

SIM4Action: An Interactive Platform for Social-Environmental Systems Mapping and Causal Analysis

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SIM4Action: An Interactive Platform for Social-Environmental Systems Mapping and Causal Analysis

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Abstract

SIM4Action is an open-source, browser-based platform for participatory analysis of complex socio-environmental systems through interactive causal network graphs. Existing systems mapping tools require practitioners to combine separate software for map construction, network analysis, and causal simulation; none provides an integrated workflow accessible to non-technical stakeholders. SIM4Action addresses this gap through a three-stage adaptive management workflow—Understand, Intervene, Monitor—implemented as dedicated analytical laboratories offering feedback loop detection, community detection, token-based causal diffusion simulation (probabilistic and deterministic modes with forward and backward propagation), multiple centrality metrics for leverage point identification, and a genetic algorithm optimiser for intervention resource allocation. Python’s scientific stack runs in-browser via Pyodide/WebAssembly, enabling zero-installation deployment. A domain-agnostic, configuration-driven architecture serves multiple system maps, each defined by a Google Sheets data source and a JSON configuration file; core analytical libraries are independently importable for scripted research pipelines. Co-designed with stakeholders over six years across seven funded projects spanning Australia, Chile, Peru, Finland, and the Western Indian Ocean region, the platform currently hosts over ten deployed system maps spanning fisheries, water governance, lithium extraction, and social welfare domains. This growing, standardised collection of causal models lays the groundwork for a broader research programme: from domain-specific case studies through cross-system structural comparisons toward a *Systems Atlas*—a large-scale repository enabling comparative analysis of socio-environmental complexity across domains, geographies, and scales. A public version is hosted at <https://sim4action.io>.

Keywords: systems mapping, causal analysis, socio-environmental systems, network analysis, participatory modelling, adaptive management

1 Metadata

1. Motivation and significance

Understanding complex socio-environmental systems requires tools that bridge the gap between qualitative systems thinking and quantitative network analysis. Researchers, policymakers, and communities increasingly use causal loop diagrams and systems maps to reason about the interconnected dynamics of ecological, economic, social, and governance factors [1, 2]. The systems and complexity sciences have been around since at least the mid-twentieth century, and interest in their application to real-world concerns has come in waves—with notable successes but also false dawns [16]. A persistent obstacle is that complexity science has historically offered one of three unsatisfying options: (i) highly technical ‘black-box’ modelling inaccessible to non-specialists, (ii) appealing metaphors and language that do not directly lead to action and are often misapplied, or (iii) overwhelming, paralysing complexity that exposes the full intricacy of a system without providing any means

to navigate it [16]. In this landscape, causal systems mapping has emerged as a particularly useful “gateway” approach—one that can relatively quickly and straightforwardly capture multi-causality, indirect effects, the uncertain boundaries of open systems, feedbacks, and multiple stakeholder perspectives [16]. Yet despite their promise as gateway tools, existing software platforms present significant limitations for applied participatory research, leaving practitioners without an integrated workflow that covers interactive visualisation, causal simulation, and structural network analysis in a single accessible platform.

SIM4Action (Social-Environmental Interactive Mapping Platform for Action) was developed to address this gap. The platform originated in 2020 as a Python/Streamlit application [3] for the ITLA Foundation in Finland, mapping systemic drivers of long-term social assistance use. Between 2020 and 2025, it was iteratively refined through participatory modelling workshops across Humboldt Current fisheries in Chile and Peru, coastal basin ecosystems in central Chile, the Western Indian Ocean, and Australian Commonwealth fisheries—with stakeholders directly shaping which features were built and how they work. During workshops in Chile and the Western Indian Ocean, participants expressed a need to explore and compare the downstream impacts of different intervention strategies on their system maps; this requirement gave rise to the token-based

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Nr.	Code metadata description	Metadata
C1	Current code version	v1.0.0
C2	Permanent link to code/repository	https://github.com/Sim4Action-Labs/sim4action
C3	Permanent link to Reproducible Capsule	
C4	Legal Code License	GNU Affero General Public License v3.0 (AGPL-3.0)
C5	Code versioning system used	git
C6	Software code languages, tools, and services used	Python 3, JavaScript (ES6+), HTML5, CSS3, D3.js, NetworkX, Pyodide, Chart.js, Graphology
C7	Compilation requirements, operating environments & dependencies	Python 3.8+; modern browser; NetworkX ≥3.0, pandas ≥2.0; internet connection
C8	Link to developer documentation/manual	https://github.com/Sim4Action-Labs/sim4action/blob/main/README.md
C9	Support email for questions	juan.castilliarho@canberra.edu.au

Table 1: Code metadata (mandatory)

Nr.	(Executable) software metadata description	Metadata
S1	Current software version	1.0.0
S2	Permanent link to executables of this version	https://github.com/Sim4Action-Labs/sim4action/releases/tag/v1.0.0
S3	Permanent link to Reproducible Capsule	
S4	Legal Software License	AGPL-3.0
S5	Computing platforms/Operating Systems	Web-based (distributed); server runs on Linux, macOS, Microsoft Windows
S6	Installation requirements & dependencies	Python 3.8+, pip (for NetworkX, pandas); modern web browser; internet connection
S7	Link to user manual	https://github.com/Sim4Action-Labs/sim4action/blob/main/README.md
S8	Support email for questions	juan.castilliarho@canberra.edu.au

Table 2: Software metadata (optional)

causal diffusion simulation that became the core of the Intervention Lab. The centrality-based Monitoring Lab emerged from collaboration with environmental regulators who needed structured approaches to monitoring programme design. In 2025, growing demands for richer interactive visualisation led to a complete re-implementation using web technologies (HTML5, JavaScript, D3.js, Pyodide), producing the current platform.

