Landscapes of passing opportunities in Football – where they are and for how long are available?

Luis I. Gómez-Jordana[1], *João Milho*[2], *Ángel Ric*[3], *Rodrigo Silva*[4] *& Pedro Passos*[1]

[1] *CIPER, Laboratory of Motor Behavior, Faculdade de Motricidade Humana, Universidade de Lisboa, Lisboa (Portugal).*

[2] *CIMOSM, Instituto Superior de Engenharia de Lisboa and IDMEC, Instituto Superior Técnico, Lisboa (Portugal).*

[3] *FC Barcelona, Barcelona (Spain); Complex Systems in Sport Research Group, Institut Nacional d'Educacio Fisica de Catalunya (INEFC), University of Lleida (UdL), Lleida (Spain).*

[4] *Instituto Dom Luiz, Faculdade de Ciências, Universidade de Lisboa, Lisboa (Portugal).*

Contact email: *luis.jordana.martin@gmail.com*

Abstract

In football, the ball carrier is continuously aiming to perform a pass that *outplays* as many opponents as possible. The *players outplayed* are the number of opposing players a ball carrier has in between her/him and her/his own goal. Using this principle landscapes of passing opportunities were created for: i) *penetrative* passes, ii) *support* passes, and iii) *backward* passes. Using data from a competitive match landscapes for each type of passing opportunities and half (1st and 2nd), were created and displayed as heatmaps. Results showed heatmaps with a variety of patterns and with more passing opportunities in the second half of the match. Furthermore, the mean time of passing opportunities were calculated and compared for each half and for each type of pass. Results display that *penetrative* passes were available over shorter periods of time than *backward* passes that were available shorter than *support* passes. There were more passing opportunities on the second half, which were also available for longer periods. Moreover, there were more passing opportunities for *penetrative* than *backwards* or *support* passes. This landscape model could provide insights for football attacking dynamics. It is a customizable tool that can be implemented in real time video analysis systems, allowing collective and individual players performance analysis.

Keywords: Heatmaps; time availability;_outplay opponents, vulnerable areas; offensive process.

1. Introduction

In football two antagonistic teams play over the hegemony of the game (de Poel, 2016; Gramsci, 1992), which demands each player to adjust her/his own decisions and actions sustained by other individuals (i.e., teammate or opponent) behaviour. Such behaviour is constrained by two types of information: i) predictive information, which specifies what has been previously planned (e.g., set pieces) and ii) emergent (prospective) information, which becomes available during performance due to players interactive behaviour specifying not only 'what to do' (e.g., pass) but also 'when', 'where' and 'how' to do it (Passos, Cordovil, Fernandes, & Barreiros, 2012; Fajen, Riley, & Turvey, 2009).

This local information is changing continuously, due to the dynamics of players' relative positioning, proximity to goal area or/and distance to field boundaries (Headrick et al., 2012; Passos et al., 2012). Moreover, players have the ability to perceive what the others can do, which in turn limit her/his own opportunities to act reciprocally demanding continuous adaptation (Gibson, 1979; Passos et al., 2012; Passos & Davids, 2015; Stoffregen, Gorday, Sheng, & Flynn, 1999).

A crucial action to maintain ball possession and create scoring opportunities is passing which is highly influenced by spatio-temporal constraints such as the dynamics of support players and opponent player's relative positions. On a football competitive match situation, the dynamics of player's relative positions define the opportunities for passing for the ball carrier. Thus, In order to perform a pass to a teammate, the ball carrier needs to actively explore the opportunities that are temporarily available to perform such a pass (Mendes, Malacarne, & Anteneodo, 2007; Ric et al., 2016). Nonetheless, due to the continuous changes of player's positions the passing opportunities emerge, persist, and dissolve within a limited time window (Araujo, Davids, & Hristovski, 2006).

Within a football match, there should be a rich set of individual and environmental constrains suggesting the existence of a diverse set of potential actions, which could be understood as a *landscape* of potential actions. These *landscapes* are defined as a huge scenario in which opportunities for action are continuously emerging, persisting and dissolving as the intentional behavior of players' is changing (Bruineberg, & Rietveld, 2014). This implies that within a performance landscape, opportunities for action, such as a gap in a defensive positioning that affords a passing opportunity, are continuously changing over very short time scales due to the interactive nature of players' movement (Rietveld & Kiverstein, 2014; Passos & Davids, 2015).

Moreover, changes in player's co-positioning are strongly influenced by technical and tactical constraints (or task constrains, as emergent properties of the performer-environment system; Balagué, Pol, Torrents, Ric, & Hristovski, 2019). Consequently, there are some areas of a football field that are over-used compared to others, suggesting that opportunities for action are not homogeneously spread across the space. Thus, we hypothesized that landscapes of passing opportunities are not distribute homogenously over the field.

