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AI-Driven Early Warning of Global Ocean Health Recovery Deficit from Longitudinal Ocean Health Index Trajectories †

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Abstract

Global ocean health assessments are commonly reported as annual scores, yet such endpoint summaries do not show whether national ocean systems have recovered from recent declines or remained unstable. This proceedings paper develops a concise recovery deficit early-warning framework using Ocean Health Index data for 220 coastal countries and territories from 2012 to 2025. The method defines a Recovery Deficit Index as the difference between 2025 and 2019 OHI scores, estimates long-term trend and interannual volatility, classifies countries into four recovery typologies, and ranks them using an Instability-Adjusted Recovery Risk score. Globally, the OHI increased from 71.85 in 2012 to 74.93 in 2019, declined to 69.50 in 2024, and recovered to 72.31 in 2025. However, only 51.75% of the 2019 to 2024 loss had been regained by 2025, leaving a global recovery deficit of 2.62 points. Country-level results show that 128 of 220 systems remained below their 2019 benchmark, including 48 high warning systems. The findings demonstrate that recovery deficit, trend, and volatility provide an interpretable basis for AI-assisted ocean health early warning and policy prioritisation.

Keywords: Ocean Health Index; earth system intelligence; recovery deficit; early warning; marine sustainability; interpretable AI; risk stratification; trajectory modelling

1. Introduction

Marine and coastal systems are increasingly exposed to overlapping ecological, climatic, and socioeconomic pressures, yet global assessment outputs are still often communicated as static score comparisons. Recent peer-reviewed studies have advanced ocean sustainability assessment, blue economy governance, regional Ocean Health Index (OHI) applications, marine machine learning, and interpretable geoscience artificial intelligence [1–8]. However, an important research problem remains unresolved: annual ocean health scores do not directly identify whether countries have recovered from recent system-level decline, nor do they separate stable recovery from volatile rebound. This is a significant gap because decision makers require early-warning evidence that combines recovery status, trajectory direction, and instability, not only current performance. The need for decision-oriented AI is also consistent with prior work on automated environmental and disaster intelligence systems, where heterogeneous signals are transformed into operational insights for strategic response [9].

This paper answers the following research question: which coastal countries and territories remained below their 2019 ocean health benchmark by 2025, and can recovery

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deficit, long-term trend, and volatility be integrated into an interpretable early-warning metric? To answer this question, this study analyses the 2025 global OHI assessment panel, containing annual index records from 2012 to 2025 for 220 coastal countries and territories [10]. The method constructs a Recovery Deficit Index (RDI), estimates country-level OHI slope and annual volatility, separates countries into four recovery typologies, and computes an Instability-Adjusted Recovery Risk (IARR) score for ranking national warning profiles. The analysis is intentionally narrower than a full forecasting study: it focuses on post 2019 recovery deficit as a concise and reproducible proceedings contribution.

This recovery-oriented approach provides a transparent basis for identifying jurisdictions that warrant closer marine sustainability assessment, without attributing changes in OHI scores to particular ecological or policy mechanisms.

2. Materials and Methods

This study used the official Ocean Health Index (OHI) 2025 global scores dataset obtained from the OHI global scores data download portal [10]. The OHI framework was originally developed as a quantitative measure of the health and benefits of coupled human ocean systems [11]. The downloaded 2025 assessment provides annual scores from 2012 to 2025 for 220 coastal countries and territories, including global and country index scores, goal scores, and component scores. The OHI project also states that previous annual scores are recalculated using the most recent methods and data, which supports temporal comparability across the 14-year panel [10]. Let the set of countries or territories be $\mathcal{R} = \{1, \ldots, R\}$, and let the annual assessment period be $\mathcal{T} = \{2012, \ldots, 2025\}$. For each country or territory $r \in \mathcal{R}$ and year $t \in \mathcal{T}$, the OHI Index score is denoted as

$$y_{r,t} \in [0, 100], \tag{1}$$

with higher values indicating stronger overall ocean health performance. The country year panel is represented as

$$\mathbf{Y} = [y_{r,t}]_{R \times T}, \tag{2}$$

where the empirical analysis used $R = 220$ countries and territories over $T = 14$ annual assessments. The global average was retained for aggregate recovery analysis, while country-level records were used for typology construction and risk ranking.