The software is grounded in the five broad functions that Barbrook-Johnson and Penn [16] identify as the core value proposition of systems mapping: (1) helping us *think* by making assumptions and mental models explicit; (2) helping us *orient* ourselves to a system by seeing positions, connections, and affected parties; (3) helping us *synthesise* disparate types of data, evidence, and stakeholder knowledge into a connected whole; (4) helping us *communicate* by creating shared representations that unearth and challenge assumptions through group discussion; and (5) helping us *extrapolate from assumptions to implications* by tracing the consequences of structural assumptions through formal analysis. A recurring challenge across all five functions is that large causal maps can become ‘horrendograms’—overwhelming diagrams that show the full complexity of a system in an unfiltered manner and can paralyse rather than inform decision-making [16]. The core innovation of Participatory Systems Mapping (PSM) as articulated by Barbrook-Johnson and Penn is to address this problem by capturing the full complexity of a system but then using network analysis and the flow of causal chains to create focused submaps that make the complexity practical and actionable without compromising on depth [16]. SIM4Action computationally operationalises this philosophy. First, it enables non-technical stakeholders to interact with complex causal network visualisations through a browser-based interface that requires no installation, supporting the orientation and communication functions. Second, it provides causal simulation capabilities—forward and backward token-based diffusion with temporal delays—that allow users to explore intervention impacts and trace root causes within their system maps, operationalising the extrapolation function. Third, it applies graph-theoretic centrality metrics to inform monitoring programme design, identifying leverage points and sentinel indicators from the network structure—using ‘system-suggested’ factors (those that network analysis reveals to have interesting structural properties) to complement ‘stakeholder-suggested’ factors (those that participants identify as important), following the dual approach to analysis advocated by PSM [16].

Users interact with the platform through a three-stage workflow aligned with adaptive management [1]: *understand* the system (structural diagnostics), *design interventions* (causal diffusion simulation), and *monitor outcomes* (centrality-based indicator selection). This workflow was not derived from a theoretical model; it crystallised from repeated observation that workshop participants naturally follow this cognitive sequence—they need to *see* the system structure before they can reason about interventions, and they need to explore interventions before they can decide what to monitor. System maps are loaded from Google Sheets—a familiar interface for participatory workshop participants that gives stakeholders ownership of their data—and rendered as interactive force-directed networks. Each analysis stage is implemented as a dedicated laboratory within the platform.

Barbrook-Johnson and Penn [16] identify three categories of software for participatory systems mapping—general-purpose diagramming tools (e.g., diagrams.net, Miro), network visualisation and analysis software (e.g., Gephi, R/Python packages), and purpose-built platforms (e.g., Kumu, PRSM)—each with characteristic trade-offs. General-purpose diagramming tools are easy to use and produce human-readable maps, but offer no automated analysis; any structural investigation must be done manually, which is time-consuming and error-prone for maps with dozens of factors and hundreds of connections. Network

analysis software enables formal computation but requires programming skills that exclude non-technical stakeholders and lacks the interactive, browser-based interfaces needed for participatory workshops. Purpose-built platforms offer appealing interfaces but tend to have limited or no analysis capabilities and their stability and longevity can be uncertain [16]. In practice, practitioners often need to combine two or more tools—building maps in one, exporting data to another for analysis, and visualising results in a third—introducing friction, data loss and barriers to real-time participatory use. Several tools support aspects of the analytical workflow required for participatory socio-environmental research, but none integrates the full set of capabilities. Mental Modeler [4] provides a web interface for constructing and running fuzzy cognitive maps via matrix multiplication, but lacks network-level structural analysis (feedback loop enumeration, community detection, centrality metrics) and temporal delay modelling. Kumu [5] offers rich network visualisation but no causal simulation engine or programmatic API, and its proprietary nature limits reproducibility. FCMpy [6] implements fuzzy cognitive map inference and learning algorithms as a Python library but provides no interactive visualisation or web interface, making it inaccessible to non-technical stakeholders in participatory settings. PRSM [7] supports real-time collaborative systems mapping through a web interface but focuses on the mapping process itself and does not include causal diffusion simulation, centrality analysis, or feedback loop detection. Table 3 summarises the key capability differences.

SIM4Action was built because the required combination of capabilities—interactive web-based visualisation, participatory data collection via Google Sheets, two-mode causal diffusion simulation with temporal delays, structural network analysis (feedback loops, community detection, centrality metrics), and a domain-agnostic configuration-driven architecture—is absent from any single existing tool. Its core analytical libraries are standalone modules with zero browser dependencies, ensuring reuse in scripted research pipelines independent of the web interface. The platform includes a comprehensive built-in primer that walks users through systems thinking concepts and the full analytical workflow, lowering the knowledge barrier for non-specialist participants.

2. Software description

2.1. Software architecture

SIM4Action’s architecture separates analytical computation from web presentation, enabling both interactive use by non-technical stakeholders and programmatic use in research pipelines. Figure 1 illustrates the platform’s layered design and three-stage workflow.

