Fisher Rainy Day Fund – A Parametric Insurance Policy

EFRM Capstone Project Spring ‘26

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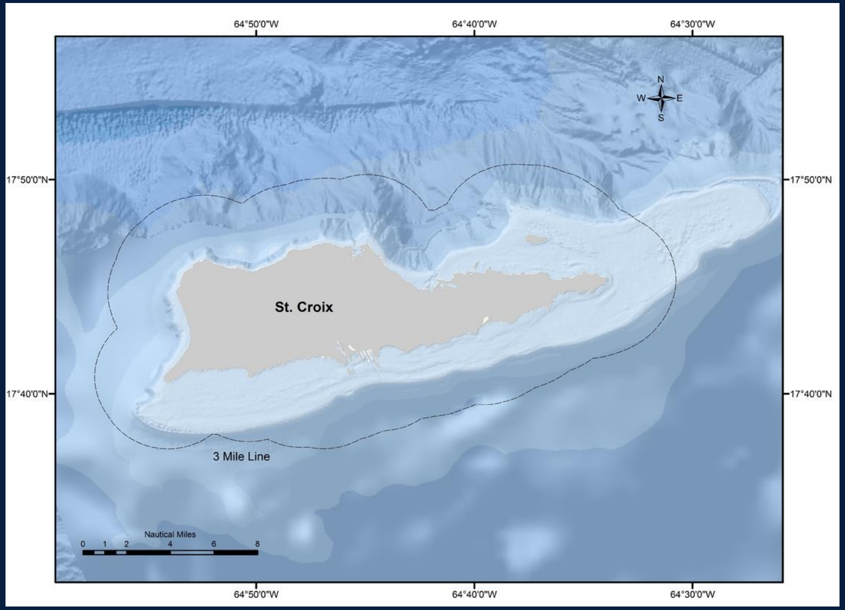
Caribbean Spiny Lobster in St. Croix, USVI

- St. Croix is about 22 miles long and 6 miles wide
- Not overfished & not subject to overfishing (SEDAR 2025)
- 40 Years of Caribbean Commercial Logbook "Census" (1985 through 2024)



source: fisheries.noaa.gov

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Commercial fishing as a business

Risk Transfer Tools

Sources of risk and uncertainty

- Market uncertainty (prices, demand)
- Cost uncertainty (inflation, competition, inputs)
- Limited control over external conditions

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To fish, or not to fish...

Weather as a constraint on fishing activity

- Safety and productivity as prerequisites for fishing
- Extreme events (e.g. hurricanes) versus routine weather disruptions
- Adaptive capacity; Limited when fishing days are lost entirely
- Expectation and acceptance of some bad-weather days annually

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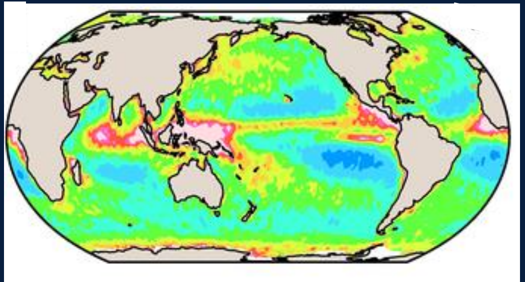
Constructing the Fishable Days Index (FDI)

- Define and quantify environmentally "fishable" days for the St. Croix Caribbean Spiny Lobster (CSL) fishery

source: stcroixtourism.com

- 40-year daily time series (Jan 1985 – Dec 2024; 14,607 days).

- Merging reported catch activity with high-resolution atmospheric reanalysis data.



Liu et. al., 2021

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Primary Data Sources

Fishing Reports	Daily trip counts and catch weights. Suppressed if < 3 trips reported (privacy).
ERA5 Wind Data	Hourly eastward (u) and northward (v) wind components, wind gust speed @ 10 m.
ERA5 Wave Data	Hourly significant wave height (greatest 33%).
Population Data	Annual USVI population estimates, for fleet-capacity normalization.

