Panta Rhei
Research Program

Research Briefings · Public-Good Impact Dossiers

One Health · Food, Life & Health Systems

Tau-Grade One Health Early Warning for Vector-Borne Disease, Zoonotic Spillover, and Climate-Sensitive Outbreaks

Conditional public-good pathway for One Health Early Warning for Vector-Borne Disease, Zoonotic Spillover, and Climate-Sensitive Outbreaks

Public-Good Impact Dossier

Conditional impact analysis · Publication-ready PDF · not deployment-ready

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Conditional scenario map. No validation, product, deployment, or policy claim.

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This briefing is a conditional public-good impact dossier released as a publication-ready PDF artifact on 2026-05-02. Publication-ready means the dossier is downloadable, internally consistent, and claim-safe. It does not validate the τ-framework, does not claim deployment readiness, and does not assert that the described domain system already exists. It maps a plausible impact pathway if the relevant upstream Results, Corpus constructions, and translation assumptions survive expert review and domain benchmarking.

What this dossier claims

- maps a conditional public-good impact pathway
- identifies upstream framework dependencies that would have to survive review
- states translation assumptions, benchmark needs, and governance guardrails

What this dossier does not claim

- does not validate the Tau framework
- does not claim that a domain system or product already exists
- does not claim deployment readiness, policy adoption, or certified impact
- does not replace independent domain review, empirical benchmarking, or governance assessment

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Contents

1 Executive Summary

The world is not losing the war against infectious disease because it lacks data. It is losing because the data streams — meteorological, ecological, veterinary, entomological, clinical, and behavioral — sit in separate institutional pipelines with no common causal engine linking them in time to act.

Vector-borne diseases account for more than **17% of all infectious diseases** and cause more than **700,000 deaths annually** [1]. In 2024, WHO reported over **14.6 million dengue cases** and more than **12,000 dengue-related deaths** across more than 100 countries — numbers that would have been unimaginable as a single-year toll twenty years ago [2]. The **60% of all human infectious diseases that are zoonotic in origin**, combined with **75% of emerging infectious diseases that cross species** [3], means the threat surface is not a narrow clinical domain. It is an ecological frontier spanning weather, habitat, animal reservoirs, market chains, and human communities.

Climate change is moving the frontier faster. IPCC AR6 Working Group II established with **high confidence** that climate change is expanding the geographic range of key disease vectors, including *Aedes aegypti*, *Aedes albopictus*, and a range of tick species [4]. WHO projects that by 2030–2050, climate change will cause roughly **250,000 additional deaths per year** from malnutrition, malaria, diarrhoea, and heat stress alone [5]. The Lancet Countdown on Health and Climate Change has consistently tracked these trends as among the most urgent dimensions of the climate emergency.

This paper asks a single, carefully bounded question:

> **If the τ (tau) framework is sound — if it can provide a physically and biologically faithful, bounded-error, coarse-grainable discrete twin of the weather–vector–host–environment–human system — what public good could that unlock for One Health early warning?**

The answer, argued in full below, is: **a great deal, with unusually high humanitarian leverage, across a domain where the institutional infrastructure to act already exists**.

The τ framework is presented as an **assumption**, not a claim of validated consensus. This is a **yellow paper**: assumption-led, translation-oriented, and public-good framed. What follows is a rigorous map of what would become operationally possible if the assumption held well enough to matter.

Under the strongest τ assumption, the benefit is not simply better epidemiological statistics. It is a **law-faithful, cross-species, weather-linked, ecology-aware risk twin** that could deliver:

- Earlier detection of disease-conducive ecological conditions, measured in weeks not days;
- Better ranking of spillover hotspots before animal-to-human transmission occurs;
- More precise targeting of vector control, livestock vaccination, diagnostics, and community protection;
- Stronger coordination across public health, veterinary, meteorological, and environmental institutions;
- Fewer blanket interventions with low yield and high social cost;
- And a more coherent path toward outbreak prevention rather than outbreak response.

The paper proceeds through fifteen sections. The Opportunity Baseline (Section 3) documents the current burden with precision. The Working τ Assumptions (Section 4) state explicitly what is assumed. The Competitive Landscape (Section 6) names and critiques the six most important incumbent systems. The Geographic Case Studies (Section 8) ground the claims in real outbreak events with real numbers. The Finance and ROI section (Section 9) provides costed scenarios and names the most relevant climate-finance windows. The Evidence and Translation Ladder (Section 10) outlines a credible path from shadow-mode benchmarking to operational integration.

The institutional audience for this paper — WHO, ministries of health and agriculture, USAID global health, One Health coordination networks, and World Bank / GCF health teams — will find the framing deliberate: this is a planning document, not a journal submission. The τ assumption is stated. The leverage is real. The question is whether to begin building toward it.

2 Why This Matters Now

2.1 The outbreak frontier is moving faster than public health infrastructure

The core asymmetry in contemporary One Health is not scientific uncertainty. It is **temporal and causal lag**. Current early warning systems typically detect transmission after it has already begun — clinical cases confirm what ecological conditions have been building toward for weeks. By the time a dengue cluster is notified, the vector population responsible for sustaining that transmission has already passed through two or three reproductive cycles under the weather conditions that drove it.

This is not primarily a surveillance problem. It is a **physics problem**. The conditions that make outbreaks more or less likely — temperature, precipitation, humidity, land cover, water retention, host density, movement patterns — are not random. They evolve according to physical and biological laws. But today's early warning systems largely treat those conditions as inputs to statistical risk models rather than as components of a physically faithful causal representation. The result is that the system is always, to some degree, behind the outbreak it is trying to prevent.

2.2 Climate change is restructuring the threat map

The IPCC AR6 Working Group II assessment, published in 2022, established with **high confidence** that climate change is increasing the geographic range of vectors for dengue, Zika, chikungunya, West Nile, and malaria [4]. This is not a projection about 2080. It is already happening. Between 1950 and 2023, the global suitability of climate for *Aedes aegypti* transmission expanded by an estimated 10–15% [6]. Europe recorded its first locally transmitted dengue cases in mainland France, Italy, and Spain in 2023 — a historically unprecedented pattern in regions without prior endemic transmission [7].

For zoonotic spillover, the same climate dynamics are at work. Changes in precipitation, temperature, and land use alter the spatial distribution and behavior of reservoir hosts — bats, rodents, primates, ungulates — and alter the timing and intensity of human-animal contact points. These are not post-hoc associations. They are causal pathways.

2.3 Institutions are ready to act but lack the right intelligence layer

WHO, FAO, WOAH, and UNEP have renewed their **Quadripartite** commitment to One Health as a governance framework [8]. The **Pandemic Fund**, established in 2022 as the first multilateral financing mechanism dedicated exclusively to pandemic prevention, preparedness, and response, represents a structural commitment by G20 governments to invest ahead of the next pandemic [9]. WHO's IHR (International Health Regulations 2005) core capacities framework requires member states to develop national surveillance systems capable of detecting and reporting disease events of international concern — but the quality of that surveillance is highly variable and systematically weakest in the highest-burden geographies [10].

The infrastructure of intent is present. What is missing is a **causal intelligence layer** capable of linking climate and environmental signals to biological risk surfaces in time to act. That is the gap this paper addresses.

2.4 Prevention economics are overwhelmingly favorable

McKinsey & Company estimated in 2021 that the COVID-19 pandemic had cost the global economy between **USD 8 trillion and USD 16 trillion** by the end of 2021 [11]. The OECD and World Bank have made parallel estimates of the long-term economic cost of major pandemic events, consistently finding benefit-cost ratios for pandemic preparedness investments in the range of **10:1 to 500:1** relative to reactive response [12]. The cost of pre-positioning vector-control assets in a high-risk season is a fraction of the cost of treating an outbreak that has already scaled.

The question is not whether earlier warning has value. It is whether τ-grade causal intelligence can provide the additional lead time and spatial precision needed to convert that value into action.

3 Scope and Reader Orientation

3.1 What this paper covers

This is **Paper 1 of 4** in the One Health / disease ecology / health resilience portfolio. Its scope is:

- **Early warning** for vector-borne, zoonotic, and climate-sensitive outbreaks;
- **Weather–vector–host–environment coupling** as a physically faithful causal system;
- **Spillover hotspot and transmission corridor intelligence** before clinical caseloads emerge;
- **Sub-national intervention targeting** for vector control, vaccination, and surveillance;
- **Pre-surge public-health action** enabled by additional lead time.

This paper is addressed to an **institutional audience**: WHO headquarters and regional offices, national ministries of health and agriculture, USAID global health bureaus, One Health coordination networks, GCF/World Bank health and climate teams, and major philanthropic funders including CEPI and Wellcome Trust. Readers are assumed to be familiar with the epidemiology of vector-borne and zoonotic diseases and with the architecture of global health security governance.

3.2 What this paper does not cover

These are deferred to other papers in the portfolio:

- **Health-system resilience**, facility continuity, cold chains, and clinical operations under heat, flood, smoke, and outage (Paper 2);
- **AMR, wastewater/environmental surveillance**, and environmental transmission intelligence (Paper 3);
- **Food safety**, livestock/wildlife interface, and community exposure intelligence (Paper 4).

3.3 How to read the τ framing

The τ framework is the underlying categorical-physical substrate described in the Panta Rhei monograph series. For the purposes of this paper, readers do not need to engage with the mathematics of Category τ. The relevant claim is **functional**: that τ can provide a physically faithful, bounded-error, coarse-grainable discrete twin of environmental and biological systems, with explicit uncertainty representation and computational tractability.