The core computational modules—`browser_analysis.py` (centrality metrics, community detection via NetworkX [8]), `feedback_loops.py` (cycle enumeration and polarity classification), `networkx_loader.py` (graph construction from tabular data), and `diffusion.js` (both diffusion algorithms with delay pipelines)—have zero browser dependencies and are importable in any Python or Node.js environment. A test suite

(45 Python + 18 Node.js tests) validates all libraries outside the browser.

Python’s scientific stack (NetworkX, pandas) runs directly in the browser via Pyodide [9] and WebAssembly, eliminating server-side compute infrastructure. A single static file server is sufficient for deployment, making the platform viable in low-resource institutional contexts. Google Sheets serves as the data source, providing a familiar collaborative interface for workshop participants and avoiding database administration overhead.

The platform employs a configuration-driven, domain-agnostic architecture: a single codebase in `platform/` serves all system maps, each defined by a JSON configuration file and a Google Sheets data source under `systems/{id}/`. New system maps can be created by non-developers through the web interface. The frontend uses plain HTML5, CSS3, and ES6+ JavaScript with no build step, lowering the barrier for researcher-developers. D3.js [11] renders force-directed network visualisation, Graphology [10] provides client-side graph operations, and Chart.js powers analytical charts.

2.2. Software functionalities

The platform’s analytical capabilities are organised into three laboratories corresponding to the adaptive management workflow.

Diagnostics Lab. A causal system map is represented as a directed weighted graph $G = (V, E)$ where nodes represent system factors and edges represent causal relationships carrying three properties: polarity (same-direction or opposite-direction influence), strength (strong, medium, weak), and temporal delay (days, months, years). The lab provides: (1) feedback loop detection via depth-first cycle enumeration with polarity classification (reinforcing vs. balancing loops); (2) community detection using both the Louvain [12] and Girvan-Newman [13] algorithms; and (3) interactive filtering by domain, polarity, strength, and temporal scale.

Intervention Lab. Perturbation propagation is modelled through a token-based causal diffusion framework with two complementary modes. *Probabilistic* (agent-based) diffusion injects discrete tokens at intervention nodes; each token independently selects outgoing edges via weighted random sampling, with polarity-aware charge flipping and configurable delay pipelines. Running N simulations produces Monte Carlo distributions. *Deterministic* (flow-based) diffusion splits continuous flow proportionally across outgoing edges, producing identical results for identical inputs. Both modes support forward propagation (cause→effect) and backward propagation (effect→cause) for root-cause analysis. An integrated genetic algorithm optimiser discovers optimal intervention resource allocations.

Monitoring Lab. The platform currently provides five centrality metrics—degree, betweenness [14], closeness, eigenvector, and Katz—and is extensible to any centrality measure available in the Python scientific stack (NetworkX). Each metric maps to a distinct practical role in monitoring programme design: degree centrality identifies hub variables, betweenness identifies

Capability	SIM4Action	Mental Modeler	Kumu	FCMpy	PRSM
Web interface	✓	✓	✓		✓
Causal simulation	✓	✓		✓	
Temporal delays	✓				
Feedback loop detection	✓				
Community detection	✓				
Centrality metrics	✓				
Forward + backward propagation	✓				
Open source	✓			✓	✓
Programmatic API	✓			✓	

Table 3: Comparison of SIM4Action with existing systems mapping and fuzzy cognitive map tools.

