# A Quantitative Framework for Assessing Wide Receiver Blocking Effectiveness Using Player Tracking Data

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**Abstract**

In the modern NFL, wide-receivers play an integral role in run-blocking. However, with scouts and coaches spending their time on evaluating catching and route-running, their abilities to perform these overlooked tasks are often ignored. In this paper, we introduce the Skill Player Downfield Blocking Effectiveness Score, a novel metric derived from player tracking data, not human evaluation. The metric incorporates changes in angles between players and the ball, the defender's speed, and the changes in geometry in both the defender and the blocking skill player. To make our metric applicable to coaches with a limited technical background, we developed a decision tree model to classify whether a player's BES was above or below median with an accuracy of 84%. Finally, we looked at a couple case studies of players with varying blocking capabilities and found that the metric aligned with both blocking abilities and expectations.

## 1 Introduction

Today's NFL is defined by high-powered, dominant passing offenses. In this league, the evaluation of wide receivers is centered around easily measurable receiving metrics: targets, receptions, yards, and touchdowns. However, this ignores a crucial yet underexplored part of their job: downfield blocking. Downfield blocks are crucial in differentiating between a small gain or a game-changing play. In screen passes, run-pass option concepts, and explosive downfield passes, a receiver's ability to redirect defenders has a significant impact on a game's script.

Previous research on offensive lineman evaluation use player accolades, draft position, and film-based grading to estimate their monetary value (Byanna and Klabjan 2020). Their clustering approach combined certain attributes like draft round and PFF grades with other qualitative elements like blocking skills, giving a well-rounded view of the player's value. However, accolades cannot translate to the receiver position, as receivers can win these awards off of their primary, non-blocking achievements alone. This forms a disconnect between the traditional methods for evaluating a player and the full range of responsibilities a receiver has in a playbook.

Existing methodologies are mixed in their applicability and usefulness. Pro Football Focus, a primarily film-based platform, offers pass and run block grades for receivers; however, the grading is done subjectively and without any publicly available metric or formula (PFF 2024). This limits the ability of analysts to build upon that metric or formulate benchmarks from the grades. Furthermore, these evaluations also introduce analyst bias, which could place more emphasis on a player's reputation or other external, subjective factors instead of looking solely at the mechanical aspects of successful blocks.

Spatial win-rate metrics like ESPN's Run Block Win Rate (RBWR) define a player "winning a block" based on "a combination of distance and orientation - the closer and squarer a blocker is to a defender, the more likely he is blocking him" (ESPN Analytics 2020). This is a more objective approach, using tracking data to estimate a player's spatial impact on each play. However, RBWR is more focused on linemen and tight ends, whose blocks take place near the line of scrimmage, making it difficult to translate directly to the blocking movements of wide receivers. Regardless, the basic logic supporting RBWR is a baseline that can be adapted for downfield wide receiver blocking.

Despite the visible impact of downfield receiver blocks by redirecting or delaying defensive backs on yards after catch (YAC), most NFL teams lack a standardized metric to evaluate this skill. As noted in the NFL Pass Evaluation report, "focusing only on linemen does not allow us to explain the results nor evaluate their share of contribution," highlighting the necessity of capturing indirect impact from everyone on the field (NFL Pass Evaluation 2023). This paper highlights the gap in current evaluation metrics, which often skim over the impact that can be made by players without touching the ball.

One of the key modeling tools used in our research is the decision tree. Decision trees allow for a more transparent and binary approach to classification. Each node in a decision tree is related to a feature and a decision threshold, and the entire path from the root to leaf contains a group of binary conditions (0 or 1) under which the model's overall prediction is made (Zhang et. al 2004). In the context of our research, it allowed us to create a model not only quantifying a receiver's blocking impact, but also one that is transparent in showing why a particular block was impactful: whether due to defender proximity, deceleration, or another factor. Unlike more black-box models like neural networks, decision trees allow experts and front offices to come up with more thresholds for the binary classification factors, like defender distance, for example, that are more consistently associated with more positive scores.

The goal of this research is to help NFL analysts and front offices answer the following question: how can we quantify a given wide receiver's blocking ability, and therefore, help them improve on those skillsets in training camp to ramp up offensive productivity? Using a combination of location tracking, existing PFF grading, and decision-tree modeling, we look to transform this skill into a more prominent component of a receiver's value.

## 2 Limitations and Future Work

Our research had a variety of limitations that can be explored.

One major difficulty faced while conducting our research was the lack of previous research done on wide receiver blocking-based impact. There are little existing metrics created specifically for wide receiver blocking, making it difficult to benchmark the decision tree's findings or build upon previous methodologies. Consequently, the methods were developed primarily from scratch, including our own definitions and criteria for block success and potential impact on a play.

The research was also done with limited access to complete, high-resolution tracking data. The dataset we used incorporated location data-frames for every 0.1 second interval; however, many of the plays did not include the full set of frames. This meant that important frames near the end of plays, when wide receivers often engage in or finish blocks, were missing. This restricted our ability to determine whether or not a receiver contributed to the final play outcome through a downfield block.

