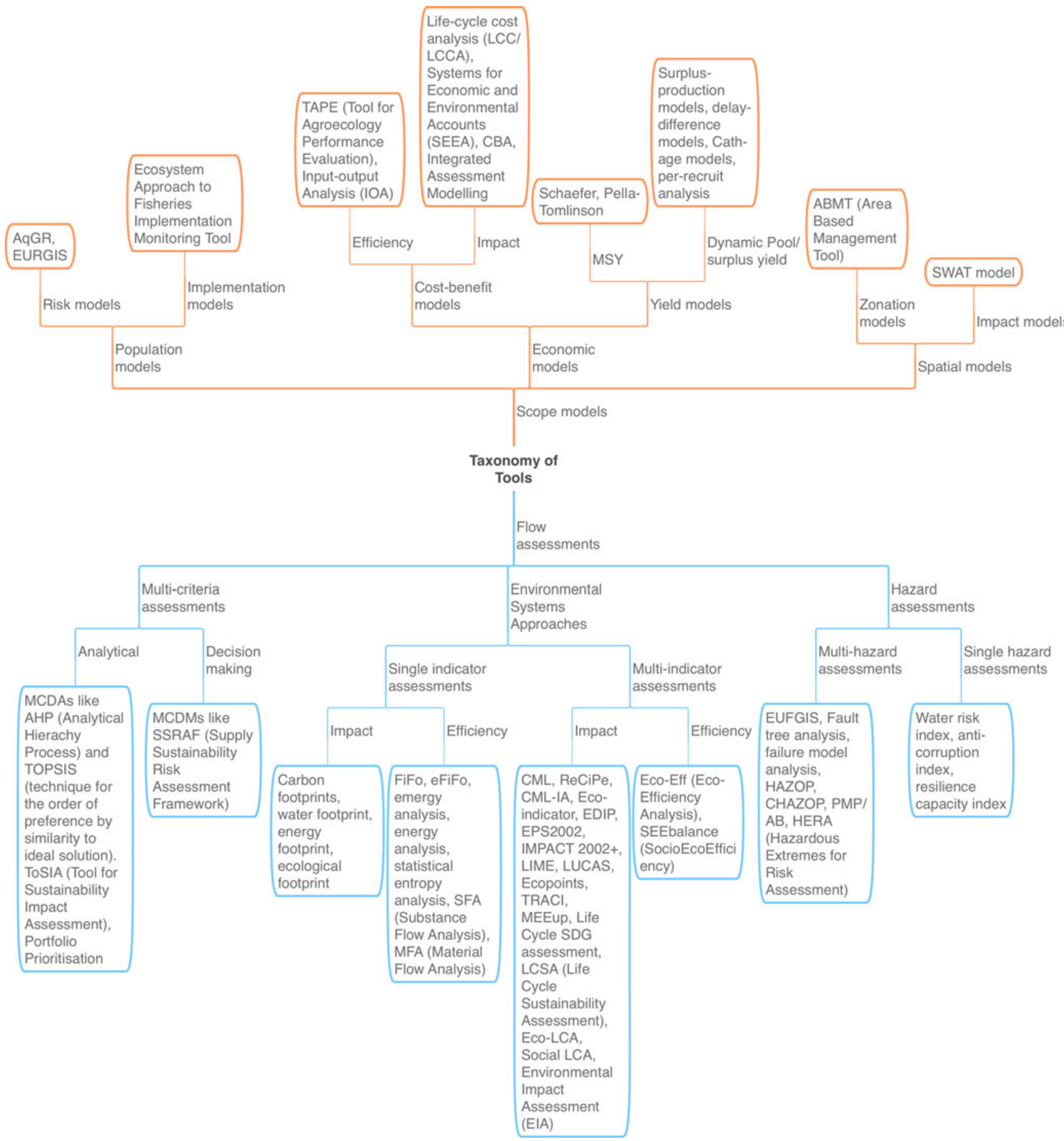

Figure 3. Taxonomy of tools – One Food Tool Examples. The figure shows the taxonomy of tools in which the fourth tier contains the specific tools applicable to the One Food case study. In the One Food case study, the practitioner would use this to identify specific tools having selected the appropriate tool types using Figure 2.

