Using artificial intelligence and forecasting to anticipate climate and resilience outcomes

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Photo from : The Malaysian Reserve

From prediction to foresight to anticipation

Today's policies and decisions have consequences for future and future generations.

The future is uncertain. Future uncertainties determine the effectiveness of today's strategies.

The future can be influenced and shaped by today's actions and decisions.

To make informed, strategic, and just decisions that address both present and future challenges effectively, we need to understand and navigate the future.

To make effective and sustainable decisions that are robust against future uncertainties, we need to explore and account for future alternatives.

To enable sustainable transition, we need to understand present and future challenges, leverage opportunities and overcome barriers to change and transformation.

The future is open, but not empty Adam & Groves (2007).

Four approaches to anticipation

1 Probable / improbable futures

→ *strategic planning*

Risk reduction

Dominates climate policy environments today.

2 Plausible futures

→ *enhanced preparedness*

Navigating uncertainty

Where the cases in this talk sit.

3 Pluralistic futures

→ *societal mobilisation*

Co-creating alternatives

Required for transformation.

4 Performative futures

→ *critical interrogation*

Political implications

Asks: whose futures are privileged?

Climate policy creates positive and negative outcomes

WHERE IMPLEMENTATION IS COHERENT

benefits are **shared.**

—Costs absorbed by capacity, ***not by the unprotected.***

—Distributional impacts ***anticipated by design.***

6× more likely under coherent policy

WHERE IMPLEMENTATION IS INCOHERENT

gains are **captured.**

—The most vulnerable ***absorb the costs.***

—Political and financial elites ***capture the gains.***

9× more likely under incoherent policy

Climate Risks and Extreme Weather

60%

of countries lack basic water information services for flood preparedness

~50%

of countries lack multi-hazard early warning systems

8×

higher disaster mortality where early warning systems are absent (WMO)

Storm Daniel, Libya 2023

Forecast 4 days ahead.
~4,000 deaths.
Communication failure.

Ahr Valley, Germany 2021

EFAS warnings issued.
>200 deaths.
Translation and trust failure.

Valencia, Spain 2024

Warnings issued.
>200 deaths.
Decision-architecture failure.

Climate data are inequitably collected: marginalised populations have the poorest data (Rolnick et al. 2022).

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Emerging complexity as a policy and foresight problem

Local climate risk

Rainfall variability, heat, flooding, soil degradation

Transboundary risk

Distant production-node shocks, commodity volatility, import dependence

Temporal dynamics

Path dependencies, feedback loops, extended sweeps of time

LOCAL

Hazard-centric early warning. Predicts what will happen here and now.

Transboundary

System-centric foresight. Anticipates what will happen there and reach here.

TEMPORAL

Path-aware planning. Designs policies that adapt without unravelling over time.

SEI

 · Extending O'Brien & Leichenko (2000); drawing on Cairney (2012), Braithwaite et al. (2018), Dzebo et al. (2025) MEF complex, EEA (2024) governance in complexity.

