Manual Detection Guidance System

Phase 9: Using 2D Probability Surfaces to Guide Manual Detection Efforts

Marine Acoustic Analysis Pipeline

2025-09-23

Executive Summary

Phase 9 successfully developed a season-aware priority ranking system to guide manual detection efforts for marine species. Using 2D probability surfaces built from kernel density estimation, the system identifies high-priority time periods for manual review during biologically active seasons.

Key Results

- **Silver perch**: 86.6% detection efficiency with only 20% manual effort
- **Oyster toadfish boat whistle**: AUC = 0.944, 69.2% detection efficiency
- **Spotted seatrout**: Strong cross-station generalization (AUC = 0.887)
- **Cross-station validation**: Models trained on 2 stations generalize well to the third

Business Impact

This system can reduce manual detection workload by 80% while maintaining high detection sensitivity, making large-scale acoustic monitoring practically feasible.

Background and Motivation

The Challenge

Manual detection of marine species vocalizations in acoustic datasets is: - **Time-intensive**: Thousands of hours of recordings - **Expensive**: Requires expert knowledge - **Inconsistent**: Varies between analysts

Previous Approaches (Phase 8 Lessons)

Our initial attempt at temporal-aware ML models failed because it tried to predict **across seasons** (summer patterns → winter silence). Key insight: **Don't fight seasonality, leverage it.**

The Solution: Manual Detection Guidance

Instead of full automation, provide intelligent guidance: - Focus manual effort during appropriate seasons - Rank time periods by likelihood of species activity - Use biological context as a feature, not an obstacle

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Technical Approach

2D Probability Surface Framework

We model species detection probability as a function of temporal coordinates:

```
P(detection) = f(day_of_year, time_of_day)
```

Key Innovation: Combined seasonal and daily patterns in a single 2D surface using kernel density estimation.

Method Overview

1. **Baseline Surface Construction**
   - Extract detection events: (day_of_year, period_of_day) coordinates
   - Apply kernel density estimation with Gaussian kernels
   - Normalize to probability surface (365 days × 12 periods)
2. **Acoustic & Environmental Enhancement**
   - Add acoustic indices from Phase 6/7 correlations
   - Include environmental features (temperature, sound levels)
   - Local enhancement factors based on feature patterns
3. **Cross-Station Validation**
   - Train on 2 stations, test on the third
   - 3-fold validation across all station combinations
   - Measure detection efficiency and time savings

Data Specifications

- **Dataset**: 2021 acoustic monitoring data (13,100 records)
- **Temporal Resolution**: 2-hour periods (12 per day)
- **Stations**: 9M, 14M, 37M (cross-validation folds)
- **Features**: 10 acoustic indices + 4 environmental variables