requirements (in our example applicability to food production or a sufficient maturity level for practitioner deployment) can be used for an initial pre-selection and followed by a more detailed evaluation. Assessing the tools is a substantial part of the process and comparing the various tools within each category to make the final selection involves many trade-offs as all have different strengths and constraints. This could be a very difficult part of the process for users because it requires a reasonably good knowledge of the tools, so a guiding mechanism is needed to support the decisions. These trade-offs will always be project and context specific, but the creation of a set of appraisal criteria provides the mechanism for structuring and prioritizing tools to reach a solution. A facilitated workshop that brings all team members together is an efficient technique for developing appraisal criteria. Through workshop discussions with the stakeholders, we identified ten criteria and reflected their importance to the One Food Risk Platform using weightings as shown in Table 1.

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Table 1. Criteria and their weighting as defined for the One Food project example

Appraisal criteria	Weighting
1. Degree of stakeholder acceptance and suitability for business and policy contexts: Method maturity, proven real-world usage, scale and trends of deployment, influential/global actors using method	Very important
2. Scientific rigor, robustness, and certainty: Are the outputs objective, reliable, consistent, are of high validity, and also provide a measure of uncertainty? Are the allocation methods (e.g. in impact assessments) robust, proven, and up-to-date?	Very important
3. Applicability and flexibility: Can the method be applied generically to all different food sectors or more than one simultaneously, and differing regions and contexts?	Very important
4. Input data readily available and accessible freely: Input data availability and accessibility, flexibility to cope with data of different levels of quality, completeness, and complexity, and quality/variability of data sources	Very important
5. Method outputs easily interpretable and understandable by a broad audience of decision-makers	Very important
6. Application of the method without substantial investments of time and resources: Independence from resources required for application – fieldwork, equipment, etc.	Very important
7. Availability and accessibility of the method itself: Open-source / restriction-free use of method vs. subscription/private models.	Moderately important
8. Method can be used to assess trade-offs or different scenarios	Moderately important
9. Documentation, transparency, and reproducibility: Documented guidelines for use, ISO standards, regulatory directives, legislation.	Moderately important
10. Method integrates with or complements other methods	Less important

Note that for application to other projects the level of weighting applied to each criteria may differ.

3.4 Validation

The final step in the methodology is validation. This requires close collaboration between both researchers and stakeholders to stress-test the performance of the tools, to assess if there are gaps in what and how results are presented and whether they are applicable to the stakeholder's aims. In our case study, the selected tools were validated by (1) assessing the ecosystems types (marine, freshwater, and terrestrial) covered; and (2) coverage of various indicator categories, for example ecosystem functions and services, environmental impact categories, spatial and temporal metrics, and biosecurity. We identified 188 tools, which were reduced to 53 tools through taxonomy and screening based on the criteria in Table 1 (Supplementary Data 1), and further screening allowed us to identify five tools most applicable for the specific intended food systems evaluation by the One Food Risk Platform. These were Life Cycle Analysis (LCA) with ReCiPe 2016 and BioScope, Life Cycle Sustainability Assessment (LCSA), Ecosystem Approach to Fisheries Implementation Monitoring Tools (EAF-IMT), Rapid Agricultural Supply Chain Risk Assessment (RapAgRisk), and Soil and Water Assessment Tool (SWAT). Underlying information can be found in the comprehensive database in Supplementary Data 1. The selection above should be treated as an example only, and any given use case will have its own requirements for the best applicable tools. We emphasize that the 'gap testing' component of validation is critically important and should be iterated several times during the validation step. There may be instances where a small suite of relatively generalist tools cover the vast majority of categories effectively, but that leave open a small and specific but important impact category, which should be covered by an appropriate 'add on' tool.

