

# Evaluation of soccer team defense based on prediction models of ball recovery and being attacked

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## Abstract

With the development of measurement technology, data on the movements of actual games in various sports are available and are expected to be used for planning and evaluating the tactics and strategy. In particular, defense in team sports is generally difficult to be evaluated because of the lack of statistical data. Conventional evaluation methods based on predictions of scores are considered unreliable and predict rare events throughout the entire game, and it is difficult to evaluate various plays leading up to a score. On the other hand, evaluation methods based on certain plays that lead to scoring and dominant regions are sometimes unsuitable to evaluate the performance (e.g., goals scored) of players and teams. In this study, we propose a method to evaluate team defense from a comprehensive perspective related to team performance based on the prediction of ball recovery and being attacked, which occur more frequently than goals, using player actions and positional data of all players and the ball. Using data from 45 soccer matches, we examined the relationship between the proposed index and team performance in actual matches and throughout a season. Results show that the proposed classifiers more accurately predicted the true events than the existing classifiers which were based on rare events (i.e., goals). Also, the proposed index had a moderate correlation with the long-term outcomes of the season. These results suggest that the proposed index might be a more reliable indicator rather than winning or losing with the inclusion of accidental factors.

## Introduction

The development of measurement technology has allowed for the generation of data on the movements in various sports games for use in planning and evaluating the tactics and strategy. For example, tracking data during a game of soccer, including the positional data of the players and ball, is commonly used for players' conditioning (e.g., running distance or the number of sprints) [1, 2]. However, during a soccer match, all 22 players and the ball interact in complex ways for scoring goals or preventing being scored (it is sometimes referred to as conceding) for each team. Hence, it is then necessary to evaluate the performance of not only individuals but also the entire team [3]. Defensive tactics are particularly considered difficult to evaluate because of the limited amount of available statistics, such as goals scored in the case of attacks.

There are three main approaches to quantitatively evaluate teams and players in soccer, mainly from an attacking perspective. The first approach is based on scoring prediction, which evaluates plays based on changes in the expected values of goals scored and conceded based on a prediction of scoring using tracking data [4–7] (reviewed in [8]) and action data such as dribbling and passing [9], as well as other rule-based methods (e.g., [10]). The second approach is used to evaluate plays such as passes and effective attacks which lead to shots. For example, a previous study evaluated the value of passes based on relationships to the expected score and the difficulty in successfully completing a pass [11]. An effective attack can be defined as a play that will likely lead to a score [12]. Previous studies have analyzed pass networks [13] and three player interactions [14, 15], as well as pass reception [16] and of the related defensive weaknesses [17]. For defenses, researchers have evaluated interception [18] and the effectiveness of defensive play by the expected value of a goal-scoring opportunity conceded [19]. For the third approach, spatial positioning of the players is evaluated by calculating the dominant region with the use of a Voronoi diagram [20] and the Gaussian distribution [21]. Recent research has also been conducted on the evaluation of movements that create space for teammates [22, 23].

However, these approaches have several limitations. For evaluation based on the prediction of scoring (i.e., the first approach), the evaluation is not reliable because it predicts events that are rare throughout a game, and the process leading up to the goals is sometimes difficult to evaluate. Furthermore, the second approach to evaluate specific plays that lead to goals and the third approach regarding positioning have difficulties in relating the evaluation to overall performance (such as wins and losses). Also, since many studies on the first and second approaches have used only the actions and coordinates of players around the ball, it would be difficult to evaluate players at greater distances from the ball and the team as a whole.

