AI-SLANDS WORKING PAPER NO. 8

AI FOR ISLAND RESILIENCE

Climate, Disasters, Food and the Sea

Andrew Jennings

Professor in Island Studies, University of the Highlands and Islands

September 2026

AI-slands Working Paper No. 8

ABSTRACT

Artificial intelligence is increasingly presented as a tool for island resilience: it can improve weather forecasting, detect wildfire risk, identify suspicious fishing activity, accelerate coral-reef monitoring and support food-system decisions. Yet predictive performance is not the same as resilience. This paper examines how AI becomes useful only through institutions able to interpret, communicate and act on its outputs. Drawing on verified evidence from Hawai'i and the Pacific, alongside global forecasting, fisheries and agricultural research, it distinguishes upstream models from the last-mile systems on which island communities depend. The cases reveal genuine opportunities but also recurring vulnerabilities: data scarcity, weak local validation, cloud and connectivity dependence, proprietary control, uneven coverage, surveillance, and the extraction of local knowledge. The paper proposes an Island AI Resilience Test covering decision fit, local validity, knowledge and rights, reach, continuity, institutional capability, distribution, and learning. It argues for island-led augmentation rather than technological substitution: global computational capability should strengthen local authority, regional cooperation, human expertise and practical fallback arrangements. AI contributes to resilience when it leaves island institutions more capable of acting with or without the model.

Keywords: artificial intelligence; island resilience; climate adaptation; disaster risk reduction; fisheries; food security; coral reefs; local knowledge

1. INTRODUCTION: RESILIENCE IS NOT PREDICTION

Small islands are frequently described through the language of exposure. Tropical cyclones, coastal flooding, drought, wildfire, coral bleaching, fisheries pressure and imported-food dependence appear together in assessments of island risk. Artificial intelligence enters this landscape with an attractive promise: earlier forecasts, faster detection and more efficient allocation of scarce resources. For governments and communities operating with limited staff across extensive ocean territories, that promise deserves serious attention.

Prediction, however, is not resilience. A forecast can be scientifically impressive and still fail to reach the people who need it. A warning can arrive and still be unusable because it is not trusted, is not available in the right language, assumes continuous connectivity, or gives no institution the authority and resources to act. A surveillance system can identify a suspicious vessel without providing a patrol asset, a legal process or a regional agreement through which the observation becomes enforcement. An image classifier can identify reef change without strengthening the community institutions that decide how a reef is used.

This paper argues that AI contributes to island resilience only when it expands the capacity of island societies to anticipate, absorb, respond to and learn from disruption. That capacity is social and political as well as technical. It resides in public institutions, community organisations, local knowledge, infrastructure, relationships of trust and the ability to continue operating when normal systems fail. The relevant question is therefore not simply whether an AI model is accurate. It is whether the wider system produces timely, legitimate and equitable action.

The paper addresses three questions. Where is AI already being used, or credibly developed, for hazards, marine management, biodiversity and food systems relevant to islands? What forms of dependence and exclusion may accompany those applications? What practical test can island governments and communities use before investing in them? The analysis draws on peer-reviewed research and verified institutional evidence, with cases from Hawai'i and the Pacific alongside global systems that shape island decision-making.

The central proposition can be stated plainly. The forecast is not the warning; the warning is not the response; and the response is not resilience. Each translation requires institutions, judgement and material capability. AI can strengthen those translations, but it can also create new points of failure if data, models and expertise remain external to the places expected to depend on them.

2. ISLAND RISK AS A SYSTEM

The vulnerabilities of small islands are not explained by physical exposure alone. The IPCC's assessment of small islands links climate risks to settlement patterns, freshwater constraints, ecosystem degradation, economic concentration, limited land and fiscal capacity, while also stressing the importance of local and Indigenous knowledge and island-led adaptation (Mycoo et al., 2022). A storm of similar intensity can therefore produce very different outcomes depending on housing, communications, transport, health services, social networks and public authority.

