PRSS: A New Metric to Quantify Pocket Collapses in the National Football League

Jahan Hafiz[1], Avi Mandhana[2], Derek Park[3], and Sohan Saleem[4]

[1]Round Rock High School, Round Rock, TX
[2]Eastside Catholic School, Sammamish, WA
[3]The Wheatley School, Old Westbury, NY
[4]Garnet Valley High School, Glen Mills, PA

November 1, 2025

Abstract

In the NFL, "quarterback pressure" refers to defensive actions that disrupt a passer's timing, decisions, and positioning. Numerous quantitative measures have been proposed, with mixed effectiveness. We introduce the Pocket Reduction Speed Score (PRSS), a geometric, tracking-based metric that quantifies how quickly the quarterback's pocket shrinks. We apply the metric to player-tracking data from the 2021 NFL regular season, compute PRSS for each play, and examine its association with yards gained. PRSS offers a continuous, interpretable measure that captures multi-defender effects and the moment of greatest pressure, complementing existing binary and closest-defender metrics while offering applications in pass-protection evaluation, scouting, and scheme design.

1 Introduction

In football, "pressure" refers to the defensive effort to disrupt a quarterback's decision-making and execution during a play. Pressure is generated by defenders rushing the passer and attempting to induce an incompletion or a sack. When under pressure, quarterbacks have less time and space to throw, which can reduce both accuracy and throw distance. The offensive line's role is to minimize pressure, affording the quarterback sufficient time to make a decision. Three primary statistics are commonly used to record pressure events: sacks, hits, and hurries. A sack occurs when the quarterback is tackled behind the line of scrimmage, a hit occurs when the quarterback is contacted after releasing the ball, and a hurry is recorded when the quarterback is forced to throw early. These measures underpin traditional pressure statistics in contemporary football analysis.

1.1 Traditional Pressure and Sack Metrics

A common approach to quantifying pressure has been to count sacks, hits, and hurries. Providers such as Pro Football Focus report these metrics, emphasizing binary outcomes indicating whether some form of pressure occurred on a given play (Pro Football Focus, 2023). Although sacks and pressures often reflect breakdowns in pass protection, they can be heavily influenced by quarterback decision-making (Lisk, 2018). Moreover, reducing complex pass-rush dynamics to yes/no outcomes obscures the spatial and temporal details of pocket breakdowns. This motivates a more nuanced, continuous measure that better captures the dynamics of pass protection.

1.2 Closest-Defender Approaches

Several lines of research evaluate offensive dynamics using metrics based on the defender closest to the quarterback. In pass-rush contexts, the material-science–inspired STRAIN metric quantifies pressure using the Euclidean distance between the quarterback and the nearest defender and the rate at which that distance is shrinking (Nguyen et al., 2023). While this moves beyond purely binary statistics, it ignores contributions from multiple defenders and lacks the full spatial context of the pocket.

1.3 Pass Block Win Rate and "Beats"

Pass Block Win Rate (PBWR), created by Brian Burke, quantifies line interactions on a play. If a rusher "beats" an offensive lineman in under 2.5 seconds and closes to within 1.5 yards of the quarterback, the rusher records a win; conversely, an offensive lineman earns a win by preventing such impact (Burke, 2019b). Although PBWR uses tracking-based time and distance, it collapses outcomes into discrete win/loss labels. Analysts have also noted that the 2.5-second threshold is relatively arbitrary (Stern, 2023). In addition, the measure treats a defensive win at 2.4 seconds the same as one at 1.3 seconds despite the latter being more dominant. If the quarterback releases the ball before 2.5 seconds, the blocker cannot earn a win and is charged with a loss only if the rusher crosses the 1.5-yard threshold before that mark. As ESPN notes, PBWR was designed primarily for broadcast consumption rather than research-grade analysis (ESPN, 2018).

1.4 Convex Hulls

The convex hull—the smallest convex polygon enclosing a set of points—has broad applications in spatial analysis. In football, it has been used to model a quarterback's "danger zone," wherein defender penetration into the region increases the risk that the quarterback will be sacked (i.e., reduces survival probability). This approach moves beyond one-dimensional distance metrics but does not incorporate the speed, direction, or quality of penetration. Nonetheless, convex-hull methods have been applied in multiple settings: in soccer, to evaluate effects of positional movement in possession (Gonçalves et al., 2017); and in football, in an extension of PBWR that flags a "beat" when a defender enters a convex zone (Burke, 2019a). These adaptations acknowledge two-dimensional structure but remain limited in capturing dynamic pocket deformation.