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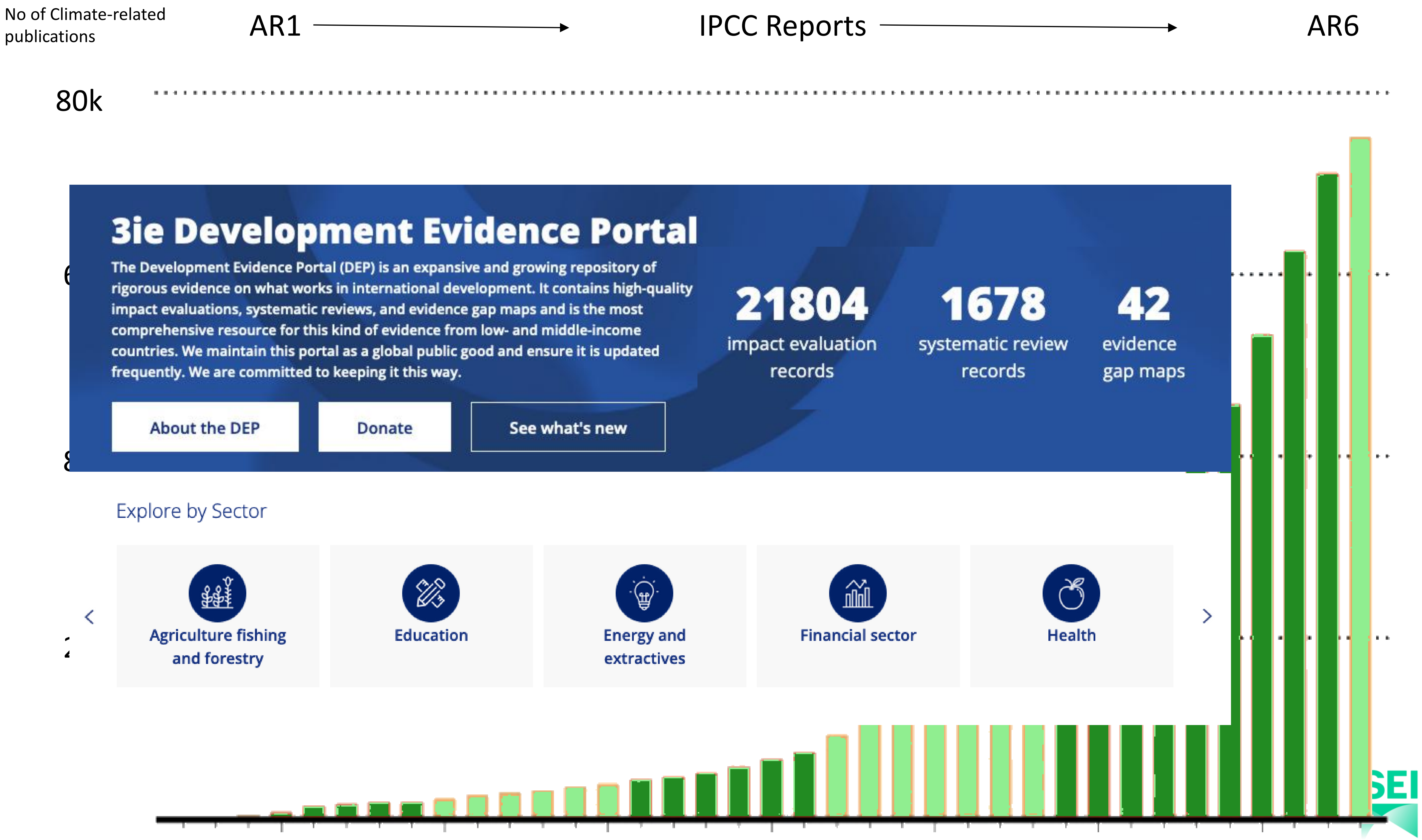
What Works? Where? How? Why?

Evidence Explosion

A mountain of evidence on Climate Action has emerged over time

Ever-increasing evidence-base on what works and what doesn’t in impact evaluations, systematic reviews, and evidence gap maps.



 · Nature Editorial (2024); Pearson (2024); Minx et al. (2017)

How can AI strengthen foresight?

01
Superforecasting & prediction markets

Aggregate dispersed human judgement; AI for calibration

02
World simulation

Physically-grounded models that run the world forward

03
Simulation intelligence

Hybrid physics + ML for systems too complex for either alone

04
AI-assisted scenario building

LLMs to expand the space of plausible futures

05
Participatory futures

AI-augmented deliberation, translation, synthesis at scale

06
Hybrid human–AI interfaces

AI as cognitive exoskeleton, not oracle

Six families of tools – Augmenting human judgement across the foresight workflow

Pérez-Ortiz (2024): "responsible computational foresight" — augmenting human judgement, not substituting for it.

Where can AI strengthen foresight?