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Data Transformation

Step 1

Generate 14,607-day continuous calendar skeleton

Step 2

Left-join NOAA data (exposes “zero-trips” days properly)

Step 3

Transform hourly ERA5 vectors into scalar wind speed

$$|W| = \sqrt{{u_{10}}^2 + {v_{10}}^2}$$

Step 4

Extract Daily Maximums for wind and waves

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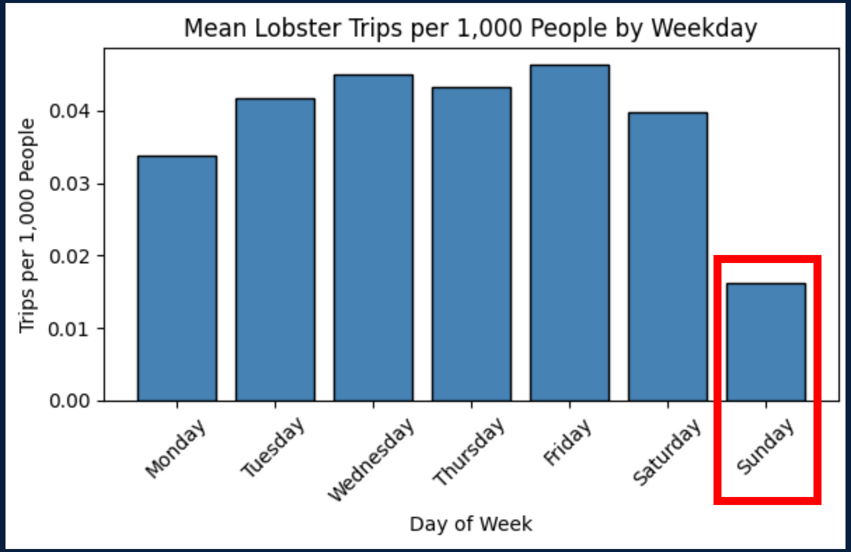
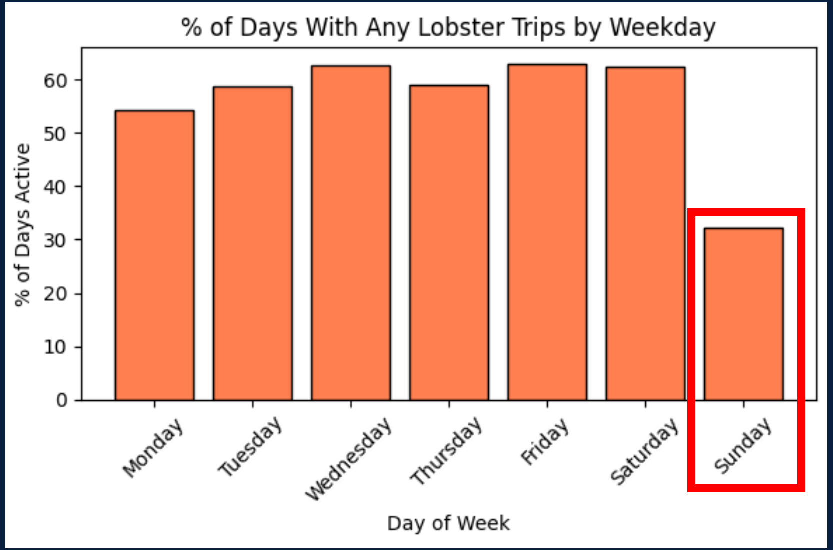
Defining Index & Removing Behavioral Bias

- **A Binary Indicator:** FDI = 1 (fishable) OR FDI = 0 (non-fishable).
- **Annual Aggregation:** Sum of daily FDI values over a 365-day season.
- **Behavioral Bias:** * Average weekday trip rate: 0.034 – 0.046 (per 1k people).
  - *Sunday trip rate: 0.016, excluded from threshold calibration to prevent cultural habits from diluting the climate signal