Due to resource and time limitations, we were also unable to compare a majority of game film across the plays we analyzed. As a result, we were forced to make some assumptions solely based on the accessible data. In particular, we conjectured potential blocking impact when a receiver was within a predetermined distance threshold from a defender and caused a substantial change in the defender's direction and acceleration. While there were many pieces of film we used to come up with these definitions, the remaining assumption creates space for errors. Without direct film validation on every play, there are inevitably plays that may have been wrongly excluded from the filtered dataset, or plays that were unnecessarily included.

Finally, a lack of financial resources rendered us unavailable to access more detailed datasets, such as higher-resolution PFF tracking data. This could have enabled more accurate block identification and use of an existing, more accepted metric for block identification and success.

Future research should look to build upon our framework, while addressing the challenges we encountered. Specifically, a similar decision-tree model utilizing a more expansive, film-validated dataset using our existing criteria for a successful block can create more precise data filtering for applicable, impactful wide receiver blocks. Using this more complete dataset can also ensure that researchers are not forced to fill in the ending gaps of plays, also making it more feasible to extend the model across multiple seasons, validating the data further and expanding upon our model's applicability for future seasons. With these improvements building on our methodology, future studies can further a more acceptable, standardized understanding of wide receiver blocking impact metrics in the NFL for managers and team analysts.

# 3 Methodology

For this research, we utilize public player tracking data made available through the NFL Big Data Bowl initiative [citation]. Specifically, our dataset encompasses player tracking information for all 32 NFL teams and their respective players, covering Weeks 1 through 8 of the 2022-2023 NFL season. The dataset is extensive, with each week's data comprising approximately 1 million rows. Each row in a given week's dataframe corresponds to a specific player's location in x-y coordinates (yards), speed ($\frac{\text{yards}}{\text{second}}$), distance (from prior time point, yards), acceleration($\frac{\text{yards}}{\text{second}^2}$), orientation (degrees), and direction of movement at a precise moment in time during a play. This data is captured at a frequency of 10 times per second via RFID tags embedded in player equipment and the ball [citation].

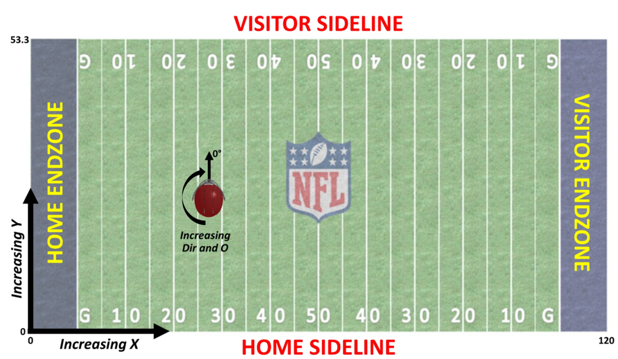


Figure 1: Caption to accompany image, cite image as well

## 3.1 Data Preprocessing and Feature Engineering

In order to select data points relevant to identifying and evaluating blocking by skill position players (wide receivers, tight ends, fullbacks, and non-ball-carrying running backs), we implemented a multi-stage filtering process and engineered key features from the raw tracking data.

### 3.1.1 Filtering and Selection of Relevant Engagements

Initial preprocessing involved removing non-player data points by excluding entries where the `club` was listed as "football". The offensive team for each play was then determined by identifying the team associated with the first "`ball_snap`" or "`handoff`" `event` in that play. Based on this, each player was assigned a `team_role` as either "offense" or "defense".

To focus on frames where blocking interactions were likely, the data was filtered for a specific list of `blocking_events`: "`ball_snap`", "`handoff`", "`pass_forward`", "`pass_arrived`", "`run`", "`qb_sack`", "`first_contact`", "`tackle`", "`play_action`", "`shift`", "`man_in_motion`", "`qb_strip_sack`", "`screen_pass`", and "`pass_outcome_caught`".

A self-join was performed on this event-filtered tracking data for each `gameId`, `playId`, and `frameId` to create pairs of offensive players (potential blockers) and defensive players. The Euclidean distance between each pair was calculated. An "engagement" was defined if this distance was less than or equal to an `engagement_threshold` of 2.5 yards. This threshold was chosen to capture interactions where a blocker is close enough to influence a defender's path or initiate contact, and using the general definition of a 'contact zone' in football blocking [citation].

These engagements were further filtered to include only those where the blocker's `position` (obtained by merging player metadata) was that of a wide receiver, designated 'WR' in the data. A crucial additional filter was applied to exclude any instance where the identified skill player blocker (identified by `nflId_BLOCKER`) was also the `ballCarrierId` for that specific play.

Finally, to isolate "downfield" blocks, we utilized the `absoluteYardlineNumber` (representing the line of scrimmage) from the plays data. A block was considered "downfield" if the blocker's x-coordinate (`x_BLOCKER`), adjusted for `playDirection`, was more than 5.0 yards beyond this line of scrimmage. Only these downfield blocking engagements by eligible non-ball-carrying skill players were carried forward for effectiveness scoring.