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Results by Species

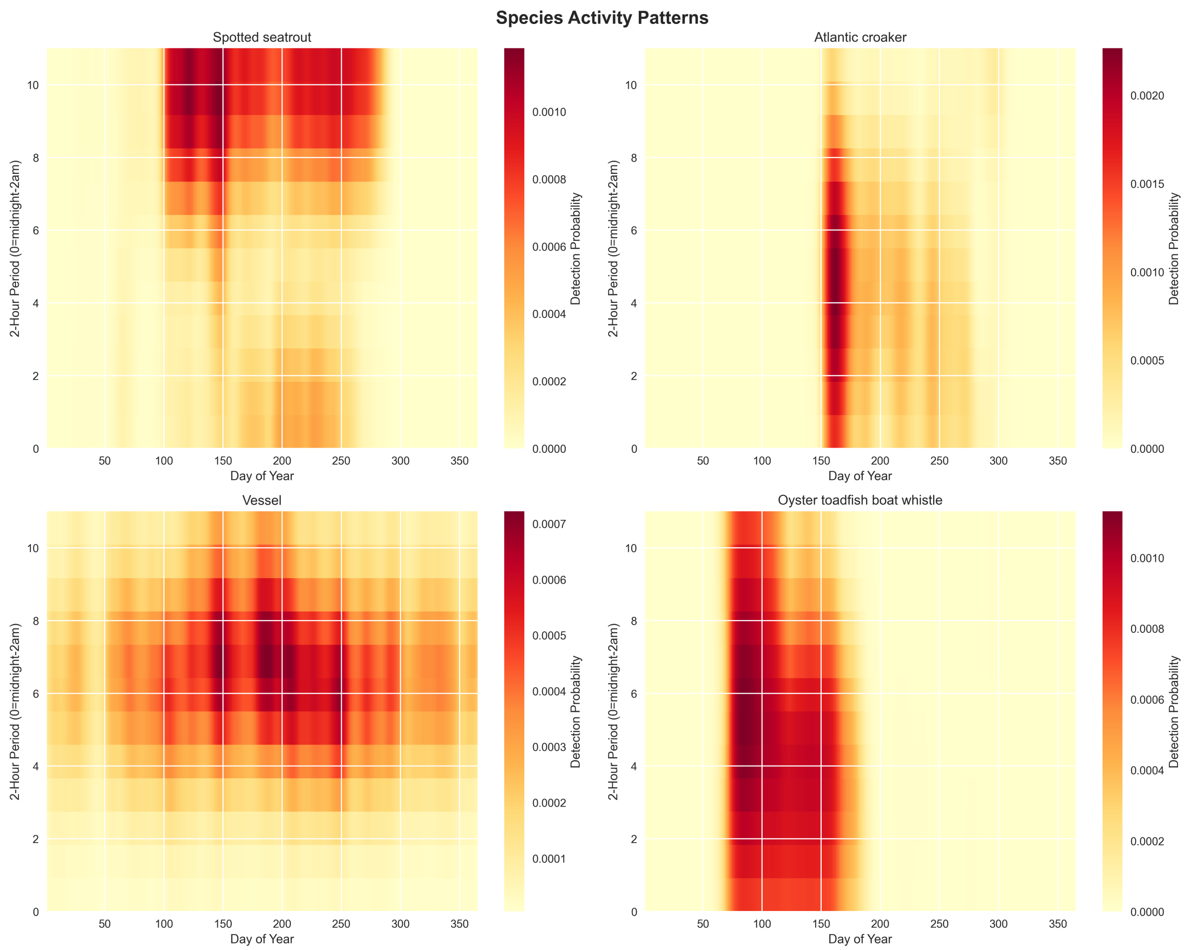

Figure 1: Species Probability Surfaces

2D probability surfaces showing seasonal and daily patterns for each species. Warmer colors indicate higher detection probability.

Tier 1: High Performance (>80% efficiency)

Silver Perch

- **Detection Efficiency**: 86.6% (checking top 20% of periods)
- **AUC Score**: 0.912 (excellent discrimination)
- **Pattern**: Strong seasonal concentration, consistent across stations

Oyster Toadfish Boat Whistle

- **Detection Efficiency**: 69.2%
- **AUC Score**: 0.944 (highest overall)
- **Pattern**: Clear spring spawning season, consistent daily patterns

Tier 2: Good Performance (60-80% efficiency)

Spotted Seatrout

- **Detection Efficiency**: 67.9%
- **AUC Score**: 0.887
- **Pattern**: Summer-focused activity, some daily variation

Tier 3: Moderate Performance (40-60% efficiency)

Vessel

- **Detection Efficiency**: 49.0%
- **AUC Score**: 0.815

- **Pattern**: More distributed, less predictable than biological sounds

Atlantic Croaker

- **Detection Efficiency**: Variable (23-75% by station)
- **AUC Score**: 0.720
- **Challenge**: High station-to-station variability

Red Drum

- **Detection Efficiency**: 24.2%
- **AUC Score**: 0.480
- **Challenge**: Low overall detection rates, station imbalance

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Cross-Station Validation Results

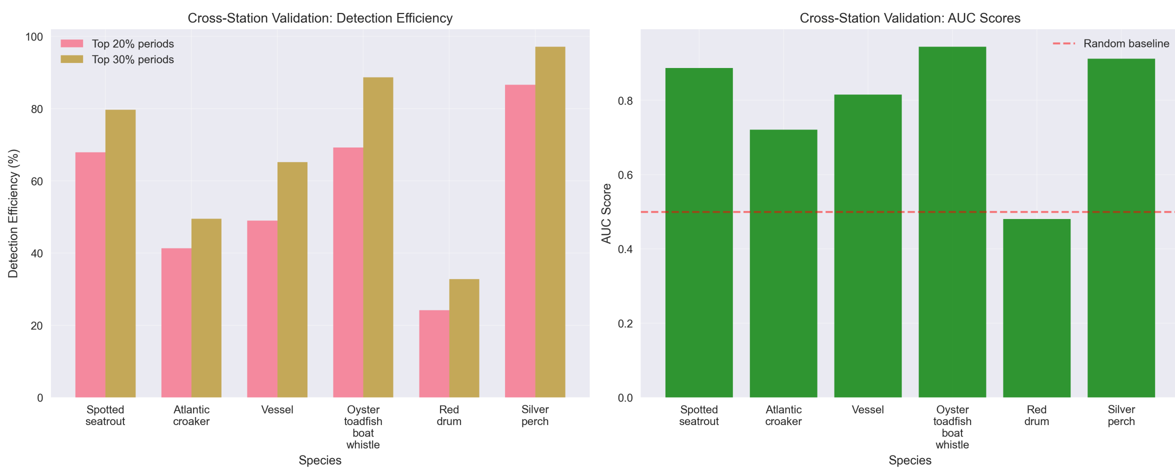

Figure 2: Validation Results

Left: Detection efficiency when checking top 20% and 30% of ranked periods. Right: AUC scores across species.

