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Close the gap: contextual influences on defensive dispersion in rugby league

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ABSTRACT

On-field spacing has been linked to successful performance in a number of sportsto date, there is limited research investigating this within rugby league. This study aims to (a) quantify the defensive dispersal during rugby league match-play and (b) identify if contextual factors are associated with the dispersal. Global Positioning System data were analysed from 47 European Super League matches (1598 player files). Defensive dispersal was calculated for 1959 defensive sets of rugby league. Linear mixed models were used to analyse the effects of contextual factors on the average defensive dispersal per set when accounting for team and fixture. On-field position and match half were found to significantly affect defensive dispersal. However, set length, play-the-ball length, and final score difference were found to have minimal impact on defensive dispersal. This study demonstrates that defensive dispersal in rugby league can be measured using GPS data and may be strongly influenced by on-field positioning. As such, it quantifies an important element of tactical preparation for rugby league teams.

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1. Introduction

Research in team sports consistently demonstrates the role of defensive spacing in determining match outcomes. In soccer, Low et al. (2020) show a relationship between defensive spacing and the number of shots conceded. In addition, they show how different spacing strategies are adopted by teams at varying positions within the league hierarchy, suggesting a relationship between defensive tactics and league performance. In American Football, Yurko et al. (2019) highlighted the role of the distance between defenders and the ball-carrier in predicting the expected gain from a carry. This emphasises the tactical significance of defensive spacing in the context of player positioning and nullifying the offensive team. Similarly, Franks et al. (2016) uncovered a notable

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association between defensive spacing and both shot selection and effectiveness in professional basketball. This discovery underscores the multifaceted impact of defensive strategies on offensive decision-making and overall team performance in basketball. These studies collectively emphasise the importance of defensive spacing across team sports, and its implications for match dynamics, strategic decision-making, and match outcomes. While this research has examined defensive spacing in sports like soccer, American football, and basketball, there's a notable lack of studies in rugby league. This gap presents an opportunity to explore how defensive spacing influences match outcomes and player performance in this sport. Closing this research gap could offer valuable insights for coaches and players aiming to optimise defensive strategies and elevate team performance on the field.

Collective team behaviour is a term which attempts to describe how individual players position themselves across the overall group and what factors may influence where they position themselves. This behaviour has been used to explain team tactics or game style (Sampaio & MaçÃs, 2012) and has become a central component of pre- and post-match analysis in many team sports because of its relationship with performance outcomes and capability to provide greater context to match events (Clemente et al., 2014). It has typically been defined via spatiotemporal metrics, such as x-axis team length, team width, and team surface area (Aguiar et al., 2015). These metrics quantify the dispersal of players and how that dispersal can expand or contract, based on the match situation. The team centroid represents the geometric centre of all one team players on the field, team length and team width describe the distance between the two players furthest apart along and across the pitch, respectively, and team surface area represents the region that surrounds all players across the field (Bartlett et al., 2012). To provide additional context to the understanding of collective behaviour, investigations have been separated into various phases of match play, such as offence and defence (Alexander et al., 2019). However, many of these studies have taken place in invasion sports which have open-ended possession times (e.g. soccer) (Gollan et al., 2020) where a team's movement behaviour is constantly influenced by emerging aspects of match play and the surrounding contextual factors. As such, the methods employed in these studies may not be directly applicable to sports with pre-defined possession periods (e.g. rugby league) where teams can be more prepared from a positional perspective, either defensively or offensively, at the start of each period of possession.