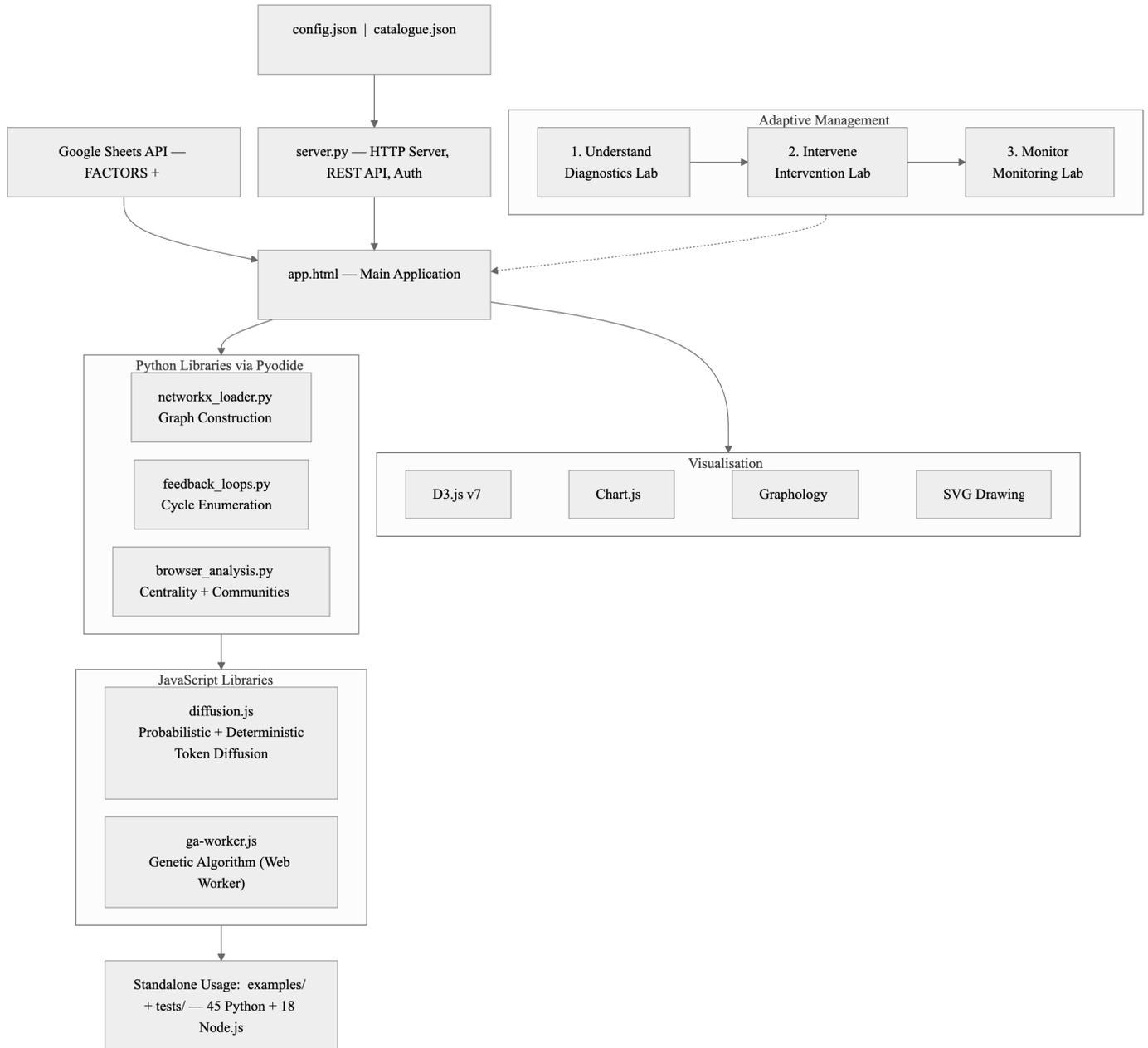


Figure 1: SIM4Action platform architecture. Data flows from Google Sheets and JSON configuration files (top) through the HTTP server to the main application (centre). The three-stage adaptive management workflow drives the interface. Core analytical libraries (bottom) have zero browser dependencies: Python modules run in-browser via Pyodide/WebAssembly; JavaScript diffusion runs natively with a Web Worker for genetic algorithm optimisation. All libraries are independently importable for scripted research pipelines and validated by an automated test suite.

bottleneck variables bridging subsystems, closeness identifies factors with rapid system-wide influence, eigenvector identifies factors connected to the most influential parts of the network, and Katz accounts for both direct and indirect influence with distance attenuation. Combining multiple metrics allows practitioners to distinguish leverage points (prime intervention targets), sentinel indicators (early warning signals), bridge variables (cross-subsystem monitors), and outcome variables (terminal nodes receiving but not propagating influence).

3. Illustrative examples

Consider a typical use case: a fisheries research team analysing the socio-environmental system around the Chilean octopus fishery using a causal map developed through participatory workshops with fishing communities. Figure 2 illustrates the platform interface through the complete workflow.

Stage 1: Understanding the system (Figure 2c–d). The team loads the octopus fishery system map from the platform’s catalogue. The force-directed network renders approximately 40 factors across ecological, economic, social, and governance domains. Using the Diagnostics Lab, they filter relationships by polarity to isolate reinforcing feedback loops—identifying, for example, a loop linking fishing effort, catch rates, income, and further investment in fishing effort. Community detection (Louvain algorithm) reveals four clusters corresponding to ecological health, economic viability, governance capacity, and social wellbeing, with bridge edges identifying the critical pathways connecting these subsystems.

Stage 2: Designing interventions (Figure 2e–f). The team uses the Intervention Lab to simulate the downstream effects of strengthening fisheries enforcement. They inject tokens at the “enforcement capacity” node using deterministic mode and observe how increased enforcement propagates through reduced illegal catch, improved stock biomass, and ultimately higher legal catch rates—with temporal delays of months to years visible in the time-series output. Switching to backward propagation from the “stock biomass” node reveals the full set of upstream factors that influence recovery, informing where additional interventions could reinforce the desired outcome. The genetic algorithm optimiser is then used to find the optimal allocation of limited resources across three candidate intervention points to maximise impact on stock recovery.

Stage 3: Monitoring outcomes (Figure 2g–h). The Monitoring Lab applies centrality analysis to recommend which factors to monitor. High-betweenness nodes (e.g., “market access”) are identified as critical bridge variables whose disruption would fragment subsystem interactions. High-eigenvector nodes connected to the most influential parts of the network are recommended as sentinel indicators for early detection of systemic shifts.

This three-stage workflow has been applied across all deployed system maps. In the water compliance domain (New South Wales, Australia), the same workflow was used to identify governance bottlenecks: community detection revealed that regulatory and compliance factors formed a distinct cluster weakly

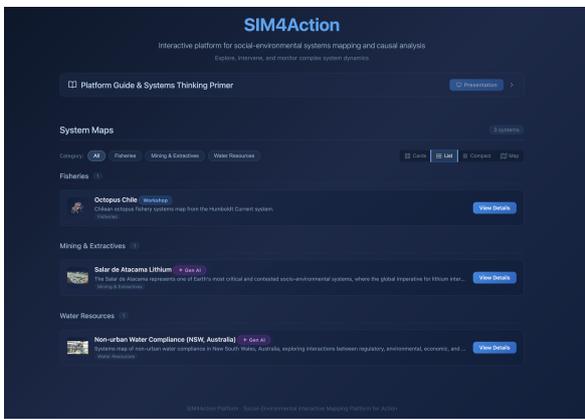
connected to on-ground environmental outcomes, while backward diffusion from water quality indicators exposed the upstream governance factors with the strongest causal influence. The consistency of the workflow across domains as different as artisanal fisheries and water regulation supports the platform’s domain-agnostic design intent.