To address these issues, we propose a method called *Valuating Defense by Estimating Probabilities* (VDEP), which utilizes the actions and positional data of all players and the ball. The main contributions of this work are as follows: (i) the proposed method is based on the prediction of ball possession and effective attacks, which occur more frequently than the rare goals; (ii) based on a comprehensive perspective related to team outcomes, we evaluated the team’s defense. Methodologically, we modified the existing method called VAEP (Valuating Actions by Estimating Probabilities) [9], which is based on the classifiers to predict scoring and conceding, so that the defensive process can be evaluated by applying the approach to ball recovery and being attacked. We validated the classifiers of the proposed and existing methods and shows that the proposed classifiers predicted the true events more accurately than the existing classifiers. Moreover, we examined the relationship between VDEP and the team performance in actual matches and throughout the season, as compared with VAEP. We also present examples of evaluating a game and a complete season of a specific team.

## Materials and methods

### Dataset

In this study, we used event data (i.e., labels of actions, such as passing and shooting, recorded at 30 Hz and the simultaneous xy coordinates of the ball) and tracking data (i.e., xy coordinates of all players and the ball recorded at 25 Hz) of a total of 45 games from week 30 to week 34 of the Meiji Yasuda Seimei J1 League 2019 season provided by Data Stadium, Inc. (Tokyo, Japan; for the details, see Acknowledgments). In all 45 games, there were 106 goals scored, 1,174 shots, 3,701 effective attacks, and 9,408 ball recoveries (all based on the provided event data). An effective attack is defined as an

event that finally ends in a shot or penetrates the penalty area. Also, ball recovery is defined as a change in the attacking team before or after the play due to some factors other than an effective attack. In this study, an effective attack is defined as *being attacked* from the defender's perspectives. When calculating VDEP and VAEP values, we used a cross-validation procedure, which repeats the learning of classifiers using the data of four weeks (36 games) and a prediction using the data of one week (9 games) five times (i.e., data of all five weeks were finally predicted and evaluated) to analyze all games [24–26].

## Proposed Method

The ultimate goal of defense in soccer is to prevent the opposing team from scoring a goal. However, since goal-scoring scenes are rare events, it may lead to ineffective training of a classifier and evaluating the events in a unreliable manner (the validation results of the VAEP method [9] will be presented later). Therefore, to reasonably evaluate the defense of a team, we propose the VDEP method to evaluate important factors for preventing goals from being scored. The VDEP method evaluates the potential increase in the number of ball recoveries and the potential decrease in the number of effective attacks. The number of effective attacks was chosen instead of the number of shots because of the following scenarios as defensive failures, in which an attacker selects to pass the ball rather than to shoot. Therefore, in this study, we evaluate the process of defense based on the expected value computed by the classifiers to predict ball recovery and being attacked in an analogous way of the VAEP method [9] based on the prediction of scoring and conceding.

Suppose that the state of the game is given by  $S = [s_1, \dots, s_N]$  in chronological order. We consider  $s_i = [a_i, o_i]$ , whereas the previous study [9, 19] uses only  $a_i$ , which includes the  $i$ th action involving the ball and its coordinates. The proposed method utilizes classifiers trained with the state  $s_i$ , which includes the feature  $o_i$  far from the ball (off-ball) at the time of the action. Since all defensive and offensive actions in this study are evaluated from the defender's point of view, the following time index  $i$  is used as the  $i$ th *event*.

Given the game state  $S_i$  of a certain interval, we define the probability of future ball recovery  $P_{recoveries}(S_i)$  and the probability of being attacked  $P_{attacked}(S_i)$  in a state  $S_i$  at an event  $i$  based on the classifier trained from the data. Defensive players are considered to act so that  $P_{recoveries}(S_i)$  becomes higher or  $P_{attacked}(S_i)$  becomes lower. Therefore, the value of defense in the proposed method  $V_{vdep}$  is defined as follows:

$$V_{vdep}(S_i) = P_{recoveries}(S_i) - C * P_{attacked}(S_i), \quad (1)$$

where  $C$  is a parameter that adjusts the values of ball recoveries and effective attacks. In this study, we adjusted these values based on the frequency of each event in the training data. As described below, we determined  $C \approx 3$  because the ratio of ball recoveries and effective attacks is approximately 3 : 1 (the value differs for each of 5-fold cross-validation). Since the main aim of this study is to evaluate the team, we define the evaluation value per game for team  $p$  as follows:

$$R_{vdep}(p) = \frac{1}{M} \sum_{S_i \in \mathcal{S}_M^p} V_{vdep}(S_i), \quad (2)$$

where  $M$  is the number of events for team  $p$  in a match and  $\mathcal{S}_M^p$  is the set of states  $S$  of team  $p$  up to the  $M$ th event. Similarly, the sum of evaluation values using only  $P_{recoveries}$  and  $P_{attacked}$  are defined as  $R_{recoveries}(p)$  and  $R_{attacked}(p)$ , respectively. For the VAEP [9] method in the previous study, the value averaged by the playing time of each player was used. However, since the time each team played the game was almost

the same, in this study, each team is evaluated by the sum of  $S_{vaep}(p)$  as the VAEP value. Also,  $S_{scores}(p)$  and  $S_{concedes}(p)$  are used in the analysis as separate evaluation values, although the VAEP [9] value is calculated based on the prediction of goals scored and conceded.

## Procedures

The feature  $a_i$  near the ball in this study was constructed using the action and tracking data with reference to the previous study [9]. Specifically, we used the types of events used in the previous study [9] (19 types including pass, shot, tackle, and so on), the start/end time of the event, the displacement of movement, and elapsed time from the start to the end of the event, the distance and angle between the ball and the goal, and whether there was a change in offense or defense from the previous event (73 dimensions in total). Moreover, in this study, the off-ball feature  $o_i$  at the time that the event occurred was included in the state  $s_i$ . Specifically, for each team, we used the x and y coordinates of positions of all players and the distance of each player from the ball, sorted in the order of closest to the ball (137 dimensions in total). We used XGBoost (eXtreme Gradient Boosting) [27], which was used in the previous study [9], as the classifier to predict ball recoveries and being attacked. Gradient boosting methods are known to perform well on a variety of learning problems with heterogeneous features, noisy data, and complex dependencies. The time range of the input  $S_i$  to the classifier was  $i$ th,  $i - 1$ th, and  $i - 2$ th actions in the previous study [9]. In this study, since the effect of  $s_{i-2}$  on the prediction performance was small in the preliminary experiments, we used  $s = [a, o]$  including the  $i$ th and  $i - 1$ th actions.

In the first classification for estimating  $P_{recoveries}(S_i)$ , we assigned a positive label ( $= 1$ ) to the game state  $S_i$  if the defending team in the state  $S_i$  recovered the ball in a subsequent  $k$  actions, and a negative label ( $= 0$ ) if the ball was not recovered. Similarly, in the second classification for estimating  $P_{attacked}(S_i)$ , we assigned a positive label ( $= 1$ ) to the game state  $S_i$  when an effective attack was made in a subsequent  $k$  actions. In both classifications,  $k$  is a parameter freely determined by the user. If  $k$  is small, the prediction is short-term and reliable, and if  $k$  is large, the prediction is long-term and includes many factors. In this study, we set  $k = 5$  based on the results of preliminary validation.

In the data used in this study, defined by  $k$  above, the total number of events for all teams was 97,335, with 35,286 positive cases of ball recovery and 13,353 positive cases of being attacked. In terms of goals scored and conceded for the calculation of the VAEP value [9], there were 753 positive cases of goals scored and 227 positive cases of goals conceded (the total number of events was the same, but we set  $k = 10$  in accordance with the previous study [9]). These indicate that goals scored and conceded are rare events compared to ball recoveries and being attacked. Therefore, the goals scored and conceded may not be correctly evaluated by the area under the receiver operating characteristic curve (AUC) and Brier scores used in the previous study [9].