Research in soccer has considered the x-axis centroid and occupancy maps to suggest teams may be more attacking by positioning players higher up the field in both offence and defence during home matches compared to away matches (Lucey et al., 2013). This behaviour may be associated with an increased possession in the attacking third and a greater number of shots on goal. Other research in soccer has used the length, width, and surface area of all players in a team to propose that while defending, teams attempt to compress the field of play by decreasing the area in which attacking players can operate (Vilar et al., 2013). Additionally, higher-ranking teams in soccer may be more effective at accomplishing this as they commonly produce lower values of length, width, and playing space when defending compared to their lower-ranked counterparts (Castellano et al., 2012). While these approaches are effective at describing team behaviour in sports, such as soccer, they have yet to be applied in sports such as rugby league. As described previously, it may be somewhat simplistic to assign a set movement behaviour to a particular tactic or game style. Collective team behaviour may not necessarily be a pre-planned team tactic or game style but constant adaption to the general state of play. Therefore, to gain a more thorough understanding of team tactics or game style, researchers should account for contextual variables, such as playing venue, opposition quality, match phase and field position (Alexander et al., 2019). Although there is a growing body of research investigating collective team behaviour in soccer (Welch et al., 2021), American football (Schmid et al., 2021) and Australian Rules Football (Seakins et al., 2023), there is a lack of research in this area in rugby league.

While many studies investigate the influence of such factors on match outcomes, individual physical or technical player outputs (Dalton-Barron, Whitehead, et al., 2020; González-Rodenas et al., 2024), few have attempted to discern any relationship between these factors and team spacing or collective behaviour (Fernandez-Navarro et al., 2018; Gollan et al., 2020). Fernandez-Navarro et al. (2018) investigated if venue, quality of opposition, match status (i.e. score differential) were related to playing style in the English Premier League (EPL). They found that all factors influence playing style to differing degrees. Although Gollan et al. (2020) did investigate if contextual factors were related to playing style in the EPL, they used a theoretical framework to describe playing style as opposed to spatiotemporal tracking like Fernandez-Navarro et al. (2018) did. In rugby league, on-field positioning can play a crucial role in determining team success, influencing both offensive and defensive strategies. Each player's position dictates their area of influence on the field, shaping the overall structure and spacing of the team. Forwards typically occupy the centre of the field, aiming to gain ground through carries. Meanwhile, backs tend to spread out across the width of the field, seeking to exploit gaps in the opposition's defence to create scoring opportunities (Woods et al., 2017). Previous research in rugby league has primarily focussed on locomotive and technical demands (Dalton-Barron, Palczewska, et al., 2020; Glassbrook et al., 2019). With no studies, to date, investigating either defensive effectiveness through tracking data or if contextual factors are linked to collective team behaviour. Given the importance placed upon defensive effectiveness, particularly line-speed and preventing the opposition gaining territory (Kempton et al., 2016; Parmar et al., 2018), increasing our understanding of what factors influence it may help improve the overall team preparation. Therefore, the aim of this study was to i) quantify defensive dispersal in rugby league using Global Positioning System (GPS) data and ii) assess if defensive dispersal is linked to contextual factors.

2. Methods

2.1. Study design

To assess defensive dispersal in rugby league, GPS and event data from 47 matches (individual game files, $n = 1958$) in the 2021 European Super League were analysed (Figure 1). Data from both the home and away teams were used.