4. Impact

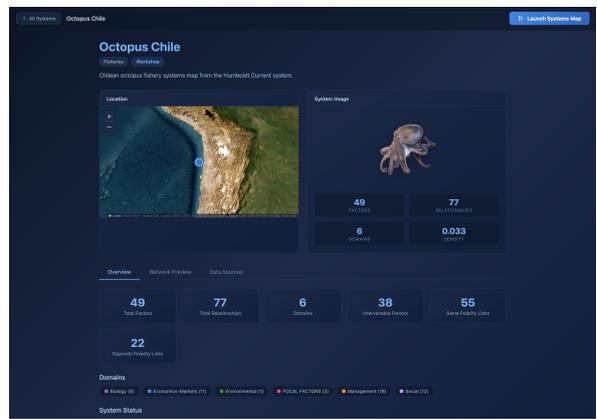
SIM4Action’s impact extends beyond the code itself: the platform embodies a conceptual framework for operationalising adaptive management through causal network analysis in participatory settings, iteratively refined through six years of real-world deployment (2020–2026) across Australia, Chile, Peru, Finland, and the Western Indian Ocean region. Barbrook-Johnson and Penn [16] note that value from systems mapping can come from both the process of building a map and from the analysis and use of its outputs, and that one must be clear about which source of value one is pursuing. SIM4Action is designed to maximise both simultaneously: the interactive platform generates value *during* workshops (through the discussions, assumption surfacing, and mutual understanding that arise from live exploration) and *after* them (through the persistent, analysable, and re-usable map artefacts it produces).

Enabling new research questions. The platform enables questions that were previously impractical without an integrated tool. Researchers can now ask: “What are the most effective combinations of intervention points to maximise systemic impact given limited resources?” (via the genetic algorithm optimiser), “What upstream factors most strongly drive a target outcome across temporal scales?” (via backward diffusion), and “Which monitoring indicators will provide the earliest warning of systemic change?” (via multi-metric centrality analysis). These capabilities directly address what Barbrook-Johnson and Penn [16] identify as the fifth core function of systems mapping: helping us extrapolate from the assumptions embedded in system maps to their practical implications—following through from the structural and causal beliefs we have encoded to see how they play out. The authors note that people sometimes think of systems mapping as inherently static and unable to do this; indeed, they identify the inability to explore dynamics as “probably the single biggest weakness” of Participatory Systems Mapping [16]. SIM4Action’s token-based causal diffusion engine directly addresses this acknowledged limitation: rather than requiring the transition to full System Dynamics modelling (which demands extensive quantitative data and specialist skills), it provides a lighter-weight simulation that traces causal pathways through a participatory map to reveal how structural assumptions propagate to distal outcomes—preserving the accessibility and transparency valued by PSM while adding the dynamic, scenario-exploration capability that PSM on its own cannot offer.

Improving pursuit of existing research questions. In fisheries management, where causal loop diagrams have long been used qualitatively [1], SIM4Action adds quantitative simulation and structural analysis to what was previously a purely visual exercise. Barbrook-Johnson and Penn [16] observe



(a)



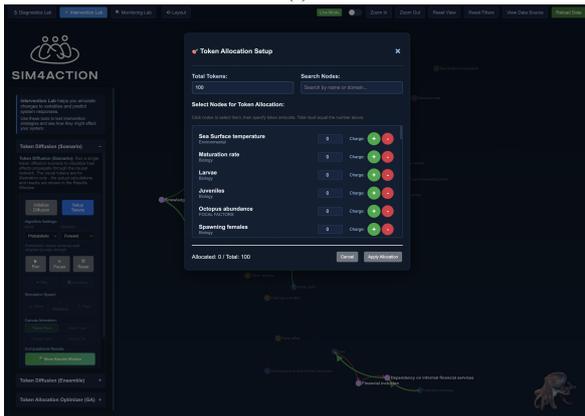
(b)



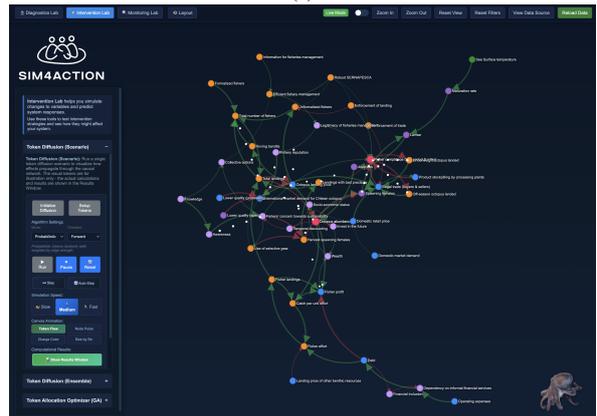
(c)