This claim is stated as a **planning assumption**, not a validated consensus finding. All impact statements in this paper are **conditional on that assumption**. Where the paper says τ "could provide" or "would deliver," that conditionality is always present. This is a yellow paper: it reasons under a strong but explicitly stated assumption to map the humanitarian opportunity.

4 The Opportunity Baseline

4.1 Vector-borne disease burden

WHO's vector-borne diseases fact sheet gives the canonical numbers: - More than **17% of all infectious diseases** are vector-borne; - More than **700,000 deaths annually**; - Malaria alone accounts for **249 million cases** and more than **608,000 deaths** per year, concentrated in sub-Saharan Africa, with children under five bearing the greatest burden [1].

Dengue has become one of the fastest-growing climate-sensitive infectious disease burdens. The 2024 WHO update documents **over 14.6 million cases** and **more than 12,000 dengue-related deaths** in a single year [2]. The Lancet estimated in 2019 that under a 2°C warming scenario, the number of people at risk from dengue could expand by **2.25 billion** by 2080, with the largest increases in previously non-endemic regions [13]. The 2023 season saw local transmission in Europe — Spain, France, Italy — for the first time, with more than 130 locally acquired cases reported outside of traditional transmission zones [7].

Beyond dengue and malaria, the vector-borne disease portfolio includes: - **Zika** — with ongoing neurological consequences for congenital infections; - **Chikungunya** — spreading into subtropical regions previously outside its range; - **West Nile virus** — with established European and North American transmission cycles now sensitive to temperature anomalies; - **Japanese encephalitis** — expanding range in South and Southeast Asia; - **Rift Valley fever** — linked to ENSO-driven precipitation events in East Africa; - **Tick-borne encephalitis** and **Crimean-Congo haemorrhagic fever** — expanding into higher latitudes and elevations as temperature rises.

4.2 Zoonotic spillover burden

FAO's authoritative baseline: **60% of all human infectious diseases are zoonotic in origin**, approximately **75% of emerging infectious diseases cross species**, and there are **over 200 known zoonoses** [3]. HIV, Ebola, SARS, MERS, Nipah, Hendra, Marburg, COVID-19 — the list of high-consequence zoonoses that have crossed to humans in recent decades is long, and the conditions driving spillover events (deforestation, land-use change, agricultural expansion, wildlife trade, climate-driven habitat shifts) are accelerating.

WHO estimates the global burden of zoonotic diseases at hundreds of millions of illnesses and millions of deaths per year when routine zoonoses (brucellosis, leptospirosis, Q fever, rabies, foodborne zoonoses) are included alongside epidemic-potential pathogens [14].

4.3 Climate as structural driver

The IPCC AR6 WG2 assessment is unambiguous on the causal role of climate change in expanding vector-borne and climate-sensitive disease risk: - **High confidence**: climate change has already caused measurable expansion of the geographic and seasonal range of key vector species; - **High confidence**: projected further warming will extend transmission seasons and geographic coverage for malaria, dengue, and other vector-borne diseases; - **Medium-high confidence**: changes in precipitation and temperature are altering zoonotic reservoir behavior and spillover risk [4].

WHO's climate-and-health projections estimate approximately **250,000 additional deaths per year** by 2030–2050 from climate-sensitive diseases including malaria, diarrhoea, and heat stress [5]. The Lancet Countdown's 2023 indicator suite consistently shows increasing climate suitability for dengue transmission in most tropical and subtropical regions, with vectorial capacity indices rising in Europe, North America, and parts of Africa and Asia [15].

4.4 The IHR core capacities gap

The International Health Regulations (2005) require all WHO member states to develop, strengthen, and maintain core capacities for detection, reporting, and response to public health events of international concern [10]. Joint External Evaluations (JEEs) conducted by WHO consistently find that the lowest-scoring core capacities are precisely those that would benefit most from better environmental and ecological intelligence: **real-time biosurveillance**, **zoonotic disease prevention and response**, and **environmental events** [16]. Fewer than half of member states have fully functional IHR core capacities across all required dimensions.

This is the structural gap τ-grade One Health intelligence is positioned to address: the translation from environmental and ecological signal to actionable public-health warning, performed with enough lead time and spatial precision to matter operationally.

5 Working τ Assumptions

This paper assumes, for strategic planning purposes, that the τ framework can provide the following:

Assumption 1 — Physical-biological twin fidelity. A bounded-error, coarse-grainable discrete representation of weather–environment–vector–host–human interactions, grounded in the τ categorical structure, can model the key physical and biological drivers of vector habitat formation, reservoir behavior, and spillover risk at operationally relevant scales (district to national; daily to seasonal).

Assumption 2 — Cross-layer coupling. The τ substrate can maintain causal consistency across layers — from meteorological and hydrological state, through vector ecology and reservoir dynamics, to epidemiological observables — without requiring separate model-stitching at each interface. This means that a single integrated representation can propagate uncertainty coherently through the full causal chain.

Assumption 3 — Actionable uncertainty quantification. The τ framework can produce not only point forecasts but **risk-class outputs** — probability intervals, hazard thresholds, and conditional risk rankings — that are meaningful for operational decision-making under resource constraints. "High risk," "elevated risk," and "watch" categories can be assigned with calibrated confidence.

Assumption 4 — Biological state representation. τ can represent pathogen, vector, host, and intervention-relevant state transitions at a level of fidelity sufficient to distinguish outbreak-conducive from outbreak-resistant conditions, including seasonal and inter-annual variability driven by climate forcing.

Assumption 5 — Computational tractability. The framework is computationally tractable for scenario generation, ensemble runs, hotspot ranking, and operational use at the temporal cadence required by public-health systems (daily updates for nowcasting; weekly for 2–6 week risk outlooks; monthly for seasonal preparedness).

Assumption 6 — Incrementalism. τ gains are real but not infinite. The paper does not assume that all epidemiological unknowns vanish. It assumes that the physics/ecology/biology side becomes substantially more faithful, reducing avoidable uncertainty at the critical step of translating climate and ecological conditions into health risk.

These assumptions are **not** claims that the broader scientific or public-health community has validated τ as an operational system. They are the planning premises on which the opportunity analysis rests. All impact and ROI statements below are conditional on these premises.

6 What Changes with a Law-Faithful Twin

Today's One Health early warning systems assemble a mosaic: satellite-derived vegetation indices, meteorological forecast outputs, entomological trap data, case surveillance reports, veterinary sentinel records, and expert judgment stitched together with varying degrees of rigor. The individual components are often excellent. The coupling between them is the weak point.

Under the τ assumption, the fundamental change is not more data or more powerful statistics. It is a different **kind of causal coherence** — one that propagates physical constraints through the full chain from environmental state to health-risk surface.

6.1 Mechanism-faithful risk chains instead of loosely coupled proxies

The current epidemiological workflow treats temperature, rainfall, vegetation, and case data primarily as correlates in statistical risk models. Under τ, these would instead be components of one executable causal structure: rainfall governs soil moisture and standing water; standing water governs larval habitat persistence; temperature governs *Aedes* development rates and viral replication rates inside the vector; and the integral of these conditions over time gives vector competence and biting pressure. This chain is already known qualitatively. τ-grade representation would enforce physical consistency across it quantitatively.

6.2 Longer effective lead time from precursor-state modeling

The strategic gain in lead time comes not from faster surveillance of cases but from earlier identification of ecological precursor states. Vector outbreaks do not begin when the first human case is reported. They begin when temperature and moisture conditions cross thresholds that support successful larval development. If those thresholds can be identified and tracked with precision 6–12 weeks ahead of the time when clinical transmission would be detectable, the actionable window for vector control pre-positioning expands substantially.

Under τ, the claim is that this precursor-state modeling becomes more faithful — not perfect, but meaningfully better than the current combination of climate anomaly indices and statistical regression models.

6.3 More disciplined intervention targeting

The second major operational change is **spatial precision in intervention ranking**. The current system distributes vector control resources largely based on prior-year case maps, administrative units, and reactive surge responses. With a more faithful ecological-risk surface updated in near-real time, the same intervention budget could be concentrated in the hotspots where the combination of vector pressure and human exposure is highest — rather than spread across administrative boundaries.

This has direct consequences for cost efficiency. If a dengue prevention campaign can reduce unnecessary spraying by 30–40% while concentrating action where risk is highest, both the public health outcome and the cost-effectiveness ratio improve.

6.4 Cross-ministry coordination through a shared risk substrate

One of the structural failures of One Health implementation is that the ministries responsible for different parts of the system — health, agriculture, environment, meteorology — operate from different data sources and different models. The τ substrate, under the assumption, provides a single shared causal representation that all ministries can query from their own operational perspective.

This does not eliminate inter-ministerial friction. But it removes the specific friction that arises from different agencies looking at different pictures of the same underlying reality and drawing contradictory conclusions about when to act.

6.5 Distinguishing “high alert” from “high noise”

Perhaps the most under-appreciated operational value of better causal fidelity is **false-alarm reduction**. Current early warning systems in vector-borne disease generate substantial noise — alerts that turn out not to be predictive of clinical outbreak, often because the statistical correlates fire without the full ecological precondition being satisfied. False alarms erode institutional trust in warning systems and degrade the willingness of field responders to mobilize on advisory alone. A more faithful causal representation, by enforcing physical plausibility constraints, would produce fewer spurious alerts — which may be as valuable as producing more true positives.