The central metric was the Recovery Deficit Index, defined as the difference between the 2025 score and the 2019 pre-decline benchmark:

$$\mathrm{RDI}_r = y_{r,2025} - y_{r,2019}. \tag{3}$$

where $\mathrm{RDI}_r < 0$ indicates incomplete recovery, whereas $\mathrm{RDI}_r \geq 0$ indicates recovery to or above the 2019 benchmark. The global recovery ratio was computed as

$$\mathrm{RR}_{\mathrm{global}} = \frac{y_{\mathrm{global},2025} - y_{\mathrm{global},2024}}{y_{\mathrm{global},2019} - y_{\mathrm{global},2024}} \times 100. \tag{4}$$

which measures the percentage of the 2019 to 2024 loss regained by 2025.

Because recovery status alone cannot distinguish stable recovery from unstable rebound, each country trajectory was also described by long-term slope and annual volatility. The slope was estimated using the ordinary least squares model

$$y_{r,t} = \alpha_r + \beta_r t + \varepsilon_{r,t}, \tag{5}$$

where β_r represents the average annual direction of change. Interannual volatility was calculated as

$$\sigma_r = \sqrt{\frac{1}{T-2} \sum_{t=2013}^{2025} \left[(y_{r,t} - y_{r,t-1}) - \bar{\delta}_r \right]^2}, \tag{6}$$

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where

$$\bar{\delta}_r = \frac{1}{T-1} \sum_{t=2013}^{2025} (y_{r,t} - y_{r,t-1}). \tag{7}$$

Equations (3), (5) and (6) jointly define recovery level, long-term direction, and instability.

Countries were assigned to four typology groups using the sign of RDI and the median volatility threshold $\sigma_{0.50} = \text{median}(\sigma_r : r \in \mathcal{R})$:

$$\text{Type}(r) = \begin{cases} \text{High warning}, & \text{RDI}_r < 0 \text{ and } \sigma_r > \sigma_{0.50}, \\ \text{Incomplete recovery}, & \text{RDI}_r < 0 \text{ and } \sigma_r \leq \sigma_{0.50}, \\ \text{Recovered but unstable}, & \text{RDI}_r \geq 0 \text{ and } \sigma_r > \sigma_{0.50}, \\ \text{Recovered and stable}, & \text{RDI}_r \geq 0 \text{ and } \sigma_r \leq \sigma_{0.50}. \end{cases} \tag{8}$$

For risk ranking, three unitless components were derived: deficit risk $q_r^{(d)}$, trend risk $q_r^{(\beta)}$, and volatility risk $q_r^{(\sigma)}$:

$$q_r^{(d)} = \frac{\max(0, -\text{RDI}_r)}{\max_{r \in \mathcal{R}} \max(0, -\text{RDI}_r)}, \quad q_r^{(\beta)} = 1 - \frac{\beta_r - \min \beta_r}{\max \beta_r - \min \beta_r}, \quad q_r^{(\sigma)} = \frac{\sigma_r - \min \sigma_r}{\max \sigma_r - \min \sigma_r}. \tag{9}$$

The final Instability-Adjusted Recovery Risk score was computed as

$$\text{IARR}_r = \frac{1}{3}\left(q_r^{(d)} + q_r^{(\beta)} + q_r^{(\sigma)}\right). \tag{10}$$

Equation (10) gives equal weight to recovery deficit, long-term decline, and volatility to preserve interpretability. Countries were then ranked by descending IARR_r, and empirical tertiles of IARR_r were used to define low, moderate, and high recovery warning tiers.