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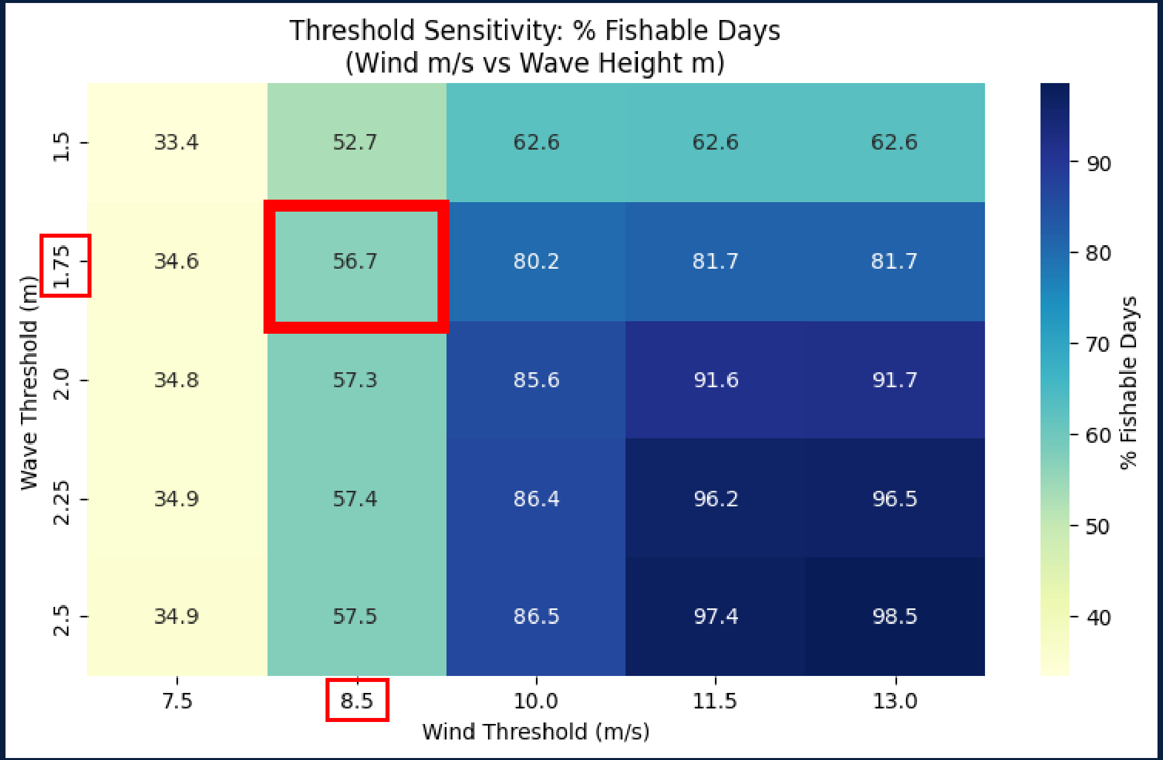
Calibrating Climate Thresholds

- **Sensitivity Matrix:** Tested 25 combinations (Wind: 7.5 to 13.0 m/s × Waves: 1.5 to 2.5 m).
- **Initial Baselines:** Small-craft literature suggests ~10.3 m/s wind (20 knots) and ~2.0 m waves.
- **Final Selected Limits**
  - Max Wind: 8.5 m/s ~ 16 knots
  - Max Waves: 1.75 m
- **Historical Result:** Yields a 56.67% fishable day rate across the 40-year study.



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Validating the FDI Against Catch Data

FDI (8.5 m/s and 1.75m)	FDI = 1	FDI = 0
Mean Trip Rate (per 1k population)	0.044	0.039
Active-Day Rate	62.5 % *	56.8% *

- * True separation is likely wider.
  - NOAA’s "rule of 3" suppresses marginal weather days to zero, making our validation conservative.