This systemic view matters for AI because data-driven tools tend to isolate a measurable task. They estimate wind, classify pixels, predict fire conditions, recognise a vessel pattern or diagnose crop stress. Such tasks can be useful, yet resilience emerges from the relation between tasks. A weather model must feed a meteorological service; that service must issue an understandable warning; emergency managers must decide what to do; transport and shelters must be available; households must be able and willing to respond; and communications must persist long enough for updates and recovery.

Island geography makes these relations unusually visible. Populations may be distributed across outer islands, valleys or coastlines connected by a small number of roads, ferries, cables and radio links. A single damaged tower or landing point can interrupt several services at once. Specialist staff may be concentrated on a capital island. National averages may obscure communities with weaker observation coverage or less reliable connectivity. In this setting, efficiency and resilience can pull in different directions. Centralising data and expertise may reduce cost in ordinary conditions, while increasing dependence during disruption.

Resilience should therefore be treated as a capacity with at least four elements. Anticipatory capacity identifies plausible hazards and emerging change. Absorptive capacity keeps essential functions operating during a shock. Adaptive capacity changes practice in response to evidence. Transformative capacity addresses the institutions and development choices that reproduce risk. AI is most often offered as an anticipatory technology. Island policy should ask whether it also supports, or undermines, the other three capacities.

This framing avoids two equal mistakes. One is technological solutionism: the assumption that better models will compensate for weak institutions or unequal development. The other is technological dismissal: the claim that externally developed systems have little value for islands. Global observation networks, regional forecasting and large-scale computation can provide capabilities that no small jurisdiction could sensibly reproduce alone. The governance task is to connect those capabilities to island authority, knowledge and fallback systems on terms that remain dependable.

3. FORECASTING HAZARDS AND REACHING THE LAST MILE

Machine learning is changing weather forecasting. GraphCast demonstrated that a data-driven model could produce skilful medium-range global forecasts and outperform a leading operational numerical system on many evaluated variables and lead times (Lam et al., 2023). The scientific advance is important for islands because improved forecasts of wind, pressure and precipitation can support cyclone preparation, marine safety, water management and energy planning. Fast inference may also allow more frequent scenarios or wider access to sophisticated products.

Yet a global model is an upstream component, not an island early-warning system. Its training data inherit the strengths and gaps of global observation and reanalysis systems. The spatial scale at which global performance is reported may conceal errors around small land masses, steep topography and local convection. Rare extremes are difficult precisely because they are rare, while climate change can move conditions beyond historical relationships. Operational meteorologists still need ensembles, observations, physical understanding and local judgement rather than a single model output.

The World Meteorological Organization's Severe Weather Forecasting Programme illustrates the institutional chain required. The programme uses a cascading process from global to regional and national centres and includes the Caribbean and South Pacific. Its stated purpose is not merely to produce forecasts but to strengthen national meteorological and hydrological services so that they can provide improved warnings and impact-based information (WMO, n.d.). The structure recognises that capability must exist where forecasts are interpreted and communicated.

For island communities, the last mile is often many miles of sea. Warning systems must account for outer islands, transient workers, tourists, fishers already offshore, people with disabilities and households without smartphones or continuous power. Multiple channels - radio, sirens, SMS, community networks and face-to-face communication - are not a sign of technical backwardness. They are resilience through redundancy. An AI-enhanced system that quietly assumes a functioning cloud service and a charged personal device may perform least well in the conditions for which it was purchased.

Evaluation should consequently extend beyond conventional accuracy scores. Relevant measures include lead time at the local scale, false alarms, missed events, warning reach, comprehension, response time, service continuity and outcomes for different communities. The model should be tested against the decision it is intended to support. A modest improvement in global forecast skill may have little value if the decision threshold is poorly calibrated locally; a less complex tool may have greater value if it is understood, repairable and integrated into routine practice.

4. HAWAI'I: WILDFIRE RISK, MICROCLIMATES AND ACTION

The development of an AI-powered wildfire forecast system in Hawai'i shows both the promise and the limits of prediction. The University of Hawai'i project, supported by the state legislature, is intended to improve an existing forecast system that relies on data from a single station at Honolulu airport. Researchers aim to use machine learning to represent the state's varied microclimates and integrate forecasts with Red Flag Warnings in collaboration with the National Weather Service, land managers, emergency agencies and county fire departments (University of Hawai'i EPSCoR, n.d.).