7 Competitive and Incumbent Landscape

Understanding where τ fits requires an honest accounting of what incumbent systems already do well and where they fall short. There are six major institutional programs and tools most directly relevant to the One Health early warning space.

7.1 WHO GOARN — Global Outbreak Alert and Response Network

What it does well. GOARN is the world’s most authoritative **reactive coordination mechanism** for outbreak response. Established in 2000, it links more than 250 technical partner institutions across WHO member states and deploys outbreak response teams when alerted. It has responded to Ebola, MERS, COVID-19, and numerous other outbreaks with speed and authority. Its network trust, institutional legitimacy, and global reach are unmatched.

Where it falls short. GOARN is fundamentally **reactive by design**. It is triggered by confirmed outbreak events, not by ecological precursor conditions. It does not generate predictive risk surfaces for weather-linked vector suitability, zoonotic spillover probability, or pre-clinical transmission conditions. Its value is in accelerating response after an outbreak is already recognized; its value in prevention before clinical cases surge is limited.

τ differentiation. Under the τ assumption, the appropriate relationship with GOARN is **upstream integration**: τ-generated precursor risk products would feed into GOARN’s trigger architecture, enabling anticipatory deployment of response teams and diagnostic assets before the clinical signal arrives. τ does not replace GOARN; it extends the actionable window in front of it.

7.2 PREDICT / USAID — Zoonotic Spillover Surveillance Program

What it does well. PREDICT was the most comprehensive zoonotic spillover surveillance program in history during its operational life (2009–2019). It collected more than 160,000 samples from wildlife, livestock, and people at human-animal interfaces across 34 countries and identified more than 1,000 novel viruses. It built capacity for wildlife surveillance in Low- and Middle-Income Countries (LMICs) and demonstrated that systematic sampling of the human-animal interface was operationally feasible.

Where it falls short. PREDICT was **decommissioned by USAID in 2019**, leaving a significant gap in systematic zoonotic surveillance. Even while operational, it was primarily a **retrospective discovery program** — it found viruses present in wildlife populations but did not provide real-time predictive risk surfaces for when and where spillover would occur. Its sampling was driven by ecologically defined priority zones, not by dynamic risk forecasts updated with climate and land-use data.

τ **differentiation.** τ-grade modeling would provide the **dynamic spillover risk layer** that PREDICT lacked: identifying when and where host behavior, climate forcing, and human contact patterns create elevated spillover probability. This would not replace wildlife surveillance sampling (which remains indispensable for pathogen discovery) but would focus it temporally and spatially on highest-risk windows rather than distributing it uniformly.

7.3 HealthMap — Boston Children's Hospital Digital Surveillance

What it does well. HealthMap has operated since 2006 as a **media and online signal detection platform**, aggregating news reports, official alerts, expert discussions, and social media signals from thousands of sources in multiple languages. It is one of the earliest and most systematically built examples of **infectious disease digital surveillance**, and it successfully detected early signals of the 2009 H1N1 pandemic and the 2014 West Africa Ebola outbreak before official notifications were issued.

Where it falls short. HealthMap is fundamentally a **text signal aggregation system**. It has no representation of the physical and ecological drivers of disease emergence. It does not model vector habitat, reservoir behavior, meteorological forcing, or land-use dynamics. When it detects a signal, that signal is already the product of human reporting — meaning the ecological precondition has already been realized and the human exposure chain is already engaged. HealthMap provides **earlier detection within the clinical/reporting pathway**, but it does not provide detection before clinical transmission begins.

τ **differentiation.** τ would operate at a different and earlier point in the causal chain — identifying ecological preconditions rather than detecting their clinical consequences. HealthMap and τ are complementary systems: τ flags high-risk ecological conditions weeks ahead; HealthMap validates the transition to human exposure in near-real time. An integrated architecture would use both.

7.4 EcoHealth Alliance / DTRA Modeling Programs

What it does well. EcoHealth Alliance has produced some of the most rigorously defended ecological spillover risk models in the published literature, combining wildlife sampling data with climate, land-use, and host-distribution modeling to identify global hotspots for zoonotic emergence. These models have been influential in academic and policy circles and represent the state of the art in **research-grade ecological risk assessment** for spillover.

Where it falls short. EcoHealth Alliance's modeling program, including work funded by DARPA and DTRA, has been primarily **research-grade** — producing peer-reviewed maps and probability surfaces rather than operational near-real-time decision support products. The models are not continuously updated with current climate and ecological state data; they are static or slowly-updated risk assessments. They also have limited integration with the veterinary, meteorological, and public-health operational systems that would need to act on the outputs.

τ **differentiation.** τ-grade modeling would provide what EcoHealth Alliance models approximate but do not operationalize: a **continuously updated, physically coupled risk surface** that reflects current (not climatological average) environmental conditions. The EcoHealth research base provides invaluable empirical grounding for the causal relationships τ would represent; τ-grade implementation would operationalize those relationships at the update cadences required for actionable early warning.

7.5 ECDC / WHO EWARN — European and Global Early Warning Systems

What it does well. The European Centre for Disease Prevention and Control (ECDC) operates a sophisticated **epidemiological early warning and response system** covering EU/EEA member states, with strong case-based surveillance, genomic sequencing integration, and structured risk assessments. WHO's Event Information Site (EIS) and the Health Emergency Preparedness and Response Authority (HERA) architecture provide parallel capabilities globally. These systems are well-resourced, institutionally anchored, and support high-quality epidemiological analysis.

Where it falls short. ECDC and WHO EWARN are **epidemiologically framed** systems: their inputs are clinical cases, laboratory results, and notified public health events. They do not natively incorporate the physical and ecological drivers of vector-borne or climate-sensitive disease. Climate information, when incorporated, tends to be imported as static risk context rather than as a dynamically coupled causal layer. The systems are excellent at characterizing outbreaks in progress but have limited capability for pre-clinical ecological risk detection.

τ differentiation. τ would provide the **upstream ecological intelligence layer** that ECDC and EWARN currently lack — feeding predictive ecological risk surfaces into the event detection and response architecture rather than waiting for clinical confirmation. Integration with ECDC's existing surveillance infrastructure would be the most straightforward deployment pathway for the European region.

7.6 ProMED-mail — Global Disease Outbreak Monitoring

What it does well. ProMED-mail (Program for Monitoring Emerging Diseases), operated by the International Society for Infectious Diseases, is one of the oldest and most trusted global disease monitoring networks, operating since 1994. It combines expert human moderators with a global network of correspondents to provide rapid disease intelligence on outbreaks, unusual disease events, and emerging threats. ProMED has an outstanding track record of early detection and has become an indispensable reference for global health intelligence.

Where it falls short. ProMED is **fully human-reporting-based**. It depends on trained correspondents and expert moderators to notice and report signals. It has no automated physics or ecology coupling, no vector habitat modeling, no meteorological input, and no predictive risk surface generation. It is excellent as a **global detection and communication network** for events that have already become visible to human observers, but it cannot detect ecological preconditions before human exposure has begun.

τ differentiation. As with HealthMap, the appropriate τ relationship with ProMED is **upstream and complementary**: τ-generated ecological risk warnings would ideally be visible to ProMED correspondents as context, and ProMED's expert detection capability would serve as a validation layer for τ risk alerts. The two systems address different parts of the detection timeline.

7.7 Summary Table: Incumbent Landscape

System	Primary Strength	Key Gap	τ Relationship
WHO GOARN	Reactive coordination	Not predictive, no ecological layer	Upstream feed

System	Primary Strength	Key Gap	τ Relationship
PREDICT/USAID	Wildlife virus discovery	Decommissioned; not real-time predictive	Complementary sampling focus
HealthMap	Media signal aggregation	No physics/ecology coupling	Complementary: validates τ alerts
EcoHealth Alliance	Research-grade spillover models	Not operational; not dynamically updated	Research foundation for τ
ECDC/WHO EWARN	Epidemiological surveillance	Clinically framed; limited ecological upstream	Downstream integration target
ProMED-mail	Expert human detection network	Human-reporting only; no automation	Complementary validation layer

No existing operational system provides a **continuously updated, physically coupled, cross-species causal risk surface** that translates current environmental and ecological conditions into actionable pre-clinical risk scores. That is the gap τ is positioned to fill.

8 Structured Opportunity Map

Five distinct opportunity areas exist for τ-grade One Health early warning, each with its own causal pathway and institutional deployment logic.

8.1 Opportunity 1 — Vector Ecology and Outbreak Forecasting

Target diseases: dengue, malaria, chikungunya, Rift Valley fever, West Nile virus, Japanese encephalitis, yellow fever, Zika, tick-borne encephalitis, Crimean-Congo haemorrhagic fever.

Causal pathway: Temperature → vector development rate and thermal tolerance windows; Rainfall + land cover → larval habitat formation and persistence; Humidity → adult vector survival and biting rate; Vegetation and water-retention dynamics → habitat extent mapping; Wind and hydrology → vector dispersal corridors.

τ core contribution: Habitat formation and persistence modeling at district to subnational scale; temperature/rain/humidity-driven vector suitability windows updated at daily to weekly cadence; local risk classes for 1–14 days (nowcasting) and 2–8 weeks (early warning) where physically meaningful; ensemble-based uncertainty bounds for intervention trigger decisions.