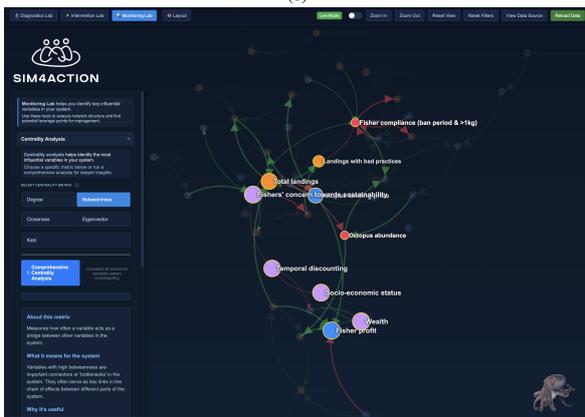
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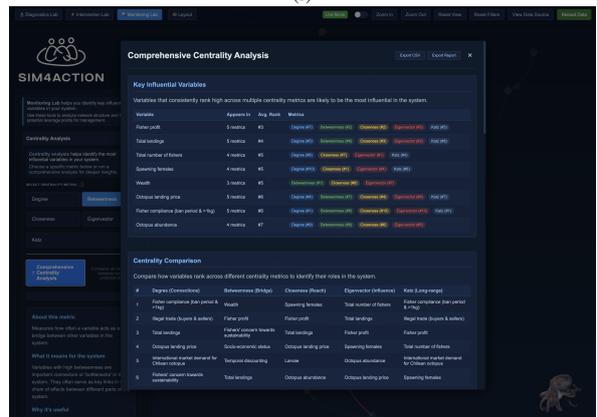
(e)



(f)



(g)



(h)

Figure 2: SIM4Action walkthrough: Chilean octopus fishery. (a) Platform catalogue with deployed system maps organised by domain, showing provenance tags (workshop or AI-generated). (b) System detail page: geographic context, structural statistics (49 factors, 77 relationships, 6 domains, density 0.033). (c) Diagnostics Lab: force-directed network with domain colour coding and filter controls for relationship type, strength, temporal scale, and feedback loops. (d) Community detection (Girvan-Newman) partitions the network into seven clusters; biological factors (sea surface temperature, larvae, spawning females) form a distinct subsystem. (e) Intervention Lab: token allocation dialogue for configuring causal diffusion scenarios across candidate intervention nodes. (f) Probabilistic diffusion in progress: tokens propagate via polarity-aware weighted random walks, visualising causal pathways in real time. (g) Monitoring Lab: betweenness centrality with node sizing; high-betweenness factors (e.g., “Total landings”, “Fishers’ concern towards sustainability”) identify bottleneck variables. (h) Comprehensive centrality analysis comparing degree, betweenness, closeness, eigenvector, and Katz metrics across top-ranked factors for leverage point and sentinel indicator identification.

332 that even when feedback loops are noticed, understood, and 389
333 discussed in CLDs, it can be difficult to turn this dynam- 390
334 ical view of a system into something usable or ‘actionable’— 391
335 organisational problem-solving cultures that revolve around 392
336 instrumental ‘button-pushing’ mindsets struggle to translate 393
337 systemic understanding into concrete decisions. SIM4Action 394
338 bridges this gap by converting abstract causal structure into tan- 395
339 gible scenario outputs: the two diffusion modes address distinct 396
340 stakeholder needs—probabilistic simulation produces uncer- 397
341 tainty bounds familiar to communities accustomed to stochas- 398
342 tic natural systems, while deterministic simulation enables the 399
343 reproducible comparisons required for policy briefing docu- 400
344 ments. The genetic algorithm optimiser further operationalises 401
345 the transition from understanding to action by discovering op- 402
346 timal resource allocations across candidate intervention points, 403
347 directly answering the ‘what should we do?’ question that sys- 404
348 tems maps alone leave open. 405

349 **Changing daily practice.** The platform has the potential 406
350 to change how participatory modelling workshops are con- 407
351 ducted. Barbrook-Johnson and Penn [16] highlight that one 408
352 of the biggest headwinds facing systems mapping is the in- 409
353 creasingly fast-paced nature of policy work and the shrinking 410
354 attention windows of stakeholders—where practitioners may 411
355 have only a half-day, often virtual, rather than the multi-day 412
356 workshops of earlier decades. This puts immense pressure on 413
357 methods to deliver value quickly and efficiently. SIM4Action 414
358 directly addresses this pressure: rather than producing static 415
359 causal maps as workshop outputs that require post-hoc anal- 416
360 ysis by researchers, facilitators use the platform during work- 417
361 shops to immediately explore the implications of the maps that 418
362 participants build—running simulations, identifying feedback 419
363 loops, and discussing centrality-based monitoring strategies in 420
364 real time. This matters because, as Barbrook-Johnson and 421
365 Penn observe, the process of mapping with others unearths a 422
366 multitude of assumptions that can then be challenged and un- 423
367 picked; the richness and depth of discussion, while maintain- 424
368 ing structure and focus, is often a surprise to first-time partic- 425
369 ipants [16]. SIM4Action amplifies this assumption-surfacing 426
370 function: when a participant proposes an intervention, the dif- 427
371 fusion engine instantly reveals its downstream consequences, 428
372 making implicit causal beliefs explicit and testable in the mo- 429
373 ment rather than in a post-workshop report. The SVG drawing 430
374 layer supports collaborative annotation during facilitated ses- 431
375 sions. Workshop participants—including fishers, NGOs, gov- 432
376 ernment regulators, and researchers—can interact directly with 433
377 the network visualisation, testing their intuitions about system 434
378 behaviour against the simulation results. This immediate ana- 435
379 lytical feedback can transform workshops from data collection 436
380 exercises into collaborative analytical sessions where stake- 437
381 holders co-produce actionable insights. 438