The problem is well suited to a place-sensitive approach. Elevation, rainfall gradients, wind exposure, vegetation, land use and ignition patterns vary sharply within and between islands. A statewide indicator derived from one location cannot adequately represent those conditions. More spatially resolved observations and modelling could help position crews and equipment, identify periods of exceptional risk and direct prevention work before ignition.

The institutional design is at least as significant as the algorithm. The project involves the agencies expected to interpret and act on the forecasts, rather than presenting a model as a finished product to be handed over. That integration should make it possible to test whether outputs match operational decisions. It also creates a route for practitioners to challenge results that conflict with experience. In a safety-critical setting, disagreement between a model and a fire officer is evidence to investigate, not an inconvenience to automate away.

The case nevertheless remains a development project, not proof of effectiveness. Public descriptions state goals and anticipated uses; they do not establish that the system has reduced losses, improved evacuation or performed reliably during severe events. That distinction is important throughout AI policy. Announcements are evidence of institutional intention. Only operational evaluation can show whether the intended benefit is realised.

A robust evaluation would compare the new system with existing practice across islands and seasons, publish uncertainty, document false positives and false negatives, and assess whether fire agencies have sufficient staff and assets to use the additional information. It should also examine public communication, including how warnings reach people during power or mobile-network failure. The resilience outcome does not lie in the forecast map. It lies in what the map allows people and institutions to do.

5. GOVERNING THE SEA: FISHERIES SURVEILLANCE

For many island states, the ocean territory is vastly larger than the land. Fisheries provide food, public revenue, employment and cultural continuity, while monitoring an exclusive economic zone by vessel or aircraft is costly. Satellite data and machine learning therefore offer a strong practical case: they can narrow an immense search space and help limited enforcement assets focus on activity that warrants attention.

Research using automatic identification system data has shown how machine learning can classify vessel behaviour and map fishing effort at global scale (Kroodsma et al., 2018). Global Fishing Watch extends this approach through public data and analytical tools designed to make activity at sea more visible. In the Pacific, fisheries practitioners describe combining vessel monitoring systems, radar, optical imagery, night-light detection and radio-frequency information. Algorithms can identify patterns, contacts and anomalies that a person could not efficiently find by scrolling through large volumes of data (Griffin and OFMP News, 2023).

The appropriate description is a force multiplier, not an autonomous enforcement system. A model can queue a possible target for further examination. It cannot by itself confirm an offence, establish jurisdiction, protect evidence, dispatch a patrol vessel or conduct a fair legal process. Nor are the data complete. Vessels can disable or manipulate transmitters; small vessels may not carry them; clouds affect optical imagery; model classifications are probabilistic; and commercial data licences can restrict what a national agency is permitted to retain or share.

These limitations have distributive consequences. Industrial fleets are not the only actors made visible. Electronic monitoring and image recognition can also place crews and small-scale fishers under continuous observation. Data that support sustainability or labour protection can be repurposed for surveillance, exclusion or commercial advantage. Island governments should define who may access vessel-level data, how long they are retained, how automated flags are contested and whether fishing communities participate in rule design.

Regional cooperation can reduce dependency. Shared analytical capacity, common standards and pooled access to satellite services may be more sustainable than separate contracts for every state. But regionalisation should strengthen national and community authority rather than relocate it to another distant centre. The test is whether island institutions gain the ability to ask their own questions, interpret evidence and take legitimate action, not merely receive alerts generated elsewhere.

6. REEFS, BIODIVERSITY AND COMMUNITY MANAGEMENT

Coral reefs are both ecological systems and social infrastructure. They support food, livelihoods, tourism, coastal protection and cultural relationships. Monitoring them is labour-intensive, particularly across remote archipelagos where travel is costly and technical capacity is uneven. Image-based AI can accelerate the classification of underwater photographs and make repeated surveys more feasible.

