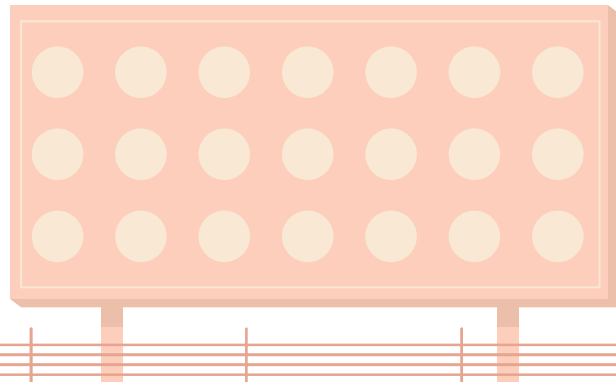


# Predicting Plays, Revaluing Rushers

Verity Nwabuisi and Cale Latimer

External Advisor: Preston Biro (Washington Commanders)



# Anticipation Wins Games

In the NFL, games are often decided by preparation and play-calling — where strategy on the sideline can be just as important as execution on the field.

## Our goals:

- Build a model that predicts the likelihood of a run or pass using pre-snap context.
- Use this model to evaluate pass rushers, with an emphasis on:
  - Their ability to generate pressure in unexpected passing situations, where disruption is often harder to achieve.



# Data

## **NFL Play-by-Play Data (2016–2023):**

Includes down, distance, quarter, yardline, score differential, time remaining, formation info, and team-specific lagged run rate.

## **NFL Player Tracking Data (2022):**

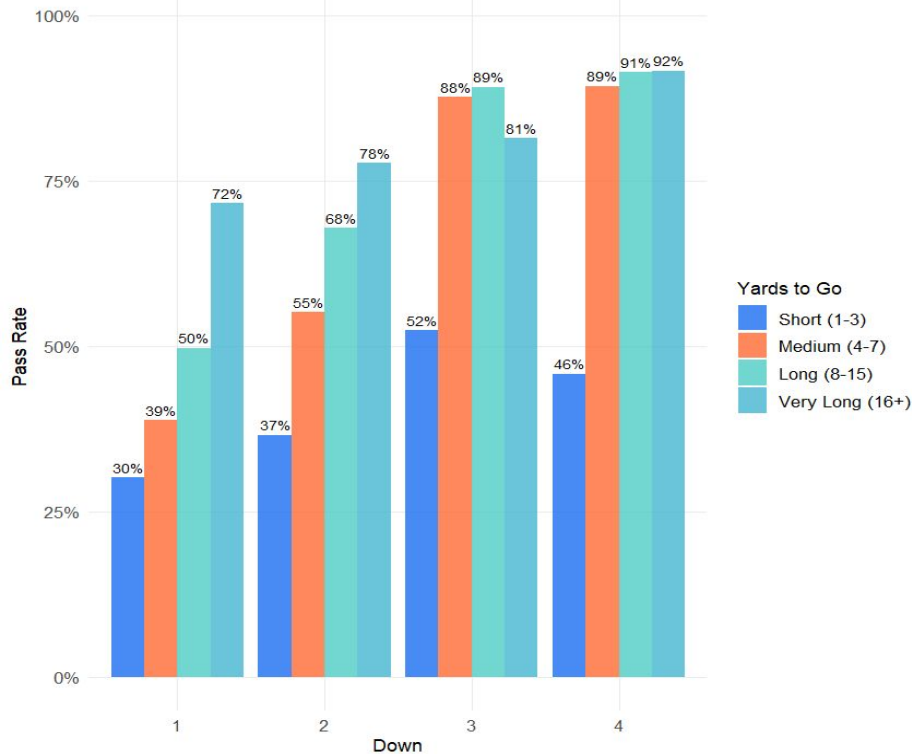
Provides (x, y) coordinates for all players and the ball on every frame, plus speed, acceleration, direction, and key event tags (e.g., ball\_snap, pass\_release, tackle).