#### 3.1.2 Key Engineered Features for Blocking Evaluation

From the filtered downfield engagement data, several key features were engineered to assess blocking effectiveness. To quantify positional advantage, we adapted two key geometric measures, Defender Leverage ($\delta_{lev}$) and Blocker Leverage ($\beta_{lev}$), from the methodology proposed by Rumsey and Deflon (2020) for evaluating blocks in run plays [Rumsey and Deflon, 2020]. These metrics are derived by projecting the ball carrier's position 0.5 seconds into the future based on their current speed and direction, a technique also outlined in their work [Rumsey and Deflon, 2020].

**Leverage Angles:**

- **Defender Leverage ($\delta_{lev}$):** Defined as $\theta_2 - \theta_1$, where $\theta_1$ is the angle created by the current ball-carrier (RB), the defender (D), and the blocker (B) (vertex at D), and $\theta_2$ is the angle created by the ball-carrier's projected future location (RB+), the defender (D), and the blocker (B) (vertex at D) [Rumsey and Deflon, 2020]. A negative $\delta_{lev}$ indicates the defender's position is worsening relative to the ball carrier's projected path as the play develops (i.e., the blocker's position is improving), which is favorable for the blocker [Rumsey and Deflon, 2020].

- **Blocker Leverage ($\beta_{lev}$):** The angle created by joining the blocker (B) to the ball-carrier's projected location (RB+) and RB+ to the defender (D) (vertex at RB+) [Rumsey and Deflon, 2020]. A smaller $\beta_{lev}$ angle generally indicates better positioning by the blocker to shield the ball carrier's path with respect to where the ball carrier is heading [Rumsey and Deflon, 2020].

**Defender Movement Impact ($I_{move}$):** This feature quantifies the blocker's influence on the defender's movement during the engagement. It is calculated based on the sum of normalized absolute changes in the defender's speed ($s_{def}$) and orientation ($o_{def}$) between consecutive frames: $\Delta_{dir} = |o_{def,t} - o_{def,t-1}|$ and $\Delta_{speed} = |s_{def,t} - s_{def,t-1}|$. These changes are then normalized using dataset-wide averages of non-zero changes ($D_{dir\_norm}, S_{speed\_norm}$) to yield $I_{move} = (\Delta_{dir}/D_{dir\_norm}) + (\Delta_{speed}/S_{speed\_norm})$.

**Yards Gained Post-Block (YGPB):** To measure the direct outcome of a block, YGPB was calculated. For each identified downfield block engagement instance (defined by the first frame of continuous interaction between a specific blocker-defender pair), we determined the yards gained by the ball carrier in a predefined window of 1.5 seconds (15 frames) following the initiation of the block, or until a play-ending event (e.g., tackle, touchdown, out of bounds) occurred, whichever came first. This was adjusted for `playDirection`.

## 3.2 Blocking Effectiveness Score (BES) Implementation

### 3.2.1 Definition and Origin

To quantify the effectiveness of the identified downfield blocking engagements by skill players, we developed a "Skill Player Downfield BES". This score is designed to provide a per-frame evaluation, integrating measures of the blocker's positional leverage (adapted from Rumsey and Deflon, 2020 [Rumsey and Deflon, 2020]), their impact on the defender's movement, and the resulting yards gained by the ball carrier (YGPB). The conceptual basis is that an effective block involves favorable positioning, influences the defender's ability to make a play on the ball carrier, and contributes to positive offensive outcomes.

### 3.2.2 On-Ball Percentage

**Definition**

We define the on-ball percentage as the normalized distance values relative to the QBs. We take the Euclidean distance by each player from the QB (in this case, we assume the QB is a heuristic for ball location). For each frame, we can calculate the on-ball percentage for each frame with the following metric.

$$\text{frame}_i = \sum_{n \in S} (x_i - x_0)^2 + (y_i - y_0)^2 \tag{1}$$

where $x_i$ and $y_i$ are the $(x, y)$ coordinates of the player at $\text{frame}_i$, and the set $S$ is the set of all offensive players during the play. Normalizing the values yields the correct on-ball percentage, which determines the percentage of which the player was close to the ball (and therefore, the defender).

$$\text{OB} = Norm(X,\ \mu = \bar{X},\ \sigma = \text{stdev}(X)) \tag{2}$$

where $X$ is the collection of all players' distances participating in the offensive play.

**Usage**

We take individual BES scores and scale based on the normalized values of the on-ball percentage. We those values as the accurate, scaled metric that we use in our results.

### 3.2.3 Core Components and Enhanced BES Calculation

The frame-level `Skill_Player_Downfield_BES` is derived from several normalized impact components:

- **Normalized Defender Movement Impact ($I_{move}$):** As described in Section 3.1.2.
- **Normalized Defender Leverage Impact ($I_\delta$):** Derived from $\delta_{lev}$ [Rumsey and Deflon, 2020]. The raw $\delta_{lev}$ is adjusted by taking its negative ($\delta_{adj} = -\delta_{lev}$), so positive values are better for the blocker, and then normalized (e.g., z-score using $\mu_{\delta\_adj}$ and $\sigma_{\delta\_adj}$) across the dataset of relevant blocks.
- **Normalized Blocker Leverage Impact ($I_\beta$):** Derived from $\beta_{lev}$ [Rumsey and Deflon, 2020]. The raw $\beta_{lev}$ is adjusted (e.g., $\beta_{adj} = 180 - \beta_{lev}$, so higher values are better) and then normalized (e.g., z-score using $\mu_{\beta\_adj}$ and $\sigma_{\beta\_adj}$).
- **Normalized Yards Gained Post-Block Impact ($I_{ygpb}$):** The raw YGPB values (from Section 3.1.2) are normalized (e.g., using min-max scaling to a 0-1 range) across the dataset.