## Evaluation and Statistical Analysis

To validate the classifier, we used the F1 score in addition to the AUC and Brier scores used in the previous study [9]. AUC is calculated by plotting the cumulative distribution function of the true positive rate against the false positive rate. AUC indicates 0.5 for random prediction and 1 for perfect prediction. Brier score is the mean squared error between the predicted probability and the actual outcome, where a smaller value indicates more accurate prediction. However, these evaluations may not be correct when there are extremely more negative than positive cases, as in this and previous studies (for example, AUC and Brier score are good even when all negative

cases are predicted for the data with only 10% positive cases). In this study, we also used the F1 score to evaluate whether the true positives can be classified without considering the true negatives. The F1 score is expressed as  $F1score = (2 \times Precision \times Recall) / (Precision + Recall)$ , where the Recall is defined as the ratio of the sum of true positives and true negatives to the number of true positives (the true-positive rate), and the Precision is defined as the ratio of the sum of true positives and true negatives to false positives. In this index, only true positives are evaluated, not true negatives. To compare F1 scores among the various classifiers for testing our hypothesis (other AUC and Brier scores are shown only as references), since the hypothesis of homogeneity of variances between methods was not rejected with Levene’s test, a one-way analysis of variance was performed. As a post-hoc comparison, Tukey’s test was used within the factor where a significant effect in one-way analysis of variance was found. Furthermore, the contribution of the input variables to the prediction of the VDEP method was calculated by SHAP (SHapley Additive exPlanations) [28], which utilizes an interpretable approximate model of the original nonlinear prediction model.

For the evaluation of defense using the VDEP and VAEP values [9], we present examples to quantitatively and qualitatively evaluate a game and a season of a specific team. Next, we examined the relationships with the outcomes of actual games (goals scored, conceded, and winning points, where win, draw, and lose were assigned as 3, 1, and 0 points, respectively) and the relationship with the team results throughout the season using the Pearson’s correlation coefficient among all 18 teams.

For all statistical analysis,  $p < 0.05$  was considered significant. However, since the sample size was small ( $N = 18$ ) in the correlation analysis, the  $r$  value indicating the magnitude of the correlation was also used as an effect size for evaluation. As described in a previous study [29], correlation coefficients of less than 0.20 were interpreted as *slight almost negligible relationships*, correlations of 0.20 to 0.40 as *low correlation*; correlations of 0.40 to 0.70 as *moderate correlation*; 0.70 to 0.90 as *high correlation* and correlation greater than 0.90 as *very high correlation*. In this study, the correlation coefficients were rounded off to the third decimal place for interpretation. All statistical analyses were performed using SciPy in the Python library.

