PLANNING TRAINING WORKLOAD IN FOOTBALL USING SMALL-SIDED GAMES' DENSITY

SEBASTIEN SANGNIER,[1] **THIERRY COTTE,**[1] **OLIVIER BRACHET,**[2] **JEREMY COQUART,**[3] **AND CLAIRE TOURNY**[3]

[1]Association Sportive Saint-Etienne (A.S.S.E) French League 1 Elite Football Club, Saint-Etienne, France; [2]PLAYSHARP, Innovation, Performance, Analytics, Clermont-Ferrand, France; and [3]CETAPS EA3832, Research Center for Sports and Athletic Activities Transformations, University of Rouen, France

ABSTRACT

Sangnier, S, Cotte, T, Brachet, O, Coquart, J, and Tourny, C. Planning training workload in football using small-sided games density. *J Strength Cond Res* XX(X): 000–000, 2018—To develop the physical qualities, the small-sided games' (SSGs) density may be essential in soccer. Small-sided games are games in which the pitch size, players' number, and rules are different to those for traditional soccer matches. The purpose was to assess the relation between training workload and SSGs' density. The 33 densities data (41 practice games and 3 full games) were analyzed through global positioning system (GPS) data collected from 25 professional soccer players (80.7 ± 7.0 kg; 1.83 ± 0.05 m; 26.4 ± 4.9 years). From total distance, distance metabolic power, sprint distance, and acceleration distance, the data GPS were divided into 4 categories: endurance, power, speed, and strength. Statistical analysis compared the relation between GPS values and SSGs' densities, and 3 methods were applied to assess models (R-squared, root-mean-square error, and Akaike information criterion). The results suggest that all the GPS data match the player's essential athletic skills. They were all correlated with the game's density. Acceleration distance, deceleration distance, metabolic power, and total distance followed a logarithmic regression model, whereas distance and number of sprints follow a linear regression model. The research reveals options to monitor the training workload. Coaches could anticipate the load resulting from the SSGs and adjust the field size to the players' number. Taking into account the field size during SSGs enables coaches to target the most favorable density for developing expected physical qualities. Calibrating intensity during SSGs would allow coaches to assess each athletic skill in the same conditions of intensity as in the competition.

KEY WORDS soccer match, physical training integrated, professional team, physical qualities

INTRODUCTION

For the past few years, integrated physical training (the athletic training with ball in specific game situations in soccer including adversaries and partners) has been used as an alternative to athletic training without a ball. This type of training relies partly on small-sided games (SSGs) (11,23,24,41). Small-sided games are training games or matches in which the size of the pitch, the number of players, and the rules of the game are different to those for traditional soccer matches (19,20). By incorporating a ball and opponents (12,31), skill and fitness coaches can develop simultaneously technical, tactics, and physical skills (18,21,22,32). Studies have compared effects on development of physical qualities between interval training without a ball and training based on SSGs (27,41,44). For example, Reilly and White (41) compared these 2 modes of training on 18 young professional soccer players in the English premier league. They compared sprint interval training of 4 × 6 minutes at 85–90% of the maximum heart rate (HR_{max}) and active recovery at 50–60% HR_{max} to small-sided 5 v 5 games with the same time pattern for working and the same mode of recovery. The different physical performance tests showed similar evolutions that led the authors to conclude that the 2 modes of training were equally effective in terms of aerobic and anaerobic results. Another study, by Impellizzeri et al. (27) on 29 young Italian soccer players, compared the effects of different types of SSGs (3 v 3, 4 v 4, and 5 v 5) with aerobic interval training of 4 × 4 minutes at 90–95% HR_{max} and 3-minute active recovery at 60–70% HR_{max}. Apart from the time spent above 95% HR_{max}, the results showed no differences in terms of intensity (% HR_{max}, rating of perceived exertion [RPE], and concentration of lactate [La]) or progress (3% running economy for each group, and 8 and 7% of high maximal oxygen uptake [$\dot{V}O_2max$], respectively). The literature clearly demonstrated that SSGs could be used as an effective training mode to enhance aerobic fitness and match performance in soccer players.

Address correspondence to Dr. Claire Tourny, claire.tourny@univ-rouen.fr.