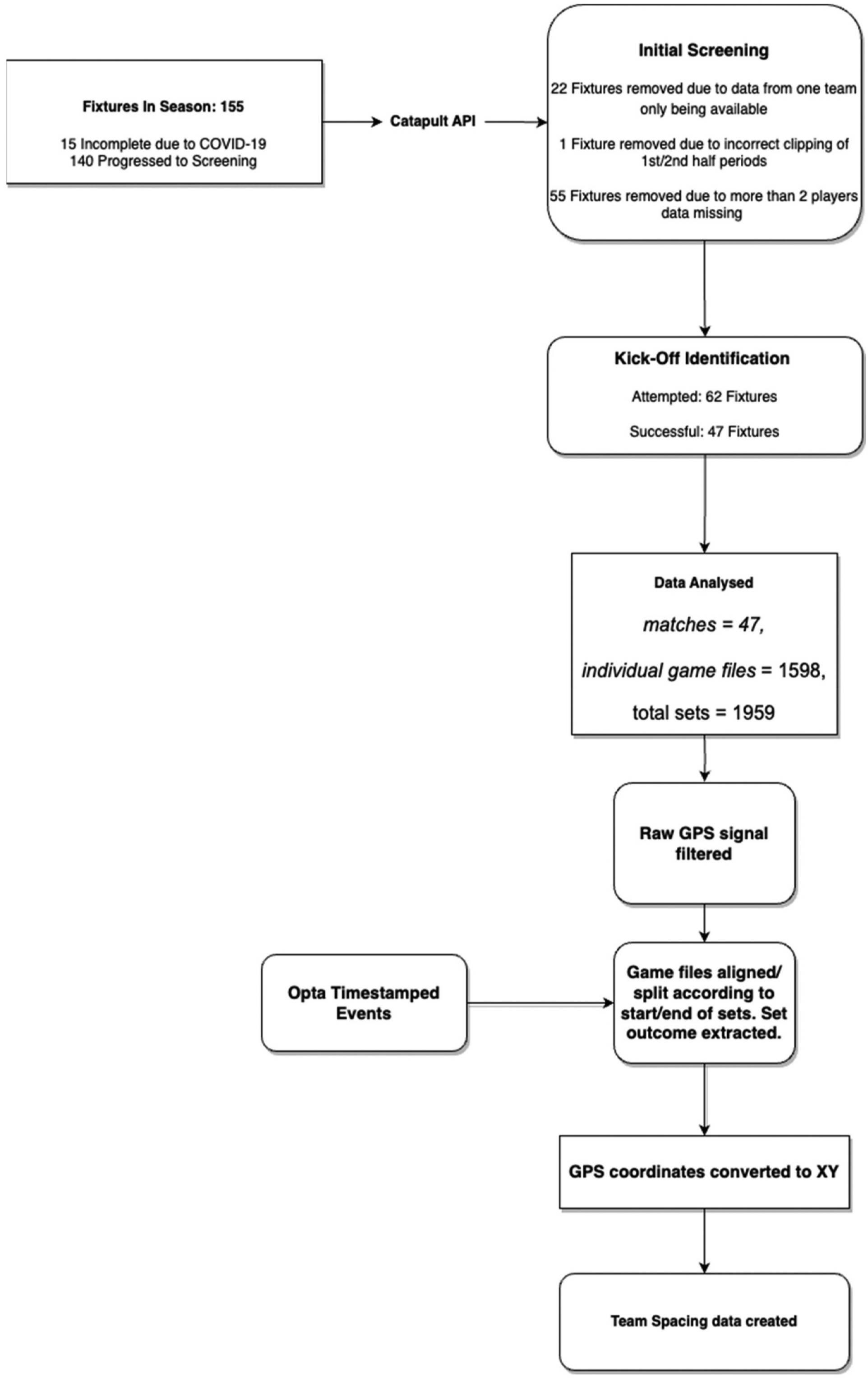

Figure 1. Flow chart outlining analysis pathway.

2.2. Data collection

Players' GPS data were recorded using a microtechnology device (Optimeye S5, Catapult Sports, Melbourne, Australia), containing a 10 hz GPS. The validity and reliability of these devices have been investigated previously (Luteberget et al., 2023) and data collection was consistent with the methods outlined by Dalton-Barron, Palczewska, et al. (2020). Match-play contact-event data was taken from Opta data provided by StatsPerform (Chicago IL, U.S.A.) and extracted online (https://www.optaprorugby.com/index.php) as extensible markup language (XML) files. Commercial match-event providers have been used previously as a data source within rugby league research (Parmar et al., 2018; Rennie et al., 2022; Sawczuk et al., 2024).

No personal data were accessible by the research team, and no identifiable data were presented: thus written informed consent was not needed by each participant, thereby conforming with the United Kingdom Data Protection Act, 2018. Consent to analyse the data was provided by the governing body. Ethics approval for the study was granted by Leeds Beckett University Ethics Committee.

2.3. Data preparation

Matches were selected for inclusion if GPS data for both home and away teams were available, a timeline of player and match events was available, and the exact kick-off time could be accurately identified through the GPS data. Given the calculation of defensive dispersal involves the distance between all players on-field, a minimum of 15 players from the match-day squad of 17 must have worn GPS for inclusion (only data where all 13 on-field players was included, when data was available for less than 15 of the 17 match-day squad, the majority of the match data was excluded). The precise kick-off time was necessary to accurately synchronise GPS and event data. Given the short time between players leaving the changing room and the game kicking off in rugby league, along with stadium interference, GPS receivers are not always connected to satellites and collecting positional data at kick-off. The main cause of matches being excluded from the final analysis was insufficient player data availability (see Figure 1). Matches were classified according to the final score difference (low difference <6 points; moderate difference 6–24 points; high difference >24 points).