1.5 Convolutional Neural Networks

Convolutional neural networks (CNNs) are well suited to predictive analyses of spatiotemporal data, including video and grid representations. Stern (2023) used CNNs to estimate pre-snap sack probability and pocket survivability from formations and spatial dynamics. A limitation of this line of work is the close coupling of pressure with sack likelihood: while sacks are a consequence of pressure, pressure also manifests through constrained escape lanes, reduced foot space, and impaired sight lines. Thus, although CNNs can forecast sack risk over the next 2.8 seconds, they narrow the concept of pressure to a failure-proximate event.

1.6 Voronoi Tessellations

Voronoi tessellation partitions the field into regions such that each point is assigned to the nearest player; each player thus controls the set of locations closer to them than to any other. In the context of quarterback pressure, this framework incorporates all defenders' positions relative to the quarterback through a pocket area. In soccer, Voronoi methods have been used to quantify space creation (Fernandez and Bornn, 2018); in football, they have been applied to estimate pocket area (Ibrahim, 2021). Unlike Ibrahim (2021), who assemble snapshots of the pocket to assess survivability over time, we quantify pressure via the maximum negative rate of change of the pocket area during a play. This yields a continuous, spatially explicit measure that captures the moment of greatest pressure.

2 Data and Sourcing

We use the publicly available play-by-play and player-tracking data released for the NFL's 2023 Big Data Bowl, covering all games from Weeks 1–5 of the 2021 season. The tracking data are sampled at 10 frames per second, with coordinates recorded in field units. We merge the tracking files with play-by-play and player tables to identify play participants and outcomes.

We focus on positions relevant to pocket formation and defensive pressure: QB, OL, DL, LB, TE, CB, RB, and S. For each play, we analyze frames from the snap to the terminal event (pass attempt, sack, or spike). Because tracking data can contain missing or duplicate locations, we apply two quality filters. First, we require at least three players with valid coordinates in a frame to compute a pocket area, excluding frames that cannot support a Voronoi partition. Second, when multiple players share identical coordinates within a frame, we retain a single instance of that location to ensure a valid Voronoi diagram and pocket-area calculation.

3 Methodology

3.1 Voronoi Tessellations

A Voronoi tessellation partitions the plane into regions such that each region (cell) contains all locations closer to its generating point than to any other in two-dimensional Euclidean space. Formally,

$$V_i = \{\, q : d(q, p_i) \le d(q, p_j),\ \forall\, j \ne i \,\}. \tag{1}$$

For each frame of a play, we construct a Voronoi diagram from the positions of the 22 players and take the quarterback's cell—hereafter the *pocket*—as the measure of interest.

Each cell is a polygon with counterclockwise-ordered vertices. We compute polygon areas using the shoelace formula (via the `deldir` package in `R`). For vertices

$$(x_{i,1}, y_{i,1}),\ (x_{i,2}, y_{i,2}),\ \ldots,\ (x_{i,n}, y_{i,n}),$$

the area is

$$A_{V_i} = \frac{1}{2}\left|\sum_{k=1}^{n} \left(x_{i,k} y_{i,k+1} - x_{i,k+1} y_{i,k}\right)\right|. \tag{2}$$

3.2 Pocket Contraction and PRSS

Let A_t denote the quarterback's pocket area in frame t and let $\Delta t = 0.1\,\mathrm{s}$ (10 Hz sampling). We quantify instantaneous pocket contraction with the forward difference

$$r_t = \frac{A_{t+1} - A_t}{\Delta t} \quad (\mathrm{yd}^2\,\mathrm{s}^{-1}).$$

To suppress spurious single-frame fluctuations (e.g., at the snap), we smooth with a five-frame rolling mean (a 0.5 s window):

$$\bar{r}_t = \frac{1}{5}\sum_{k=0}^{4} r_{t+k}.$$

The *Pocket Reduction Speed Score* (PRSS) for a play is the most negative smoothed rate over its duration,