These normalized impact scores are combined into a raw composite score ($X_{raw\_skill\_downfield}$) using tunable weights ($w_{move}, w_\delta, w_\beta, w_{ygpb}$), with weights for this analysis being $w_{move} = 1.0, w_\delta = 0.5, w_\beta = 0.5, w_{ygpb} = 0.75$:

$$X_{raw\_skill\_downfield} = (w_{move} \cdot I_{move}) + (w_\delta \cdot I_\delta) + (w_\beta \cdot I_\beta) + (w_{ygpb} \cdot I_{ygpb}) \tag{1}$$

We chose these example weights ($w_{move} = 1.0, w_\delta = 0.5, w_\beta = 0.5, w_{ygpb} = 0.75$) because we hypothesize that the most direct influence a blocker has is physically altering the defender's speed and orientation.

Consequently, the Defender Movement Impact ($I_{move}$) was assigned the highest weight ($w_{move} = 1.0$), as it aims to capture this clear, tangible disruption. The Yards Gained Post-Block Impact ($I_{ygpb}$) also received a significant weight ($w_{ygpb} = 0.75$) as it directly measures a key offensive outcome stemming from the block. The leverage components, Normalized Defender Leverage Impact ($I_\delta$) and Normalized Blocker Leverage Impact ($I_\beta$), which quantify crucial positional advantages based on concepts of leverage at the point of attack discussed by Rumsey and Deflon (2020), were assigned slightly lower weights ($w_\delta = 0.5, w_\beta = 0.5$) in this initial configuration. While these positional aspects are essential for setting up a successful block, their immediate translation into a definitive play success can be influenced by subsequent actions and ball-carrier decisions. Thus, these specific weights represent a reasoned starting point for this study, prioritizing directly observable impacts and outcomes while still valuing advantageous positioning. As noted, these weights are considered tunable and could be subject to further refinement in future work. This $X_{raw\_skill\_downfield}$ score is then scaled to a non-negative range (e.g., 0 to 5 using min-max scaling based on the observed range of $X_{raw\_skill\_downfield}$ across the dataset) to produce $X_{scaled\_skill\_downfield}$. The final frame-level `Skill_Player_Downfield_BES` is calculated as:

$$\texttt{Skill\_Player\_Downfield\_BES} = 1 - e^{-X_{scaled\_skill\_downfield}} \tag{2}$$

This transformation bounds the score typically between 0 and 1, where a score closer to 1 indicates higher effectiveness.

#### 3.2.4 Player-Level Aggregation and Volume Adjustment

To evaluate players over a period (e.g., the 8-week dataset), the frame-level `Skill_Player_Downfield_BES` scores are aggregated for each blocker. We calculate the mean and median `Skill_Player_Downfield_BES`, total `blocking_frames` (count of engagement frames), and mean/median/total YGPB.

To slightly reward players for higher involvement in these generally positive downfield blocking situations, a `Volume_Adjusted_Skill_Player_Downfield_BES` is also computed at the player level. This is done by first calculating a `normalized_block_volume`:

$$\texttt{normalized\_block\_volume} = \frac{\log(1 + \texttt{blocking\_frames})}{\log(1 + \max(\texttt{blocking\_frames}))} \tag{3}$$

This log-transformed and scaled volume (ranging approximately 0-1) is then used to apply a small bonus to the player's mean BES, controlled by a `bonus_weight` (e.g., 0.1 for a 10% max bonus):

$$\texttt{Vol\_Adj\_BES} = \texttt{mean\_Skill\_Player\_Downfield\_BES} \times (1 + (\texttt{bonus\_weight} \times \texttt{normalized\_block\_volume})) \tag{4}$$

The resulting `Vol_Adj_BES` is clipped to a maximum of 1.0. This adjusted metric provides a player-level score that considers both the quality and quantity of their downfield blocking engagements.

#### 3.2.5 Comparative Analysis

[Placeholder: Describe the statistical methods used to compare your BES (or other metrics) with PFF grades (e.g., correlation, agreement measures, significance testing). State the purpose of this comparison clearly.]

### 3.3 Predictive Model for Blocking Effectiveness (Decision Tree)

Beyond developing a metric to rate blocking effectiveness, we wanted to create a model to predict this metric using other types of data. Instead of aiming to predict the continuous BES score, the aim to classify whether a BES score was above or below the median was chosen as a relevant metric for NFL scouts and coaches wanting a quick summary on whether a player is "good" at blocking.