Where AI adds value across the foresight workflow, and where it can mislead

UPSTREAM — technical | **INTERPRETIVE** | **DOWNSTREAM — institutional**

1 Detection	2 Prediction	3 Impact	4 Understanding	5 Calibration	6 Operations	7 Communication
Signals from satellite, sensor, text, social media	Forecasting hazards rainfall, yield, prices	Translating hazard into consequence	Explaining drivers, not just outcomes	Knowing when the model is wrong	Embedding outputs in decision pipelines	Translating output into action by people

Camps-Valls et al. (2025): “failure can occur at any stage — but most current failures are downstream.” Storm Daniel, Ahr Valley and Valencia all failed at stages 6–7, not 1–2.

AI–informed tools and methods

Method	AI-augmented form	Best for policy questions about…
Horizon scanning	LLM signal extraction from news, scientific literature, social media; weak-signal detection across multilingual sources	What's emerging that we might miss? Early indicators of disruption.
Trend analysis	ML projection of multivariate trends; remote sensing for environmental trends at high resolution	How are conditions changing — where, how fast, in which direction?
Impact & uncertainty mapping	Simulation intelligence: hybrid physics–ML models; ensembles that quantify deep uncertainty	What might happen if…? What are the cascading consequences?
Scenario development	Generative AI for narrative diversity; agent-based modelling for emergent dynamics	Under different plausible futures, what holds? What fails?

OECD (2021) Global Scenarios 2035; Vervoort & Gupta (2018)

AI and Anticipatory Governance

Probable futures — risk reduction

OPPORTUNITY

ML hazard prediction at unprecedented spatial/temporal resolution; impact-based forecasting.

TRAP

AI optimises for what is measurable, narrowing the future to the training data. Climate non-stationarity is the failure mode.

Plausible futures — preparedness

OPPORTUNITY

Generative AI to expand the scenario space; simulation intelligence for low-likelihood, high-consequence events.

TRAP

“Garbage in, gospel out” — model outputs taken as authoritative once dressed in numbers.

Pluralistic futures — co-creation

OPPORTUNITY

AI-augmented multilingual deliberation; synthesis of community knowledge at scale; lower cost of participatory foresight.

TRAP

Reproduction of dominant framings; exclusion of non-text, non-digital, oral-tradition knowledge.

Performative futures — critical interrogation

OPPORTUNITY

AI to surface whose futures are privileged in existing forecasts; audit of model assumptions.

TRAP

AI itself is developed and deployed by a small set of actors with their own framings — a performative force in its own right.

Default AI deployment is Approach 1. Approaches 2–4 require deliberate institutional design.

Structural Risks and Implications

#	Structural risk	Implication for institutional design
1	Data inequity reproduced: populations most exposed have the poorest data.	Verification and benchmarking frameworks (e.g. WMO WP-MIP).
2	Climate non-stationarity: the future doesn't look like the training data.	Preserve the "challenge function": uncomfortable scenarios stay in.
3	"Garbage in, gospel out": model output dressed in numbers acquires false authority.	Authoritative voice anchored in national meteorological services.
4	Approach 1 default: AI optimised for measurability narrows the future to what's known.	Public–private–academic partnerships that retain public-interest framing.
5	Asymmetric power: AI developed and deployed by a small set of actors with their own framings.	Invest in new competencies: AI literacy, ethical oversight, communication.

Camps-Valls et al. 2025; Pérez-Ortiz 2024; WMO Bulletin 74(2), 2025; OECD 2021; CEPA 2021

Climate Data Needs and Capacity Gaps

Capacity Gaps in relation to collection and release of climate data in Sierra Leone

- EPA relies on outside consultants to conduct technical assessments such as national communications to UNFCCC
- Meteorological Agency lacks radar and other necessary equipment for data Collection
- Sharing of climate-relevant data and information is not consistent or enforced
- Low literacy rate; limited number of civil society engaged in climate issues
- Formats are not in open data and not included on open data portal as a mandatory requirement across agencies
- Unclear roles and responsibilities or overlap of efforts
- Availability of geo-location or high-resolution data is limited
- Challenge in developing greenhouse gas inventories
- Technical and human capacity to collect, analyze, and disseminate agro-climatology data on timely basis is limited