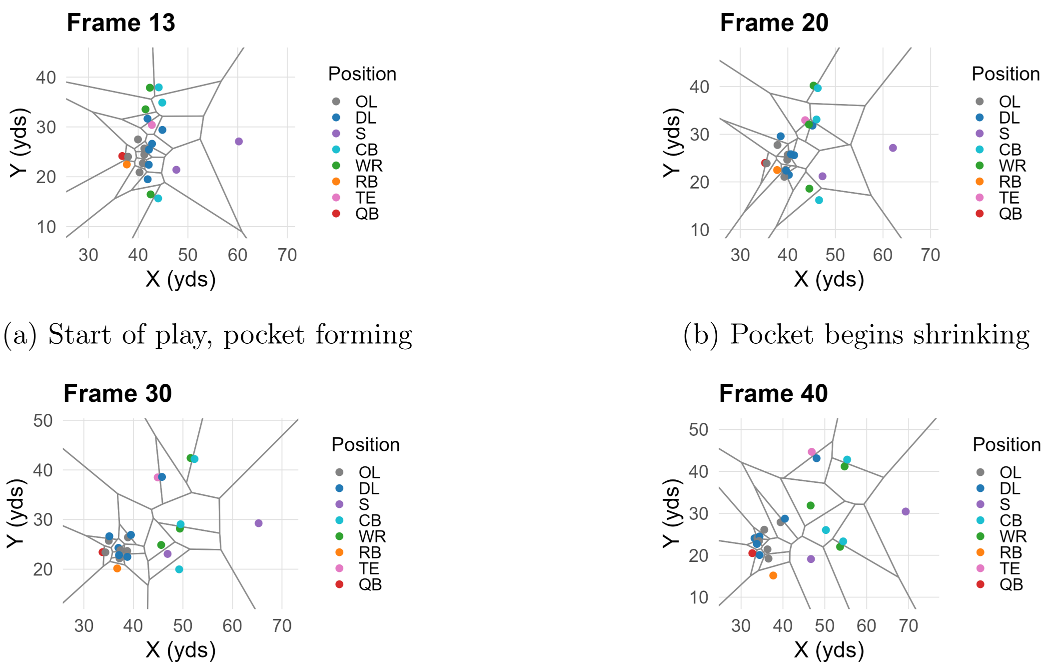
$$PRSS = -min_t barr_t,$$

so that larger values indicate faster pocket collapse (PRSS is nonnegative by construction and equals the magnitude of the steepest pocket-area decline). Using a windowed rate (rather than a single-frame difference) emphasizes sustained contractions driven by multiple defenders and mitigates the influence of transient spikes, which are almost always recorded as discrete events such as a hurry or sack.

3.3 Illustrative Example

Figure 1 shows selected frames from the 2021 Week 1 Cowboys–Buccaneers game; as the play progresses, defenders claim a larger share of the field and the quarterback's pocket shrinks.

The corresponding pocket area and its frame-to-frame contraction rate are shown in Figure 2; the moment of rapid collapse appears as the most negative segment of the smoothed rate, which defines PRSS for the play.



(a) Start of play, pocket forming

(b) Pocket begins shrinking

(c) Pocket collapse

(d) Pass released

Figure 1: Voronoi partitions for selected frames.