3. Results

The global recovery profile confirms that the post 2019 OHI decline was only partially reversed by 2025. The global index was 71.85 in 2012, 74.93 in 2019, 69.50 in 2024, and 72.31 in 2025. As shown in Table 1, the global score increased by 3.08 points from 2012 to 2019, declined by 5.43 points from 2019 to 2024, and then recovered by 2.81 points in 2025. The 2025 value remained 2.62 points below the 2019 benchmark, meaning that only 51.75% of the 2019 to 2024 loss had been regained.

Table 1. Global OHI recovery profile using 2019 as the benchmark.

Metric	Value
Global OHI score in 2012	71.85
Global OHI score in 2019	74.93
Global OHI score in 2024	69.50
Global OHI score in 2025	72.31
Change from 2012 to 2019	3.08
Drop from 2019 to 2024	−5.43
Recovery from 2024 to 2025	2.81
RDI, 2025 versus 2019	−2.62
Share of 2019 to 2024 loss regained by 2025	51.75%

Country-level evidence shows that incomplete recovery was widespread rather than exceptional. Of the 220 countries and territories, 128 were still below their 2019 OHI level in 2025, while 92 had recovered to or exceeded it. The typology comprised 48 high warning systems, 80 incomplete recovery systems, 48 recovered and stable systems, and 44 recovered but unstable systems. Table 2 reports the four recovery typologies. The high warning group contained 48 systems, with the lowest mean 2025 score of 67.88, the largest average deficit of

−6.04 points, a negative mean slope of −0.434, and high mean volatility of 3.15. By contrast, recovered and stable systems had a higher mean 2025 score of 73.87, a positive mean RDI of 2.11, a positive mean slope of 0.217, and the lowest mean volatility of 1.47.

Table 2. Country-level recovery typology based on RDI and temporal volatility.

Typology	Countries	%	Mean 2025	Mean RDI	Mean Slope	Mean Volatility
Incomplete recovery	80	36.36	70.85	−2.72	−0.019	1.89
High warning systems	48	21.82	67.88	−6.04	−0.434	3.15
Recovered and stable	48	21.82	73.87	2.11	0.217	1.47
Recovered but unstable	44	20.00	71.39	4.24	0.303	3.27
Total	220	100.00	70.97	−0.86	−0.003	2.54

Figure 1 plots countries in the recovery warning space defined by Equations (3) and (6). The vertical reference line separates recovered and unrecovered systems, and the horizontal reference line separates lower and higher volatility systems. Myanmar, Vanuatu, Papua New Guinea, Indonesia, and Tuvalu appear in the high-deficit region, indicating strong evidence of incomplete recovery. Myanmar recorded the largest deficit, with its 2025 score 19.38 points below its 2019 level, followed by Vanuatu at −15.68, Papua New Guinea at −12.26, Indonesia at −11.36, and Tuvalu at −11.25. In contrast, Benin, Glorioso Islands, Togo, Micronesia, and Guinea exceeded their 2019 levels by 13.78, 10.00, 9.89, 9.40, and 9.05 points, respectively.