Intervention leverage points: Pre-positioning of larval source reduction teams; trigger-based indoor residual spraying campaigns; targeted bed-net distribution; larval control in identified high-density breeding sites; community alerts for personal protection.

8.2 Opportunity 2 — Zoonotic Spillover Hotspot Intelligence

Target events: Bat-to-human spillover (Nipah, Hendra, Ebola, SARS, MERS, rabies); rodent-to-human spillover (Lassa, hantavirus, plague); ungulate-to-human spillover (Rift Valley fever, anthrax, brucellosis, Q fever); wildlife-livestock-human interface spillover events at markets, abattoirs, and agricultural frontiers.

Causal pathway: Climate forcing → reservoir habitat and population dynamics; Seasonal rainfall/temperature → host behavior, roosting patterns, foraging range; Land-use change → host habitat contraction and spillover edge formation; Agricultural calendar and market events → human-animal contact intensity; Pathogen shedding → reservoir infection prevalence under environmental stress.

τ **core contribution:** Structured hotspot ranking by reservoir-behavior risk and contact-intensity windows; identification of seasonal high-risk periods 8–12 weeks ahead; integration of climate-driven reservoir behavior with known spillover pathway geography.

Intervention leverage points: Pre-emptive behavior change campaigns before high-risk harvest/market seasons; enhanced veterinary surveillance during identified risk windows; targeted health messaging in spillover interface communities; pre-positioning of diagnostic rapid-response capacity.

8.3 Opportunity 3 — Climate-Sensitive Outbreak Preparedness

Target events: Extreme rainfall → leptospirosis, cholera, hepatitis A/E, schistosomiasis; drought-to-flood transition → Rift Valley fever, vector habitat reset; Anomalous warm seasons → extended mosquito transmission windows; El Niño/La Niña events → regional vector and reservoir dynamics; post-typhoon/cyclone → water-borne and vector-borne disease surge.

Causal pathway: ENSO state → regional precipitation and temperature patterns; Precipitation → standing water, flooding, water-contamination pathways; Temperature anomaly → vector development acceleration or thermal stress suppression; Post-disaster displacement → exposure intensity at human-water-vector interface.

τ **core contribution:** Forward translation from climate hazard state into disease-risk surface at sub-national resolution; seasonal preparedness scoring for high-risk geographies; integration with national disaster risk management architecture.

Intervention leverage points: Pre-outbreak health worker deployment; pre-positioning of diagnostic kits, oral rehydration supplies, and vector control materials; community preparedness communication synchronized with climate forecast windows.

8.4 Opportunity 4 — Cross-Species Intervention Optimization

Target interventions: livestock ring-vaccination campaigns in advance of vector season; wildlife surveillance intensification before identified spillover windows; livestock movement advisories during high-risk ecological transitions; larval habitat control timed to pre-transmission vector suitability peaks.

τ **core contribution:** Intervention sequencing and prioritization under bounded uncertainty; integration of animal-health, veterinary, and public-health intervention calendars with a common risk surface; cross-sector resource allocation optimization across a shared causal substrate.

8.5 Opportunity 5 — Local Risk Products for Public Action

Target outputs: Subdistrict mosquito-risk maps updated weekly; animal-market biosecurity risk scores updated by season; school and health-facility catchment area alerts; community-level risk communications calibrated to local ecological conditions.

τ **core contribution:** Localized, decision-ready risk products that can be issued without waiting for full outbreak confirmation; risk-class outputs (not point forecasts) that support proportionate action; transparent uncertainty ranges that build institutional and community trust over time.

9 Geographic Case Studies

9.1 Case Study 1 — Dengue Climate Expansion, 2022–2024

Background. Dengue is caused by four serotypes of dengue virus (DENV 1–4), transmitted primarily by *Aedes aegypti* and *Aedes albopictus*. It is the fastest-spreading vector-borne viral disease in the world. WHO has classified dengue as a priority disease requiring urgent research and response; its 2024 fact sheet documents **over 14.6 million cases and more than 12,000 deaths** globally in 2024 alone [2].

The 2023–2024 surge. The dengue outbreak of 2023–2024 was historically exceptional on multiple dimensions. Globally, 2023 saw approximately **5.2 million reported dengue cases** — already a record — followed by a further escalation in 2024 [2]. Brazil experienced its most severe dengue outbreak on record in early 2024: more than **3.5 million cases** reported through the first six months, including more than 1,500 deaths, overwhelming health system capacity in several states [17]. Peru, Argentina, and Colombia also recorded large outbreaks.

In Europe, the 2023 season saw the first confirmed locally acquired dengue cases in multiple historically non-endemic countries: **130+ local dengue cases** were reported in Spain, Italy, France, and Croatia in 2023 — all acquired without travel to endemic regions [7]. This confirmed what climate models had projected: the *Aedes albopictus* range expansion into Southern and Central Europe, driven by warming summers and the persistence of the species through milder winters, had created conditions for endemic dengue establishment.

The lead-time gap. Current outbreak forecasting systems for dengue operate primarily in **reactive mode**: surveillance data from notified cases is aggregated at national level, model-based forecasts are generated from historical climate-case correlations, and public health advisories are issued after transmission has already been detected. The effective warning window for actionable pre-positioning — concentrating vector control assets, triggering community messaging, pre-positioning diagnostics — is typically **4–6 weeks behind the ecological conditions that drove the outbreak** [18].

τ opportunity. Under the τ assumption, temperature and humidity fields combined with land-cover and water-retention dynamics provide a physically faithful substrate for tracking the formation of *Aedes* larval habitat 6–12 weeks before the vector population peak that drives clinical transmission. If this precursor tracking can be demonstrated to have 70–80% sensitivity at a 6-week lead time with a false-alarm rate below 30% (benchmarks derived from current meteorological-epidemiological modeling performance [19]), the actionable advance window for vector control pre-positioning expands from near-zero to 4–8 weeks.

The practical consequence for Brazil 2024 alone: a 4-week earlier intervention window across the highest-risk districts of São Paulo, Rio de Janeiro, and Bahia — where vector control capacity exists but was deployed reactively — could have reduced peak transmission pressure by an estimated **20–40%**, based on published models of vector control timing efficiency [20]. Even a 20% reduction in a 3.5-million-case outbreak represents more than **700,000 cases averted** and several hundred deaths prevented in a single country in a single season.

Climate trajectory. The Lancet's 2019 analysis, using CMIP5 models under a 2°C warming scenario, estimated that global dengue risk could expand to include an additional **2.25 billion people** by 2080 [13]. Under current emissions trajectories (closer to 3–4°C by 2100), the expansion timeline accelerates. This is not a future risk — it is a risk that is already being realized on a multi-year trend, as the 2024 data confirm.

Key numbers for this case study: - 5.2 million dengue cases globally, 2023 (WHO) - 14.6 million cases, 2024 (WHO) - 3.5 million cases, Brazil 2024 - 130+ local European cases, 2023 (first endemic-free transmission) - Current warning lag: 4–6 weeks behind ecological preconditions - τ-targeted advance window: 6–12 weeks - Potential actionable gain: 4–8 weeks additional lead time for vector control pre-positioning

9.2 Case Study 2 — Nipah Virus Bangladesh: Recurrent Spillover, 2001–2023

Background. Nipah virus (NiV) is a paramyxovirus transmitted to humans primarily from *Pteropus* (fruit bat) reservoir hosts, with the index pathway in Bangladesh linked to contamination of raw date palm sap. NiV is classified as a **WHO priority pathogen** due to its high case fatality rate, its pandemic potential from limited human-to-human transmission in clusters, and the absence of licensed vaccines or therapeutics. It has caused **14 recognized outbreaks in Bangladesh between 2001 and 2023**, with additional outbreaks documented in India and a significant 2018 outbreak in Kerala, India [21].

The case fatality burden. WHO's assessment of Nipah in Bangladesh gives a case fatality rate of approximately **62%** — among the highest case fatality rates of any recognized zoonotic pathogen [22]. Most outbreaks cluster between **January and March**, corresponding to the peak date palm sap harvesting season in Bangladesh. Bats access sap containers placed at the base of date palms overnight; their saliva and excreta contaminate the sap, which is then consumed raw as a delicacy.

The climate pathway. The Nipah spillover mechanism is directly sensitive to climate variables: - **Temperature and humidity** govern the bat roosting and foraging calendar, including the timing and intensity of the winter fruiting season that drives bat movement near human settlements; - **Rainfall patterns** influence the seasonal productivity of bat food sources and the timing of range shifts toward agricultural edges; - **Harvest season timing** is itself partially temperature-dependent, as date palm sap yields are influenced by ambient temperature.

Studies of Bangladeshi Nipah outbreaks have identified that **outbreak events cluster under precipitation and temperature conditions that can be characterized 60+ days in advance** using meteorological forecast products [23]. The Jan–March window is predictable in its existence but variable in its intensity year-to-year as a function of specific climate conditions in the preceding November–December period.

The current detection gap. Under current surveillance protocols, Nipah outbreaks in Bangladesh are detected only **after the first human cluster is clinically confirmed** — typically through the appearance of encephalitis cases in district hospital referral systems. By the time the cluster is recognized and an investigation team is deployed, a further **1–3 weeks** of potential exposure have typically elapsed, with associated secondary human-to-human transmission risk in family and hospital settings [24].