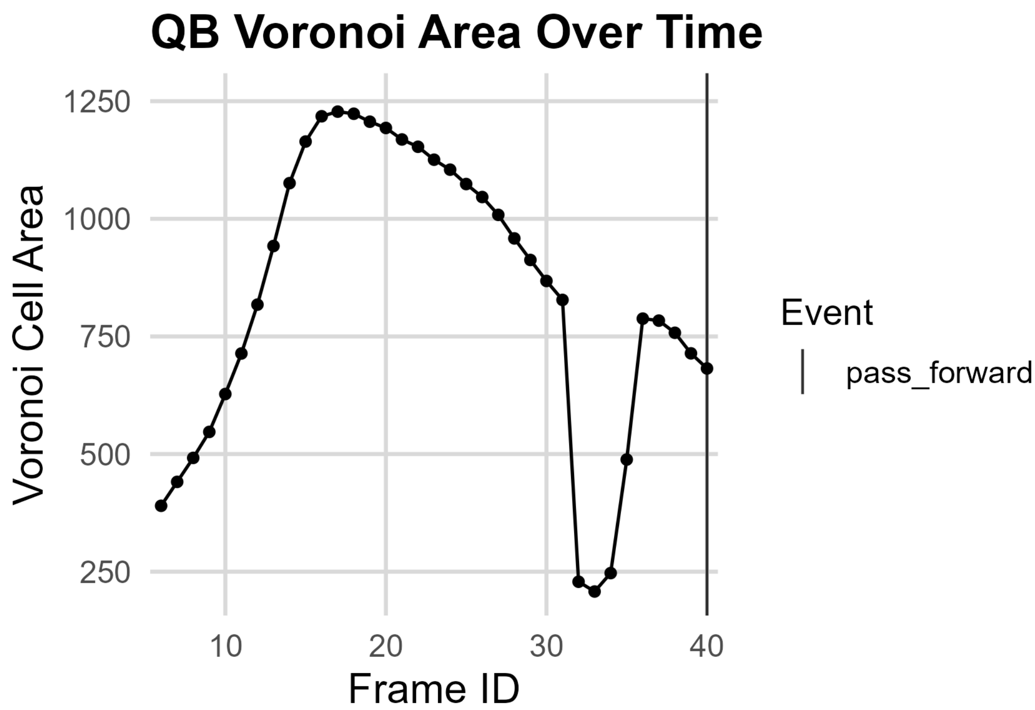
4 Results

4.1 Binned Average Yards Gained vs. Average PRSS Allowed

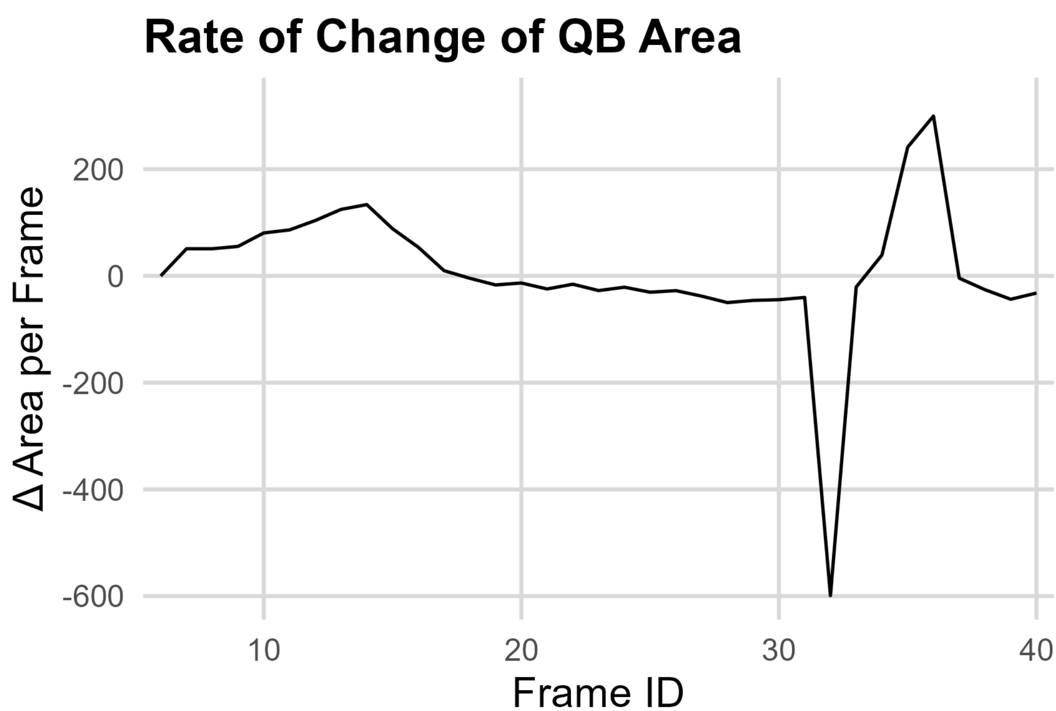
We expect offensive success to decline as pressure increases. We visualize this relationship in Figure 3, binning plays by PRSS allowed (10-unit bins) and, for each bin, plotting the mean yards gained against the bin's mean PRSS allowed. Recall that PRSS is the magnitude of the most negative smoothed rate of pocket-area change; higher PRSS indicates faster pocket collapse. The fitted line exhibits a negative slope, and the coefficient of determination ($R^2 = 0.522$) indicates a moderate linear association between higher PRSS allowed (faster collapse) and fewer yards gained. On its own, this establishes face validity for PRSS as a pressure metric.