Expertise

Access to technology

Standardisation

Enforcement

Stakeholder Participation

Coordination

Data Granularity

Openness of data

Capacity Gaps in relation to collection and release of climate data in Tanzania

- Quality of specific data sets (historical and real-time data), frequency, consistency
- Civil society not using Access to Information law to access data
- When available, data is not open or free or publicized
- Cost of data acquisition
- Complexity of data that is available
- Data not in open formats and not included on open data portal as a mandatory requirement across agencies
- Coverage or comprehensiveness of data
- Limited availability of geolocation or high-resolution data
- Weak coordination across government, academic, and civil society stakeholders on climate and open data needs and requirements
- Lack of data granularity
- Outdated or partial data or lack of timely data
- Priority data sets not collected by government, only academia

Worker, J., Excell, C., 2018. Climate Change Open Data for Sustainable Development: Case Studies From Tanzania and Sierra Leone. Global Partnership for Sustainable Development Data.

Thank You!

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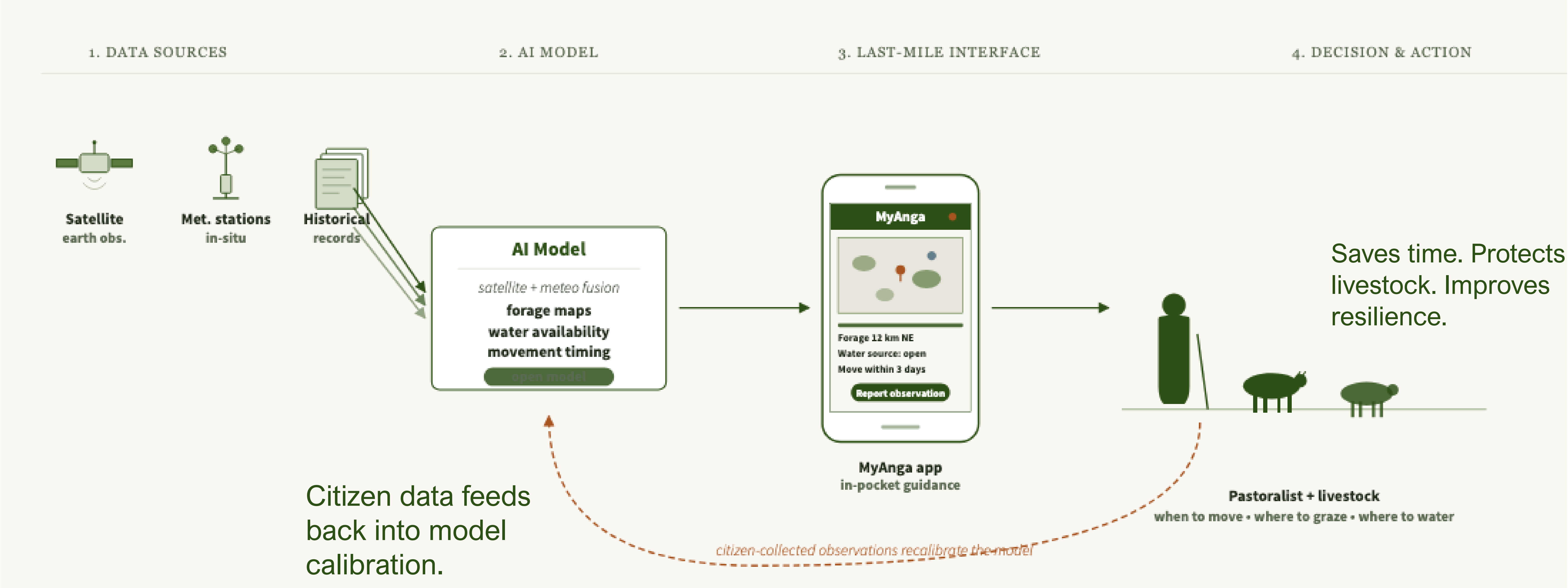
Example: Last-mile AI



WMO Bulletin 74(2), 2025 (Jean, Pappenberger, Chan et al.); Anticipation Hub. Cf. Nepal BIPAD portal — same logic applied to flood early warning in Asia-Pacific. Trust as relational and progressive: McGovern et al. (2024).