A decision tree model was chosen as a descriptive yet fairly accurate way of predicting blocking performance.

#### 3.3.1 Model Objective

The decision tree model was designed to predict a binary label derived from the volume adjusted BES score, whether it was above or below the median performance. A decision tree was chosen for its interpretability, as it offers a way for coaches and scouts with minimal knowledge of predictive modeling to not only obtain reliable predictions but also understand the logic behind them. Decision trees offer human-readable rules that provide transparency for those who aren't technically versed, critical for a metric that could be used for roster decisions and even contract negotiations.

#### 3.3.2 Feature Selection for the Model

For this decision tree model, four features were used. First, median yards gained per block was incorporated as a simple to determine metric that does not require advanced film review. Next, normalized block volume was considered, measuring how often a player was asked to block. This was to avoid incorporating the frequency that the player blocks itself into the model; many star receivers excel at blocking but do not get many assignments due to a desire to focus on catching. Next, the median skill of the downfield player was considered, to ensure players who were assigned to tougher defenders were not penalized. Finally, the total yards per frame was considered.

Beyond computing medians or normalizing volume, there was minimal feature engineering. Features were selected for their theoretical relevance in predicting blocking ability, with the model itself used to determine which ones were most important.

#### 3.3.3 Model Training and Validation

The dataset was split into training and testing with a 4:1 split. A simple DecisionTreeClassifier from Scikit learn was used to implement our model. The depth was limited to four deep to make the model comprehensible and avoid overfitting. In addition, each leaf had a minimum of five samples to ensure the model was statistically significant. We also had a balanced weighting to weigh the minority more heavily, though this didn't affect much as there was naturally a relatively equal amount of those above and below the BES median. No cross validation was applied as sampling ensured the results were robust.

#### 3.3.4 Performance Evaluation

Table 1: Decision Tree Model Performance on Test Set

| **Class** | **Precision** | **Recall** | **F1-Score** | **Support** |
|---|---|---|---|---|
| Effective Block (1) | 0.82 | 0.87 | 0.84 | 31 |
| Ineffective Block (0) | 0.87 | 0.81 | 0.84 | 32 |

Our model had an 84.13% accuracy rate, meaning that it was significantly better than the expected 50% from random guessing. The high precisions and recalls for both categories indicate that the model is effective at classifying both; neither category is significantly more accurate than the other. High F1 scores indicate strong certainty about the model's classifications.

### 3.4 Application and Extrapolation of the Model/Metric

The decision-tree classifier is applied in three ways: it scores every qualifying block each week to generate rolling "good-block" rates that highlight sudden drops in form; it transfers unchanged to other seasons—achieving 81% percent accuracy on 2021 tracking data—which shows the BES features generalize across years and schemes; and it assigns probabilities to receivers who lack PFF grades, giving teams an objective screen for low-snap or practice-squad players.

## 3.5 Software and Tools

We used Python to do our data analysis, specifically these libraries: pandas for dataframe manipulation, numpy for array manipulation, and matplotlib and seaborn for visualization.

# 4 Results

## 4.1 Blocking Effectiveness Score

### 4.1.1 Distribution

We accumulate player scores for Weeks 1-8 by calculating BES scores for each of the 4827 frames that met the criteria stated previously in section 3.1.1. These scores are then adjusted for volume, and the distribution of our final volume-adjusted BES scores for the 2022-2023 NFL season is shown in the figure below.

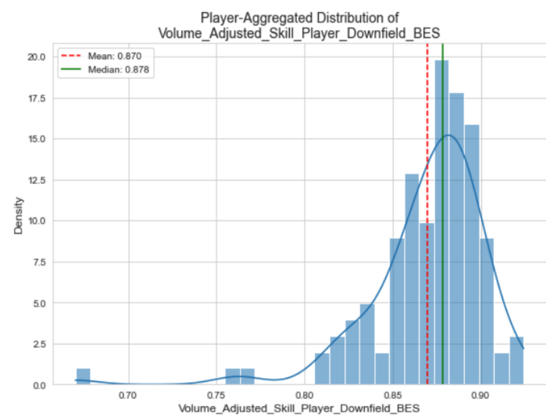


Figure 2: Player-aggregated distribution of the Volume-Adjusted Blocking Effectiveness Score (BES). The data, from 181 receivers, shows a slightly left-skewed distribution with a mean of 0.870 (dashed red line), and median of 0.878 (solid green line).

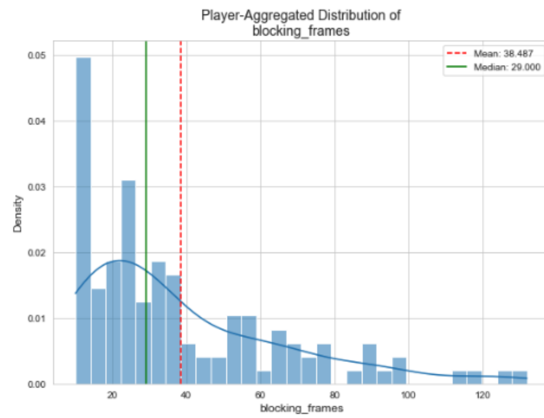


Figure 3: The distribution of the total number of `blocking_frames` a receiver was involved in across all plays is shown above. Its clear that the distribution is markedly right-skewed, indicating that most receivers engage in a relatively small number of blocking frames, while a smaller subset of receivers are involved in a significantly higher volume of blocking engagements.

