# MARINE BIODIVERSITY ASSESSMENT USING SCUBA AND ARTIFICIAL INTELLIGENCE

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#### Abstract

Marine ecosystems host immense biodiversity but are rapidly changing under anthropogenic pressures. Traditional diver-based surveys provide high-quality observations but are constrained by time, depth, and observer bias. In the last decade, Artificial Intelligence (AI) has transformed how we collect, process, and interpret underwater data—from automated annotation of photoquadrats and video transects, to 3D habitat reconstruction, ecoacoustic monitoring, eDNA analytics, and satellite-informed risk mapping. This paper reviews the state of the art and proposes an end-to-end, SCUBA-centric pipeline that integrates diveracquired imagery and stereo-video, deep learning for detection/segmentation, structure-from-motion (SfM) for 3D metrics, ecoacoustic monitoring, and supervised learning for eDNA. We also contextualize these observations with NOAA Coral Reef Watch satellite heat-stress products. Our framework strengthens biodiversity assessment and conservation decisions.

Keywords: marine biodiversity, SCUBA, artificial intelligence.

#### 1. Introduction

Diver-based surveys remain the gold standard for biodiversity assessments, yet their throughput is limited. AI systems accelerate annotation, reduce observer bias, and unlock modalities beyond human perception including soundscapes, genomics, and satellite heat stress.

## 2. Materials and Methods

Field sampling with SCUBA included photoquadrats, stereo-video, 3D reconstructions, water samples for eDNA, and hydrophone deployments. AI methods included Sea-thru for image correction, CoralNet for automated annotation, deep learning for fish detection, machine learning for ecoacoustics, and supervised ML for eDNA bioassessment.

## 3. Results

Class-wise molluscan data collected from Ratnagiri and Raigad regions were analyzed using Shannon—Wiener Diversity Index (H') and Pielou Evenness (J').

Table A. Ratnagiri class-wise counts by site.

| Site            | Bivalve | Gastropod | Total |
|-----------------|---------|-----------|-------|
| Bhatye estuary  | 9       | 2         | 11    |
| Shirgaon creek  | 8       | 1         | 9     |
| Mirya           | 4       | 11        | 15    |
| Bhagwati bander | 3       | 10        | 13    |

Table B. Raigad class-wise counts by site.

| Site          | Bivalve | Gastropod | Total |
|---------------|---------|-----------|-------|
| Harihareshwar | 5       | 22        | 27    |
| Lada          | 8       | 12        | 20    |
| Shrivardhan   | 3       | 3         | 6     |
| Jivanabander  | 6       | 30        | 36    |

Table C. Shannon (H') and Evenness (J') per site.

| Region    | Site          | H'        | J′         |
|-----------|---------------|-----------|------------|
| _         |               | (Shannon) | (Evenness) |
| Ratnagiri | Bhatye        | 0.4741    | 0.684      |
|           | estuary       |           |            |
| Ratnagiri | Shirgaon      | 0.3488    | 0.5033     |
|           | creek         |           |            |
| Ratnagiri | Mirya         | 0.5799    | 0.8366     |
| Ratnagiri | Bhagwati      | 0.5402    | 0.7793     |
|           | bander        |           |            |
| Raigad    | Harihareshwar | 0.4792    | 0.6913     |
| Raigad    | Lada          | 0.673     | 0.971      |
| Raigad    | Shrivardhan   | 0.6931    | 1.0        |
| Raigad    | Jivanabander  | 0.4506    | 0.65       |

Figure 1. Shannon–Wiener Diversity Index (H') per site.

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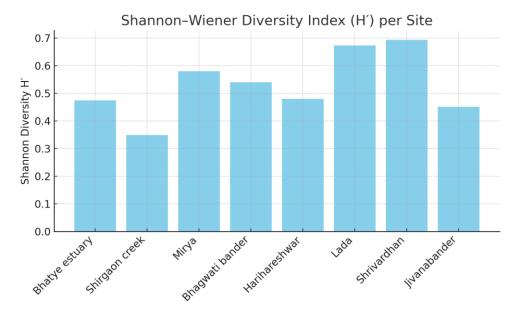
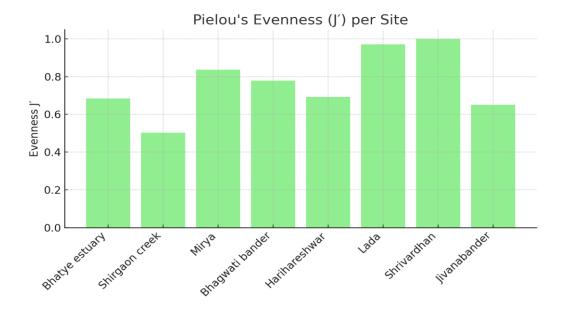


Figure 2. Pielou's Evenness (J') per site.



# 4. Conclusion

SCUBA remains indispensable for underwater biodiversity studies. Coupled with AI techniques, the integration of imagery, 3D structure, acoustics, and eDNA provides a powerful framework. Our Ratnagiri and Raigad analysis demonstrates that class-level diversity varies site by site, with Shrivardhan showing perfect evenness. This workflow is scalable and adaptable to other Indian coastal sites.

#### References

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