τ opportunity. Under the τ assumption, a physically faithful model of Pteropus bat roosting behavior, seasonal movement patterns, date palm harvest calendar, and temperature/humidity conditions would allow **seasonal risk characterization 8–12 weeks before peak exposure conditions emerge**. This is not a prediction of specific outbreak occurrence — the stochastic elements of bat-sap contact and individual human exposure remain irreducible. It is a prediction of **elevated-risk season windows** in specific geographic areas with sufficient precision to trigger preemptive sap-safety behavior campaigns.

The intervention leverage is substantial. Bangladesh's public health authorities, working with icddr,b (the International Centre for Diarrhoeal Disease Research, Bangladesh) and WHO, have demonstrated that **behavior change campaigns** focused on covering date palm sap containers and avoiding raw sap consumption can effectively eliminate the spillover pathway when they reach target communities in advance of the season [25]. The bottleneck is **timing and targeting**: campaigns need to reach the right communities before the high-risk harvest window opens, not after the first human case is confirmed.

A τ-grade seasonal risk signal 8–12 weeks ahead would allow behavior change campaigns to be deployed with 4–8 weeks of preparation time before the risk window opens — compared to the current situation in which response begins after outbreak confirmation. In a disease with a 62% case fatality rate and no approved therapeutic, the difference between pre-campaign and post-cluster response is measured directly in lives: **Bangladesh has recorded between 3 and 45 human cases per outbreak event**, and multiple outbreaks have been amplified by nosocomial transmission in hospitals where early case isolation was insufficient [24].

Kerala 2018 case comparison. The 2018 Nipah outbreak in Kerala, India, killed 17 of 19 confirmed cases (89% CFR) before it was contained. The outbreak was contained largely through aggressive contact tracing and hospital infection control — reactive measures applied after cluster recognition. The Kerala government and WHO subsequently invested in improved surveillance and response capacity. Under a τ scenario, the combination of seasonal risk prediction and behavior change campaign pre-positioning would target precisely the detection window before cluster formation, when prevention is still available.

Key numbers for this case study: - 14 outbreaks, Bangladesh 2001–2023 (WHO) - 62% case fatality rate (WHO) - Outbreak events cluster January–March - Precipitation patterns governing bat behavior: predictable 60+ days in advance - Current detection: only after first human cluster confirmed - τ-targeted advance window: 8–12 weeks before peak risk season - Intervention leverage: behavior change campaigns to cover sap containers, proven effective when deployed pre-season - Nosocomial amplification potential: high without early case isolation

9.3 Case Study 3 — Rift Valley Fever East Africa 2006–2007 (Supporting)

Background and event. The 2006–2007 East Africa Rift Valley Fever (RVF) outbreak was one of the largest recorded, affecting Kenya, Somalia, and Tanzania. WHO estimates record more than **150,000 human infections** (including a substantial asymptomatic fraction), **684 confirmed deaths**, and **USD 60 million in direct livestock losses** in Kenya alone [26]. The outbreak was driven by an exceptional La Niña rainfall event that created ideal conditions for the *Aedes* and *Culex* mosquito species that serve as RVF vectors: widespread flooding created large permanent and semi-permanent pools in the pastoralist landscape of northeastern Kenya and the border areas with Somalia.

Prior warning and response gap. The International Research Institute for Climate and Society (IRI) at Columbia University and FEWS NET (the Famine Early Warning Systems Network) had issued **6–8 week warnings** prior to the outbreak onset, based on ENSO forecasts and rainfall probability indices [27]. These warnings were technically sound but operationally insufficient: the response to the warnings was inadequate to prevent the outbreak, partly because the spatial precision of the risk mapping was insufficient to concentrate veterinary vaccination campaigns and human exposure prevention in the specific pastoralist areas most at risk.

τ improvement opportunity. The IRI/FEWS NET warning demonstrated that **ENSO-driven rainfall prediction can provide actionable advance notice for RVF risk**. The τ addition would be local rainfall field forecasting at district to sub-district resolution, allowing spatial targeting of pre-positioning to within a 40–60 km radius rather than the 150–200 km radius achievable with the 2006 forecast tools. At the same time, a τ-faithful representation of the mosquito vector habitat dynamics under the forecast rainfall scenario would sharpen the timing of the risk window to within 2–3 weeks rather than the 4–6 week precision of the 2006 warning.

Counterfactual estimate. If the RVF warning in 2006 had been spatially precise enough to concentrate the available livestock vaccination capacity on the highest-risk pastoralist zones, and if the behavioral warning campaign for human exposure had been deployed with 4 weeks of lead time rather than 1 week, published models of RVF outbreak dynamics suggest a **40–60% reduction in peak human case incidence** would have been achievable [28]. Applied to the observed outbreak, this represents approximately 60,000–90,000 fewer human infections and 300–400 fewer deaths — in a single outbreak event.

10 Finance, ROI, and Climate-Finance Eligibility

10.1 The economic case for prevention

The foundational economic argument for τ-grade One Health early warning is straightforward. McKinsey's 2021 estimate places the economic cost of the COVID-19 pandemic at **USD 8–16 trillion** by end of 2021 [11]. The World Bank has estimated that **pandemic preparedness investment of USD 10 billion per year globally** — a figure that includes early warning systems, surveillance capacity, and preparedness infrastructure — would be sufficient to bring the world to a level of preparedness that could substantially reduce the severity of the next pandemic [9]. That investment level represents roughly **1/800th of the estimated cost of a single major pandemic event**.

For vector-borne disease specifically, the economic burden is large and largely preventable. WHO estimates the global economic burden of dengue at approximately **USD 8.9 billion per year** in direct healthcare costs and productivity losses [29]. Malaria's economic burden is estimated at more than **USD 12 billion per year** in Africa alone [30]. Rift Valley fever costs the East African livestock sector hundreds of millions of dollars per major outbreak. These are not theoretical future costs — they are current annual expenditures that better early warning would partially avert.

10.2 Scenario A: National Vector-Borne Disease Climate Intelligence Platform

Scope. A national-scale τ-grade vector-borne disease climate intelligence platform for a high-burden country (population 50–200 million; dengue and/or malaria endemic; existing national public health institute with surveillance infrastructure). The platform would deliver: - Daily updated vector suitability maps at district resolution; - 2–8 week risk outlooks at subdistrict resolution for intervention targeting; - Seasonal preparedness dashboards for national emergency operations center; - Integration with meteorological forecast services and national surveillance reporting systems.

Cost estimate. Based on comparable digital-health platform builds in LMICs, with adaptation for τ physics integration: - Platform development and integration: **USD 1.5–3M** (one-time); - Data infrastructure and integration (meteorological feed, satellite, surveillance): **USD 0.5–1M** (one-time); - Operational staffing and maintenance: **USD 0.8–1.5M per year**; - Training and institutional capacity building: **USD 0.5–1M** (one-time); - **Total Year 1–3 investment: USD 3–8M** across development and initial operation.

Benefit-cost framing. A 15–20% improvement in vector-control targeting efficiency (more spray-missions in hotspots, fewer in low-risk areas) would reduce the cost of a national dengue prevention program by roughly USD 5–20M per outbreak cycle in a high-burden country (based on typical national vector control budgets of USD 30–100M per year in high-burden settings). A single major outbreak prevented or substantially attenuated adds healthcare cost savings of USD 20–100M (direct treatment costs for major dengue outbreak in a country like Brazil, Philippines, or Bangladesh). The **benefit-cost ratio at 5-year horizon: approximately 3:1 to 10:1** under conservative assumptions.

30–50% cost reduction in vector control through better targeting vs. reactive: this is achievable based on published evaluations of risk-stratified vs. blanket spraying campaigns in dengue-endemic countries [31]. Applied to national budgets, the savings from targeting efficiency alone can exceed the platform development cost within 2–3 outbreak cycles.

10.3 Scenario B: Regional Zoonotic Spillover Early Warning Network

Scope. A regional (4–8 country) τ-grade zoonotic spillover early warning network covering a high-risk ecological interface zone (e.g., the Mekong basin; East African highlands; Central and West Africa bat spillover corridor; Bangladeshi-Indian Nipah belt). The network would deliver: - Seasonal spillover risk forecasts updated monthly at district resolution across the network; - Cross-border reservoir behavior risk products (bat movement, livestock trade, market calendar integration); - Pre-season intervention trigger recommendations for behavior change, livestock vaccination, and surveillance intensification; - Shared alerting system with national health ministries and WHO regional offices.

Cost estimate: - Platform architecture and multi-country integration: **USD 4–8M** (one-time); - Participating country capacity building and data integration: **USD 2–4M** per country × 4–6 countries = **USD 8–24M**; - Regional coordination infrastructure and staffing: **USD 1.5–3M per year**; - **Total Year 1–5 investment: USD 15–40M** across development and first operational phase.

Benefit-cost framing. The pandemic prevention cost calculus is the most compelling frame. COVID-19 cost USD 8–16 trillion. A single moderate pandemic event (comparable to H1N1 2009, which caused an estimated USD 45–55 billion in direct economic losses) costs 1,000× more than a USD 15–40M early warning network. Even a **1-in-50 chance of the network preventing or attenuating one regional pandemic event** over a 20-year operational lifetime yields an expected return of **USD 900 million to USD 32 billion** against a USD 15–40M investment — implying expected **benefit-cost ratios in the range of 25:1 to 800:1** [12].

Prevention is 500 times cheaper than response (McKinsey 2021). The threshold question is not whether to invest, but how to build the platform with appropriate technical rigor and institutional accountability.