00(00)/1–11

Journal of Strength and Conditioning Research

Table 1. Regression models based on the selected GPS parameters.*†

GPS parameter	Best regression model (with no game data)	R^2	RMSE	AIC	p
D_Tot ($m\cdot min^{-1}$)	y = 19.243lnX − 5.029	0.873	6.965	281.504	<0.001
EEE ($kJ\cdot kg\cdot min^{-1}$)	y = 0.11lnX − 0.036	0.849	0.044	−133.934	<0.001
D_Mp ($m\cdot min^{-1}$)	y = 7.042lnX − 15.255	0.867	2.616	201.206	<0.001
#_Mp ($number\cdot min^{-1}$)	y = 0.001x + 0.024	0.605	0.051	−119.661	<0.001
D_Sprint ($m\cdot min^{-1}$)	y = 0.18x – 0.844	0.867	0.599	80.301	<0.001
#_Sprint ($number\cdot min^{-1}$)	y = 0.001x − 0.046	0.899	0.038	−144.745	<0.001
D_Acc ($m\cdot min^{-1}$)	y = 1.321lnX − 0.629	0.515	1.218	138.519	<0.001
#_Acc ($number\cdot min^{-1}$)	y = 0.212lnX − 0.230	0.562	0.178	−19.332	<0.001
D_Dec ($m\cdot min^{-1}$)	y = 1.157lnX − 0.418	0.469	1.17	135.258	<0.001
#_Dec ($number\cdot min^{-1}$)	y = 0.104lnX − 0.096	0.347	0.136	−41.200	<0.001

*GPS = global positioning system; RMSE = root-mean-square error; AIC = Akaike information criterion; EEE = estimated energy expenditure; CI = confidence interval.

†All the selected models were based on the data sets from training sessions. All the correlations are significant ($p < 0.05$). For linear model, the 95% CI is based on asymptotic normality. For nonlinear model, the 95% CI is based on second-order Taylor expansion and Monte Carlo simulation.

However, it was important to look at the results of these studies in detail, as a number of the parameters affecting the intensity of the SSGs differed from one study to another (39). Many studies had shown that HR_{max}, [La], and the RPE increased as the surface area of the pitch increases (23,29,36). The authors suggested that the increase in surface area of the pitch provided both more time for players to be in possession of the ball as well as forcing players who do not have possession to run greater distances to intercept the ball. Inversely, when the number of players increased, Rampinini et al. (39) noted a reduction in HR_{max}, [La], and RPE in all 4 types of SSGs (3 v 3, 4 v 4, 5 v 5, and 6 v 6). These authors were in agreement with a number of publications (13,25,35) which demonstrated that the fewer the players the greater the degree of intensity. All these studies had in common the fact that they examined the number of players and the surface area of play as separate parameters. It was also possible to combine these 2 parameters to examine the density of players per meter squared. This key concept consisted in calculating the theoretical surface area of play per individual by dividing the total surface area of play by the number of players. Little and Williams (31), in one of the few studies to look at the influence of the ratio of players per meter squared, use 6 combinations of different numbers of players and surface areas of play (≈100 vs ≈ 120 vs ≈ 190 m^2 per player). In this study, the physiological markers (HR and RPE) increased when the number of players and the surface area of play decreased. Hill-Hass et al. (26) confirmed these conclusions using a ratio of 150 m^2 per player for the 3 format of 3 v 3, 4 v 4, and 6 v 6. In a similar study, Casamichana and Castellano (5) looked at 3 other player densities (75, 175, and 275 m^2). These authors found that there was a significant difference between the SSGs of 75 m^2 and 275 m^2 for all but one of the variables considered (total distance covered, distance covered per minute of play, maximum speed reached, distance covered in each of the speed categories, the work-to-rest ratio, and sprint frequency), the exception being the distance covered at speeds <7 $km\cdot h^{-1}$. Although it was relevant to look at player density, these studies only investigated a small number of possible player ratios per meter squared. Yet, there was an enormous range of possible densities in the SSGs which could be varied throughout a season and depending on the trainer's objectives. Thus, knowing more about the evolution of these physiological parameters, regardless of the density, would increase our understanding of the physical demands of SSGs. The training load could be evaluated by HR (and [La]) because of numerous research had demonstrated that HR was a valid indicator representative of exercise intensity in soccer (14,26). However, there were several limitations when using HR in SSGs, Little and Williams (31) pointed out that HR underestimates high-intensity anaerobic activity in SSGs (2 v 2). Krustrup et al. (30) came to the same conclusion with respect to the weak correlation between [La] and intensity in SSGs. Also, the validity and reproducibility of parameters derived from global positioning system (GPS) to quantify the training load have been well recognized in the literature (3,9,28,30,31,45). The authors underlined the interest in accurately monitoring intensity by GPS during SSGs' drills intended for physical development to allow for the improvement of performance parameters.