4. Applying the new methodology to drive impact

By providing a taxonomy we aim to open the door to a wave of new sustainability methodology to drive impact. There are specific ways in which the taxonomy, as illustrated by Figures 2 and 3, should be applied for effective tool selection. As we highlighted earlier, a practitioner would consult the taxonomy (e.g. Figure 2) with a specific set of desired output metrics (e.g. impact metric, efficiency metric), or a specific set of input variables available to them (e.g. energy flows, material flows, system boundaries), or a combination of the two, and would identify these on the smallest branches of the tree. They would then work back up the branches of the tree to identify which category of tool would be most appropriate for use (e.g. environmental systems approaches, multi-indicator assessments). The practitioner would then refer back to the taxonomy (e.g. Figure 3) to work down from the tool category they have identified (e.g. multi-indicator assessments, impact) to select candidate tools from the list in the smallest branch (e.g. SimaPro, ReCiPe), and assess which would be most appropriate for their application, data availability, and desired outputs.

In the case of the One Food project, the taxonomy of tools as a working model is now being used to support new efforts that will drive impact in decision-making on food systems interventions. The tools identified as most applicable for food systems environmental evaluation are being integrated into the evidence base for the One Food Risk Tool so that the interventions the tool explores can be assessed using defensible methodologies. The final One Food Risk Tool, which remains under development, will comprise an integrated scoring system and visual representation of the hazard impacts for the whole food system and its component parts, and a risk mitigation matrix to quantify the benefits of hazard intervention. Making our taxonomy of tools selection approach publicly available is a key component of the One Food Risk Tool pathway. By ensuring our flexible and working model is accessible we allow for academic and stakeholder discussion, constructive criticism and manipulation of the approach before and as it is applied to diverse scenarios, facilitating optimal tailoring and refinement. It also ensures the tool is tailored with as generic a form as possible, reducing the cost and time required to a wider range of sectors. Crucially, it also allows exposure to other fields of scientific expertise, in particular AI, where the rapid rate of technological progress could facilitate rapid integration of the taxonomy of tools model into existing systems, and aid in filling out existing gaps such as the lack of needed and appropriate primary data in certain areas of application.

AI is set to play a powerful role in accelerating the development and integration of the taxonomy of tools approach, and in making the pre-assessment process we outline more time and cost effective. Off-the-shelf AI tools are already becoming increasingly competent at summarizing and extracting information from the scientific literature (de la Torre-López et al., 2023; Richards et al., 2024; Scheepens et al., 2024) and with effective prompt engineering (i.e. crafting queries for tools such as ChatGPT Clavié et al., 2023) they could help to come up quickly with an initial list of tools that could be supplemented by expert input – reducing the time spent searching for tools (i.e. reaching a higher point on a discovery curve more quickly). Furthermore, machine learning clustering techniques could help to speed up the process of developing an initial taxonomy that could be refined and expanded again with expert input. Assessment of different tools against criteria currently requires quality reasoning skills and more explainable AI that is currently lacking (although may develop in the near future Rawal et al., 2022), which means expert input will still be required to critically appraise each tool. However, using AI for the previous steps of summarization and classification may still help accelerate this appraisal process. Few examples of AI-assisted tool selection currently exist, but those that do typically focus on situations where a objective function can be defined to optimize for different quantitative values such as in selecting cutting tools in engineering (Saranya et al., 2018), whereas risk-based tool selection, as this paper presents, often requires more qualitative, nuanced criteria and deliberation, although ordinal categories could be used, for example, low, medium, high, to provide an initial assessment. Nevertheless, machine learning and AI in general, particularly through using decision trees, could be highly useful for not only clustering tools based on summarizing their attributes, but also generating interactive guides to help users select tools based on their individual preferences and selection criteria. Currently, there is a trend towards making clustering and thus taxonomy building more interpretable for this purpose (Bertsimas et al., 2021).