382 **Deployment breadth.** SIM4Action currently hosts over ten 439
383 causal system maps spanning: Humboldt Current fisheries (oc- 440
384 topos, southern hake) in Chile and Peru; Australian Common- 441
385 wealth fisheries (Southern and Eastern Scalefish and Shark 442
386 Fishery, Northern Prawn Fishery, Northwest Shelf Trap Fish- 443
387 ery) under the Blue Economy CRC Seafood Futures pro- 444
388 gramme; coastal basin ecosystems in central Chile; water re- 445

source compliance in New South Wales, Australia; lithium
brine extraction from the Salar de Atacama, Chile; and long-
term social assistance systems in Finland. The successful ap-
plication of the same framework across domains as different
as artisanal fisheries and lithium mining suggests the generalis-
ability of the underlying conceptual model.

Funded research projects. Development has been supported
by seven internationally funded projects: the ITLA Founda-
tion (Finland, 2020); the Walton Foundation through Advanced
Conservation Strategies (Chile and Peru, 2021–2024); the Min-
deroo Foundation and WIOMSA under the HIF-ID Blue pro-
gramme (Western Indian Ocean, 2023–2025); CSIRO and the
Blue Economy CRC with Austral (Australia, 2024–2026); the
Natural Resources Access Regulator and UNSW (New South
Wales); and Proyecto Anillo through Pontificia Universidad
Católica de Chile.

Reuse and extensibility. Barbrook-Johnson and Penn [16]
advocate treating system maps as “living documents”—
repositories of collective knowledge that can be accessed again
and again, updated as understanding evolves, and re-used
across projects—and urge practitioners to build in a legacy
plan for how maps will be maintained after a project ends.
SIM4Action’s architecture embodies this principle structurally.
Because system maps are stored in Google Sheets—a familiar,
cloud-hosted interface that stakeholder communities already
know how to use—maps remain editable by their creators long
after a workshop concludes. The configuration-driven design
means new system maps can be added without code changes:
a non-developer provides a Google Sheets URL and basic
metadata through the web interface, and the platform auto-
matically generates the corresponding analytical environment.
The standalone analytical libraries (`browser_analysis.py`,
`feedback_loops.py`, `diffusion.js`) can be imported into
scripted research pipelines independent of the web interface,
as demonstrated by working examples in the `examples/`
directory and validated by an automated test suite (45 Python +
18 Node.js tests). The platform distinguishes map provenance
(workshop vs. `gen_ai` source types), supporting emerging hy-
brid approaches where AI-drafted causal maps are validated
through participatory workshops.

Community-driven development. A central tenet of Partic-
ipatory Systems Mapping is that maps should be ‘owned’ by
the stakeholders who create them, rather than by researchers
[16]. Barbrook-Johnson and Penn further distinguish between
value derived from the *process* of mapping (the discussions,
mutual understanding, and knowledge generated during con-
struction) and value from the *outputs* (the map itself and the
insights it produces), noting that practitioners often underesti-
mate how much participants gain from the reflective process
[16]. SIM4Action was designed with both sources of value
in mind. Its features were co-designed with stakeholders who
shaped the platform through participatory workshops across
seven projects—the three-stage workflow itself emerged from
the practical cognitive sequence that workshop participants nat-
urally follow, rather than from a purely theoretical design pro-
cess. The repository includes contribution guidelines, issue
templates, and a public discussion forum to support commu-

446 nity engagement beyond the original project teams, ensuring⁵⁰⁰
447 that the platform’s evolution remains responsive to practitioner⁵⁰¹
448 needs. ⁵⁰²

449 5. Conclusions ⁵⁰³

450 SIM4Action provides an integrated, open-source platform for⁵⁰⁷
451 participatory socio-environmental systems analysis, combining⁵⁰⁸
452 interactive network visualisation, causal diffusion simulation,⁵⁰⁹
453 and graph-theoretic monitoring analysis in a single browser-⁵¹⁰
454 based tool. Barbrook-Johnson and Penn [16] argue that the⁵¹¹
455 philosophy underpinning systems mapping is one of deeply⁵¹²
456 participatory, holistic, and humble engagement with complex⁵¹³
457 adaptive systems—accepting that we cannot force or control⁵¹⁴
458 these systems, but can work with them to steer and nurture de-⁵¹⁵
459 sired change. They observe that current interest in complex-⁵¹⁶
460 ity science represents a moment of great opportunity, but also⁵¹⁷
461 a point at which failure to move beyond previous high-water⁵¹⁸
462 marks may see interest decline rapidly; what is needed are tools⁵¹⁹
463 that give these ideas and their practitioners “a foothold on the⁵²⁰
464 beach” so that they are not dragged back when the wave of in-⁵²¹
465 terest inevitably recedes [16]. SIM4Action is designed to be⁵²²
466 one such tool. Its three-stage adaptive management workflow⁵²³
467 (Understand, Intervene, Monitor) was co-designed with stake-⁵²⁴
468 holders across seven funded projects in Australia, Chile, Peru,⁵²⁵
469 Finland, and the Western Indian Ocean over six years, aim-⁵²⁶
470 ing to ensure that the analytical capabilities address real practi-⁵²⁷
471 tioner needs rather than theoretical convenience. The domain-⁵²⁸
472 agnostic, configuration-driven architecture has been applied⁵²⁹
473 across fisheries, water governance, lithium extraction, and so-⁵³⁰
474 cial welfare domains, with over ten deployed system maps. The⁵³¹
475 separation of standalone analytical libraries from the web pre-⁵³²
476 sentation layer ensures that the computational core is reusable,⁵³³
477 testable, and scriptable. ⁵³⁴