In a football match, the ball carrier is continuously aiming to perform a pass that increase probability to score a goal at the end of the ball possession or at least decrease the probability of losing the ball. Previous research showed that passes that outplayed more opponents increases the chance to score goals (Rein, Raab & Memmert, 2017). Therefore, we propose the *outplay principle* to categorize the different types of passes that characterize a landscape model of passing opportunities in football. The *outplayed* opponents are the number of opposing players a ball carrier has in between her/his and her/his own goal (Silva et al., 2014, Duarte et al., 2012). The passing opportunities were divided on three categories of passes depending on the number of opponents outplayed: i) *penetrative* pass (a potential pass to a teammate which outplay more opponents than the ball carrier), ii) *support* pass (an hypothetical pass to a teammate which outplay the same number of opponents than the ball carrier), and iii) *backward* pass (a potential pass to a teammate which outplay less opponents than the ball carrier; see Figure 1 for a detailed explanation).

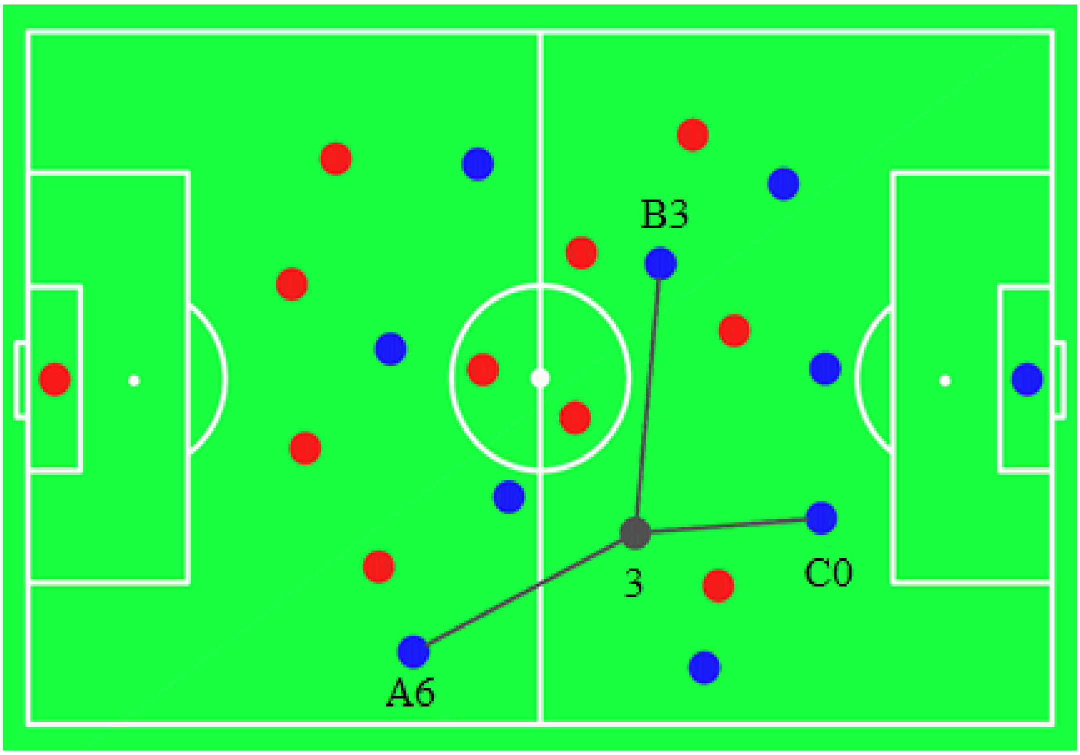

Figure 1: Blue team corresponds to the attacking team while the red team is the defensive team. The black dot corresponds to the ball carrier. The numbers near each attacking player correspond to his/her outplay opponents. Letter A corresponds to a penetrative pass, as the attacking player outplays more opponents than the ball carrier, letter B corresponds to a support pass as the attacking player outplays the same number of opponents as the ball carrier, while the letter C corresponds to a backward pass as the attacking player outplays less opponents than the ball carrier.

There is a time dimension associated with passing opportunities. Thus, the time that each passing opportunity was available was expected to vary along both halves of a football match and for the different types of passes expressing the defensive team ability to cover potential passing areas. Due to player's interactive behavior, the landscapes of passing opportunities, expressed as heatmaps, are also expected to change along halves and for the different type of passes.

2. Methods

2.1. Data acquisition

The data analyzed in this study corresponds to an official football match, which provide a sample of 445 ball carries for the analyzed team. The data was kindly provided by a professional football club and corresponds to bi-dimensional (*x* and *y*) coordinates of each player recorded at 25 fps as well as events corresponding to shots, passes, ball carries, fouls, cards, substitutions, kickoff and goals. The final score was 2-2, with the two goals of the analyzed team and one of the opposing team scored in the first half, while the other goal was scored in the second half. At minute 63, one player of the opposing team received a red car leaving its team playing with 10 players.

2.2. Algorithm description

The first step was to calculate the number of opponents between each player of the attacking team and his own goal. Then the number of outplayed opponents by each attacking player were compared to the ones outplayed by the ball carrier. This comparison serves to divide the passing opportunities into three categories of passes: i) *penetrative*, ii) *support*, and iii) *backward*.