10.4 Named Climate-Finance Windows

World Bank Pandemic Fund / One Health HSES (Health System Resilience). The Pandemic Fund, hosted at the World Bank, is the primary multilateral financing mechanism for pandemic prevention, preparedness, and response. Its initial capitalization of USD 1.6 billion (as of 2023) supports technical assistance and investment in IHR core capacity building, particularly in LMICs. τ-grade One Health intelligence platforms fall squarely within the Pandemic Fund's mandate for **early warning and surveillance** — one of the Fund's four investment pillars [9].

CEPI — Coalition for Epidemic Preparedness Innovations. CEPI's mandate includes investment in **outbreak detection and platform preparedness technologies**. Under its 2022–2026 strategy, CEPI has committed to accelerating outbreak response to 100-day vaccine development, with complementary investment in the surveillance infrastructure that would trigger such response earlier. A τ-grade ecological early warning layer that accelerates spillover detection by 4–8 weeks maps directly onto the CEPI value chain upstream of vaccine deployment.

Wellcome Trust — Pandemic Preparedness Program. Wellcome's Climate and Health programme and its pandemic preparedness portfolio both support investment in **surveillance, diagnostics, and data systems** for emerging infectious disease. The climate-disease intersection — vector-range expansion, spillover under climate stress — is an explicit funding priority.

Green Climate Fund (GCF) — Climate-Health Nexus. GCF has established a health co-benefit lens for climate adaptation investments. τ-grade vector-borne disease climate intelligence platforms — which are explicitly designed to translate climate signals into health risk warnings — are structurally eligible as **climate adaptation investments with health co-benefits**. The key framing is that the platform is a climate-risk management tool that happens to have its primary measurable co-benefit in health outcomes.

USAID GHSA — Global Health Security Agenda. USAID's GHSA supports countries in developing IHR core capacities, with particular focus on **real-time biosurveillance** and **zoonotic disease** — the two IHR dimensions where τ-grade ecological intelligence is most differentiated. GHSA bilateral programs typically fund capacity building over 3–5 year cycles at USD 5–25M per country.

11 Evidence and Translation Ladder

The path from research concept to operational One Health intelligence must be built in phases that respect both the technical maturity of τ and the institutional trust requirements of public-health systems. The following four-phase ladder reflects operational realism.

11.1 Phase 1 — Shadow Mode and Benchmark Integration (Months 0–18)

Objective: Establish that τ-grade ecological risk modeling adds demonstrable value relative to current systems in a controlled, parallel, non-disruptive deployment.

Activities: - Deploy τ as a parallel risk engine alongside existing meteorological forecasts, surveillance platforms, vector-control dashboards, and veterinary early-warning systems in 1–2 pilot geographies; - Generate daily and weekly risk products without injecting them into operational decision chains; - Retrospective validation against historical outbreak records: assess sensitivity, specificity, lead time, and false-alarm rate for vector habitat formation forecasts, spillover risk windows, and climate-hazard-to-health-risk translations; - Institutional partnership building with national public health institutes, WHO regional offices, and national meteorological services.

Success gates: - Sensitivity $\geq$70% at 4-week lead time for vector suitability peaks in pilot region; - False-positive rate $\leq$35% for high-risk alerts; - Successful data integration with at least one meteorological and one surveillance data stream per pilot site; - Stakeholder endorsement from at least one national health ministry for Phase 2 progression.

11.2 Phase 2 — Hotspot Ranking and Intervention Support (Months 12–36)

Objective: Use τ outputs operationally for risk ranking and pre-positioning advice, while maintaining final decision authority within existing governance frameworks.

Activities: - Publish weekly risk bulletins for participating geographies, endorsed by national public health institute; - Support vector-control planning cycles with τ-generated hotspot rankings and risk outlook products; - Integrate τ outputs into national early-warning dashboard and emergency operations center reporting; - Begin cross-sector joint working: public health, veterinary, meteorological agency sharing common risk substrate; - Develop and deploy spillover risk pre-season products for at least one high-priority zoonotic corridor.

Success gates: - Documented instances of τ risk signal preceding clinical outbreak confirmation by $\geq$3 weeks in at least two outbreak events; - National vector-control program documenting changed resource allocation based on τ hotspot outputs; - Cross-ministry One Health coordination meeting using shared τ risk products at least monthly.

11.3 Phase 3 — Integrated Operational Use (Months 30–60)

Objective: Embed τ outputs into One Health task-force workflows, public-health emergency operations centers, veterinary response systems, and climate-health services as a standard intelligence layer.

Activities: - Full integration with national IHR reporting and alert systems; - Formal trigger protocols linking τ risk-class outputs to vector-control deployment authorizations; - Regional scaling across neighboring countries with shared vector and zoonotic risk zones; - Capacity building for national biostatisticians and epidemiologists in interpreting τ risk outputs; - Evaluation of cost-efficiency outcomes: vector-control targeting efficiency, resource utilization, intervention timeliness.

Success gates: - τ-triggered anticipatory actions documented in $\geq$3 country-level public health response events; - Peer-reviewed evaluation of lead-time improvement and cost-efficiency relative to pre-τ baseline; - Cross-border risk product endorsed by at least one regional body (e.g., Africa CDC, ASEAN APSED, PAHO SIDA).

11.4 Phase 4 — Cross-Border and Multilateral Scaling (Months 48–96)

Objective: Use common τ risk products for transboundary disease corridors, regional surveillance, donor financing triggers, and shared response protocols.

Activities: - Integration with WHO Regional Office surveillance and alerting infrastructure; - Pandemic Fund reporting alignment: τ outputs as evidence basis for early warning and preparedness investments; - Development of cross-border spillover risk products covering transboundary movement corridors; - Contribution to global zoonotic spillover risk atlas; - GHSA / IHR capacity scoring credit for countries with operational τ-integrated early warning.

12 Stakeholder Map and Change Management

12.1 Primary decision-makers and institutional champions

Ministries of Health hold the mandate for human disease surveillance and response. They are the primary authority for national IHR implementation and the primary client for early warning products. Their key concern is **actionability**: they need risk products that support specific operational decisions, not additional dashboards that require epidemiological interpretation.

Ministries of Agriculture and Veterinary Services hold the mandate for livestock and zoonotic disease monitoring. They are co-responsible under One Health for the animal-human interface and are typically the lead agency for managing animal reservoir outbreaks that precede human spillover. Their key concern is **lead time for livestock vaccination** and movement control, which requires 4–8 weeks of advance notice for productive deployment.

National Meteorological and Hydrological Services provide the environmental data inputs that τ depends on. They are natural integration partners and, in many countries, already provide climate services to health ministries. Their key concern is **attribution**: they need to understand what the τ layer adds to their own forecasting capability and where responsibility for forecast skill lies.

WHO Regional and Country Offices serve as the primary multilateral coordination point for IHR implementation, early warning, and outbreak response coordination. They are key institutional partners for regional scaling (Phase 3–4) and are the primary channel for GCF/World Bank/Pandemic Fund alignment.

National Public Health Institutes (NCDC India, CPHL Bangladesh, Kenya KEMRI, Brazil Fiocruz, etc.) are the technical centers of excellence for national surveillance and outbreak response. They are the most likely institutional home for τ-grade early warning platform development and operation.

12.2 Secondary stakeholders and beneficiaries

Humanitarian health actors (ICRC, MSF, IRC health programs) are operational users of outbreak intelligence in fragile and conflict-affected settings, which are often the most severely affected by climate-sensitive disease outbreaks with the least institutional capacity to detect them.

Local government and community health workers are the front-line responders who translate risk products into community-level action. Platform design must produce outputs that are interpretable and actionable at this level, not only at national dashboard level.

Academic and research institutions (EcoHealth Alliance, CGIAR, LSHTM, Harvard TH Chan School of Public Health, Institut Pasteur) are natural peer-validation partners and research collaborators for benchmark development and peer-reviewed evaluation.

12.3 Change management considerations

Trust-building sequencing. Institutional trust in new risk-prediction tools in public health is slow to build and fast to lose. The shadow-mode Phase 1 architecture is not merely a technical benchmark exercise — it is a trust-building mechanism. The discipline of generating forecasts in advance, recording them against outcomes, and publishing the verification statistics is the essential institutional-trust investment.

Avoiding "black box" risk. Public health decision-makers are appropriately skeptical of risk outputs from systems they cannot interrogate. The τ deployment architecture must include interpretable risk explanations — not just risk scores — and must provide clear attribution of which environmental and ecological drivers are generating which risk-class outputs.

Multi-ministerial governance from the start. One Health programs consistently fail when one ministry attempts to own the whole system. The τ deployment must have formal joint governance structures from Phase 2 onward, with clear terms of reference for each agency's role in the shared risk substrate.

13 Gender, Equity, and Labor Dimensions

13.1 Differential burden by gender

Vector-borne and zoonotic disease burden is not gender-neutral. Women in many high-burden settings bear disproportionate exposure through **domestic water collection** (which creates larval *Aedes* habitat in household water storage), **subsistence agricultural work** at wildlife-livestock interfaces, **caregiving of sick children** (which increases secondary dengue and malaria exposure in household settings), and **date palm sap collection** and preparation (a primarily female activity in parts of Bangladesh's Nipah-endemic zones). Early warning systems that do not account for gendered exposure pathways will systematically underperform in protecting the populations at highest contact risk.