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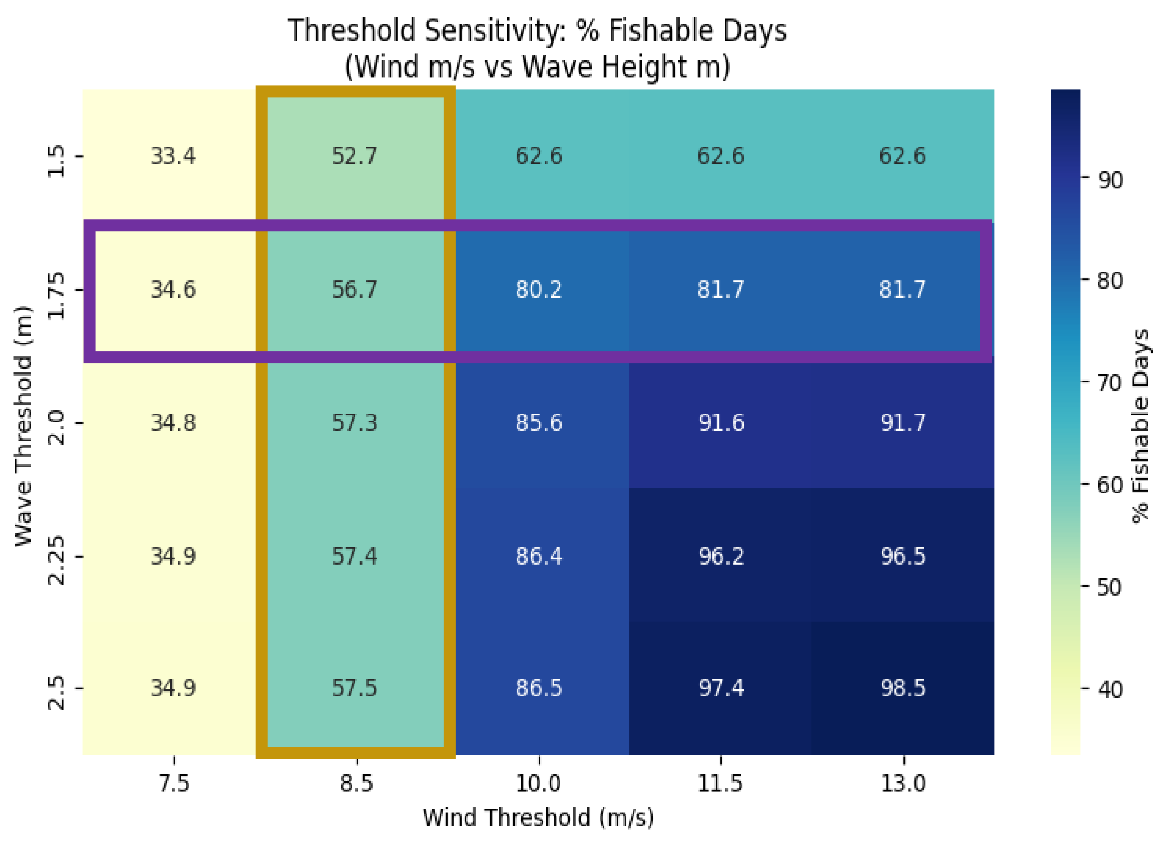
Index Dynamics & Risk Drivers

- *Wave Sensitivity:* narrowly varies FDI 4.8%
- *Wind Sensitivity:* widely varies FDI 47.1% (10x greater)
- **Binding Constraint:** Wind speed dominates the St. Croix operational environment.



