TriKirby Index

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Abstract

The TriKirby Index is a percentile-based pitch command metric designed to quantify a pitcher's ability to consistently repeat release direction and release location at the pitch-type level. Using pitch-level TrackMan data from NCAA Division I baseball, the metric captures within-pitch variability in vertical and horizontal release angles and release locations, normalizing performance relative to peer pitchers within each pitch type. These consistency measures are transformed into percentile scores to ensure interpretability and comparability across the NCAA D1 landscape. Feature importances derived from a Random Forest regression model are used to weight each release component, allowing the index to account for nonlinear relationships in pitch command. The resulting TriKirby score provides a robust, data-driven evaluation of pitch command that supports player development, pitch design, and comparative scouting. This framework was applied to UC San Diego Baseball to generate actionable insights for coaching decisions and performance optimization ahead of the 2026 season.

1. Introduction

Pitch command is a critical component of pitching performance. Prior work, such as the Kirby Index, has demonstrated that release variability provides a process-based framework for evaluating command by emphasizing mechanical repeatability rather than outcome statistics. However, existing approaches often rely on linear assumptions, fixed weighting schemes, or professional-level data, limiting their generalizability to collegiate baseball. This study introduces the **TriKirby Index**, a pitch-type–specific command metric that quantifies release consistency across NCAA Division I pitchers using TrackMan data and machine-learned feature importance weights derived from a Random Forest regression model. By normalizing performance within pitch type at the national level, the TriKirby Index provides a scalable and interpretable framework for evaluating any pitch type's command and informing player development in collegiate baseball.

2. Coding Scheme

This study integrates two complementary pitch-level datasets to construct and evaluate the TriKirby Index:

2.1 NCAA Division I Pitching Dataset 2025

Pitch-level TrackMan data encompassing all NCAA Division I pitchers during the 2025 regular season. This dataset serves as the population-level reference for percentile normalization, feature weighting, and cross-pitcher comparability.

2.2 UC San Diego Fall 2025 Scrimmages and Official Games Dataset

Pitch-level TrackMan data collected during UC San Diego baseball fall scrimmages and official intra-squad games. This dataset provides high-resolution internal evaluations of UCSD pitchers and enables comparison against the NCAA Division I baseline.

Both datasets share identical measurement schemas and were processed using a unified pipeline to ensure methodological consistency.

3. Models and Methods

3.1 Data Collection and Preprocessing

Pitch-level TrackMan data were collected for NCAA Division I baseball, including UC San Diego pitchers, across scrimmages and official league games. For each pitch, release characteristics and pitch location information were retained, and pitches were grouped by pitcher and pitch type. To ensure statistical stability, only pitcher–pitch type pairs with a minimum of 30 recorded pitches were included in subsequent analyses.

3.2 Release Consistency Metrics

Four release-based features were selected to quantify mechanical repeatability: vertical release angle (VRA), horizontal release angle (HRA), vertical release location (vRel), and horizontal release location (hRel). For each pitcher and pitch type, the standard deviation of each feature was computed, capturing within-pitch variability. These variability measures serve as process-based indicators of pitch command, with lower variability corresponding to greater consistency.

$$\sigma_{\mathrm{VRA},p,t}, \quad \sigma_{\mathrm{HRA},p,t}, \quad \sigma_{\mathrm{vRel},p,t}, \quad \sigma_{\mathrm{hRel},p,t}$$

(Figure 1)

3.3 Percentile Normalization

To enable fair comparison across pitchers, each release variability metric was normalized within pitch type using percentile ranks computed across the full NCAA Division I population. Percentiles were inverted such that higher values correspond to better command, yielding four normalized consistency scores bounded between 0 and 1. This normalization ensures interpretability and removes scale dependence across features.

$$\mathrm{SD}^{\mathrm{pct}}_{p,t} = 1 - \mathrm{rank}_{\mathrm{pct}}\left(\mathrm{SD}_{p,t}\right)$$

(Figure 2)