4.2 PRSS Allowed by Team

We next summarize team-level pressure by averaging PRSS allowed across plays for each team in Weeks 1–5 of 2021; Figure 4 visualizes this ranking. The ordering aligns with context from this span: the Broncos, Jets, and Cardinals exhibit the highest mean PRSS allowed with shaky lines, while the Steelers and Browns ranked among the best offensive lines in



(a) Pocket area A_t



(b) Smoothed contraction rate $\bar{r}_t$ (PRSS is the minimum)

Figure 2: Pocket dynamics over the same play: area (top) and contraction rate (bottom).

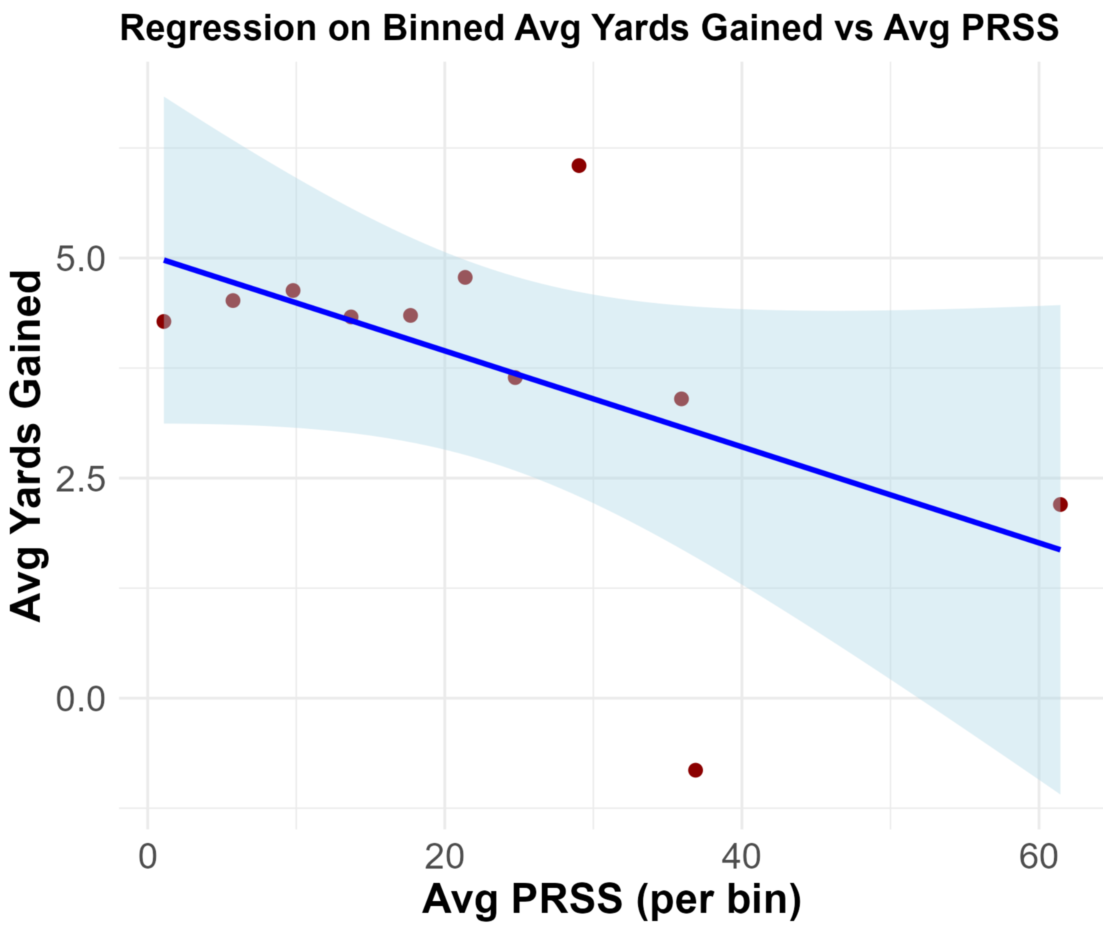


Figure 3: Mean yards gained versus mean PRSS *allowed* by 10-unit PRSS bins (Weeks 1–5, 2021). The fitted line has a negative slope; $R^2 = 0.522$.