τ-grade household and village-level risk products should be designed with **gender-disaggregated exposure pathways** in mind: where is the larval habitat formation risk concentrated relative to female-dominated domestic water storage practices? Where are the behavior change intervention leverage points that are primarily accessible through female community health networks?

13.2 Equity in benefit distribution

Climate-sensitive disease outbreaks fall most heavily on **the poorest and most geographically marginalized communities** — those with the least infrastructure for water management, the least access to healthcare, and the least political voice in resource allocation for vector control. An early warning system that improves risk intelligence at national capital level but does not improve subdistrict targeting for the most vulnerable communities may fail to reach the populations most at need.

The deployment architecture must explicitly include **last-mile risk product design**: what does a τ-generated district risk score mean for a community health worker visiting households in a peri-urban flood zone? The institutional answer to this question determines whether the system produces equity benefits or reinforces existing inequities in health system access.

13.3 Labor and livelihood dimensions

Early warning systems that issue risk alerts affecting **market closures**, **livestock movement restrictions**, or **agricultural calendar changes** have direct labor and livelihood consequences for pastoralists, farmers, market workers, and date palm tappers. The governance framework (Section 14) must include proportionality requirements: interventions recommended on the basis of τ risk outputs must be demonstrably necessary, targeted, and time-limited — not blanket restrictions that impose disproportionate livelihood costs on vulnerable populations.

14 Benchmark Suite and Success Metrics

A credible τ One Health programme must prove itself on benchmark problems that are legible to external institutions, independently verifiable, and meaningful to the public-health stakeholders who must ultimately rely on its outputs.

14.1 Benchmark 1 — Dengue Hotspot Lead Time and Spatial Precision

Definition: In a dengue-endemic setting with historical outbreak data at district resolution over $\geq$5 years, generate τ-based weekly vector suitability and outbreak risk forecasts at 1-week, 2-week, 4-week, and 8-week lead times. Evaluate against observed outbreak onset dates and district-level case peaks.

Target performance: - 4-week lead time: $\geq$70% sensitivity, $\leq$35% false-positive rate for district-level high-risk alerts; - 8-week lead time: $\geq$55% sensitivity, $\leq$45% false-positive rate; - Spatial precision: area under ROC curve (AUC) $\geq$0.75 for district-level risk ranking.

Comparison baseline: Current best-in-class dengue forecast models (NOAA/IRI seasonal-climate-to-health tools; ECDC dengue risk maps).

14.2 Benchmark 2 — Malaria Vector Window Prediction

Definition: In a malaria-endemic savanna or highland setting, identify Anopheles breeding-condition windows (standing water + temperature threshold) at sub-district resolution, 3–6 weeks ahead. Evaluate against entomological surveillance trap data and case reports.

Target performance: - 3-week lead time: $\geq$65% sensitivity for breeding-condition onset; AUC $\geq$0.70 for sub-district risk ranking; - False-alarm rate for “high-risk weeks” (those triggering IRS deployment recommendation): $\leq$30%.

14.3 Benchmark 3 — Zoonotic Spillover Seasonal Risk Windows

Definition: For a Nipah-endemic district of Bangladesh, generate seasonal risk scores for each January–March window based on prior-year precipitation and temperature patterns (November–December), bat roosting behavior model, and harvest calendar. Evaluate against recorded human case occurrences 2001–2023.

Target performance: - Correct identification of $\geq$10 of 14 outbreak-year January–March windows as "elevated risk"; - False escalation rate (high-risk season forecast without outbreak): $\leq$40%; - Geographic precision: if district-level forecast available, AUC $\geq$0.70 for district-level risk ranking within the endemic zone.

14.4 Benchmark 4 — Climate-Hazard to Outbreak-Risk Translation

Definition: For a Rift Valley Fever risk zone in East Africa, translate ENSO/La Niña rainfall forecasts into sub-national vector habitat risk surfaces at 8-week lead time. Evaluate against historical outbreak onset locations and livestock case data.

Target performance: - 8-week lead time: $\geq$60% sensitivity for district-level high-risk identification; - Spatial precision improvement over IRI ENSO-based hazard map: $\geq$40–60 km improvement in centroid distance between forecast hotspot and actual outbreak epicenter.

14.5 Benchmark 5 — Intervention Efficiency

Definition: In a setting where τ-generated risk products are used to rank vector-control deployment districts, compare: (a) proportion of intervention resources reaching outbreak-district-weeks in τ-targeted allocation vs. (b) historical reactive allocation in matched outbreak seasons.

Target performance: - τ targeting: $\geq$25% improvement in fraction of vector-control resources deployed to districts that subsequently experienced case peaks, relative to reactive baseline; - No increase in total intervention budget relative to comparator.

14.6 Benchmark 6 — False-Alarm Rate and Operational Trust

Definition: Track the ratio of high-risk alerts issued to confirmed outbreak events (or elevated case loads) in the alert districts within the forecast window. Monitor over minimum 24-month operational period.

Target performance: - False-alert ratio $\leq$2:1 (i.e., no more than 2 high-risk alerts for every 1 confirmed elevated-risk event); - No catastrophic false negatives (outbreaks rated "low risk" within 2 weeks of onset): fewer than 1 per year across the pilot geography.

15 Governance Guardrails

One Health intelligence systems are powerful and — if misused — potentially harmful. The following guardrails are non-negotiable in any τ deployment architecture.

15.1 Assumption discipline and no-overclaiming

τ-generated risk products must carry explicit statement of the assumption basis and uncertainty bounds. No risk product should be presented as a "τ prediction" as if the assumption were validated consensus. Every output should carry a clear label of the form: "This risk estimate is generated under a τ physics assumption; uncertainty bounds represent the range of risk-class membership probabilities." This discipline protects institutional credibility and ensures that stakeholders understand the epistemic status of what they are using.

15.2 Human rights and anti-stigmatization

Hotspot intelligence must never be used as a basis for indiscriminate stigma, coercive discrimination, or punitive measures against communities, occupational groups, ethnic populations, or species. The history of disease mapping includes examples of outbreak attribution being weaponized against marginalized communities. τ risk products must be designed with explicit audit trails that prevent such misuse, and governance frameworks must include independent oversight mechanisms.

15.3 Public accountability and auditability

All τ-generated intervention trigger recommendations must be auditable: the data inputs, the model parameters, the risk-class boundary conditions, and the uncertainty bounds must be accessible to public health authorities and, where appropriate, to affected communities. Black-box risk scores are not acceptable in public health operations.

15.4 Data minimization, privacy, and proportionality

Where τ risk products incorporate individual-level mobility data, health-seeking behavior, or community-level demographic information, data governance must apply principles of minimization (collect only what is necessary), proportionality (use only for the stated public health purpose), and local legitimacy (communities should be aware of and consenting to the use of their data in risk modeling).

15.5 Cross-sector joint governance

One Health coordination consistently fails when one ministry attempts to own the entire system. The τ deployment architecture must require **joint governance** with clearly defined decision rights and responsibilities for public health, animal health, environmental, and meteorological agencies. Terms of reference should specify: who is responsible for data quality at each layer; who has authority to issue τ-based public alerts; who has authority to trigger τ-informed intervention recommendations; and who holds accountability for false-alarm consequences.

15.6 IHR alignment and notification discipline

τ-generated risk products that meet IHR Article 12 criteria for potential public health emergencies of international concern (PHEIC) must follow IHR notification pathways through the WHO International Health Regulations framework, not bypass them. The system must be designed to strengthen IHR compliance, not create parallel structures that undermine it.

15.7 Ecological ethics

One Health deployment must not instrumentalize animals, ecosystems, or ecological systems purely as inputs to human optimization. The One Health framework explicitly recognizes the interdependence and intrinsic value of human, animal, and environmental health. τ deployments should reflect this commitment by designing interventions that are minimally invasive of wildlife and ecosystem integrity consistent with public health objectives.

16 SDG Mapping and Bottom Line

16.1 SDG alignment

τ-grade One Health early warning for vector-borne, zoonotic, and climate-sensitive outbreaks is structurally aligned with multiple Sustainable Development Goals:

SDG 3 — Good Health and Well-Being. Targets 3.3 (end epidemics of malaria, neglected tropical diseases, and combat vector-borne diseases), 3.b (universal health coverage), and 3.d (strengthen countries' capacity for early warning and risk reduction) are directly addressed by τ-grade One Health early warning infrastructure.

SDG 13 — Climate Action. Target 13.1 (strengthen resilience and adaptive capacity to climate-related hazards) is addressed through the τ translation of climate signals into actionable health risk intelligence.

SDG 15 — Life on Land. Target 15.5 (halt biodiversity loss) and 15.9 (integrate ecosystem values into planning) are served by an ecological intelligence layer that tracks wildlife-human interfaces without requiring destructive surveillance.

SDG 17 — Partnerships for the Goals. The cross-ministerial, cross-institutional architecture of τ One Health deployment — linking health, agriculture, environment, and meteorological services — is itself a demonstration of the multi-stakeholder partnerships SDG 17 requires.

16.2 IHR Core Capacities

τ-grade One Health intelligence most directly strengthens the following IHR (2005) core capacities: - **C2 — Surveillance**: real-time biosurveillance capacity through ecological precursor monitoring; - **C3 — Response**: anticipatory deployment capability and pre-clinical trigger systems; - **C9 — Zoonotic events**: integrated zoonotic spillover early warning; - **C10 — Food safety events**: ecological risk flagging for climate-sensitive food safety hazards; - **C11 — Chemical events**: environmental hazard tracking (tangential but applicable in flood-related contamination scenarios); - **C13 — Radiation emergencies** (not applicable).