After this, the algorithm identify the potential receivers, and creates for each one, two potential passing lines: i) for the receiver current position; ii) for the receiver estimated position 1 sec later as long as the receiver was running at velocity higher than 2 m/s (Figure 2). A constant ball speed of 10 m/s was assume for all potential passes.

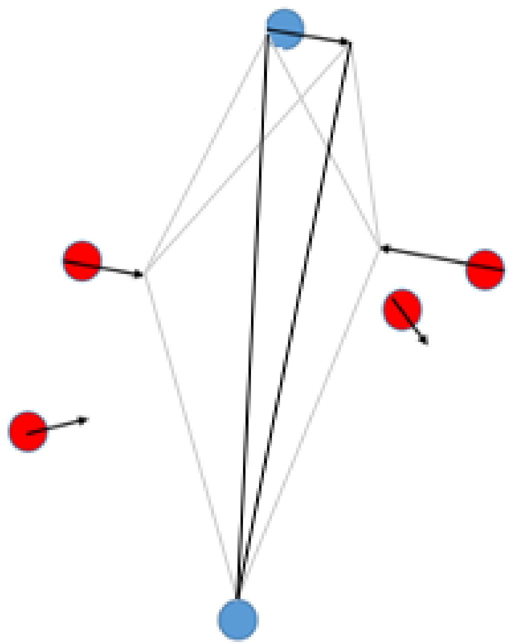

Figure 2. Depiction of the polygon that specifies opportunities for passes. Blue circles represent the ball carrier and the receiver; red circles represent defenders closed to the hypothetical passing line. The black arrows correspond to the velocities of the players. The black lines are the two hypothetical passing lines, one to the actual position of the player and one to the position in the next second. The grey lines represent the boundaries of the geometric figure.

If any of the two possible passes were available, the area of availability was define by a polygon with vertices on the two extremities of the potential passing line, and the two nearest defenders to that passing line (see Figure 2). When there were no defensive players, the sideline was used as an alternative.

To analyze if these potential passing lines were intercepted, coverage areas were defined supported on defender's velocity (Grehaigne, Bouthier, & David 1997). A crucial issue was the players' ability to change his running line direction. It was assumed that this ability to change the running line direction was dependent on the velocity at which a player was running in a specific moment on time (see figure 3 for a visual explanation, and Appendix 1 for further explanation).