ReefCloud, developed by the Australian Institute of Marine Science, is an open-source platform that uses AI to support reef monitoring and reporting. The ReefCloud Pacific programme has worked with representatives from Micronesia, Melanesia and Polynesia, including training intended to build regional capability. AIMS reports that Sea Women of Melanesia used the tools during a crown-of-thorns starfish outbreak and supplied findings to the Papua New Guinea government within 48 hours (AIMS, 2025). This is a valuable example because the claimed benefit is not classification speed alone; it is faster movement from observation to a management audience.

The programme also illustrates a more credible model of transfer. Workshops with practitioners and community-based management networks seek feedback on monitoring needs, while training trainers can distribute knowledge beyond a single external team. Open access reduces one form of lock-in.

Standardised data may allow comparison across sites and time. These features make the platform potentially more useful to island institutions than a closed product that returns only a score.

Standardisation nonetheless involves choices. A classifier recognises categories defined in a training process. Those categories may not correspond to the ecological distinctions or cultural values used by a community. Image datasets may represent some reef types, depths and water conditions better than others. Automated analysis can also shift funding away from field knowledge even though fieldworkers decide where, when and how images are collected and interpret what change means.

Community-based reef management therefore requires a two-way relationship. Local knowledge should inform survey design, categories and interpretation; AI can then expand the scale and speed of analysis. Results should return in forms useful for local decisions, not disappear into a regional database. Data governance must recognise collective interests in ecological knowledge and sensitive locations. A technically open platform is not automatically a socially open process if communities cannot shape its questions or control subsequent use.

7. FOOD SYSTEMS: HIGH PROMISE, THIN EVIDENCE

Island food systems combine environmental risk with dependence on transport, fuel and external markets. The Global Action Programme on Food Security and Nutrition in Small Island Developing States highlights limited land and water, exposure to climate shocks, high import dependence and the importance of fisheries and local production (FAO, 2017). AI is increasingly proposed for crop diagnosis, irrigation, pest detection, yield forecasting, logistics and market information. Each application could be relevant to islands, but the evidence base demands caution.

A recent evidence review of AI in food and agriculture found many promising applications but limited rigorous evidence of effectiveness in smallholder settings. It emphasised region-specific data, co-creation, institutionalisation and outcomes beyond model accuracy (Lakshminarayan et al., 2025). This matters for islands because tools trained on large continental datasets may not recognise local cultivars, soils, pests or production systems. A phone-based diagnosis is of little value if recommended treatments are unavailable, unaffordable or ecologically inappropriate.

The most useful island applications may be less spectacular than autonomous farming. Demand forecasting could reduce waste in food imports. Local weather and soil information could support water allocation. Computer vision might assist extension workers rather than replace them. Port and shipping data could reveal supply-chain risks before shelves empty. Fisheries and reef monitoring can support food security when they are linked to locally managed harvest decisions. In each case, AI is one part of a service whose effectiveness depends on people, supplies and institutions.

There is also a risk of narrowing food resilience to production efficiency. Island food systems carry cultural, nutritional and ecological values that are not captured by yield. Optimisation can encourage dependence on proprietary inputs, standardised varieties or fragile logistics. Data-intensive agriculture may advantage larger operators able to afford sensors and connectivity. If public support follows the most measurable farms, subsistence and customary production can become less visible even when they provide essential social resilience.

The thin island-specific evidence is itself a finding. Governments should not treat the volume of agricultural AI marketing as proof that a system will work in a small-island context. Trials should begin with a clearly defined local decision, compare the tool with existing practice and measure labour, cost, inclusion, nutrition and ecological effects. Farmers and fishers should have a meaningful role in deciding what problem is worth automating.

8. LOCAL KNOWLEDGE, LANGUAGE AND LEGITIMACY

Island communities possess detailed knowledge of weather, water, currents, species, soils, safe places and social vulnerability. Such knowledge is neither static folklore nor a substitute for scientific

forecasting. It is a living body of observation and practice connected to language, authority and place. Research on ecosystem-based adaptation in the Pacific shows both the value of Indigenous and traditional knowledge and the danger of treating it as a set of fragments to be extracted into externally designed projects (Nalau et al., 2018).