# Innate Trends Exist in Playcalling

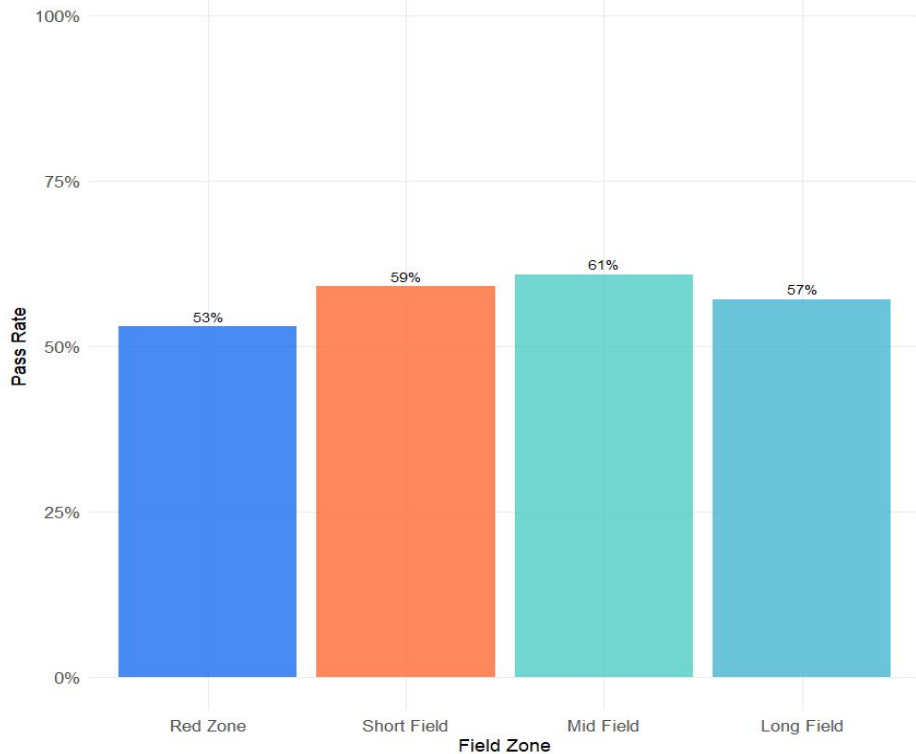
## Pass Rate by Down and Distance

Clear patterns emerge in situational play calling



## Pass Rate by Field Position

Field position significantly influences play selection



# Methods

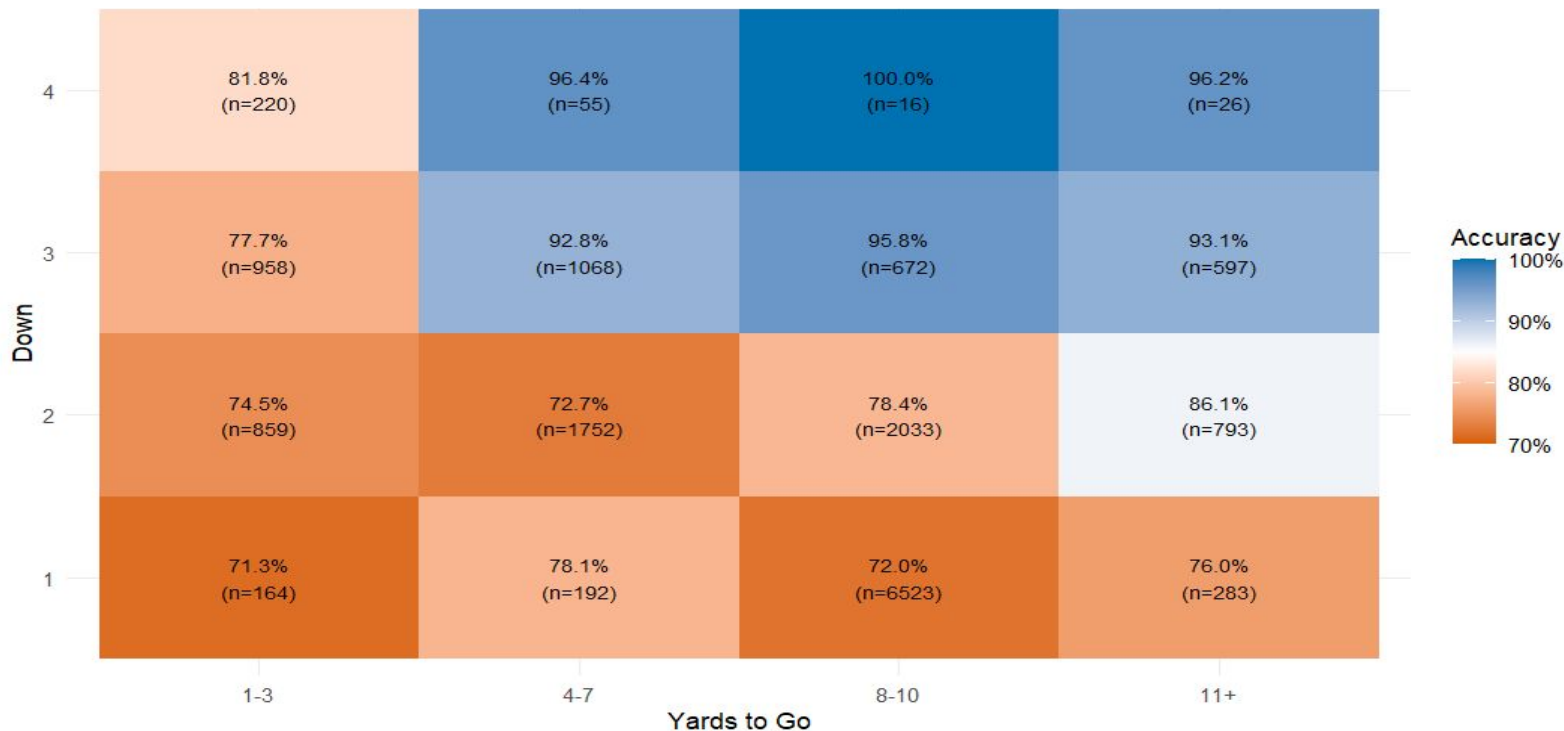
Our modeling pipeline had three stages, each adding more football context:

- **Stage 1 – Baseline:**  
Used XGBoost with core features like down, distance, score, and time. Trained on data from 2016–2023. Achieved ~70% accuracy but lacked awareness of formation and team tendencies.
- **Stage 2 – Formation-Aware:**  
Added team identity and alignment features to reflect offensive style, improving contextual relevance. Still used XGBoost and the 2016–2023 data.
- **Stage 3 – Tracking-Enhanced:**  
Integrated player locations and spacing using tracking data from Weeks 1–9 of the 2022 season. Switched to generalized additive models (GAMs) to better model spatial patterns and have better calibrated probabilities, boosting accuracy by 5–10%.

We used the final models to compute surprisal, helping assess how unexpected a play was—useful for evaluating defensive reactions.