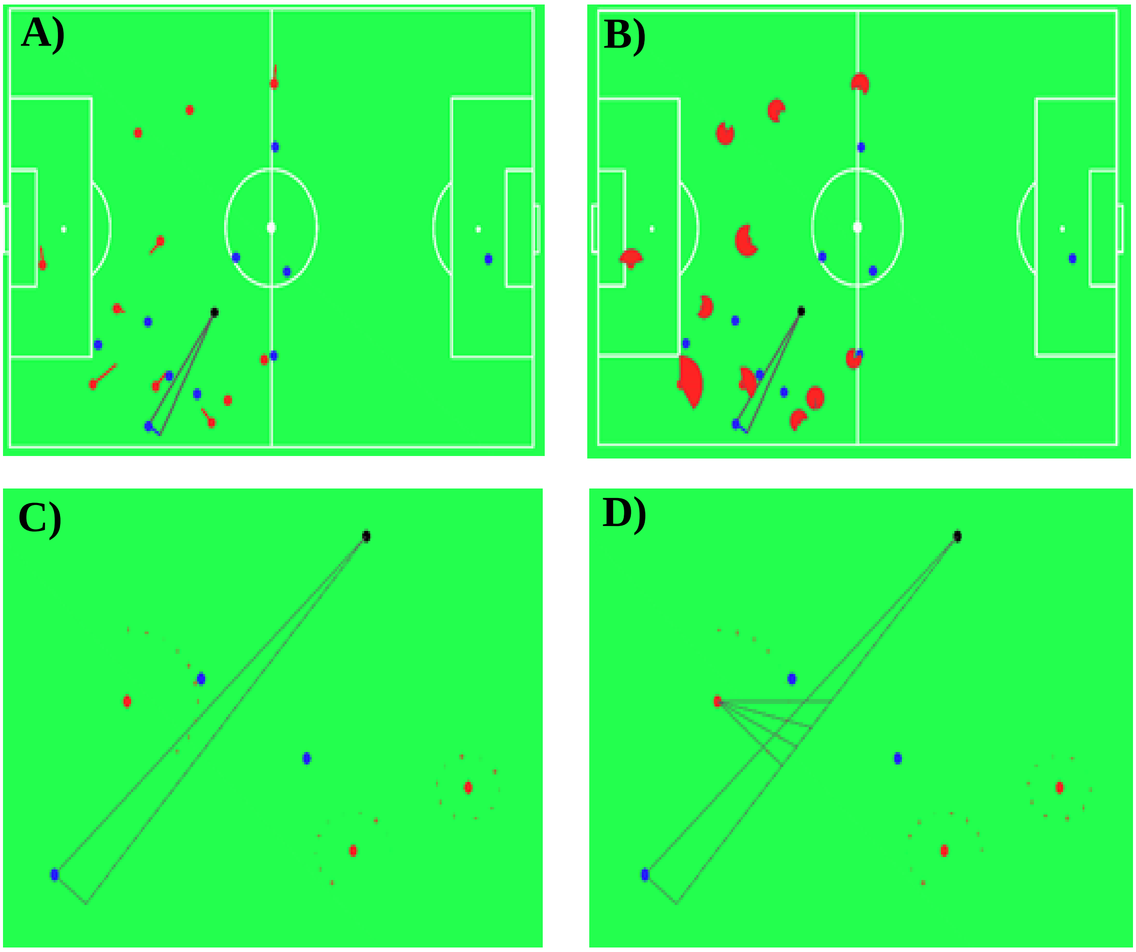

Figure 3: The situation depicted corresponds to a frame of time. The team red is the defensive team while the blue team is the attacking team, with the black dot corresponding to the ball carrier. The grey line correspond to the two possible available potential passes that can be calculated. First, (A) the algorithm calculates the velocity of the defensive players. After that, coverage areas are calculated (B). These areas are formed using a series of points, ten of which are depicted in figure C and D as red cross, for three different players. Finally, segments (D) are formed to the passing lines, which by a simple cross multiplication gives the time the player took to arrive to the passing line through each of these segments. If the time the pass takes to get to this point is higher than what the player takes to get to the same point, as in this situation, the pass is not marked.

2.3. Model validation

To validate the model, the algorithm was run 1 sec before each effective pass using the ball carrier and the receiver of each effective pass to observe if the effective passes were marked as passing opportunities. We ran the model over 640 effective passes performed by both teams on this match.

2.4. Landscapes of passing opportunities

To illustrate the landscape of passing opportunities for the team under analysis, a heatmap was created for each type of passes (i.e., *penetrative*, *support* and *backward*) and for each half. To build the heatmap the field was divided into 100x70 square. The heatmaps were created by overlapping the polygon shapes (please see Figure 2) available on each frame of time. To do so, on each frame a square had a passing opportunity was marked. The total count of marked squares, which set the color of the heatmap, was divided by the sampling frequency. This means that the number of marked square correspond to the amount of time that an area had passing opportunities available.

2.5. *Time of passing opportunities analysis*

Beyond visual inspection of the heatmaps, the time that each potential pass was available was calculated. This enables to know the mean time the passes were available per half, and by type of pass. Additionally the mean time that each player had passing opportunity and the mean time that each player offered a passing opportunity was calculated. This calculus were made for each type of pass and for each half.

2.6. Statistical analysis

The statistical analysis were performed using Rstudio (Rstudio 1.138; RStudio, Inc., Boston, MA). For all the statistical analysis the level of significance was set to values lower to $p<0.05$.

An ANOVA for the time the passes were available with factors (Half x TypeOfPass) was performed. This allows to know if the mean time differs across the different type of passes as well as across the halves. In case they were needed Tukey post hoc analysis were run to analyze the main effects and/or interactions. Allowing to know for the time that passes were available which levels differ in between them. Results are presented as a mean ± standard deviation.

In order to analyze if the total amount of passing opportunities per half, and type of passes differ a goodness of fit Chi-square analysis (Bentler, & Bonett, 1980) was run with factors (HalfxTypeOfPass), assuming that the passes were distribute homogenously over the two factors. This allows testing if the amount of the passing opportunities differ for each type of pass and between the two halves. When needed post-hoc analysis were run as a Chi-square for each pair of levels of the two factors to analyze what were the type of passes that differ and if they differ across halves.

3. Results

3.1. Model validation

Of the 640 effective passes performed in the course of the match, the algorithm detected 84.38% of those passes.

3.2. *Total amount of passes*

There were 4128 passing opportunities. The results of the Chi-square was significant ($\chi^2_{(2,4120)}=18.381$, $p<0.001$). Post-hoc analysis revealed that *support* (N=1254) and *backward* (N=1230) available passing opportunities were not different between each other. It also revealed that the amount of passing opportunities differ over halves (1st: 1424, 2nd: 2704) and in between *penetrative* (N= 1643) and the others type of passes. Meaning that *penetrative* passing opportunities were more common than the other two types of passes, been available passes more common in the second half than in the first half.