## Results

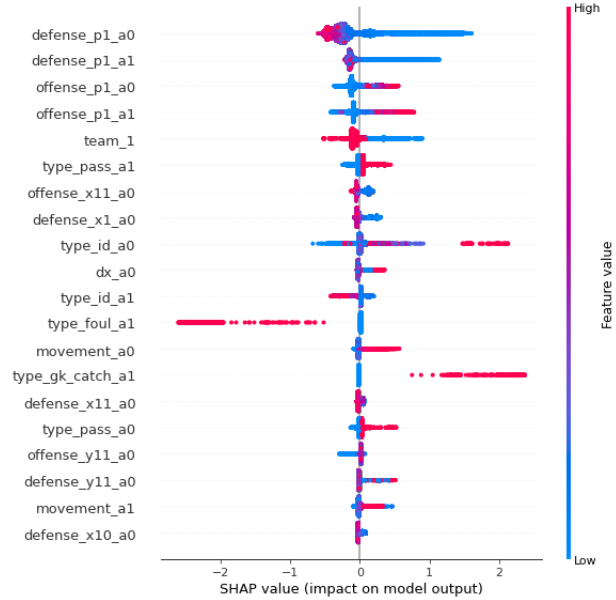
### Validation of Classifiers

To validate the VDEP and VAEP [9] methods, we first investigated the prediction performances of their classifiers. In Table 1, the classifiers of VDEP shows more accurate predictions compared to those of VAEP [9] (note that the output and number of occurrences to be predicted are different). The AUCs of  $R_{recoveries}$  and  $R_{attacked}$  in VDEP were better than those of  $S_{scores}$  and  $S_{concedes}$  in VAEP, and vice versa in regard to the Brier scores. However, again, these indices may not be validly evaluated because they include a large number of true negatives in the evaluation (thus, we did not perform statistical analysis in these variables). Instead, the F1 score was calculated, and the statistical analysis identified significant main effect among  $R_{recoveries}$ ,  $R_{attacked}$ , and  $S_{scores}$  ( $F = 144.40$ ,  $p < 1.0 \times 10^{-6}$ ;  $S_{concedes}$  was eliminated because of the average is near zero value). The post-hoc analysis shows that F1 scores of VDEP ( $R_{recoveries}$ ,  $R_{attacked}$ ) were significantly higher than that of  $S_{scores}$  ( $ps < 0.002$ ). This indicates that the VDEP method predicted true positives correctly, while the VAEP did not.

Next, the contribution of the input variables to the prediction of the VDEP method was calculated by SHAP [28]. For  $R_{recoveries}$ , in Fig 1, the distance to the ball of the defender closest to the ball had the highest contribution, followed by the events where

Table 1. Evaluation of classifiers for the proposed and conventional methods.

	AUC	Brier score	F1 score
$R_{recoveries}$	$0.770 \pm 0.014$	$0.184 \pm 0.009$	$0.522 \pm 0.036$
$R_{attacked}$	$0.862 \pm 0.003$	$0.079 \pm 0.003$	$0.484 \pm 0.038$
$S_{scores}$ [9]	$0.698 \pm 0.066$	$0.007 \pm 0.002$	$0.201 \pm 0.021$
$S_{concedes}$ [9]	$0.701 \pm 0.040$	$0.003 \pm 0.001$	$0.000 \pm 0.000$



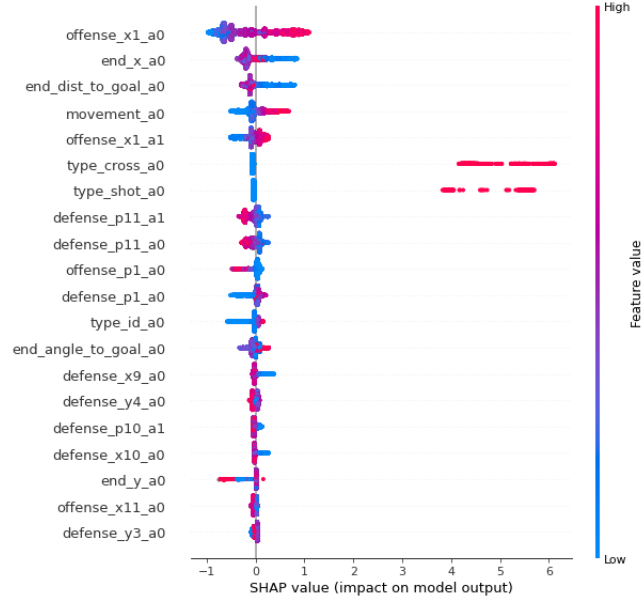
**Fig 1. Contribution of the input variables to the prediction of  $P_{recoveries}$ .** The input variables related to the prediction of  $P_{recoveries}$  are presented in the order of their contributions. Of the top 20 features, those at the top had greater contribution than those at the bottom. Each dot represents each event. The color represents the value of the feature (blue and red indicate low and high, respectively). The horizontal axis shows the impact on the prediction (strongly positive and negative impacts are plotted to the right and left, respectively). For example, when the value of  $type\_foul\_a1$  is 1, the prediction is likely to be zero.

there was an offensive or defensive change immediately beforehand. For  $R_{attacked}$ , in Fig 2, the x-coordinate of the attacker closest to the ball (in the direction of the goal) and the displacement of the attacker from the beginning to the end of the action had the largest contribution, followed by the distance to the ball of the defender closest to the ball.