AI creates new opportunities for combination and new risks of appropriation. Community observations can improve local datasets; language technologies can broaden access; and pattern analysis may connect long-term records with current environmental change. But converting knowledge into training data can detach it from the people and obligations that give it meaning. Sensitive ecological locations, customary practices or oral histories may become accessible to agencies or companies that were never granted authority to use them.

Consent must therefore concern purpose and governance, not simply collection. Communities need to know what is being recorded, how it will be labelled, who can access it, whether it will train a reusable model and how benefits will return. Some knowledge should not be digitised. Some data may be suitable for local use but not publication. Collective rights and customary authority may be more relevant than an individual click-through agreement.

Language is equally important. A warning translated automatically into an island language can widen reach, but emergency language demands unusually high reliability. Literal translation may miss place names, customary instructions or the social tone that makes a message credible. Human review and pre-agreed terminology are essential. Where language resources are scarce, an apparently inclusive interface may produce lower-quality service for the very group it claims to include.

Legitimacy grows through participation before deployment. Community members should help define the problem, identify acceptable errors and decide how outputs enter local decision-making. This is not an optional consultation stage added after technical design. It is part of model validity. An alert that is routinely ignored is operationally inaccurate, however strong its statistical score.

9. WHEN RESILIENCE TECHNOLOGY CREATES FRAGILITY

AI systems can create concentrated dependencies even when they are designed for resilience. Cloud processing may depend on an overseas data centre and an intact cable. Sensors require power, calibration and replacement parts. Models require updated data and specialist maintenance. Subscription costs may rise after a pilot. A public agency may be unable to inspect a proprietary system or move its data when a contract ends. These are not peripheral procurement details. They determine whether a service remains available during a crisis and whether an island can govern it afterward.

Data scarcity produces another fragility. Small populations and rare events limit the examples available for training and validation. Combining data across islands may improve statistical power while erasing meaningful differences. A system may perform well on the capital island and poorly in an outer island without the aggregate metric showing it. Climate change further weakens the assumption that past relationships will persist. Models should therefore express uncertainty and be monitored for spatially uneven error and drift.

Automation can also weaken institutional memory. If staff cease practising manual interpretation or paper-based procedures, a high-performing system may reduce the capacity to act without it. Resilience requires graceful degradation: essential functions should continue at a lower level when sensors, networks or vendors fail. Regular exercises should test offline communications, manual thresholds and authority for overriding automated advice.

False precision presents a political risk. Maps and scores can make contested choices appear objective. A risk model may direct protection toward assets with high monetary value while undervaluing customary land, subsistence areas or communities with weak data. A fisheries anomaly score may be treated as guilt. A crop recommendation may conceal assumptions about

acceptable chemicals or water use. Human oversight is meaningful only when decision-makers understand those assumptions and can disagree without penalty.

Finally, resilience investments can reproduce archipelagic inequality. Sensors and high-bandwidth tools tend to cluster where deployment and repair are easiest. Outer islands may receive a simplified service or become data collection sites for models governed elsewhere. Paper 7 described this condition as algorithmic peripherality. In resilience policy, the consequence can be severe: those most exposed to disruption may depend on the weakest part of the technical chain.

10. THE ISLAND AI RESILIENCE TEST

Island institutions need a practical way to distinguish useful systems from attractive demonstrations. The Island AI Resilience Test is intended for early design, procurement, pilot review and post-deployment audit. It does not assign a single score. A system may be strong in one dimension and unacceptable in another; safety, rights or continuity failures should not be averaged away.

Dimension	Required question
1. Decision fit	What decision will change, who has authority to act, and what happens after an alert?
2. Local validity	Has performance been tested for each relevant island, hazard, language and ecological setting?
3. Knowledge and rights	Were affected communities involved, and are consent, collective interests and sensitive knowledge protected?
4. Reach and usability	Can people understand and use the output through accessible, trusted and multilingual channels?
5. Continuity	Will essential functions continue during power, network, sensor or vendor failure?
6. Institutional capability	Can island organisations interpret, challenge, maintain and replace the system?
7. Distribution	Are costs, errors, surveillance burdens and benefits examined across islands and social groups?
8. Learning and accountability	Are uncertainty, incidents, outcomes and model changes documented, reviewed and open to challenge?