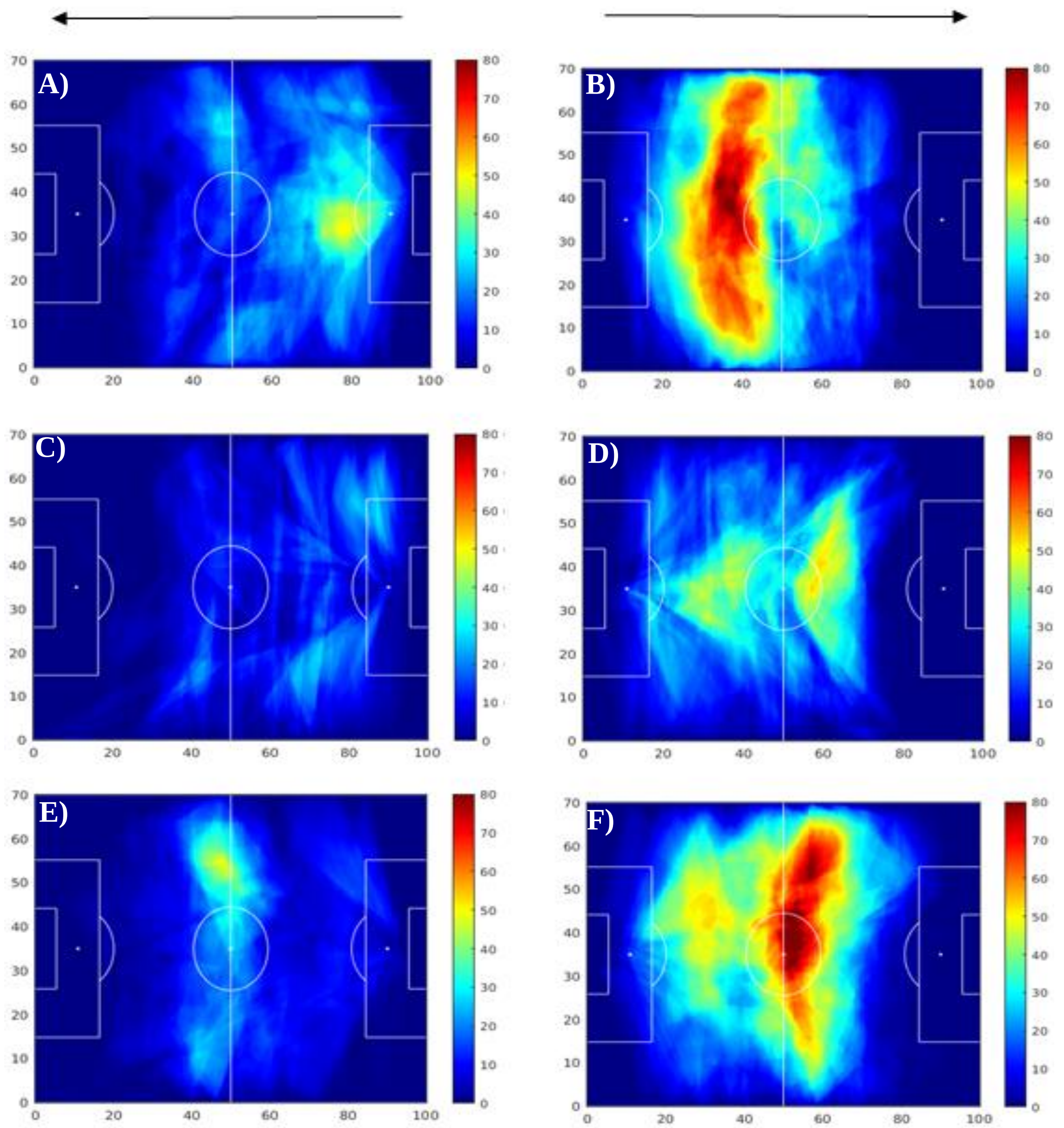

Figure 4: Heatmaps of penetrative passing opportunities are shown, with the first half in the left side and the second half in the right side (4.A and 4.B). Support passing opportunities 4.C and 4.D. backward passing opportunities 4.E and 4.F. The direction of attacking is display as black arrows on top of the heatmaps. The color scale is arrange from 0 passing opportunities available in that square to 80 seconds of time of passing opportunities available in that square.

3.3. Landscapes of passing opportunities

In the first half, most opportunities for *penetrative* and *support* passes (Figure 4.A, and 4.C) were created in the center lane of the attacking team own field. Whereas opportunities to perform *backward* passes concentrated mostly in the midfield dropped to the right lane of the field (Figure 4.E). The lower passing opportunities in the first half produce heatmaps with lighter colors than those of the second half.