# Offenses are Less Predictable on Early Downs



# Evaluating Rushers With Surprisal

## Surprisal Definition

Surprisal is defined as the negative logarithm of the probability of what actually happened:

$$\text{Surprisal} = -\log(\text{probability of observed event})$$

This measures how “surprising” or “informative” an event is — rarer events have higher surprisal.

## Why Surprisal Matters









Surprisal measures how unexpected a play is — rarer events (like a pass in a run-heavy look) get higher scores. This helps:

- Highlight pass rushers who succeed in unpredictable situations
- Weight sacks and hits by difficulty
- Go beyond raw stats with context-aware metrics






Final metric: Rate = 
$$\frac{\text{Weighted Sacks} + \text{Weighted Hits}}{\sum_{j \in \text{All Pass Snaps}} \text{Surprisal}_j}$$

# Surprisal Reveals Hidden Value






## TOP 8 OVERALL (BY WEIGHTED RATE)

RANK	PLAYER	TEAM	WEIGHTED	RAW
1	 James Smith-Williams	WAS	0.0758	0.0617
2	 Jerry Hughes	HOU	0.0537	0.0689
3	 Montez Sweat	WAS	0.0486	0.0837
4	 Nick Bosa	SF	0.0484	0.1368
5	 Maxx Crosby	LV	0.0466	0.0669
6	 Myles Garrett	CLE	0.0460	0.0948
7	 Dorance Armstrong	DAL	0.0435	0.0638
8	 Aaron Donald	LA	0.0397	0.0441