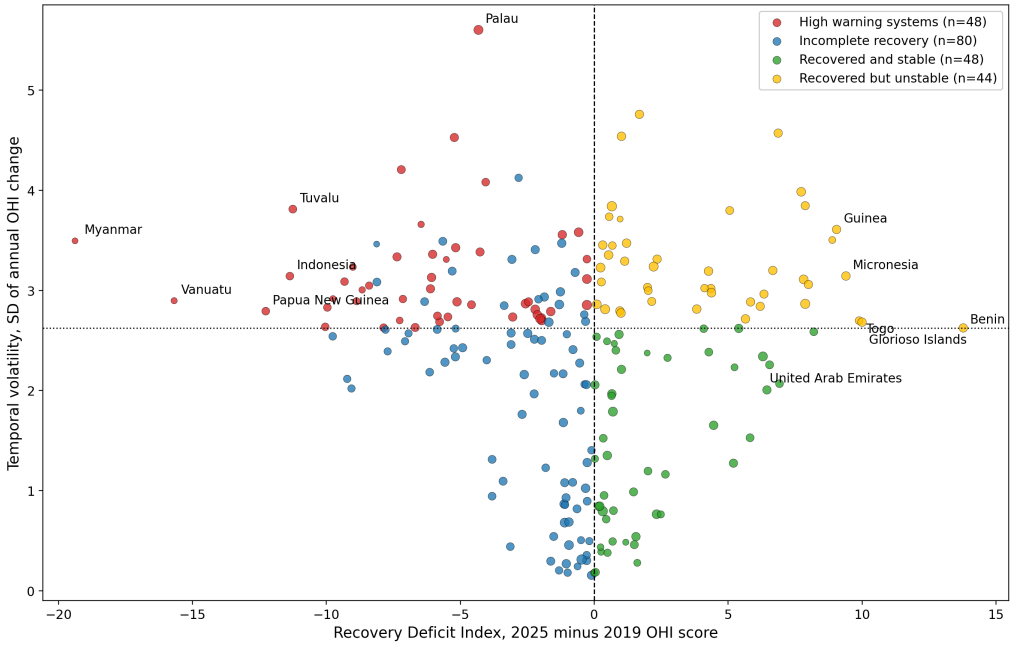

Figure 1. Recovery deficit and temporal volatility early-warning space. The vertical reference line separates countries below and above their 2019 OHI benchmark, while the horizontal reference line separates lower- and higher-volatility systems. Colours indicate the four recovery typology groups.

As seen from Table 3, the warning tier distribution further confirms that the recovery signal was not evenly distributed across national systems. The high recovery warning tier contained 73 countries and territories, with a mean 2025 OHI score of 67.35, a mean RDI of −5.46, a mean slope of −0.379, and mean volatility of 3.06. The low warning tier also contained 73 systems, but its mean 2025 score was 73.20 and its mean RDI was positive at 1.53. The moderate tier contained 74 systems, with a mean 2025 score of 72.34 and mean RDI of 0.90.

Table 3. Recovery warning tiers based on Instability-Adjusted Recovery Risk.

Warning Tier	Countries	%	Mean 2025	Mean RDI	Mean Slope	Mean Volatility
Low recovery warning	73	33.18	73.20	1.53	0.294	1.27
Moderate recovery warning	74	33.64	72.34	0.90	0.103	2.70
High recovery warning	73	33.18	67.35	−5.46	−0.379	3.06
Total	220	100.00	70.97	−0.86	−0.003	2.54

Figure 2 ranks the 20 countries and territories with the highest IARR scores. The top cases were Vanuatu, Myanmar, Palau, Bermuda, and Papua New Guinea, with IARR values of 0.771, 0.727, 0.669, 0.637, and 0.628, respectively. The position of Palau is especially informative because it had a comparatively high 2025 OHI score but remained in the high warning group due to incomplete recovery, negative long-term slope, and the highest volatility among the highlighted cases. Table 4 reports the ten highest IARR countries and territories, demonstrating how the composite score integrates deficit, direction, and instability.