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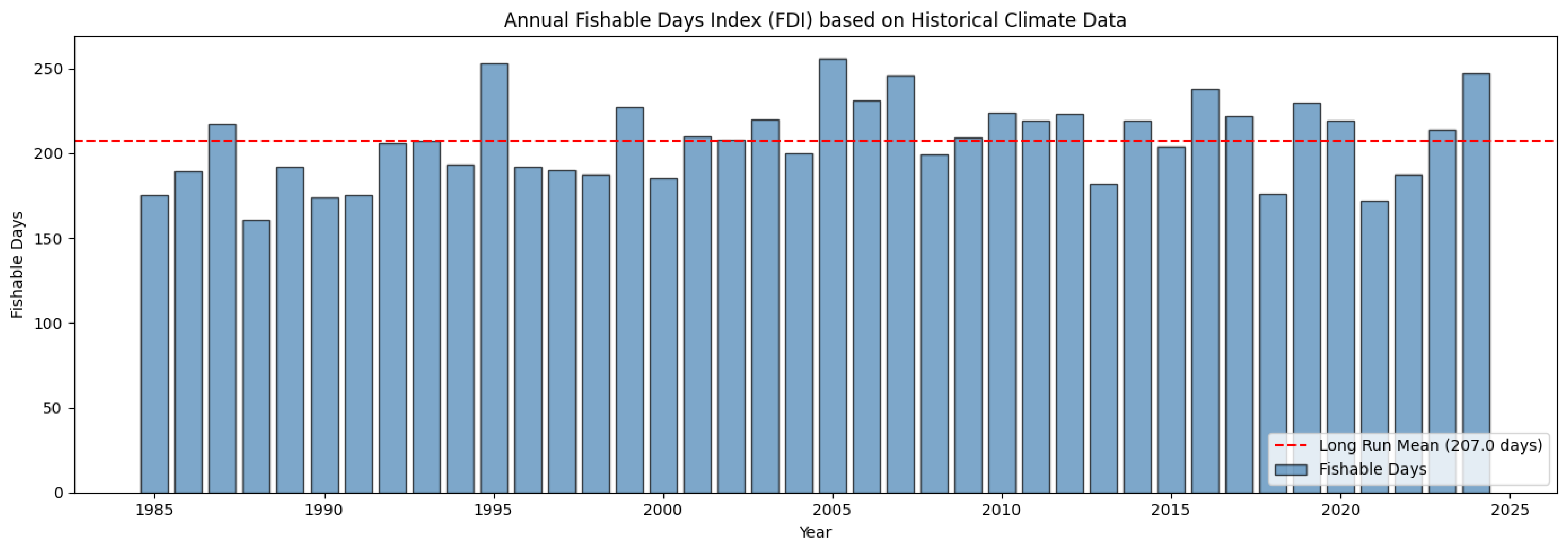
Average Annual Fishable Days

- **Given Thresholds:** 8.5 m/s and 1.75 m
- **Average FDI per Year (1985-2024):** ~207 days



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Methods: Weather Index Construction for Fishability

- Binary index: Fishable = 1, Non-fishable = 0
- Based on: wind speed ***and*** wave height threshold
- Total fishable days over contract period

Seasonal fishable-day index as, $N = \sum_{j=1}^{T} X_j$

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Methods: Poisson-Binomial Modeling Framework

- Each calendar day has a unique probability, pj
- Days are independent
- Total fishable days follow Poisson-binomial

Trigger probability under the strike limit, $E[N] = \sum_{j=1}^{T} p_j$

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Methods: Weather Derivative Pricing Framework

- **Trigger condition:** Fishable days < Strike, *K*
- **Formula 1 (Trigger Probability):** $P(N < K)$
- **Formula 2 (Final Pricing Formula):**

$$\textit{Price of Weather Derivative}, \boldsymbol{V_0 = e^{-r\tau} \times L \times P(N < K)}$$

Discounting Factor

Trigger Probability

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Result: Effect of Wind & Wave Thresholds

Wind threshold (m/s)	Wind threshold (knots)	Wave threshold (m)	Fishable days (%)	Mean annual FDI (days)	SD of annual FDI (days)	
7.5	14.58	1.50	33.35	121.80	21.29	Strict
8.5	16.52	1.50	52.69	192.42	21.70	
8.5	16.52	1.75	56.67	206.95	23.95	Selected
8.5	16.52	2.00	57.31	209.30	24.07	
13.0	25.27	2.50	98.47	359.60	3.96	Loose

Threshold choice strongly affects index behavior

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Result: Annual Fishable Days Distribution

Item	Value
Contract start date	01/01/xxxx
Contract end date	12/31/xxxx
Contract length (days)	365
Contract length (years)	1.0
Expected fishable days during contract	206.80
Mean contract FDI (days)	206.78
Standard deviation of contract FDI (days)	23.94
Average profit per fishable day ($)	330.00