478 By providing a platform where stakeholders can move flu-⁵³⁵
479 idly from structural understanding through intervention design⁵³⁶
480 to monitoring, SIM4Action offers a practical response to the⁵³⁷
481 long-standing challenge of making complexity science action-⁵³⁸
482 able in real-world participatory settings. It aims to address the⁵³⁹
483 three historic pitfalls identified by Barbrook-Johnson and Penn⁵⁴⁰
484 [16]—black-box inaccessibility, metaphorical vagueness, and⁵⁴¹
485 paralysing complexity—by embedding formal network analy-⁵⁴²
486 sis and causal simulation within an interface designed for non-⁵⁴³
487 technical participants, producing outputs that are intended to⁵⁴⁴
488 be simultaneously rigorous and legible. Ongoing development⁵⁴⁵
489 is integrating AI-assisted causal map generation from scientific⁵⁴⁶
490 literature, with early results already showing promising poten-⁵⁴⁷
491 tial to compress the time required to develop baseline causal⁵⁴⁸
492 maps from years to weeks. These AI-drafted maps are validated⁵⁴⁹
493 and refined through participatory workshops, accelerating the⁵⁵⁰
494 initial mapping phase while preserving the community engage-⁵⁵¹
495 ment that gives these maps their legitimacy and local relevance.⁵⁵²
496 Beyond map construction, a natural next frontier is embedding⁵⁵³
497 AI agents directly into each analytical laboratory. Consider⁵⁵⁴
498 a fisheries management workshop where a facilitator has just⁵⁵⁵
499 loaded a 60-node causal map of an artisanal octopus fishery.⁵⁵⁶

In the Diagnostics Lab, an AI agent could examine the net-
work structure and surface observations that human analysts
might overlook—flagging, for instance, that two reinforcing
feedback loops share a single bottleneck node whose removal
would fragment a critical subsystem, or that an isolated cluster
of governance factors has no causal pathway to the ecological
outcomes it is meant to protect. In the Intervention Lab, the
agent could act as an analytical co-pilot: after a stakeholder pro-
poses injecting resources at “enforcement capacity,” the agent
might note that backward diffusion from the desired outcome
reveals three upstream nodes with stronger aggregate influence,
suggest an alternative allocation, and explain the trade-offs in
plain language—translating network-theoretic results into the
decision vocabulary of the room. In the Monitoring Lab, the
agent could synthesise centrality results across multiple met-
rics and recommend a parsimonious set of sentinel indicators,
explaining why each was chosen and what early-warning signal
it would provide. Critically, such agents would not replace the
participatory process but augment it: they would lower the ana-
lytical expertise required to extract insight from complex maps,
enabling smaller teams and shorter workshops to achieve the
depth of analysis that currently demands specialist facilitation.
The platform’s architecture—with its standalone analytical li-
braries, structured data model, and browser-based execution
environment—provides a ready foundation for this integration,
positioning SIM4Action not only as a current analytical tool
but as an extensible platform for the emerging generation of
AI-augmented participatory systems research.

This paper represents the foundational layer of a broader
research programme organised around the platform. The
next phase involves detailed, domain-specific case studies—
applying the full three-stage workflow to individual socio-
environmental systems and evaluating the analytical insights
it produces against domain expertise and empirical outcomes.
Candidate systems include non-urban water compliance gover-
nance in New South Wales (Australia), Humboldt Current arti-
sanal fisheries in Chile and Peru, and lithium brine extraction
in the Atacama. Each case study would contribute a rigorously
documented system map to a growing, standardised collection.
As this collection expands, a third research tier becomes pos-
sible: cross-system structural comparisons. With dozens of
causal maps expressed in a common graph format and analysed
through identical metrics, questions that are currently beyond
reach begin to open up. Do certain feedback loop archetypes—
reinforcing poverty traps, balancing regulatory cycles—recur
across unrelated domains? Are there universal structural sig-
natures in network topology that predict system resilience or
fragility? Do governance subsystems consistently exhibit weak
causal coupling to the environmental or social outcomes they
are designed to influence, regardless of the domain? Does the
ratio of reinforcing to balancing loops correlate with a system’s
susceptibility to regime shifts? The long-term ambition is to
develop what we term a *Systems Atlas*: a large-scale, openly
accessible repository of participatory causal system models that
enables comparative analysis across domains, geographies, and
scales—moving from individual system understanding toward
a structural science of socio-environmental complexity.

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Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the author used Anthropic Claude Opus 4.6 in order to assist with software architecture analysis, manuscript drafting, literature synthesis, and code development. The Perplexity API was used for AI-assisted extraction of causal maps from scientific literature that are included in the public version of the platform. After using these tools, the author reviewed and edited all content thoroughly and takes full responsibility for the content of the published article.

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