Figure 1 describes the data flow including the steps involved in data preparation and data pre-processing. All steps were completed in R (version 4.2.0). For the extraction of the team dispersal, longitude, latitude and raw Doppler-derived speed and acceleration for each player were downloaded through Catapult's proprietary Application Programming Interface (API). To remove erroneous data within each file, sampling points within the speed and acceleration vectors were identified according to previously identified criteria: number of connected satellites ≤10, Horizontal Dilution of Precision (HDOP) ≥1, velocity $>10\ \text{m}\cdot\text{s}^{-1}$, acceleration $>\pm 6\ \text{m}\cdot\text{s}^{-2}$. Once identified, the erroneous data was removed and replaced with imputed data as outlined by Dalton-Barron, Palczewska, et al. (2020).

The start and end time of each set within a match were extracted from the Opta event data. Sets were included for analysis based on the following inclusion/exclusion:

- The start/end point of the set to be clearly identified within the event data
- The final event of the set led to a clear set outcome
- Positional data were available for all on-field players throughout the set
- The set duration was greater than 10 seconds

    - <10 seconds led to limited player dispersal and were not representative of overall data
- Repeat Sets or "6 again" penalty sets were removed from the dataset as they were considered outliers.

Within the event data, possession data is coded as a sequence of plays, which begins when a team obtains possession of the ball and ends when the team loses possession of the ball (i.e. due to an error, handover, field kick, penalty, drop goal or try) (Sawczuk et al., 2021). Identifying the team in possession through the event data allowed researchers to identify the team defending. Set outcomes were determined from the final player action of the set extracted from the Opta event data. If the set ended with the attacking team kicking or committing an error (e.g. dropped ball) it was considered a positive defensive outcome. If the set ended with the attacking team scoring or the defensive team committing an error (e.g. attempted steal) it was considered a negative defensive outcome.

The set times were then used to split the GPS data and the longitude and latitude converted to XY coordinates using the "sf" package (Pebesma, 2018) in R and the data for each player within the set were aligned chronologically. Following which a 13×13 matrix of distances from all players within a team to each other was created at each time-point within a set. This led to a dataset with 78 datapoints per timepoint.

Defence dispersal was calculated by averaging the distance between each player and all other players on their team. This was initially calculated per timepoint, then averaged across each set within the final dataset. This defensive dispersal variable, which provided a single value summary of the team's spacing, was used within the modelling process.

Contextual factors extracted from the match event data were final score difference (absolute difference between the winning and losing team final score), match half (first or second half, golden point excluded due to varied length), distance from defending team try line, set duration (time in seconds from the first play the ball of a set until either match clock is stopped or the defensive team gains possession, classified as short, medium, long duration), average play the ball length (average time from each play the ball within a set). Set length and play the ball length were classified as short, medium or long by splitting them into three groups with equal number of observations in each group. See Table 1 for a breakdown on the final data included per game.

Table 1. The number of games and mean ± standard deviation of sets per game, set length and play-the-ball (PTB) length.

Games (n)	47
Sets Per Game (n)	41.68 (±9.5)
Set Length (s)	40.73 (±17.86)
PTB Length (s)	8.21 (±2.77)

3. Data analysis

To evaluate the effect of contextual factors on team spacing in rugby league linear mixed models were used. Final score difference, match half, set length and average play ball length were discretised by categorising them into distinct groups. Each contextual factor was added to its own model as the dependent variable. These models compared both between and within zones of the field for each contextual factor. As pitch positioning has been shown to affect team tactics in other sports (González-Rodenas et al., 2023), to account for reduced pitch area for a team to defend/disperse in, distance from the defending team's try line was included as an interaction in each model. Club and fixture were included as random effects to account for any tactical priorities specific to a single club or fixture. All statistical analyses were completed in R (version 4.3.2) using the glmmTMB (Brooks et al., 2017) and emmeans (Lenth, 2024) packages.