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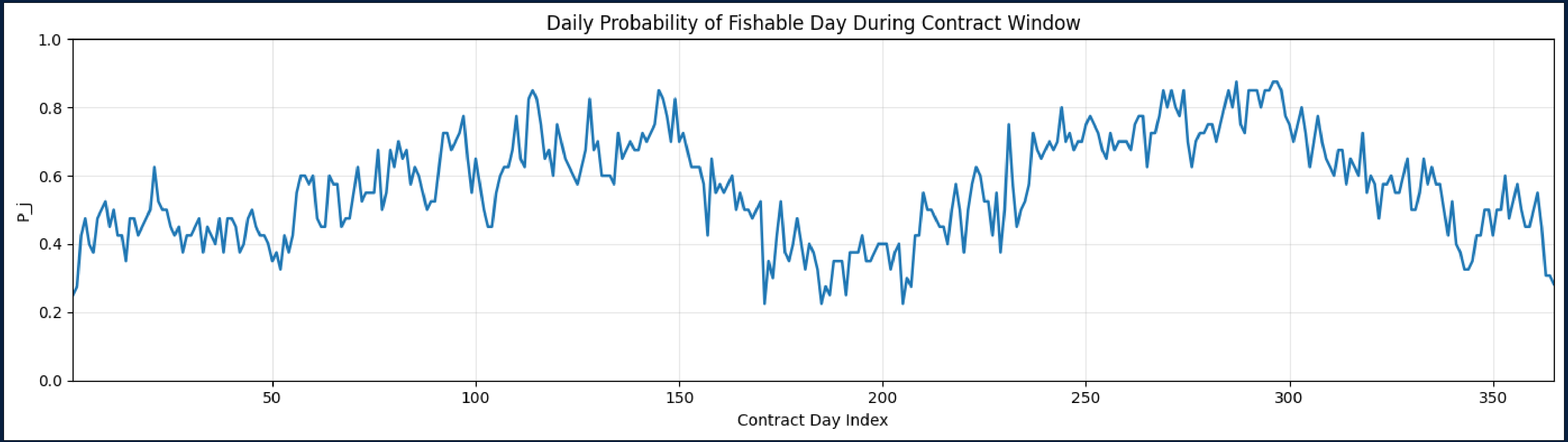
Result: Seasonal Variation in Fishability



Probability is NOT constant → justifies Poisson-binomial

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Result: Trigger Probability Across Varying Strikes

Strike percentage (%)	Strike days	Fixed payout, (L) ($)	Trigger probability, (P(N<K))	Weather derivative price ($)
80	165	13,785.75	0.000002	0.02
81	167	13,125.75	0.000004	0.06
82	170	12,135.75	0.000019	0.23
83	172	11,475.75	0.000049	0.54
84	174	10,815.75	0.000119	1.24
85	176	10,155.75	0.000276	2.70
86	178	9,495.75	0.000610	5.58
87	180	8,835.75	0.001289	10.98
88	182	8,175.75	0.002605	20.52
89	184	7,515.75	0.005032	36.45
90	186	6,855.75	0.009303	61.46
91	188	6,195.75	0.016460	98.28
92	190	5,535.75	0.027895	148.81
93	192	4,875.75	0.045302	212.86
94	194	4,215.75	0.070555	286.64
95	196	3,555.75	0.105465	361.38