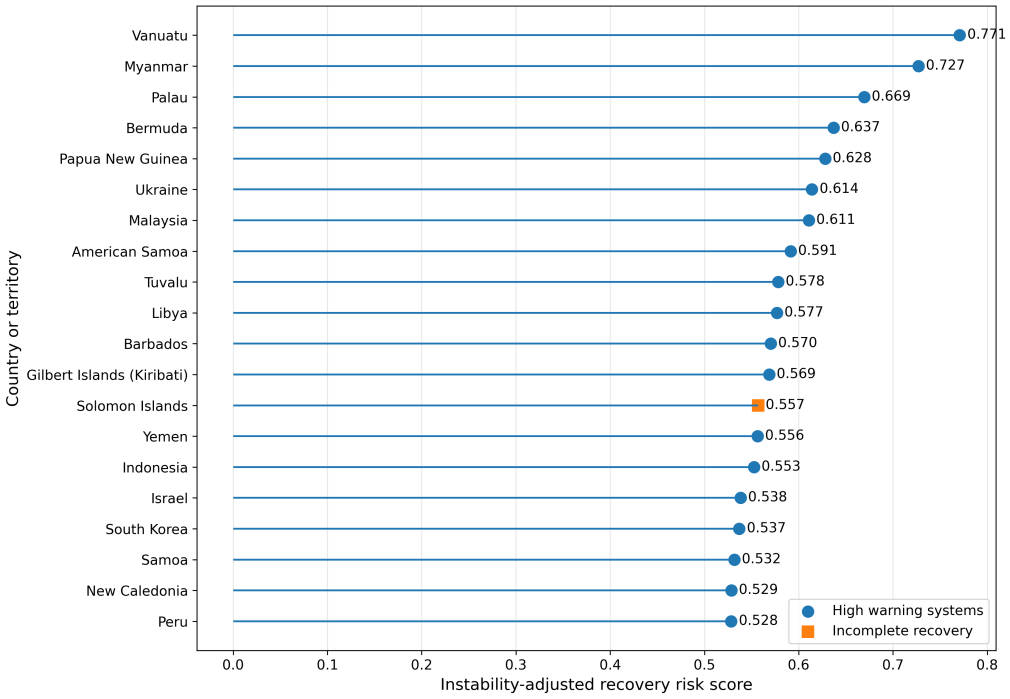

Figure 2. Top 20 countries and territories by Instability-Adjusted Recovery Risk score. Markers identify the recovery typology class, and numerical labels report the corresponding risk score.

Table 5 illustrates how the proposed typology distinguishes different empirical recovery profiles. Vanuatu and Myanmar show severe recovery deficits, with 2025 scores 15.68 and 19.38 points below their 2019 benchmarks, respectively. Solomon Islands and Sri Lanka also remained below their 2019 levels, but with lower volatility than the high warning cases. In contrast, the United Arab Emirates and Saint Lucia exceeded their 2019 scores while maintaining comparatively stable trajectories. Benin and Micronesia also exceeded their 2019 benchmarks, but their higher volatility indicates that recovery and stability should not be interpreted as identical outcomes.

Table 4. Top ten countries and territories by Instability-Adjusted Recovery Risk.

Country or Territory	IARR	RDI	Slope	Volatility
Vanuatu	0.771	−15.68	−1.464	2.90
Myanmar	0.727	−19.38	−0.261	3.49
Palau	0.669	−4.32	−0.867	5.60
Bermuda	0.637	−7.20	−0.894	4.21
Papua New Guinea	0.628	−12.26	−0.816	2.79
Ukraine	0.614	−9.75	−0.996	2.92
Malaysia	0.611	−9.32	−0.943	3.09
American Samoa	0.591	−8.87	−0.946	2.89
Tuvalu	0.578	−11.25	−0.024	3.81
Libya	0.577	−5.52	−1.093	3.31

Table 5. Representative country and territory diagnostics across the four recovery typologies.

Country or Territory	Recovery Typology	2019	2025	RDI	Slope	Volatility
Vanuatu	High warning systems	69.91	54.23	−15.68	−1.464	2.90
Myanmar	High warning systems	71.74	52.36	−19.38	−0.261	3.49
Solomon Islands	Incomplete recovery	75.58	65.82	−9.76	−0.711	2.54
Sri Lanka	Incomplete recovery	71.31	62.25	−9.06	−0.168	2.02
United Arab Emirates	Recovered and stable	79.24	85.54	6.30	0.715	2.34
Saint Lucia	Recovered and stable	65.49	73.69	8.20	0.616	2.59
Benin	Recovered but unstable	58.48	72.26	13.78	0.887	2.62
Micronesia	Recovered but unstable	64.31	73.71	9.40	−0.309	3.14

Overall, the results indicate that post 2019 ocean health recovery was partial, uneven, and risk-stratified. The global recovery ratio shows incomplete aggregate recovery, the typology shows that most countries remained below their 2019 benchmark, and the IARR ranking identifies systems where incomplete recovery coincided with adverse trend and high instability.