4. Results

Defensive team dispersal was significantly different at all distances from the try line when analysed on its own (see Table 2), increasing from 25.8 m within 0-33 m of their own try line to 28.3 m when defending closer to the opposition's try line ($p < 0.01$). Significant differences were also found when comparing between the first and second halves at the

Table 2. The mean (95% CI) for defensive dispersal, in metres, at each distance from the defending team's try line compared between set halfs, play the ball lengths, set lengths and final score difference.

		Distance from own try line (m)		
		0–33	33–66	66–100
Defensive Dispersal at each 3rd of the field		25.8$^{\$, \wedge}$ (25.1–26.7)	26.7$^{\wedge}$ (25.8–27.5)	28.3 (27.3–29.2)
Set Half	1st Half	23.63* (22.9–24.35)	24.04* (23.14–24.94)	25.96* (24.9–27.02)
	2nd Half	28.09 (27.36–28.82)	28.94 (28–07–29.80)	30.51 (29.46–31.57)
PTB Length	Short (0-7sec)	25.05** (24.25–25.85)	25.12** (23.87–26.38)	27.93 (26.37–29.49)
	Medium (7–8.6sec)	26.05 (25.23–26.87)	26.84 (25.78–27.91)	27.81 (26.29–29.32)
	Long (8.6+sec)	26.75 (25.87–27.64)	27.29 (26.30–28.27)	28.59 (27.47–29.71)
Set Length	Short (0-35sec)	23.93*** (24.10–25.77)	25.92 (24.89–26.95)	27.95 (26.81–29.09)
	Medium (35-47sec)	25.57*** (24.77–26.37)	26.51 (25.27–27.75)	28.26 (26.30–30.22)
	Long (47sec+)	27.01 (26.17–27.85)	27.51 (26.49–28.54)	28.67 (27.37–29.97)
Final Score Difference	Low (0–6 points)	25.85 (24.78–26.92)	26.13 (24.78–27.47)	28.24 (26.63–29.84)
	Moderate (6–24 points)	25.52 (24.63–26.42)	26.31 (25.26–27.37)	26.89$^{\#}$ (25.13–27.29)
	High (24+ points)	26.21 (25.13–27.29)	27.85 (26.48–29.22)	30.16 (28.64–31.67)

Significance: $p \leq 0.05$, \$ significantly different to team spread at 33–66, ^ significantly different to team spread at 66–100, *significantly different to 2nd half at same distance from try line, **significantly different from long PTB lengths at same distance from try line, ***significantly different from long set lengths at same distance from try line, #significantly different from high score difference at same distance from try line same distance from the team's own try line ($p < 0.01$ for all comparisons). Short PTB lengths were found to be significantly different from long PTBs for both 0–33 m ($p < 0.01$) & 33–66 m ($p = 0.042$) from own try line, and no other differences were found within PTB length. Short and medium set lengths were found to be significantly different from long set lengths at 0–33 m ($p < 0.01$) only with no other differences found. Final score difference was found to be significantly different at 66–100 m when comparing moderate to high score differences ($p < 0.019$).

5. Discussion

The use of spatiotemporal tracking data in rugby league has led to a large body of research investigating their use in quantifying external training load (Dalton-Barron, Palczewska, et al., 2020; Glassbrook et al., 2019). More recently, Collins et al. (2022) and White et al. (2021) explored the use of such tracking data along with data mining techniques to extrapolate movement sequences. While this recent work has tried to move beyond the use of summary data, these methodologies still align with the perception that this data exists to inform the physical preparation of rugby league teams. This is the first study to utilise GPS data in rugby league from a tactical preparation perspective. By doing-so it adds objective measurement of an area which practitioners consider important but previously could only assess subjectively. Notably, it was found that both on-field position and match-half significantly affect defensive dispersal. In addition, limited differences are observed when assessing the affect of PTB length, set length and final score difference have on defensive dispersal. While the influence of on-field position may align with a team's tactical set-up responding to the differing approaches of the offensive team, the changes due to match-half may be reflective of fatigue affecting player decision-making and physical capability