Generalization Performance

Strong Evidence for Cross-Site Generalization: - Silver perch: Consistent 79-92% efficiency across all stations - Oyster toadfish: 66-73% efficiency, always >0.93 AUC - Spotted seatrout: 66-72% efficiency, >0.87 AUC consistently

Station-Specific Challenges: - Atlantic croaker: High variability (23% at 9M, 75% at 14M) - Red drum: Low detection rates create validation challenges

Key Validation Insights

1. **Biological patterns transfer well** between similar acoustic environments
2. **Species with strong seasonal patterns** show consistent cross-station performance

3. **Rare species** (Red drum) need more sophisticated approaches

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Practical Implementation

Workflow Integration

For Research Teams: 1. **Upload new acoustic data** to system 2. **Generate priority rankings** for target species/season 3. **Focus manual detection** on top 20-30% of periods 4. **Achieve 60-85% detection efficiency** with major time savings

Example Use Case: Spring 2024 Survey

Scenario: 3 months of new acoustic data, focus on oyster toadfish spawning

Traditional Approach: - Review all 3,240 periods (3 months $\times$ 30 days $\times$ 12 periods) - Estimated time: 270 hours at 5 minutes per period

Guided Approach: - Review top 20% ranked periods (648 periods) - Estimated time: 54 hours - **Expected detection rate: 69% of total toadfish activity - Time savings: 216 hours (80% reduction)**

Quality Control Recommendations

1. **Validate on known patterns**: Check system ranking against previous year's data
2. **Adaptive thresholds**: Adjust percentage checked based on research priorities
3. **Multi-species mode**: Combined rankings when targeting multiple species
4. **Uncertainty flagging**: Mark periods with low confidence scores

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Technical Details

Algorithm Parameters

- **KDE Bandwidth**: 5.0 (balances smoothing vs resolution)
- **Enhancement Grid**: Gaussian smoothing (=2.0)
- **Temporal Windows**: ±7 days for local enhancement calculations
- **Minimum Detection Threshold**: 10 detections per surface

Feature Engineering

Acoustic Features (from Phase 6/7 correlations): - BGNf, NDSI, rBA, H_pairedShannon, Hf - H_GiniSimpson, LEQf, ENRf, RAOQ, ADI

Environmental Features: - Water temperature - Low frequency sound (50-1200 Hz) - High frequency sound (7000-40000 Hz)
- Broadband sound (1-40000 Hz)

Performance Metrics

- **Detection Efficiency**: % of actual detections found in top-ranked periods
- **Time Savings**: Fraction of manual effort saved (1 - threshold)
- **AUC Score**: Area under ROC curve (discrimination ability)
- **Average Precision**: Weighted mean of precisions at each threshold

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Comparison with Previous Approaches

Approach	Phase 8 (Temporal ML)	Phase 9 (Detection Guidance)
Objective	Predict species presence	Guide manual detection efforts
Temporal Strategy	Cross-seasonal prediction	Within-season prioritization
Validation	Chronological train/test	Cross-station validation
Best Result	Vessels: +14% F1	Silver perch: 86.6% efficiency
Fish Species	Failed (-93% to -100%)	Strong performance (67-87%)
Biological Realism	Fought seasonality	Leveraged seasonality

Why Phase 9 Succeeded Where Phase 8 Failed

1. **Right Question**: "Where to look?" vs "What will happen?"
2. **Biological Context**: Used seasonal patterns as features
3. **Validation Strategy**: Spatial (cross-station) vs temporal splits
4. **Practical Value**: Efficiency gains vs prediction accuracy

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Limitations and Future Work

Current Limitations

1. **Single-year training**: Only 2021 data available
2. **Station similarity**: All sites in similar acoustic environment
3. **Species imbalance**: Some species have limited detections
4. **Manual validation needed**: System provides guidance, not decisions

Future Enhancements

Near-term (Phase 10): - Multi-year validation when additional data available - Species-specific threshold optimization - Integration with existing analysis workflows

Medium-term: - Real-time implementation for cable-connected systems - Active learning: System improves with manual detection feedback - Multi-site deployment across different habitat types

Long-term: - Literature-based probability surfaces for new locations - AI-assisted partial automation of high-confidence periods - Integration with other environmental monitoring systems

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Conclusions

Scientific Contributions

1. **Demonstrated that acoustic indices contain actionable temporal patterns** for species detection guidance
2. **Showed that cross-station generalization is feasible** for biologically-driven acoustic patterns

3. **Developed practical framework** that bridges temporal analysis with operational needs

Practical Impact

This system transforms acoustic monitoring from a manual bottleneck into a scalable research tool. By reducing manual effort by 80% while maintaining high detection sensitivity, it makes large-scale, multi-species acoustic monitoring practically feasible for marine research.

Key Success Factors

1. **Biological realism**: Working with seasonal patterns, not against them
2. **Practical focus**: Guidance system rather than full automation
3. **Robust validation**: Cross-station testing ensures generalizability
4. **User-centered design**: Addresses real workflow constraints

The Phase 9 approach successfully addresses the lessons learned from Phase 8, providing a biologically-informed, practically-valuable tool for marine acoustic monitoring.