football. Additionally, while the Raiders' offensive line did not grade out well in 2021, Derek Carr's 2nd-ranked 2.54 average time to throw likely contributed to a low PRSS allowed. This indicates that PRSS captures not only offensive line integrity, but team-to-team differences in scheme and quarterback play.

Taken together, the play-level relationship (yards vs. PRSS allowed) and the team-level rankings provide evidence that PRSS captures meaningful variation in pocket collapse. PRSS allowed behaves consistently with domain expectations and offers a continuous, interpretable summary of pressure.

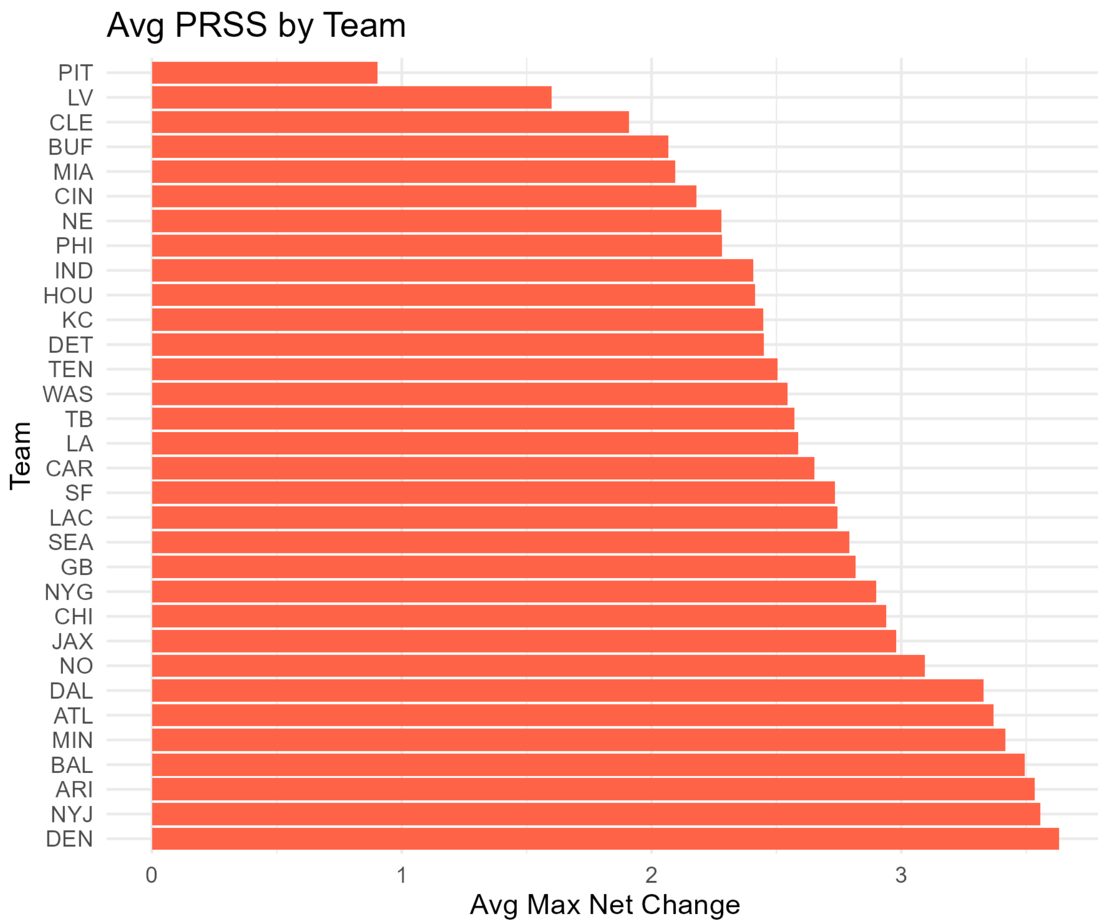


Figure 4: Mean PRSS *allowed* by team (Weeks 1–5, 2021).