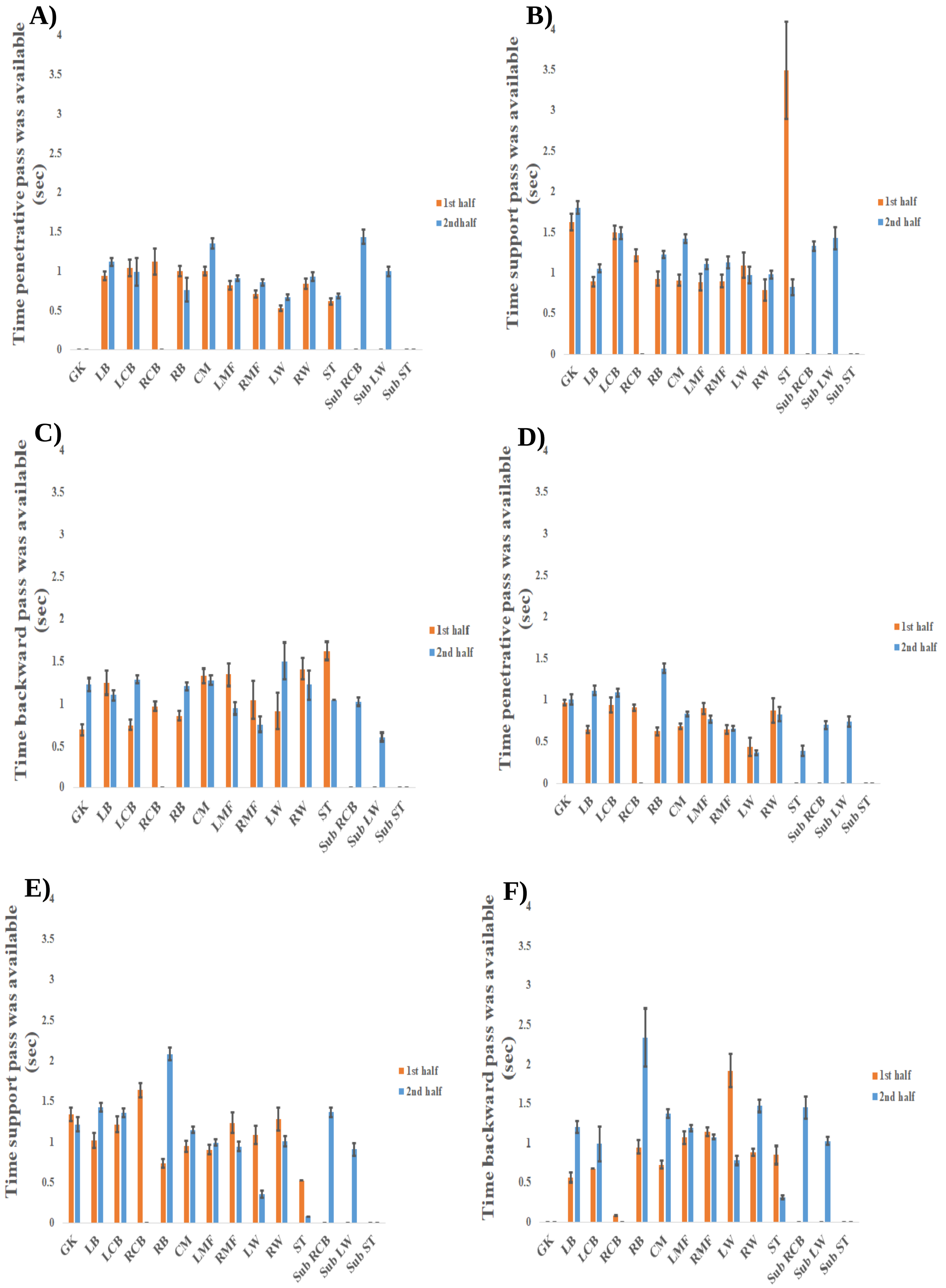

Figure 5: Mean time the passing opportunities were available per player with error bars corresponding to the standard error of the mean. Orange bars corresponding to the first half, and blue bars corresponding to the second half. In case there was no bar, the player did not have any of this type of passing opportunities available. A) corresponds to penetrative passing opportunities available as a receiver, B) corresponds to support passing opportunities available as a receiver, C) corresponds to backward passing opportunities available as a receiver, D) corresponds to penetrative passing opportunities available as ballcarrier, E)corresponds to support passing opportunities as ballcarrier and F) corresponds to backward passing opportunities as ballcarrier.

In the second half, opportunities for *penetrative* passes where more common up the field being more concentrated in the midfield and more evenly distributed in all three lanes (Figure 4.B). In addition, *support* passes opportunities are mainly concentrated in the mid lane, closest to the opposing goal but still in the midfield (Figure 4.D). Finally, opportunities for *backward* passes were mostly concentrated in the midfield and slightly dropped to the left lane (Figure 4.F).

3.4. Time that passing opportunities were available

In figure 5, the results for the time that passing opportunities were available per player are presented. The results of the ANOVA showed a significant effect of the factor TypeOfPass ($F_{(2,4120)}$=15.69, p<0.001; *Penetrative*:0.91± 1.00; *Support*:1.27± 1.21, *Backward*: 1.13±1.16). Therefore, passing opportunities that outplayed at least one player (*penetrative*) were available less time than passing opportunities for *backward* passes, which in turn were available less time than passing opportunities that did not outplay (*support*) any players. There was also an effect of factor Half ($F_{(1,4120)}$=36.91; p<0.001, First: 0.99± 1.12, Second:1.13± 1.13). There was no effect of the interaction.