Joint External Evaluation scores for C2 and C9 are among the lowest globally, and improving them is a stated priority for WHO, the Pandemic Fund, and USAID GHSA. τ-grade ecological intelligence is precisely the investment that would move JEE scores in these critical capacity dimensions.

16.3 Bottom Line

The case for τ-grade One Health early warning does not rest on extraordinary claims. It rests on three straightforward observations that are already fully documented in the public health and climate science literature:

First, the disease burden is real, large, and growing. More than 700,000 annual deaths from vector-borne diseases. More than 14.6 million dengue cases in a single year. Sixty percent of all human infectious diseases with zoonotic origins. Climate change expanding the frontier. These are not model projections — they are current counts.

Second, the intervention leverage is high. Prevention is 500 times cheaper than response. Vector control directed at the right place at the right time is demonstrably more effective than reactive surge response. Behavior change campaigns deployed before spillover seasons outperform campaigns deployed after outbreak confirmation. The limiting factor is **lead time and spatial precision** — exactly what τ-grade causal intelligence would deliver under the assumption.

Third, the institutional infrastructure to act is present. WHO, FAO, WOAH, UNEP, the Pandemic

Fund, CEPI, Wellcome, GCF, and USAID GHSA are all deployed in this space with resources and mandates aligned to the opportunity. They are not waiting for permission to invest in better ecological intelligence. They are waiting for a system capable of delivering it.

Under the τ assumption, this is one of the most humane and strategically powerful public-good applications of the framework. It sits at the intersection of climate, ecology, animal systems, public health, and human vulnerability — exactly where a law-faithful cross-species causal twin provides its highest humanitarian leverage.

If the τ physics holds to the degree required for this application, the benefit is not scientific elegance. It is: - earlier warnings, measured in weeks rather than days; - fewer deaths from preventable outbreaks; - fewer wasted interventions in low-risk areas; - stronger preparedness for the next pandemic; - and a more coherent way of protecting the living web in which human health actually exists.

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This dossier is Paper 1 of 4 in the Panta Rhei Impact One Health Portfolio. All impact statements are conditional on the τ physics assumption stated in Section 4. This is a planning document, not a regulatory submission or validated clinical guidance.

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Source: Full manuscript text integrated from Public-Good Briefing draft.

18 Dossier accountability addendum

The following addendum records the release-facing accountability layer for this dossier: claim boundaries, baseline evidence, upstream dependencies, translation assumptions, scenario bands, scorecard rationales, benchmark requirements, governance guardrails, and related Panta Rhei surfaces. It is intentionally downstream of the full source argument above.

Impact thesis

A Public-Good Briefing showing how a law-faithful tau ecology-biology-health twin could provide unusually high humanitarian leverage in One Health early warning for vector-borne diseases, zoonotic spillover, and climate-sensitive outbreaks. The v3 impact thesis is conditional: a Tau-grade vector-borne disease, zoonotic spillover, climate-sensitive outbreak early-warning twin would become valuable if it improves benchmarked public decisions while preserving transparent uncertainty, reviewability, and governance control.

18.1 Public-good burden and baseline evidence

A Public-Good Briefing showing how a law-faithful tau ecology-biology-health twin could provide unusually high humanitarian leverage in One Health early warning for vector-borne diseases, zoonotic spillover, and climate-sensitive outbreaks. The public-good burden is treated here as an institutional decision problem: existing agencies already monitor parts of the domain, but the operational handoff from data to timely, auditable action remains incomplete.

18.1.1 External evidence baseline

- **WHO**, Global Antibiotic Resistance Surveillance Report 2025 [6]: AMR surveillance baseline.
- **FAO, UNEP, WHO, and WOAH**, One Health Joint Plan of Action [2]: One Health governance baseline.
- **UNEP**, Bracing for Superbugs: Strengthening Environmental Action in the One Health Response to AMR [5]: environmental AMR pathway baseline.
- **WHO**, Wastewater and Environmental Surveillance: Summary for Antimicrobial Resistance [7]: wastewater and environmental surveillance baseline.
- **WOAH**, One Health [8]: animal-health and zoonotic-risk governance context.
- **CDC**, National Wastewater Surveillance System [1]: operational wastewater surveillance reference.

18.2 Current institutional landscape

The relevant landscape includes public agencies, research infrastructures, standards bodies, development-finance channels, and domain review communities represented in the evidence base, including CDC, FAO, UNEP, WHO, and WOAH, UNEP, WHO, WOAH. These references are evidence and adoption surfaces, not endorsements or deployment partners.

18.3 Capability gap

The practical gap is a benchmarkable translation gap: current systems expose useful data or partial models, but they do not yet provide a single law-faithful, bounded-error decision layer for vector-borne disease, zoonotic spillover, climate-sensitive outbreak early-warning twin.

18.4 Tau framework dependency map

Surface	Role in this dossier
Build the Tau-Kernel	finite address and scalar foundation
Recover Core Mathematics	mathematical bridge and model interface
Derive Physics	physical readout and domain translation candidate
Results lane	upstream consequences to be mapped precisely during release preparation
direct-registry-mapping-withheld	no direct Registry object is asserted until a substantive Corpus mapping is available
public-docs-mapping-withheld	TauLib module links are asserted only where public documentation exposes a clear surface
Release Manifest	release baseline
Predictions and Falsification	empirical accountability route

18.5 Translation assumptions and missing engineering

Required domain model: **vector-borne disease, zoonotic spillover, climate-sensitive outbreak early-warning twin**.

First benchmarkable test: vector suitability, spillover-risk, and outbreak-warning lead time against surveillance and climate records.

- domain-specific model construction
- data ingestion and validation
- benchmark harness
- pilot protocol
- independent review workflow

18.6 Impact mechanism chain

Public-good burden → external evidence baseline → τ capability hypothesis → upstream Results / Corpus / Verify dependency → translation assumptions → benchmarked pilot → governed adoption pathway.

18.7 Scenario bands

Band	Scenario summary	Confidence
Conservative	A narrow shadow-mode pilot improves one bounded decision task for One Health Early Warning for Vector-Borne Disease, Zoonotic Spillover, and Climate-Sensitive Outbreaks without operational authority.	medium
Realistic	A reviewed prototype strengthens several public-sector workflows for One Health Early Warning for Vector-Borne Disease, Zoonotic Spillover, and Climate-Sensitive Outbreaks after benchmark comparison with incumbent systems.	medium-low
Optimistic	A reusable public-good intelligence layer becomes plausible for One Health Early Warning for Vector-Borne Disease, Zoonotic Spillover, and Climate-Sensitive Outbreaks after external validation and transparent governance review.	low

18.8 Impact scorecard

Public-good scale	5/5	The affected public-good burden is large or institutionally significant within the portfolio.
Tau fit	4/5	The proposed pathway depends on coupled state, bounded uncertainty, and compositional modelling rather than isolated prediction alone.
Evidence proximity	5/5	The evidence base is anchored in public institutions, official monitoring systems, or established scientific reviews.
Measurability	4/5	A first benchmark can be framed against incumbent public datasets, institutional records, or operational decision metrics.
Adoption readiness	3/5	Adoption remains conditional on domain review, governance fit, data access, and institutional integration.
Equity leverage	5/5	The pathway can prioritize underserved or vulnerable populations where public access and safeguards are built in.

18.9 Candidate pilot pathways

regional One Health early-warning pilot with health, animal-health, climate, and environment agencies

18.10 Benchmark suite and success metrics

Type	Incumbent baseline	Required Tau benchmark	Success metric	Validator
translation benchmark	current public or institutional systems in the domain	vector suitability, spillover-risk, and outbreak-warning lead time against surveillance and climate records	pre-registered accuracy, latency, uncertainty, or decision-quality metric	independent domain reviewers
governance benchmark	existing audit, disclosure, and reporting practice	transparent assumption, data, model, and failure-mode disclosure	reviewable evidence pack and adverse-outcome protocol	public-sector or expert governance panel
equity benchmark	current access, service-quality, or exposure disparities	documented pathway for underserved or vulnerable users without hidden exclusion	distributional benefit and risk review before pilot expansion	equity, community, or public-interest review process

18.11 Governance and risk guardrails

- Human oversight for any operational use.
- Public benchmark disclosure before institutional adoption.
- Equity access review for underserved or vulnerable communities.
- Data-rights and privacy controls for operational datasets.
- Misuse-prevention and adverse-outcome monitoring.
- Adverse-outcome monitoring with a documented escalation path.
- External domain review before pilot expansion.

18.12 Related Results / Corpus / Verify / Publications

This dossier is downstream of Results, Corpus, Verify, and Publications surfaces. It is not a Registry object. Direct Registry or TauLib links are asserted only where the mapping is substantive rather than decorative.

18.13 Bibliography and external evidence

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Panta Rhei Research Program

Public-Good Impact Dossier

Tau-Grade One Health Early Warning for Vector-Borne Disease, Zoonotic Spillover, and Climate-Sensitive Outbreaks

Dossier ID: PGID-OH-03 Portfolio: One Health Release: May 2026 publication-ready release

Conditional scenario map. Domain review pending. Deployment, product, validation, certified-impact, and policy-commitment claims are not made.

Public contact and review routes

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