The resulting percentile-based release consistency metrics are shown as these variables below:

$$\mathrm{sd\_vra\_pct}, \quad \mathrm{sd\_hra\_pct}, \quad \mathrm{sd\_vrel\_pct}, \quad \mathrm{sd\_hrel\_pct}$$

(Figure 3)

3.4 Machine Learning Models

Let the feature vector for each pitch be shown below in figure 4.

$$\mathbf{x} = (\mathrm{VRA},\ \mathrm{HRA},\ \mathrm{vRel},\ \mathrm{hRel})$$

(Figure 4)

Two supervised learning models were employed. Logistic regression was initially used as a baseline model to validate the linear relationship between release consistency features and pitch command–related outcomes, providing interpretability and directional insight. To account for nonlinear relationships and feature interactions, a Random Forest regression model was then trained using the same release consistency features to predict pitch location outcomes.

3.5 Feature Importance and Weighting

Feature importances were extracted from the trained Random Forest model and used as weights in the final TriKirby Index formulation. These importances quantify the relative contribution of each release component to pitch command and are inherently normalized such that their sum equals one. By leveraging Random Forest–derived feature importances, the TriKirby Index incorporates nonlinear effects while maintaining a transparent, weighted structure.

$$\boldsymbol{\beta} = (\beta_{\mathrm{VRA}}, \beta_{\mathrm{HRA}}, \beta_{\mathrm{vRel}}, \beta_{\mathrm{hRel}})$$

(Figure 5)

Each coefficient represents the *relative contribution* of a release component to pitch command, measured as the average reduction in prediction error across all trees.

By construction, the feature importances satisfy:

$$\sum_{i=1}^{4} \beta_i = 1$$

(Figure 6)

3.6 Derivation of the TriKirby Index Equation

The TriKirby Index is constructed to quantify pitch command as a function of release repeatability while remaining interpretable and comparable across NCAA Division I pitchers. The formulation proceeds through a sequence of normalization, modeling, and weighting steps that culminate in the final composite score.

First, pitch command is operationalized through four release consistency components: vertical release angle, horizontal release angle, vertical release location, and horizontal release location. For each pitcher–pitch type pair, the standard deviation of each component is computed, capturing within-pitch variability and serving as a direct measure of mechanical repeatability.

Because raw variability values are not directly comparable across pitchers or pitch types, each standard deviation is converted into a percentile-based consistency score within pitch type.

To determine the relative importance of each release component, supervised machine learning models are applied. Logistic regression is first used as a baseline to validate linear relationships between release consistency and pitch command outcomes. A Random Forest regression model is then trained to capture nonlinear effects and interactions among release components. Feature importances extracted from the Random Forest model provide data-driven weights that reflect each component's contribution to pitch command.

$$\mathrm{TriKirby}_{p,t} = \beta_{\mathrm{VRA}} \cdot SD^{\mathrm{pct}}_{\mathrm{VRA},p,t} + \beta_{\mathrm{HRA}} \cdot SD^{\mathrm{pct}}_{\mathrm{HRA},p,t} + \beta_{\mathrm{vRel}} \cdot SD^{\mathrm{pct}}_{\mathrm{vRel},p,t} + \beta_{\mathrm{hRel}} \cdot SD^{\mathrm{pct}}_{\mathrm{hRel},p,t}$$

(Equation 1)

Finally, the TriKirby Index is defined as a weighted linear combination of the percentile-based release consistency scores, using the Random Forest–derived feature importances as coefficients. This formulation preserves interpretability while incorporating nonlinear structure learned from the data, yielding the final composite score shown in Equation (2).

$$\mathrm{TriKirby}_{p,t} = \beta_1 \cdot \mathrm{sd\_vra\_pct}_{p,t} + \beta_2 \cdot \mathrm{sd\_hra\_pct}_{p,t} + \beta_3 \cdot \mathrm{sd\_vrel\_pct}_{p,t} + \beta_4 \cdot \mathrm{sd\_hrel\_pct}_{p,t}$$

(Equation 3)

This is the final equation that the TriKirby Index is derived from.