The test should be applied before procurement and repeated after deployment. Evidence should include operational exercises and user experience, not only technical documentation. Any critical failure in safety, rights or continuity requires redesign or rejection rather than compensation by strengths elsewhere.

11. A POLICY AGENDA FOR ISLAND-LED RESILIENCE

First, begin with a decision rather than a technology. Agencies should specify the action that better information is expected to change, the person or institution authorised to act, and the resources required. If those elements are absent, improving prediction will not close the implementation gap.

Second, invest in public and regional capability. National meteorological services, emergency agencies, fisheries authorities, environmental organisations, extension services and local governments need staff able to evaluate and challenge models. Regional organisations can pool scarce expertise, negotiate access to satellite and cloud services, maintain common infrastructure and create peer review without requiring every island state to reproduce the same specialist team.

Third, procure for continuity and exit. Contracts should define data access, portability, documentation, update responsibilities, security, costs after the pilot and procedures if a vendor

withdraws. Critical systems should have offline modes and manual fallbacks. Where open-source tools are suitable, funding should include maintenance and training rather than assuming that open code is cost-free.

Fourth, require place-based evaluation. Performance should be reported by island, community or ecological zone where sample sizes permit, with safeguards against disclosure. Evaluation should include false alarms, missed events, reach, response time, service outages, user trust, workload and distribution of benefits. Pilot success should be judged against existing practice and an explicit counterfactual, not against the absence of any technology.

Fifth, govern environmental and community data as a shared resource with differentiated rights. Open data can support regional science and accountability, but openness is not always appropriate for sacred knowledge, vulnerable species locations or personally identifiable vessel and farm data. Governance should specify who decides, who benefits and who can require correction or deletion.

Sixth, finance the institutions around the model. Observation stations, radio networks, local enumerators, reef monitors, firefighters, patrol crews and extension workers may produce more resilience than another dashboard. AI budgets should include the human and physical capabilities needed to use the output. The relevant unit of investment is the whole service, not the algorithm.

Seventh, preserve plural knowledge. Scientific models, professional judgement and community knowledge should be designed to interrogate one another. Disagreement should trigger review. Island languages and locally meaningful categories should be supported through human-led translation and terminology work, especially in emergency communication.

Finally, publish learning, including failure. Small jurisdictions cannot afford to repeat the same pilots without accumulating evidence. Public registers of projects, evaluations, outages, costs and contract lessons would help islands learn collectively and reduce dependence on vendor claims.

12. CONCLUSION

AI can make important contributions to island resilience. It can improve global weather forecasts, represent local fire risk, direct scarce surveillance assets, accelerate reef analysis and support food-system decisions. The strongest examples do not replace island institutions. They make those institutions better able to see, decide and act.

That distinction is the paper's main conclusion. Resilience is not located inside a model. It is produced through a chain of observations, interpretation, communication, authority, material response and learning. Every link has a geography. Every link can fail. For islands, where infrastructure and specialist capacity may be concentrated and where the last mile crosses water, those relations must be designed explicitly.

The Island AI Resilience Test offers a way to do so. It asks whether a system fits a real decision, performs under local conditions, respects knowledge and rights, reaches those at risk, survives disruption, strengthens institutional capability, distributes benefit fairly and supports learning. A system that passes only the accuracy test is not ready for resilient public use.

The policy objective should therefore be island-led augmentation: access to global science and computation combined with local authority, regional cooperation, redundant infrastructure and the ability to refuse, adapt or replace a system. Under those conditions, AI can help islands prepare for hazards and environmental change without exchanging one vulnerability for another.