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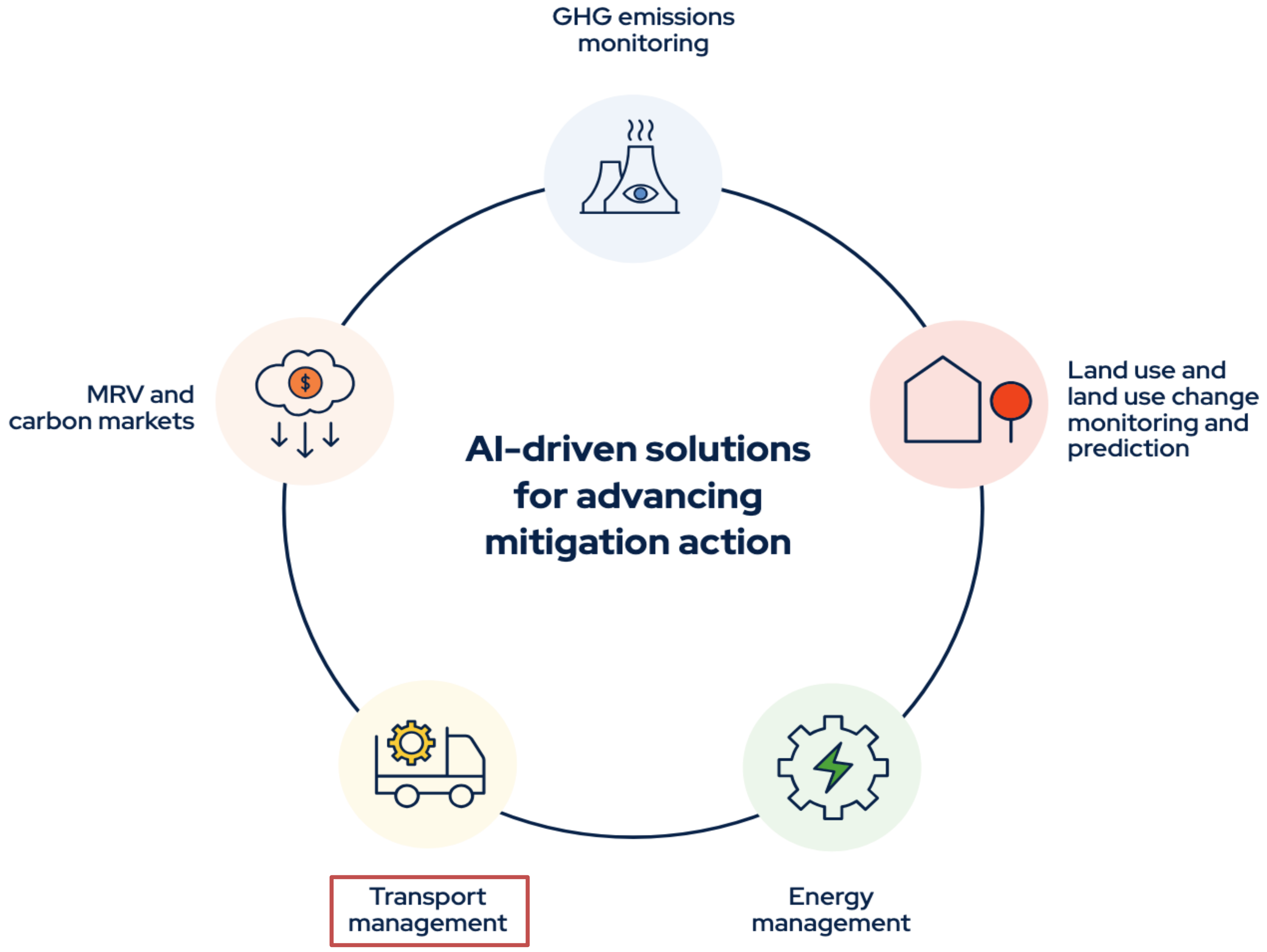
AI and Digital Technologies for Climate Adaptation Action



UNFCCC (2023)

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