## TOP 5 FALLERS (BY RANK CHANGE)

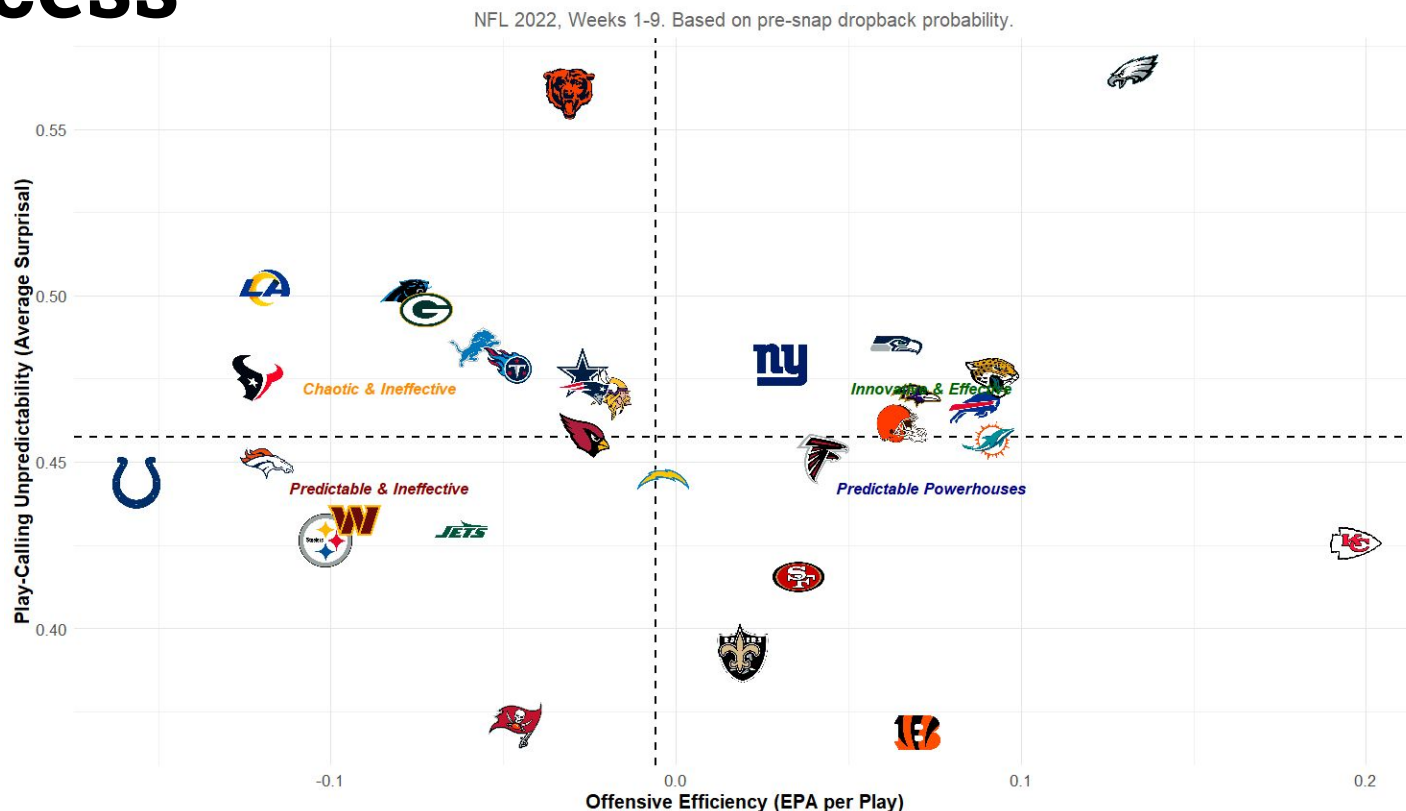
PLAYER	NEW	OLD	CHANGE
 Josh Sweat	50	4	-46
 Cameron Heyward	56	19	-37
 Gregory Rousseau	47	13	-34
 Daron Payne	44	11	-33
 Jonathan Allen	59	28	-31