## Examples of Team Defense Evaluation

### Evaluation of a defensive play

An advantage of the VDEP method is the ability to show the effectiveness of the formation of the defending team against the attacking team at a particular moment in the game. For example, with the use of VDEP for a goal conceded, it can be easily understood where the factor of the goal is placed in the series of events. As an example, consider the first goal in the match between Yokohama F. Marinos and FC Tokyo shown in Fig 3. A positive VDEP value can be interpreted as a good defense and a negative value as a bad defense. In this example, the VDEP values were positive in all



**Fig 2. Contribution of the input variables to the prediction of  $P_{attacked}$ .** The input variables related to the prediction of  $P_{attacked}$  are shown in the order of their contribution. The configuration is the same as in Fig 1. For example, when the value of offense\_x1\_a0 is positively and negatively large, the prediction value is also likely to be positively and negatively large, respectively.

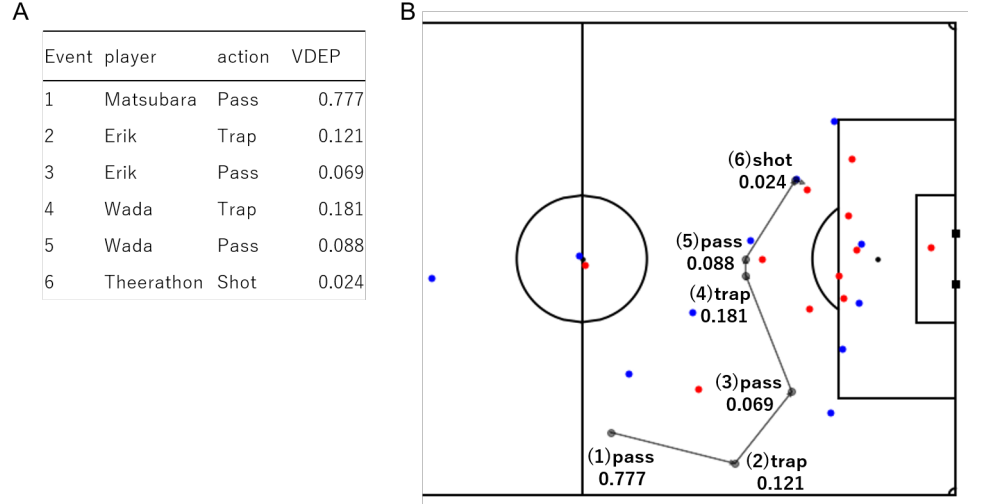
events, indicating that the defense was not so bad that the goal was conceded. However, to be precise, the VDEP values decreased between Matsubara’s pass and Erik’s trap, and between Erik and Wada’s trap and pass, suggesting that the goal was conceded because of a forward pass or because the ball holder was allowed to go free.

### Evaluation of a game

Since it is sometimes difficult to score goals in soccer, the team that dominates the game does not always win. Therefore, to continuously strengthen the team, it is necessary to analyze the game regardless of the immediate outcomes. The VDEP method is expected to be used as a more stable evaluation index than wins and losses which are limited by contingent factors.

For example, in the match between Yokohama F. Marinos and FC Tokyo, Yokohama won the match by a score of 3 to 0. We examined the reasons for the unexpectedly large gap in the matchup of the two top teams (the numbers of shots taken by both teams were the same in the game). Although  $R_{recoveries}$  for Yokohama (0.371) was better than that for Tokyo (0.348),  $R_{attacked}$  and  $R_{vdep}$  for Tokyo (0.116 and 0.049) were better than that for Yokohama (0.159 and -0.040). These indicate that Tokyo’s defense made it difficult for Yokohama to score goals. As in this game, there are cases where the evaluation results do not match the game outcome even if the defensive evaluation is good, due to the quality of shots taken by the attackers (note that the proposed method did not reflect how likely an effective attack is to score). Thus, the use of the VDEP method to quantitatively evaluate the defense of each match will allow for a more detailed analysis than wins and scores.