4. Results

The TriKirby Index was computed for each pitcher–pitch type combination using NCAA Division I pitching data and UC San Diego Fall 2025 scrimmage data. Results demonstrate substantial variability in pitch command both across pitch types and among pitchers within the same pitch classification. Across NCAA Division I, elite pitches (TriKirby > 0.80) were consistently observed among fastballs, sliders, changeups, and cutters, indicating strong release repeatability at all pitch-types. At the team level, UC San Diego pitchers displayed a diverse distribution of command profiles across their arsenals, with several pitchers ranking highly within individual pitch categories relative to the NCAA baseline of 0.50. Pitch-specific rankings revealed that strong command does not necessarily generalize across all pitch types for a given pitcher, reinforcing the importance of pitch-level evaluation rather than aggregate pitcher scores. Full rankings and pitch-level summaries are provided in the downloadable TriKirby Index spreadsheet (Figure 5).

TriKirby Index Spreadsheet - Sheet1.pdf

(Figure 5)

5. Discussion

The TriKirby Index is directly inspired by the original Kirby Index framework, which introduced release point variability as a principled, mechanics-based proxy for pitch command rather than outcome-based performance alone (Fast, 2016). Subsequent refinements to the Kirby Index emphasized the importance of separating directional and spatial components of release consistency while preserving interpretability across pitch types (Fast, 2019). Building on this foundation, the TriKirby Index extends the Kirby framework by operating explicitly at the pitch-type level, normalizing scores within pitch type across NCAA Division I pitchers, and incorporating nonlinear structure through Random Forest–derived feature importances.

Results from the NCAA-wide analysis reinforce the core insight of the Kirby Index: tighter release consistency corresponds to improved pitch command, but this relationship is highly pitch-dependent. Several pitchers exhibited elite command in secondary offerings despite average fastball command, underscoring the limitations of pitcher-level aggregation. By leveraging machine learning to weight release components while retaining a linear composite score, the TriKirby Index preserves the interpretability emphasized in the Kirby Index literature while adapting the methodology to modern tracking data and collegiate baseball contexts.

From an applied standpoint, the TriKirby Index provides actionable insight for player development, pitch usage optimization, and scouting. Coaches and analysts can identify which specific pitches drive a pitcher's command profile and tailor development plans accordingly, aligning with the original motivation behind the Kirby Index: translating biomechanical repeatability into practical baseball decision-making.

7.7 Limitations

First, the TriKirby Index focuses exclusively on release consistency and does not directly incorporate outcome-based metrics such as whiff rate, expected run value, or batted-ball quality. Second, pitch counts vary substantially across pitchers and pitch types; while minimum pitch thresholds were applied, smaller samples may still introduce noise. Third, the Random Forest feature importances are data-dependent and may shift across seasons, competitive levels, or tracking systems. Finally, the model does not explicitly account for contextual factors such as batter handedness, game state, or pitch intent.

7.8 Future Research

Future work will extend the TriKirby framework by integrating outcome-based metrics (e.g., xwOBA, whiff probability) alongside release consistency to model pitch effectiveness more holistically. Longitudinal analysis across multiple seasons could be used to study command development and injury risk. Additional modeling approaches, including Bayesian hierarchical models and neural networks, may further refine feature weighting while maintaining interpretability. Finally, expanding the framework to professional and amateur datasets would allow for cross-level validation of the TriKirby Index.

6. Conclusion

The TriKirby Index introduces a novel, interpretable, pitch-level command metric grounded in release consistency and machine learning–derived feature importance. By normalizing performance within pitch types and leveraging percentile-based scoring, the model enables fair comparisons across NCAA Division I

pitchers. Results from NCAA and UC San Diego data demonstrate the index's ability to surface meaningful differences in pitch command that are not captured by traditional aggregate metrics. The TriKirby Index provides a practical tool for player evaluation, development, and decision-making in modern baseball analytics.

7. References

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