The distribution of the player-aggregated BES reveals that most players involved in qualifying downfield blocking engagements achieve scores concentrated between approximately 0.80 and 0.95. This clustering towards the higher end of the scale is partly due to the BES formula ($1 - e^{-X}$, where $X$ is our scaled skill downfield variable defined earlier), which naturally yields scores approaching 1 for effective underlying blocking actions. Additionally, the initial data filtering for relevant engagements likely isolates situations where players are already exerting influence. Thus, the concentration of high scores suggests that players meeting these criteria generally demonstrate a competent level of blocking contribution, with the BES metric primarily differentiating proficiency within this group of actively and effectively engaged blockers.

The observed distributions of the underlying metrics provide crucial context for understanding the nature and utility of the composite Blocking Effectiveness Score (BES). While the relatively symmetric distribution of mean YGPB suggests a fairly consistent average yardage outcome (around 1.6 yards) when a downfield block is executed effectively (Figure 4), the pronounced right skew in both total YGPB (Figure 5) and, critically, `blocking_frames` (Figure 3) highlights a significant disparity in player involvement and cumulative raw impact. We hypothesize that the distribution of total yards gained postblock is highly skewed to the right because there is a relationship between the number of downfield-blocking opportunities a receiver has and how strong that their team's running game is. This suggests that this statistic should not be looked at

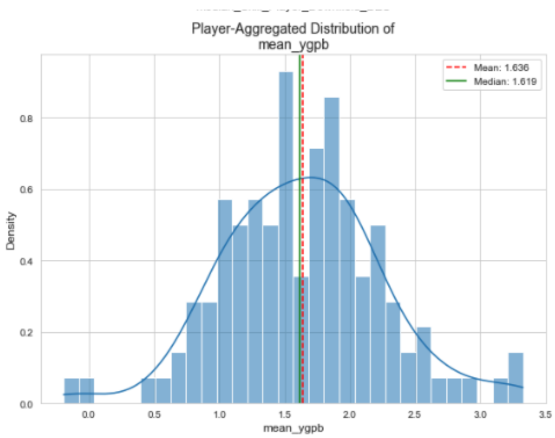


Figure 4: Distribution of average Yards Gained Post-Block (`mean_ygpb`) per distinct blocking engagement for all the receivers. The distribution is relatively symmetric, centered around a mean of 1.636 yards (dashed red line) and a median of 1.619 yards (solid green line).

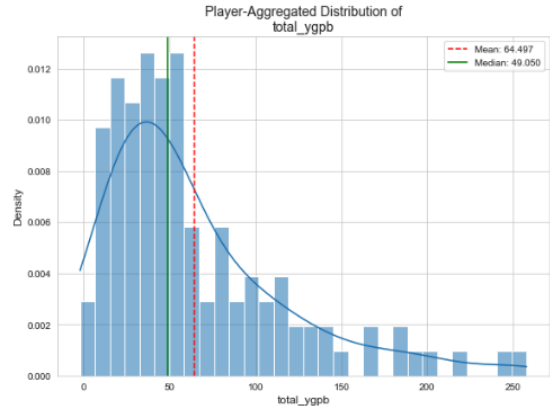


Figure 5: Distribution of `total_ygpb` accumulated by each of the 181 players. The pronounced right skew, with a mean of 64.497 yards (dashed red line) substantially exceeding the median of 49.050 yards (solid green line), highlights that a smaller number of players account for a disproportionately large share of total yards gained post-block.

in a vacuum, and that overlaying film with respective BES scores for each downfield blocking opportunity can further help contextualize why certain blocks are more effective than others according to the BES, and how a player's technique contributes to these scores.

The player-aggregated BES scores, which themselves tend to cluster at the higher end (typically 0.80-0.95 as seen in its distribution, Figure 2), reflect that the framework effectively filters for and then grades meaningful downfield blocking engagements. The `Volume_Adjusted_BES` then attempts to balance per-instance blocking quality (derived from leverage, defender impact, and YGPB) with the sheer volume of these engagements. Consequently, the BES as a whole aims to offer a nuanced evaluation, capable of identifying players who are not only efficient in their blocking technique and immediate impact but also those who are frequently tasked with these important, albeit unevenly distributed, downfield responsibilities.