With further information integration using approaches including AI, the taxonomy of tools has potential wide and high impact for industry and policymaking beyond the One Food project, being applicable to a wide variety of other non-food sectors, and also to specific sub-sectors of the food system with their own unique needs. For example, the mining and extraction sector, which like food production has a close connection to the environment, currently tends to use EIA (Environmental Impact Assessment) and often places most emphasis on LCA to monitor its environmental and carbon footprints, like many industrial sectors (Sida, 1998). However, as we have argued, this approach may miss the many other potential risks to, and impacts caused by, the sector, if the correct type of LCA or combination of LCA with other tools is not selected. For example deforestation and habitat destruction, soil erosion, biodiversity loss and human-wildlife conflict, impacts on watersheds, and the potential hazards for the sector associated with climate change such as flooding and inundation, destabilizing of ground or strata failure, which should be included alongside or within LCA (Wang et al., 2021). Our approach has clear benefits for policymaking because the taxonomy provides a robust and defensible tool selection process. By using the taxonomy to identify desired output metrics, this can allow the practitioner to select the most efficient possible range of tools that can deliver these outputs, helping minimize investments of time and economic resources. A similar approach could be used to identify relevant tools for analysis of the broad range of social and economic or public health impacts. The taxonomy selection approach also has the capability to be applied to more specific but still highly diverse sub-sectors of the food industry, such as the aquaculture sector. The aquaculture sector is already one of the most progressive food sectors and utilizes a wide range of sustainability key performance indicators (KPIs), ranging from Feed Conversion Ratios to animal escape incident percentages to benthic impact metrics (MOWI, 2023). However, the relative importance of KPIs can easily become lost amongst such complexity, which can lead to an overzealous focus on some metrics at the expense of others, for example on carbon footprint, when other factors such as harmful algal blooms and antibiotic resistance may pose a far greater risk (Quiñones et al., 2019). Here a formal weighting process as present in parts 3.2 and 3.3 of our approach can help provide clarity, and identify which specific impact metrics play the most important role in a given risk scenario.

5. Conclusion

At present, there is not a 'one size fits all' tool for environmental hazards and impact assessment but a plethora of tools, and no one tool can do the entire job. This means that policy decision-makers and industry face the challenge of selecting from a range of different tool options and being able to adequately justify their choice in decision making. The approach we developed for fast tracking tool selection provides an effective, transparent, and repeatable methodology that improves decision making. It is agnostic and can be used for any analysis that requires selection and deployment of multiple tools. Customizing the tiers in the taxonomy can enable universal applicability across sectors. We applied this approach and developed a taxonomy of tools in the context of food production systems. This allowed visualization of how tools relate to each other, and in the case of the One Food project is allowing the development of the One Food Risk Platform to provide effective simplification to decision making.

The taxonomy approach builds on and provides a valuable addition to the currently limited range and scope of approaches discussed in the literature for tool selection. Unlike approaches we discussed earlier, such as ISO 14001, the taxonomy of tools specifies particular tools, facilitating more specific decision making by practitioners. The taxonomy of tools is also less restrictive in its range of available tools than approaches such as CASBEE which are very much focused on the built environment (bin Hishammuddin et al., 2019), or LCA which is in essence just one tool. Crucially, the taxonomy of tools is also one of the first approaches specifically designed with AI in mind, with the vision that AI systems can allow key data gaps regarding inputs and primary data to be plugged more quickly, facilitating more rapid model optimization and application over time.

There are still hurdles to overcome and extensive space for development and optimization. There is a need for improved approaches to integrate different tools. Our analyses for the One Food project indicate this will be difficult, but that comprehensive analysis can still be achieved, by using detailed maps of inputs and outputs for each tool to identify information overlaps, and what flows can be assessed in parallel or as synergies and which flows can be inputs to another method. There is also a need to streamline data collection, accessibility, and quality to avoid magnification of errors during modeling, avoid double counting, and ensure optimal compatibility of tools. We also encourage the establishment of a robust method appraisal framework across sectors, as was done in the One Food project, to validate tool selection approaches and ensure they are highly relevant.

In summary, the novel taxonomic approach developed here provides an easy-to-use way for practitioners to identify available input data variables and desired output metrics in order to select the most appropriate tools to manage a given sustainability risk. The approach is flexible, adaptable, and has global applicability across sectors needing to make difficult decisions in an efficient and effective manner.

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