Non-linear increase in risk

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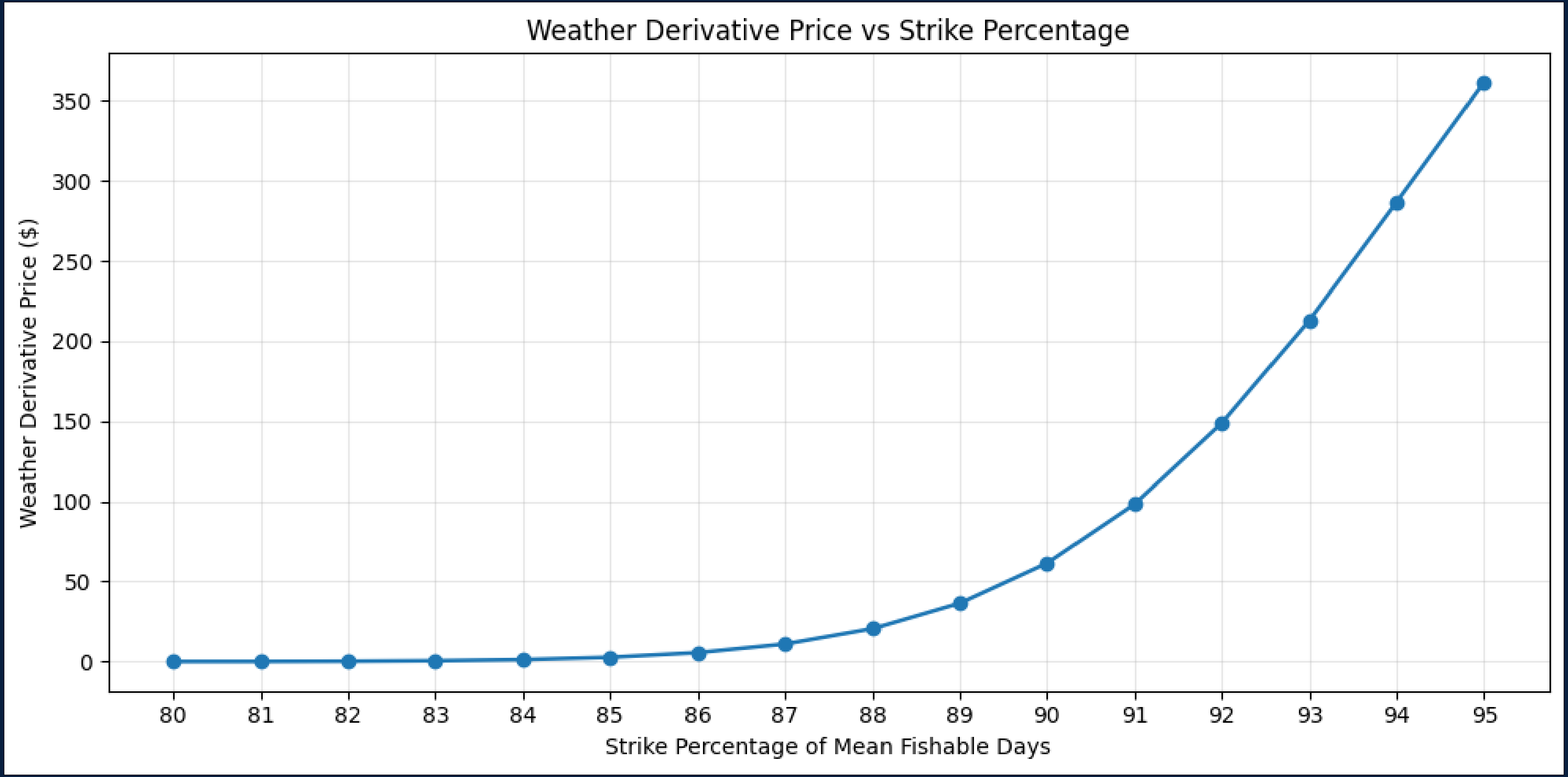
Result: Weather Derivative Price vs Strike



Price is driven mainly by trigger probability

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Discussion: Interpretation of Pricing Results

- ❑ The price **does not** increase smoothly.
- ❑ It gradually increases initially, then very fast (exponential curve shape @ ~87%).
- ❑ At low strike levels ($\leq$ 87%), the contract would almost never trigger (< 0.001). So, these strikes are not useful.
- ❑ At higher strike levels, the trigger happens more often. So, financial protection becomes meaningful.
- ❑ Even though payout decreases, the higher trigger chance increases the premium.

- ❑ **Therefore:** trigger probability is more important than payout size.

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Caveats

- Existing Insurance Experience and Novelty
- Data challenges in small-scale fisheries
    - Limited historical and reporting data
    - Constraints on monitoring losses
- Exclusion of insurance operating costs and reinsurance
- Treatment of all "bad weather" days as equivalent

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Conceptual Motivation for Rainy-Day (Weather Derivative) Parametric Insurance

- Lost fishing days are a measurable economic loss
- Separation of weather risk from ecological overfishing risk
- Transparency and trust – potential to incentivize more data

Benefits include:

- ✅ Predefined triggers based on objective, observable conditions.
- ✅ No influence by the insured.
- ✅ Customization and fast payouts.