In the current study it was found the further a team defended from their own try line, the greater the defensive dispersion. Regardless of the contextual factor included within the analysis the increased dispersal remained constant. This aligns with similar research in Australian Rules Football (AFL) which found teams showed a tendency to group around their goal when the ball was closer to it (Spencer et al., 2019). Moreover, Welch et al. (2021) observed a similar trend in soccer, where teams tend to be more organised and focused on reducing available space in defence. While this will be, in part, due to less space on-field for them to occupy it may also be reflective of a tactical response to the offensive team's effort. The more space the offensive team has to attack into, the more varied, and possibly less predictable, their potential attacking options become, leading to the defensive team increasing their defensive spacing. This is in line with Eaves and Broad (2007) who found teams use less variation in their attacking options the closer to the try line they get. Future research should investigate the potential interaction between the offensive team movement and the defensive dispersal of the defending team. Overall, the increased dispersal in defence appears to be a multifaceted phenomenon influenced by both contextual constraints and tactical considerations. Further research may wish to examine if defensive dispersal near the try line varies between teams, potentially indicating the presence of a tactical influence.

Here, it was found that teams were considerably more dispersed in the second half when compared to the first. In addition, longer play-the-balls and longer sets led to significant increases in defensive dispersal. This may be indicative of longer periods of ball in play, allowing less time for defensive players to reposition effectively in the defensive line. In other sports temporal effects play a significant role in shaping team spacing (Low et al., 2020), influencing how players position themselves throughout the course of a match. Figueira et al. (2018) found that intra-team coordination in football decreased in the second half compared to the first. Within rugby league, given the short duration of each play-the-ball (Table 1), unless the offensive team significantly disrupts the defensive line, the defensive line remains relatively stable until the final play-the-ball of the set. The more stable the defensive line remains, the less defensive dispersal is likely to change across a set.

Interestingly, it was found that the final score margin had minimal relationship with defensive dispersal. This observation defies expectations, particularly in games with a low score margin where teams may potentially adopt a more conservative approach reducing dispersal. Conversely, a team trailing by a significant margin may adopt a more expansive style of play, spreading out across the field in search of scoring opportunities. This interplay between score margin and defensive dispersal contrasts with findings from studies in other sports, such as soccer and basketball, where the score has been shown to exert a notable influence on player positioning (Almeida et al., 2014; Santos et al., 2017). This underscores the complexity of tactical decision-making and strategic adaptation within different sporting contexts.

Many studies have investigated the locomotive demands of team sport athletes with change across a fixed time epoch (full match, half match, etc.) included (Brewer et al., 2010; Dwyer & Gabbett, 2012; Wisbey et al., 2010). However, there is limited research available which describes the influence of time on collective team behaviour. Findings from this study suggest that regardless of field position teams occupy greater space in the second half than compared to the first half (Table 2). Future research should seek to split matches into more discrete time periods (e.g. quarters) to assess if this change occurs organically across a game or is more representative of a change in playing style.

While other sports have investigated team spacing, many of the methods utilise tracking data collected through means other than GPS (e.g. optical tracking, RFID, LPS) which can have increased accuracy when assessing on-field positional changes (>1 m) in player position (Rico-González et al., 2020; Torres-Ronda et al., 2022). As the positional accuracy of the GPS units used in the present study has been shown to be ±1.53 m (Luteberget et al., 2023), when used with such methods, they may not be sensitive enough to detect changes. A general limitation of the use of spatial data to determine defensive success in rugby league, or similar team sports, is weaknesses in defensive positioning may not always be detectable through player positioning. Often offensive players use deception (e.g. feint, side-step) to off-balance defensive players and while this change in body-posture or weight-shift does not lead to a change in positional data, it can be enough to allow offensive success.

6. Conclusion

This study measured defensive dispersal of rugby league teams and how the dispersal changes based on several contextual factors. It was assessed using defensive dispersal across a set of rugby league match-play. Defensive dispersal was significantly different based on on-field position and match half. Set length, play the ball length and final score difference had limited influence on total team spread. Future research should assess if the temporal effect on team spread is due to fatigue-related measures, tactical alterations or other factors.

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