## TOP 5 RISERS (BY RANK CHANGE)

PLAYER	NEW	OLD	CHANGE
 Logan Hall	9	56	+47
 D.J. Jones	22	62	+40
 Al-Quadin Muhammad	40	74	+34
 Aaron Donald	8	40	+32
 Matt Ioannidis	28	59	+31



# Surprisal Reveals Strategy—Not Success



# Discussions

## Insight:

Surprisal-adjusted pass-rush scores elevate under-the-radar disruptors (e.g., Dorance Armstrong, Logan Hall) and deflate some headline names once context is stripped away.

## Limitations:

- **Identity-blind:** Ignores team, coaching style, and individual skill.
- **Short window:** Based on only Weeks 1–9 of the 2022 season.
- **Static view:** Doesn't model post-snap dynamics (e.g., RPOs, motion, scrambles).

## Future Directions:

- Incorporate player grades, coaching tendencies, and fatigue to build talent-aware predictions.
- Add contextual layers to pass-rush evaluation—O-line strength, slide protections, and double teams.



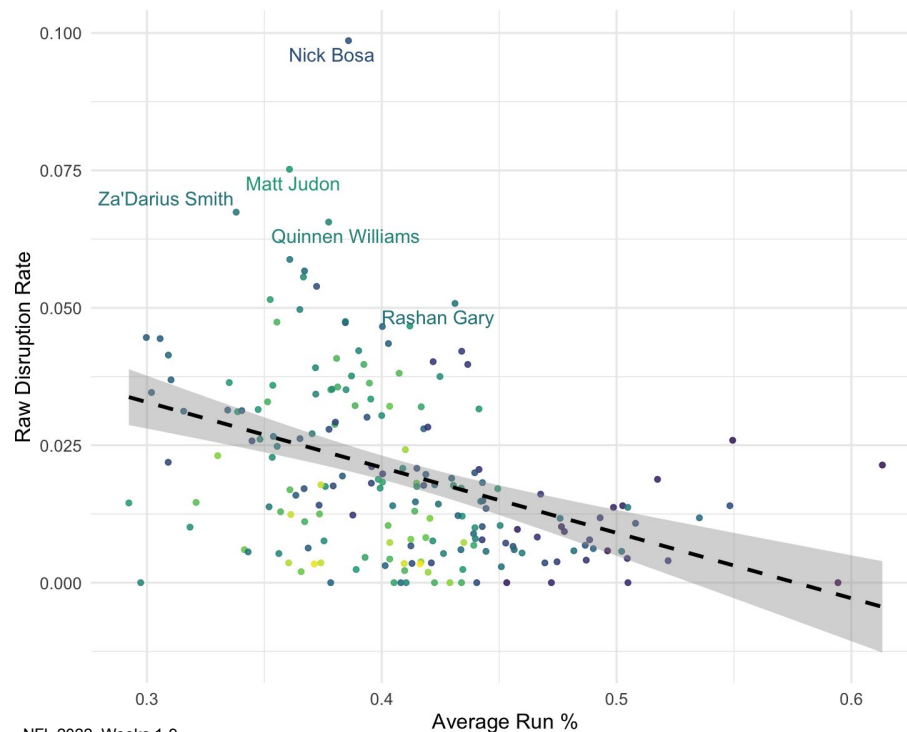
# Q/A








# Appendix



# The Top Disruptors Outperform Model Expectations



RANK	PLAYER	TEAM	RAW RATE	EXPECTED RATE	OVERPERFORMANCE
1	 <b>Nick Bosa</b>	SF	0.0986	0.0226	0.0760
2	 <b>Matt Judon</b>	NE	0.0752	0.0256	0.0496
3	 <b>Quinnen Williams</b>	NYJ	0.0656	0.0236	0.0420
4	 <b>Za'Darius Smith</b>	MIN	0.0674	0.0283	0.0391
5	 <b>Rashan Gary</b>	GB	0.0508	0.0172	0.0336

# Calibration