#### 4.1.2 Correlation

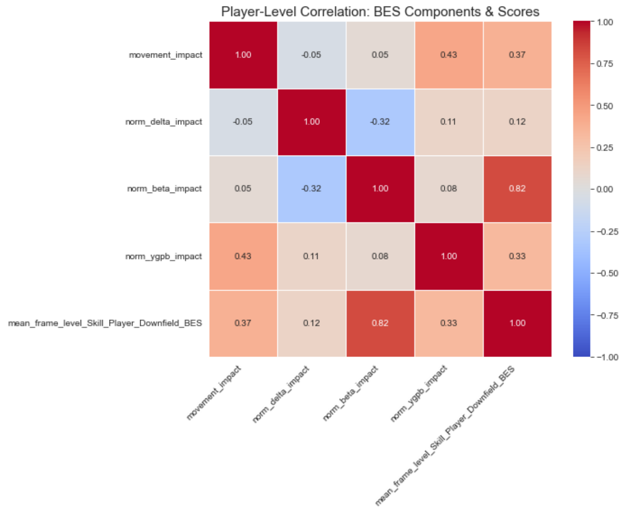


Figure 6: Player-level Pearson correlation matrix for BES components and the mean frame-level BES across 181 players. Color intensity and numerical values represent the strength and direction of linear correlations between each pair of metrics.

The correlation matrix (Figure 6, depicting player-level correlations) reveals that both the average `movement_impact` and the average `norm_ygpb_impact` exhibit moderately positive correlations (0.37 and 0.33, respectively) with the mean frame-level BES. This is intuitive, as significantly altering a defender's speed and direction (`movement_impact`) and directly contributing to the ball carrier gaining more yards (`norm_ygpb_impact`) are both desirable outcomes of a block that would logically contribute to a higher overall effectiveness score. However, the strongest correlation is between `norm_beta_impact` and the mean frame-level BES, with a strong positive coefficient of 0.82. This suggests that, at the player-aggregated level, achieving favorable blocker leverage—being well-positioned to shield the ball carrier's projected path from the defender—is the most dominant individual factor associated with a higher average frame-level BES in this analysis.

Maybe more commentary later

#### 4.1.3 Tabular Aggregation

Table 2: Sample of WRs by Volume-Adjusted Blocking Effectiveness Score for Weeks 1-8, 2022-2023 Season.

| **Category** | **Player Name** | **Team** | `Vol_Adj_BES` | `mean_ygpb` | `blocking_frames` |
|---|---|---|---|---|---|
| *Top 7 Players* | | | | | |
| 1. | Devante Parker | MIA | 0.924 | 2.02 | 96 |
| 2. | Devonta Smith | PHI | 0.923 | 2.16 | 115 |
| 3. | Drake London | ATL | 0.921 | 2.31 | 72 |
| 4. | Mason Kinsey | TEN | 0.920 | 4.25 | 4 |
| 5. | Brandon Aiyuk | SF | 0.914 | 2.06 | 125 |
| 6. | Denzel Mims | DEN | 0.913 | 2.18 | 19 |
| 7. | Deonte Harty | NO | 0.912 | 2.35 | 2 |
| | | ⋮ | | | |
| *Bottom 7 Players (out of 181 total players)* | | | | | |
| 175. | Kyle Phillips | TEN | 0.758 | 1.35 | 9 |
| 176. | K.J. Osborn | MIN | 0.750 | 0.00 | 18 |
| 177. | Trent Sherfield | MIA | 0.719 | 0.00 | 10 |
| 178. | Ihmir Smith-Marsette | CHI/KC | 0.670 | 0.73 | 7 |
| 179. | Mike Woods | CLE | 0.650 | -0.50 | 3 |
| 180. | Jarvis Landry | NO | 0.550 | 0.10 | 10 |
| 181. | Trent Taylor | CIN | 0.481 | 0.00 | 1 |

Sample scores for the 181 eligible wide receivers are shown above, along with their mean yards gained post block, as well as the number of frames that captured them blocking downfield. At first glance, we see wide receivers who are often credited as great blockers [citation], such as Brandon Aiyuk, Devonta Smith, and Drake London near the top of our list. One thing to note is that these scores could be heavily influenced by outlier rushing/YAC performances and abilities by teammates, as three of these teams ranked top 10 in yards after catch, and four of them ranked top 10 in rushing yards per game up till this point of the 2022-2023 season [citation]. The players that were at the bottom had a small number of blocking frames captured relative to other players, which may have offered an unfair sample size to evaluate their blocking abilities, as these most likely corresponded to only a few downfield run plays. However, the yards gained per block suggests that their blocks during these plays and frames were not quite impactful in creating space for the ball carrier, which suggests their lower ranking is a reflection of limited engagement and lower effectiveness when they did the block.

# 5 Case Studies

We propose looking at different players given their BES score to evaluate their blocking capabilities. We take a look at higher ranked BES metric players versus lower ranked players to compare the accuracy of the metric in pass blocking.

## 5.1 Pass Blocking

### 5.1.1 Brandon Aiyuk

Brandon Aiyuk plays wide receiver for the San Francisco 49ers. He is commonly utilized blocking concepts, although he most commonly lines up in the slot or outside wide receiver. Here, we take a look at two instances where Aiyuk has successively completed two reps of blocking in passing and rushing plays.