Statistically, correlation analysis was performed between the outcome of the game and the proposed and existing indices (analyzed data is given in S1 Data). In the case of  $R_{vdep}$ , there were moderate positive correlations with winning points



**Fig 3. Example of defensive play analysis.** (A) The VDEP value for each event is indicated, including the type of action, and the player who took the action. (B) The position of all players when the shot was performed are visualized (red: defending team; blue: attacking team) and the flow of the event with the ball. In this scene, the VDEP values were positive in all events, suggesting that the defense was not so bad that the goal was conceded. The VDEP values decreased between Matsubara’s pass and Erik’s trap, and between Erik and Wada’s trap and pass, suggesting that the goal was conceded because of a forward pass or because the ball holder was allowed to go free.

( $r_{16} = 0.464, p = 0.050$ ) and low positive correlation with goals scored ( $r_{16} = 0.392, p = 0.106$ ). In the case of  $S_{vae}$ , there were high positive correlation with winning points ( $r_{16} = 0.830, p < 0.001$ ) and very high positive correlation with goals scored ( $r_{16} = 0.953, p < 0.001$ ). It is obvious that  $S_{vae}$  can accurately predict the number of goals scored in a match because it is based on the prediction of scores. Interestingly, even though  $S_{vae}$  is also based on the prediction of conceded goals, it had slight almost negligible relationships with goals conceded ( $r_{16} = -0.040, p > 0.05$ ). On the other hand,  $R_{vdep}$  had low correlation with the goals scored in the game ( $r_{16} = -0.245, p > 0.05$ ).

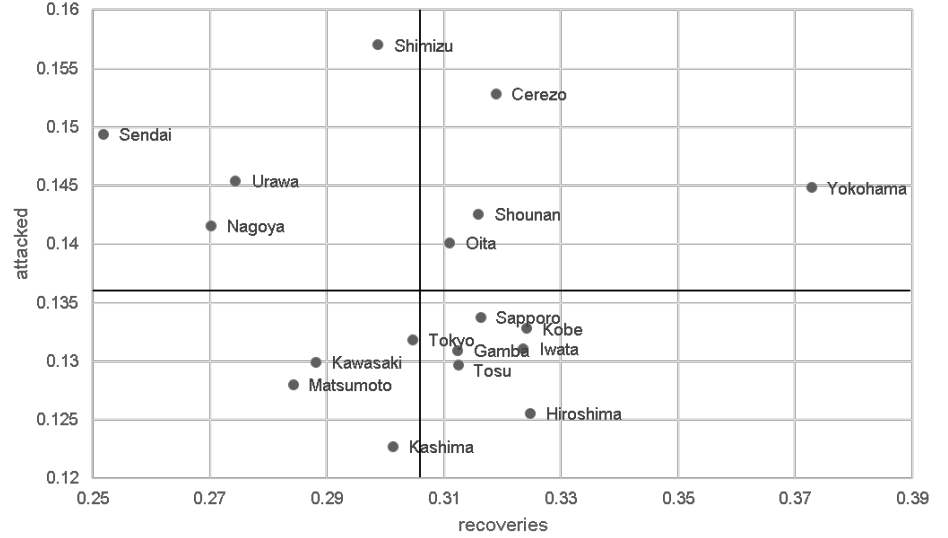
### Defensive evaluation of teams in multiple games

It is also possible to characterize and evaluate team defenses throughout a season using the VDEP values in multiple games. Fig 4 shows the average VDEP values for each team. For example, Yokohama was able to defend with a high probability of recovering the ball, suggesting the probability of a high number of goals (see S1 Data). On the other hand, the probability of being attacked was also high, suggesting that the team adopted a high-risk, yet high-return, defensive tactic. Meanwhile, Hiroshima that had the fewest number of goals conceded in the league (see S1 Data), shows high probability of ball recovery and low probability of being attacked, suggesting that these properties led to the low number of goals conceded.