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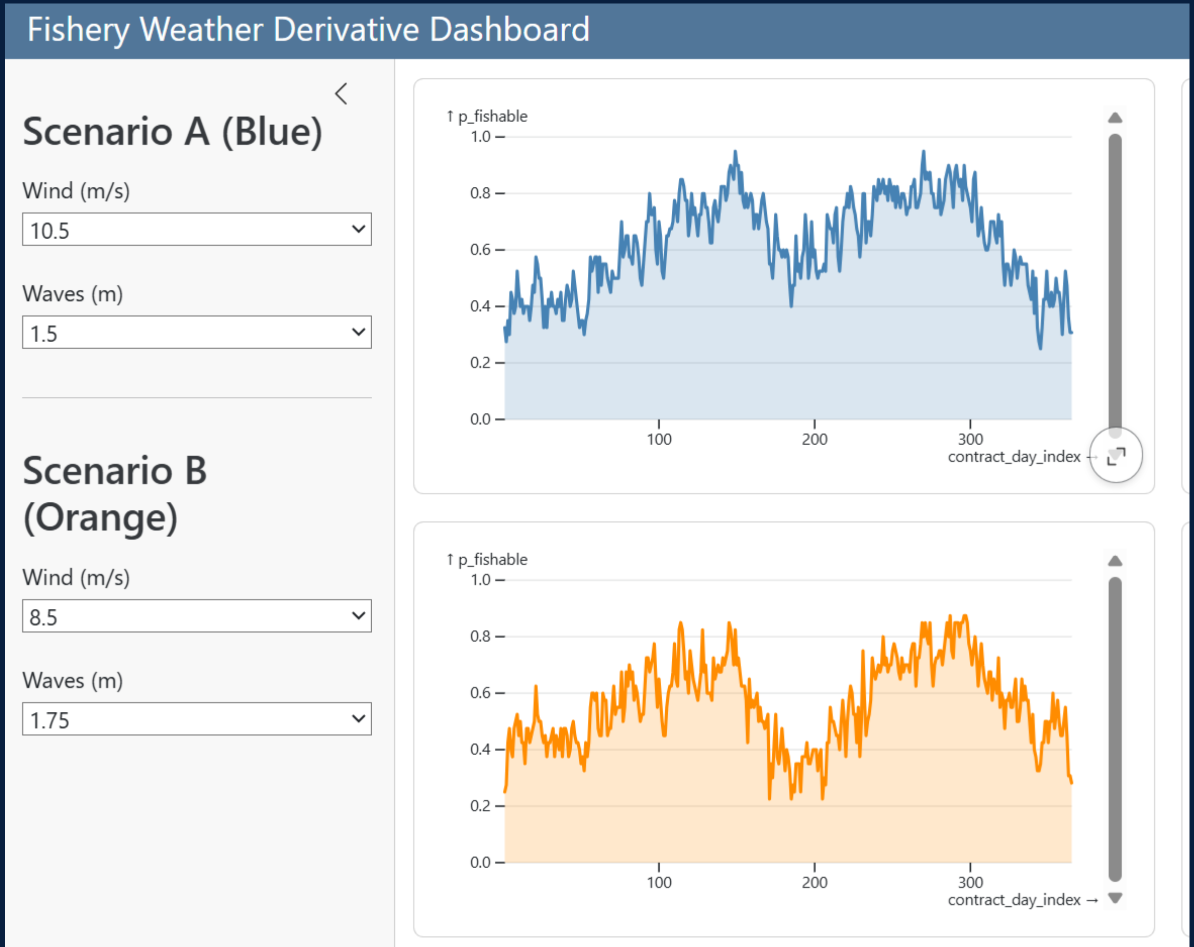
Enabling Insight Through Interactive Exploration of Weather Derivatives



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Conclusions

Purpose of the pricing exercise

- Understanding two-factor weather derivatives
- Identifying caveats and hypothetical concerns
- Using pricing as a learning and exploratory tool

On the horizon...

- Ongoing improvements in biological and economic data
- Further customization and probability modeling

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