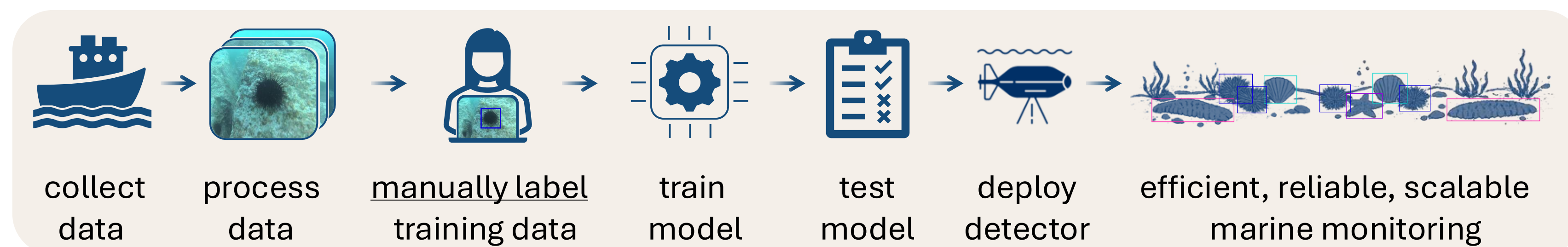


The Problem: Domain Shift in Underwater Object Detection



must repeat for new / changed conditions ...but underwater environments vary greatly with environmental and acquisition factors.

Habitat-rich Boulder Reef Flat, Sandy Seabed Dark, Obscured Scene



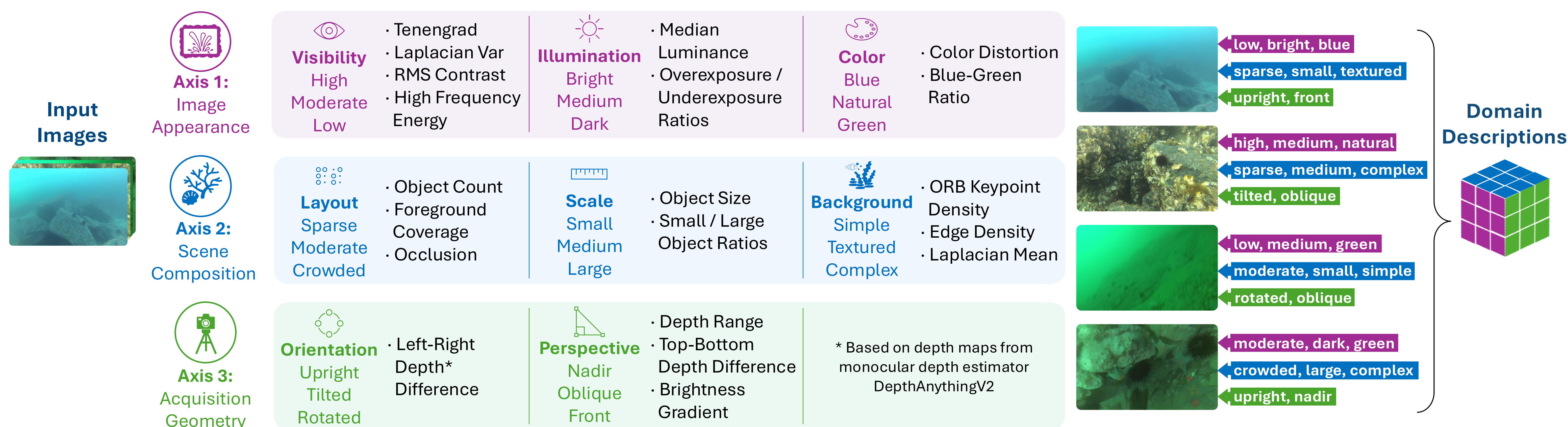
Standard aggregate performance metrics (e.g. mAP) hide domain-specific failure modes. **We need domain-aware evaluation!**

Our Research Questions

- How can **domain variability** in underwater imagery be **decomposed** into **interpretable** and **measurable factors** that enable consistent grouping of images?
- To what extent do **domain-specific factors** influence object **detection performance** across different conditions?

Method Overview: Automated Underwater Domain Labeling

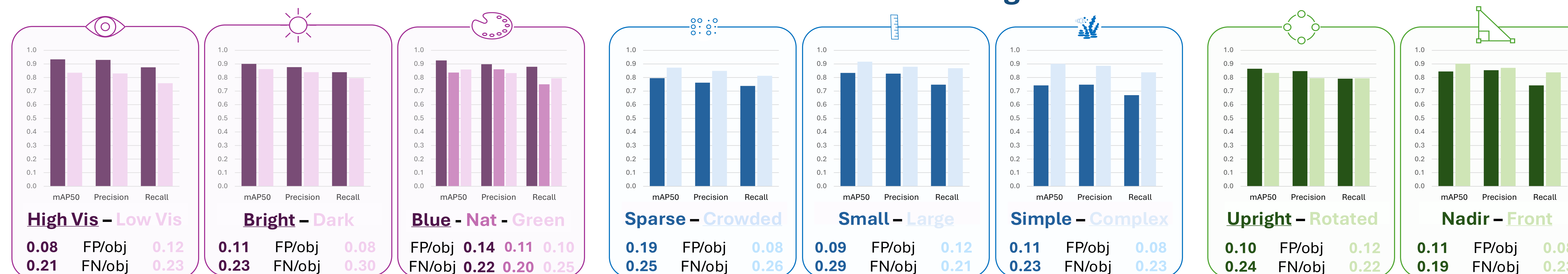
Decompose into 3 Axes → Quantify Properties → Convert into Categorical Labels → Assign Axis-wise Labels



Our Contributions

- Underwater Domain Labeling Framework** to systematically characterize domains based on physically meaningful factors
- Unified & Consistent Domain Annotations** for two public underwater object detection datasets that enable structured comparison
- Empirical Analysis** showing performance variations with domain properties and revealing failure modes for targeted improvements

Results for DUO and RUOD-4C: Performance Varies With Domain Categories



Results reveal clearly favorable conditions - some expected (high visibility, large objects), others counterintuitive (crowded, complex scenes) - demonstrating that our framework captures meaningful domain differences relevant to model behavior.

Outlook

- Investigate **interactions** between object **classes** and **domain factors**
- Leverage domain labels to **develop domain-aware training strategies**
- Build a large-scale **domain-labeled benchmark dataset**



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Datasets:

We thank the contributors of DUO (Detecting Underwater Objects, Liu *et al.*, ICME 2021) and RUOD (Rethinking general Underwater Object Detection, Fu *et al.*, Neurocomputing 2023).

Experiments:

We train a YOLO26n detector on mixed-domain data and rely on its standard mAP, Precision, and Recall output. Error rates are manually computed at IoU = 0.5 and confidence threshold = 0.5.



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