4. Practical implications

The mean time the passing opportunities were available change with the type of passes, as well as over the match halves. The time that each passing opportunity was available was higher in the second half than in the first half. This is probably related to a player of the opposing team been sent off (red card) on minute 63 which probably created additional difficulties to his own team to close passing lines.

Concerning the type of pass, *penetrative* passing opportunities had less time available than *backward* passing opportunities which have less time available than *support* passing opportunities. These results could be related with the potential risk that each type of pass could create to the defending team. A *penetrative* pass, by placing the ball onto a player that its outplaying more players than the ball carrier, is hypothetical more dangerous for the defending team than a *support* or *backward* pass. These characteristics may increase the defenders effort to intercept them and consequently the time available of each *penetrative* passing opportunity was shorter than for *support* or *backward* passing opportunities. Theoretically, this should mean that *support* passing opportunities had more time available, but the results suggest otherwise which could be explain by a possible increased pressure to recover ball possession close the opposing goal (Headrick et al., 2012; Ric et al., 2017).

These processes highlights the sensitivity of this landscape model to changes in task constraints. It also highlights the possibility that the *outplaying principle* could be defined as an emergent property of an environmental-organismic system (Balagué et. al., 2019). This principle characterize the relation of the ball carrier and the (potential) receivers with the spatial positioning of the opposing players.

Concerning the landscape of passing opportunities along the match, the heatmap was lower in the first half than in the second half. In the first half, although the team score two goals there is few passing opportunities of the three types of passes in the last third of the opposing side of the field. It is noteworthy that one of the goals was due to a technical mistake of the *goalkeeper* (i.e., miss pass towards a *striker*). On the second half passing opportunities are more common but still, there is little to no passes in the last third of the opposing side of the field.

Regarding the mean time that passing opportunities were available, it is noteworthy that for the *support* passes, the higher mean time for the *striker* as a receiver exhibited in figure 5.B is due to him been open for the *right wing* in the last seconds of the first half. The two teams waited passively until the half ended leading to unusual high times for passing opportunities. In the second half it was the *right back* as ball carrier that had mean times for passing opportunities open for longer. Again, this could be related with the red card to an opposing player (minute 63') that could create increased difficulties to the defensive team in closing the gaps (see Figure 5.D, 5.E, and 5.F).

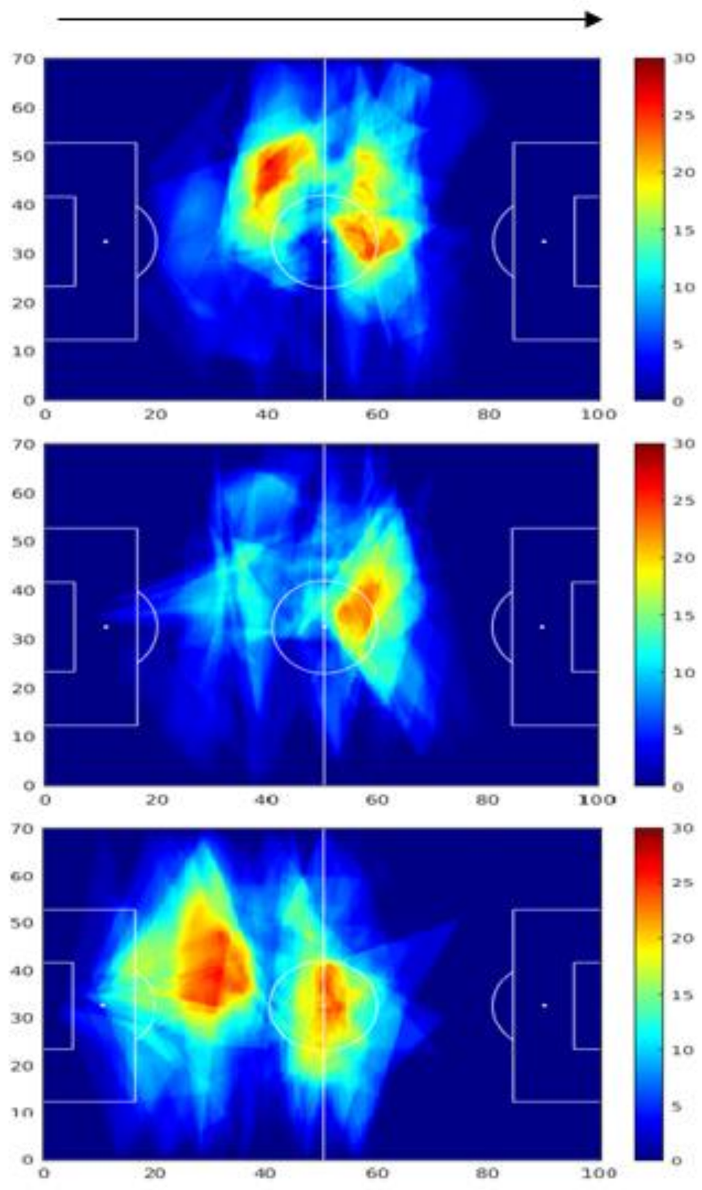

Figure 6. Heatmaps for the second half corresponding to an individual player, the Center Midfielder for A) penetrative passing opportunity, B) support passing opportunity and C) retreat passing opportunity. The results go from dark blue meaning that the square was under passing opportunity for 0 seconds, and dark red meaning the square was under passing opportunity for over 30 seconds. The black arrow indicates the direction of attack.