4. Discussion and Conclusions

This study contributes a compact empirical framework for converting longitudinal OHI scores into interpretable early-warning evidence. The main scientific implication is that recovery cannot be assessed from endpoint scores alone. All OHI values in this analysis are measured on the standard 0 to 100 Index scale, while trajectory slope is measured in OHI points per year, volatility is measured as the standard deviation of annual OHI point changes, and the IARR score is a unitless composite ranging from lower to higher warning intensity. These measured units make the evidence directly interpretable: the global score increased by 3.08 points between 2012 and 2019, lost 5.43 points between 2019 and 2024, and recovered 2.81 points in 2025. However, the remaining global RDI of −2.62 points means that the rebound restored only 51.75% of the prior loss. The result is therefore not simply a visual recovery pattern, but a quantified incomplete recovery signal.

The country-level evidence further shows why a recovery deficit approach is useful for scientific and policy interpretation. A majority of the analysed systems, 128 of 220 countries and territories, or 58.18%, remained below their 2019 benchmark in 2025. The 48 high warning systems had a mean 2025 OHI score of 67.88, which was 5.99 points lower than the recovered and stable group mean of 73.87. Their mean RDI was −6.04 points, compared with 2.11 points for recovered and stable systems, producing an 8.15-point difference in recovery position. Their mean annual volatility was also 3.15 OHI points, more than twice the 1.47-point volatility of recovered and stable systems. This contrast indicates that the high warning group is not defined only by lower current condition, but by the joint empirical pattern of lower recovery, adverse direction, and higher instability.

The IARR ranking adds further evidence that composite early warning can reveal cases that would be less visible under endpoint scoring alone. In the highest warning tier, the mean 2025 OHI score was 67.35, the mean RDI was −5.46 points, the mean slope was −0.379 points per year, and the mean volatility was 3.06 OHI points. In comparison, the low warning tier had a mean 2025 score of 73.20, a positive mean RDI of 1.53 points, a positive mean slope of 0.294 points per year, and a much lower mean volatility of 1.27 OHI points. The top-ranked IARR cases, including Vanuatu at 0.771, Myanmar at 0.727, Palau at 0.669, Bermuda at 0.637, and Papua New Guinea at 0.628, show that high warning is generated by different combinations of deficit, trend, and volatility. Palau is especially informative because its high warning status is driven less by a low current score than by incomplete recovery, negative long-term slope, and very high volatility.

The proceedings contribution is intentionally focused and diagnostic. It does not claim causal attribution for the observed recovery deficit, and it does not replace detailed regional ecological assessment. Instead, it provides a reproducible screening method for identifying countries and territories that warrant closer diagnostic attention. Future work can extend the framework by connecting RDI and IARR outputs to goal-specific OHI drivers, climate exposure, governance capacity, marine-protected area coverage, fishery pressure, tourism disruption, and independent ecological indicators. In conclusion, this study shows that global ocean health recovery remained incomplete in 2025, with 128 of 220 systems below their 2019 benchmark and 48 classified as high warning systems. The proposed RDI and IARR metrics offer a transparent pathway for early warning, comparative monitoring, and evidence-based prioritisation in ocean health governance.

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Informed Consent Statement: Not applicable.

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Conflicts of Interest: The author declares no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
IARR	Instability-Adjusted Recovery Risk
OHI	Ocean Health Index
RDI	Recovery Deficit Index

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