Statistically, we performed the correlation analysis between the team’s performance over the whole season and the evaluation indices (the data is shown in S1 Data).  $R_{vdep}$  had moderate positive correlations with winning points ( $r_{16} = 0.397, p = 0.103$ ), and low correlation with goals scored ( $r_{16} = 0.342, p = 0.162$ ) and goals conceded ( $r_{16} = -0.291, p = 0.239$ ). Meanwhile,  $S_{vae}$  had moderate positive correlation with goals scored ( $r_{16} = 0.497, p = 0.034$ ), but slight almost negligible relationships with



winning points ( $r_{16} = 0.177, p > 0.05$ ) and goals conceded ( $r_{16} = -0.098, p > 0.05$ ). In the case of VDEP, the correlation coefficients with the game performances and those with the entire season were similar, whereas, in VAEP, the associations were very different.



**Fig 4. Defensive evaluation of teams in multiple games.** The vertical axis is  $R_{attacked}$  and the horizontal axis is  $R_{recoveries}$ . The vertical and horizontal lines are the averaged values of  $R_{attacked}$  and  $R_{recoveries}$  among all teams, respectively. The more points plotted to the right, the more likely the defense is to recover the ball, and the more points plotted below, the less likely the defense is to concede. The black line is the league average. For example, Yokohama defended with a high probability of recovering the ball. On the other hand, the probability of being attacked was also high, suggesting that the team adopted a high-risk yet high-return defensive tactic.

## Discussion

In this study, we proposed a method to comprehensively evaluate a team's defense related to the team's performance, based on the prediction of ball recovery and being attacked, which occur more frequently than goals, using player actions and positional data of all players and the ball. First, we verified the proposed and existing indices based on the prediction performance. Second, we quantitatively analyzed the defensive evaluations of the proposed and existing methods. Finally, we discuss the limitations of the proposed methods and future perspectives.

The proposed VDEP and VAEP [9] evaluate players and teams based on the assumption that the prediction is accurate. To validate the classifiers, the previous study [9] used AUC and Brier scores. However, as mentioned above, these indices may not be reliably evaluated because they include a large number of true negatives. Therefore, we computed the F1 score and the results showed that the VDEP method predicted true positives correctly, while the VAEP did not. This suggests that the VDEP method was a reliable method that can evaluate defensive performances based on accurate predictions.

Regarding the team evaluations using the proposed and existing indices, the correlation analysis revealed moderate positive correlation between the season outcome

(winning points) and the proposed VDEP value, whereas there were strong positive correlations between the game outcome (winning points and goals scored) and the existing VAEP value [9]. Furthermore, overall, in the VDEP value, the correlation coefficients with the analyzed game performances and those with the entire season were similar, whereas those of the VAEP value were very different. These results suggest that  $R_{vdep}$  could be a well-balanced indicator to evaluate both attacks (after the ball recovery) and defense itself (prevention of being attacked and the ball recovery). On the other hand, the VAEP method [9] is based on the prediction of offensive play and shows no correlation with the goals conceded. We expect that the use of VDEP in addition to the various indicators used so far will lead to the continuous strengthening of the team, regardless of immediate wins and losses which would be associated with contingent factors.

There are several recommendations for future studies. The first is the increase in the number of analyzed games for more accurate prediction of longer-term game performances. The second is the determination of the weighting constant  $C$  in Equation 1 for ball recovery and being attacked. Although this study determined  $C$  based on the number of occurrences of both events, the constant should be determined in more suitable ways for the practical values in soccer. The last is the evaluations of individual players. Since VDEP evaluates team defense, it is difficult to evaluate the performance of individuals. For example, future studies are necessary to compute the change in VDEP when a player moves in different directions.

## Supporting information

**S1 Data.** Analyzed data.

## Acknowledgments

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