REFERENCES

Australian Institute of Marine Science (AIMS) (2025) 'AIMS AI technology helps coral reef monitoring across the Pacific', 12 November. Available at: https://www.aims.gov.au/information-centre/news-and-stories/aims-ai-technology-helps-coral-reef-monitoring-across-pacific

Beijbom, O., Edmunds, P.J., Roelfsema, C., Smith, J., Kline, D.I., Neal, B.P., Dunlap, M.J., Moriarty, V., Fan, T.-Y., Tan, C.-J., Chan, S., Treibitz, T., Gamst, A., Mitchell, B.G. and Kriegman, D. (2015) 'Towards automated annotation of benthic survey images: variability of human experts and operational modes of automation', PLOS ONE, 10(7), e0130312. https://doi.org/10.1371/journal.pone.0130312

Food and Agriculture Organization of the United Nations (FAO) (2017) Global Action Programme on Food Security and Nutrition in Small Island Developing States. Rome: FAO. Available at: https://www.fao.org/3/i7135e/i7135e.pdf

Global Fishing Watch (n.d.) 'Our technology'. Available at: https://globalfishingwatch.org/our-technology/

Griffin, P. and OFMP News (2023) 'The tech helping tackle illegal, unreported and unregulated fishing', TunaPacific, 9 October. Available at: https://tunapacific.ffa.int/2023/10/09/the-tech-helping-tackle-illegal-unreported-and-unregulated-fishing/

Kroodsma, D.A., Mayorga, J., Hochberg, T., Miller, N.A., Boerder, K., Ferretti, F., Wilson, A., Bergman, B., White, T.D., Block, B.A., Woods, P., Sullivan, B., Costello, C. and Worm, B. (2018) 'Tracking the global footprint of fisheries', Science, 359(6378), pp. 904-908. https://doi.org/10.1126/science.aao5646

Lakshminarayan, M. et al. (2025) The Use of Artificial Intelligence in Food and Agriculture Systems: The State of the Art. London: Foreign, Commonwealth and Development Office and 3ie. Available at: https://www.grtd.fcdo.gov.uk/wp-content/uploads/2025/11/State-of-Art-Report.pdf

Lam, R., Sanchez-Gonzalez, A., Willson, M., Wirnsberger, P., Fortunato, M., Alet, F., Ravuri, S., Ewalds, T., Eaton-Rosen, Z., Hu, W., Merose, A., Hoyer, S., Holland, G., Vinyals, O., Stott, J., Pritzel, A., Mohamed, S. and Battaglia, P. (2023) 'Learning skillful medium-range global weather forecasting', Science, 382(6677), pp. 1416-1421. https://doi.org/10.1126/science.adi2336

Mycoo, M., Wairiu, M., Campbell, D., Duvat, V., Golbuu, Y., Maharaj, S., Nalau, J., Nunn, P., Pinnegar, J. and Warrick, O. (2022) 'Small Islands', in Pörtner, H.-O. et al. (eds) Climate Change 2022: Impacts, Adaptation and Vulnerability. Cambridge: Cambridge University Press, pp. 2043-2121. https://doi.org/10.1017/9781009325844.017

Nalau, J., Becken, S., Schliephack, J., Parsons, M., Brown, C. and Mackey, B. (2018) 'The role of Indigenous and traditional knowledge in ecosystem-based adaptation: a review of the literature and case studies from the Pacific Islands', Weather, Climate, and Society, 10(4), pp. 851-865. https://doi.org/10.1175/WCAS-D-18-0032.1

United Nations Office for Disaster Risk Reduction (UNDRR) and World Meteorological Organization (WMO) (2022) Global Status of Multi-Hazard Early Warning Systems: Target G. Geneva: UNDRR and WMO. Available at: https://www.undrr.org/publication/global-status-multi-hazard-early-warning-systems-target-g

University of Hawai'i EPSCoR (n.d.) 'AI-powered wildfire forecast system for Hawai'i is goal of UH researchers'. Available at: https://hawaii.edu/epscor/ai-powered-wildfire-forecast-system-for-hawai%CA%BBi-is-goal-of-uh-researchers/

World Meteorological Organization (WMO) (n.d.) 'Severe Weather Forecasting Programme'. Available at: https://community.wmo.int/site/knowledge-hub/programmes-and-initiatives/severe-weather-forecasting-programme-swfp

SOURCE NOTE

Sources and links were checked on 21 September 2026. Peer-reviewed research and official institutional materials were preferred. Organisational pages are used for limited factual claims about their own programmes; project announcements are treated as statements of intention rather than evidence of achieved impact. Product and programme claims should be reassessed as systems develop, and operational performance should be verified independently before procurement or safety-critical use.