- `Volume_Adjusted_BES`: 0.895
- Total YGPB: 257.77 yards across 125 `blocking_frames`

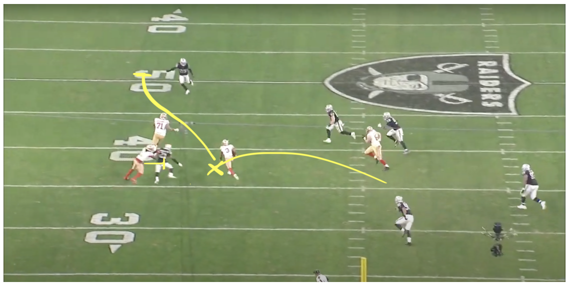

Figure 7: Screen pass to Ray-Ray McCloud

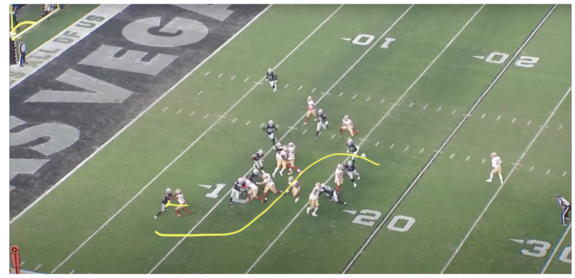

Figure 8: Run play to Jordan Mason

In Figure 7, the frame shows a screen pass from quarterback Brock Purdy (#13) to wide receiver Ray-Ray McCloud (#3). Aiyuk (#11) is shown on the left side of the frame. Aiyuk blocks the defender, forcing him into a lateral motion while McCloud follows the lead offensive lineman blocker. According to the leverage, acceleration, and speed parameters of the formula, we postulate that the blocks that Aiyuk executes are of high quality compared to the rest of the league.

In Figure 8, the frame shows a stretch play executed by quarterback Brock Purdy (#13) to running back Jordan Mason (#24). Aiyuk is lined up as an outside wide receiver as shown in the figure. While executing the play, Mason has the opportunity to run through a hole created by Aiyuk and the left tackle (offensive lineman). Aiyuk holds the block and maintains contact with the defensive back while Mason runs through the gap.

Both figures serve as an example for Aiyuk's elite pass blocking ability. **We have Aiyuk ranked as the 5th-best pass block receiver in the NFL**. His ability to hold blocks and redirect defensive backs' motion is a testament to his quality as a dual-threat receiver and blocker.

#### 5.1.2 Stefon Diggs

In the 2022-2023 season, Stefon Diggs was the premier wide receiver for the Buffalo Bills, known primarily for this route running and production as a pass catcher. However, his involvement in blocking schemes and downfield blocks reveals inconsistencies in his impact. According to the BES metric, Diggs lives among the bottom-tier of wide receivers in terms of blocking effectiveness:

- `Volume_Adjusted_BES`: 0.815
- Total YGPB: 50.52 yards across 33 `blocking_frames`

Below, we examine two plays highlighting Diggs' low blocking effectiveness:

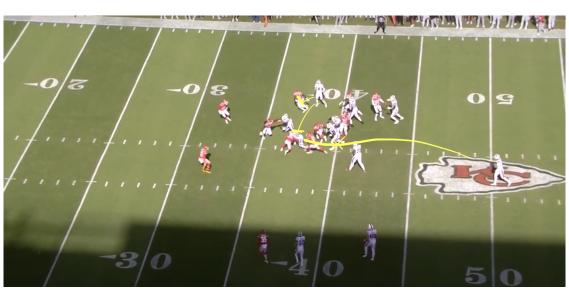

Figure 9: Run play to Devin Singletary

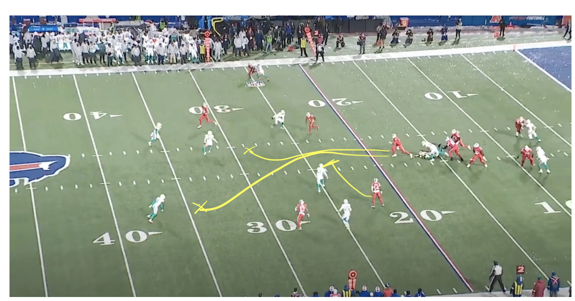

Figure 10: Josh Allen quarterback run

In Figure 9, Diggs (14) is placed in a primary blocking position on a cornerback during a running back draw play to Devin Singletary (26). Despite being in position, he withdraws from contact with the defender before the ball-carrier was tackled. The defender is now able to close in on the ball carrier with minimal disruption near the back-half of the play. The film validates Diggs' lower BES; his lack of leverage fails to alter the defender's path. Furthermore, as the defender nears the ball carrier, he accelerates with Diggs failing to impede his movement or orientation. Taking these factors into account, his lower BES is valid.

In Figure 10, Diggs is placed downfield in an optimal blocking position on a linebacker. Despite being in position, he fails to initiate contact with the defender, despite being one of the only available blockers in the area. The linebacker is easily able to evade Diggs and makes the tackle on the quarterback. Diggs fails to establish any leverage on the defender and makes no impact on the defender's speed or orientation. The yards gained by the ball carrier through this non-block from Diggs is below zero, therefore, again, validating his low BES score.

Coaches aiming to improve his blocking effectiveness could focus on:

- Earlier engagement timing
- Maintaining leverage through contact till the ball carrier is tackled