5 Discussion

5.1 Conclusions

Across Weeks 1–5 of 2021, PRSS allowed—the most negative smoothed rate of pocket-area change—tracked offensive performance in the expected direction: the higher the PRSS allowed, the fewer yards gained. This pattern supports PRSS as a continuous, spatially grounded pressure metric. In our sample, PRSS summarized pocket collapse more informatively than traditional binary or threshold indicators (e.g., hits, hurries, "beats") and offers richer context to describe the performance of quarterbacks, offensive lines, and opposing pass rushes.

5.2 Limitations and Future Directions

A first limitation is that Voronoi partitions are symmetric and Euclidean: they treat all players identically and ignore differences in speed, acceleration, and agility, which can bias "control" estimates for mobile quarterbacks or elite rushers. A natural next step is to develop motion-aware regions (e.g., weighted or anisotropic Voronoi/power diagrams and time-to-reach or reachability formulations) that incorporate velocity and acceleration so pocket control reflects movement capacity, not just location.

Second, pressure manifests differently across play families (true dropback, rollouts, quick game/RPO), which complicates cross-play and cross-quarterback comparisons. To address this, analyses should be stratified by play type and protection scheme, with within-stratum models that control for down, distance, time-to-throw, and chip/help indicators, enabling cleaner attribution to pocket contraction.

Third, our findings depend on several design choices (five-frame smoothing, coordinate-quality filters) and a limited sample (Weeks 1–5, 2021). Future work could explore different window lengths and filtering rules, extend to full-season and multi-year samples, and report reliability (test–retest, year-over-year stability) to assess robustness.

Fourth, the observed association with yards gained ($R^2 = 0.522$) is correlational and may be partially confounded by scheme or opponent strength. Explicit causal identification or quasi-experimental strategies would be necessary to isolate a clear causal effect between pocket collapse and play success.

Finally, yards gained captures only one facet of offensive success. Expanding outcomes to expected points added (EPA), success rate, time-to-pressure, and sack or turnover-worthy-play rates would test the breadth and operational relevance of PRSS.

In summary, PRSS offers a continuous, interpretable lens on pocket dynamics that aligns with domain expectations and yields actionable insight for evaluation and game planning, while motivating motion-aware refinements and broader validation.

5.3 Reproducibility

Our full code and results are public on GitHub for reproducibility.

6 Acknowledgments

We would like to express our sincere gratitude to Professor Abraham J. Wyner and Wharton's Moneyball Academy for providing us with this opportunity and supporting us throughout the research process. We also extend special thanks to Jonathan Pipping, Victoria Lee, and Kenny Watts for their guidance, insights, and expertise in helping us refine our research and improve the quality of our presentation and paper.

References

Burke, B. (2019a). Creating better nfl pass-blocking and pass-rushing stats: An analytics explainer and faq. https://www.espn.com/analytics. ESPN, November 22, 2019.

Burke, B. (2019b). Pass block win rate explained. https://www.espn.com/analytics. ESPN Analytics Blog.

ESPN (2018). Advanced nfl stats. https://www.espn.com/nfl/stats. ESPN.com.

Fernandez, J. and Bornn, L. (2018). Wide open spaces: A statistical technique for measuring space creation in professional soccer. In *MIT Sloan Sports Analytics Conference*.

Gonçalves, B., Coutinho, D., Travassos, B., et al. (2017). Effect of player position on movement and ball possession patterns in soccer. *Journal of Sports Sciences*.

Ibrahim, P. (2021). Quantifying the pocket: Voronoi diagrams and survival analysis for offensive line performance. In *CMSAC Conference Proceedings*.

Lisk, J. (2018). Sacks are a quarterback stat. The Big Lead, October 19, 2018.

Nguyen, Q., Yurko, R., and Matthews, G. J. (2023). Here comes the strain: Analyzing defensive pass rush in american football with player tracking data. *The American Statistician*, 78(2):199–208.

Pro Football Focus (2023). Nfl pressure statistics. https://www.pff.com. Accessed 2025-10-31.

Stern, B. (2023). *Evaluating Quarterback Pressure: A Machine Learning Approach*. Undergraduate thesis, Harvard University.