This type of analysis could allow technical staff and performance analysts to scan the attacking deficits and strengths of a team identifying what areas of the field were available for passing opportunities. Additionally, this model can be integrated with players tracking systems (e.g., video; GPS) allowing a real-time analysis of the heatmaps created as well as the time that passing opportunities were available. Another possibility would be create heatmaps for specific players as receivers or ball carriers as well as to a group of players such as the *strikers* or the defenders. This could allow for a further understanding of the passing opportunities that specific players had (as ball carrier or receiver) throughout the match or set of matches (see figure 6 for an example). Further analysis could incorporate additional contextual information such as field zone (Rein, Raab, & Memmert, 2017), interaction context (Castellano-Paulis, Hernández-Mendo, Morales-Sánchez, & Anguera-Argilaga, 2007), or defensive strategy (Low et al., 2019).

It is noteworthy that the model in its actual state needs future improvement. Three issues for further research are pointed: i) the modelling of ball displacement assuming a constant velocity should be reformulated (see Spearman, Basye, Dick, Hotovy, & Pop (2017) for a possible solution). This may lead to an over or underestimation of the passing opportunities available on a match as 'real' balls do not fly with a constant velocity through all trajectory; ii) the *outplay principle* to categorize passes requires an accuracy improvement. Apart from *penetrative* passes, a *backward* pass can also increase the probability to score a goal (Fernández, Bornn, & Cervonne, 2019). Close to the goal, a pass *backwards* that creates a better angle to score, could be a better decision than a *penetrative* that leaves the receiver in a worst angle to shoot to the goal. Previous research showed the location of the goal was a relevant task constrain in Futsal (Vilar, Araújo, Davids, & Travassos, 2012). Thus, a model upgrade should include variables as the angle and distance to the goal, in order to weight the effect of the *outplay principle* in the landscapes of passing opportunities; iii) finally, the addition to the model of how player's individual technical, tactical and physical characteristics influence passing opportunities is needed.

In conclusion, a model of passing opportunities was built in order to depict landscapes of passing opportunities applying the *outplay principle* as a way to divide passes into different functional categories. The current landscape model was able to detect 84.38% of the real passes that occur on a match. The different type of passes (*penetrative*, *support*, and *backward*) were open for different time windows probably due to the defensive team been more willing or capable to block the different types of passing opportunities, which suggests that the model is sensitive to task constraints such as the *outplay principle*. In sum, the heatmaps created with this model display a landscape of passing opportunities allowing identify the most vulnerable areas accordingly with the different types of passes.

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7. Appendix1

7.1. Coverage areas

After calculating the velocity of each player, table 2 of Grehaigne et. al. (1997) which identifies turning capabilities depending on the velocity of each player, was adapted in such a way that velocity percentile 90 of each player was set as the point that had a lower turning capability (40º) and velocity 0 m/s was stablish as having the highest turning capability (360º). This allow the areas to be slightly personalize for each player such that quicker players are assumed to be able to turn more at higher velocities than slower players.

Then, in each moment in time, the angle (α_p) in the field of the vector velocity of each player was defined. The coverage area was then defined, using trigonometric simple rules, as N=200 points that went through angles α_t+(α_p/2) and α_t-(α_p/2). To do so, each of these points was calculated using:

$$x_n = x_p(t) + v_{tp}(t) \cdot \Delta t \cdot \sin(\alpha_n) \quad (1)$$
$$y_n = y_p(t) + v_{tp}(t) \cdot \Delta t \cdot \cos(\alpha_n) \quad (2)$$

where y_p and x_p are the position of the player in a given point in time, v_{tp} is the total velocity of the player in a given point of time, Δt=0.04s is the time interval, α_n is one of the 200 angles defined as defined above, and x_n and y_n are the point of each n points of the coverage area. In case the velocity of the players were under 1.5 m/s value of v_{tp} was assume as 1.5. This was done because players even when not moving always cover some area of the field. If this value was not set to 1.5, players that were moving slowly will be measure as covering no space, which could be considered unrealistic as static players would cover no area.

After defining the coverage areas imaginary ‘coverage segments’ were painted from the player, passing through the set of points defined at the perimeter of the areas to the first sideline that these segments intersect with. In the case that any of these segments intersect with the potential passing line, the time that took the player to arrive at this passing line was calculated with a simple cross multiplication assuming the time the player took to arrive to any of the points define as above was 1 second. For the sake of simplicity in this work, it was assumed that players took the same time to travel through any of these possible segments. A passing opportunity was created when the time that defenders took to arrive at the passing line was bigger than the time the ball took to arrive at these same points (Spearman et. al., 2017).