Therefore, the main purpose of our study was to assess the relation between training workload and SSGs' density in soccer using GPS data to quantify workload. The hypothesis was that training workload was linked to SSGs' density. The second purpose of this study was to examine the relationship between models of physical qualities as a function of the density of SSGs and match. The

Table 2. Comparison between GPS parameters values recorded during games and those predicted by each regression model build from the SSG (±*SD*).*

GPS parameter	Recorded games' data			Average recorded value	Predicted value	Min	Max
D_Tot ($m\cdot min^{-1}$)	107.594 ± 8.25	108.280 ± 6.85	108.901 ± 9.17	108.258 ± 0.65	108.08	106.15	110.00
EEE ($kJ\cdot kg\cdot min^{-1}$)	0.610 ± 0.02	0.619 ± 0.04	0.610 ± 0.03	0.61 ± 0.01	0.61	0.60	0.62
D_Mp ($m\cdot min^{-1}$)	29.011 ± 5.42	31.019 ± 4.98	30.278 ± 5.17	30.102 ± 1.02	26.14	25.41	26.86
#_Mp ($number\cdot min^{-1}$)	0.255 ± 0.06	0.366 ± 0.10	0.245 ± 0.04	0.289 ± 0.07	0.32	0.27	0.37
D_Sprint ($m\cdot min^{-1}$)	5.164 ± 1.87	7.408 ± 1.73	6.217 ± 1.55	6.263 ± 1.23	5.51	4.96	6.06
#_Sprint ($number\cdot min^{-1}$)	0.413 ± 0.08	0.455 ± 0.06	0.391 ± 0.07	0.419 ± 0.03	0.43	0.40	0.47
D_Acc ($m\cdot min^{-1}$)	6.452 ± 1.05	7.513 ± 1.25	6.545 ± 1.02	6.837 ± 0.59	7.13	6.80	7.47
#_Acc ($number\cdot min^{-1}$)	0.867 ± 0.17	0.928 ± 0.13	0.805 ± 0.12	0.867 ± 0.06	1.02	0.97	1.06
D_Dec ($m\cdot min^{-1}$)	5.915 ± 1.03	7.109 ± 1.07	6.308 ± 1.04	6.444 ± 0.61	6.39	6.06	6.71
#_Dec ($number\cdot min^{-1}$)	0.509 ± 0.04	0.615 ± 0.25	0.48 ± 0.03	0.534 ± 0.07	0.52	0.48	0.56

*GPS = global positioning system; SSG = small-sided game; EEE = estimated energy expenditure.

hypothesis was to show that physical qualities extracted by GPS's data did not changing in proportion with the increase of the density per player.

Methods

Experimental Approach to the Problem

To review the assumptions of this study, during the period October to December of the 2015–2016 season, the physical performances have been examined during 65 SSGs and 3 friendly matches (in the same field and same conditions). In terms of analysis of these full-length matches, the physical performances were examined over 2 time periods: the average for the 8 first minutes, to equate to the SSGs; and the average for the whole match. The whole data recorded (by GPS) in match and in training (SSGs) with the same players were examined a posterior of the period of study.

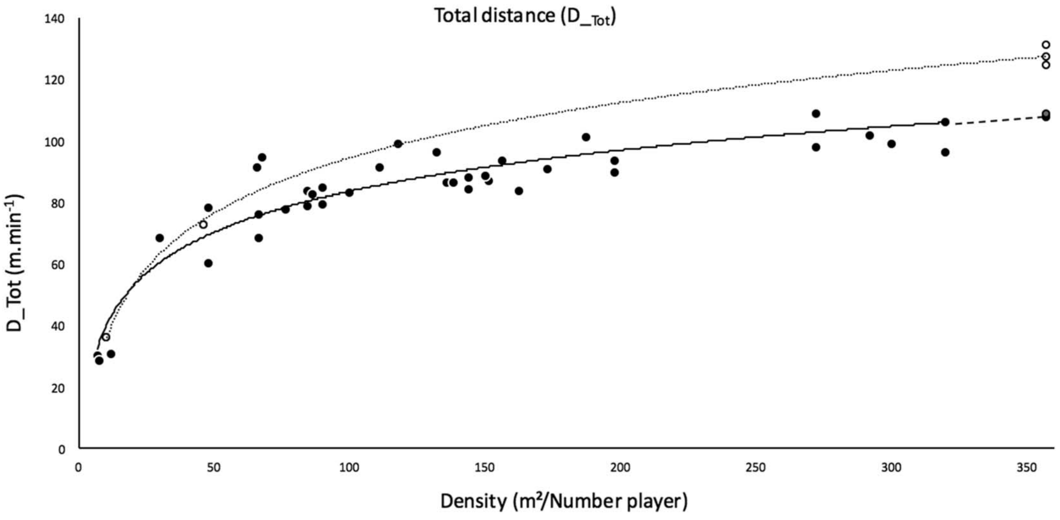

Figure 1. Total distance run per minute ($m\cdot min^{-1}$) as a function of the player density per meter squared in the SSGs (●), during the full 90-minute match (◉), and during the first 8 minutes of the match (○). ———Logarithmic regression model based on the performances of SSG, ··········logarithmic regression model based on the performances of the first 8 minutes of the match, and - - - - - -extrapolation of the regression models for the SSGs using match density. SSG = small-sided game.

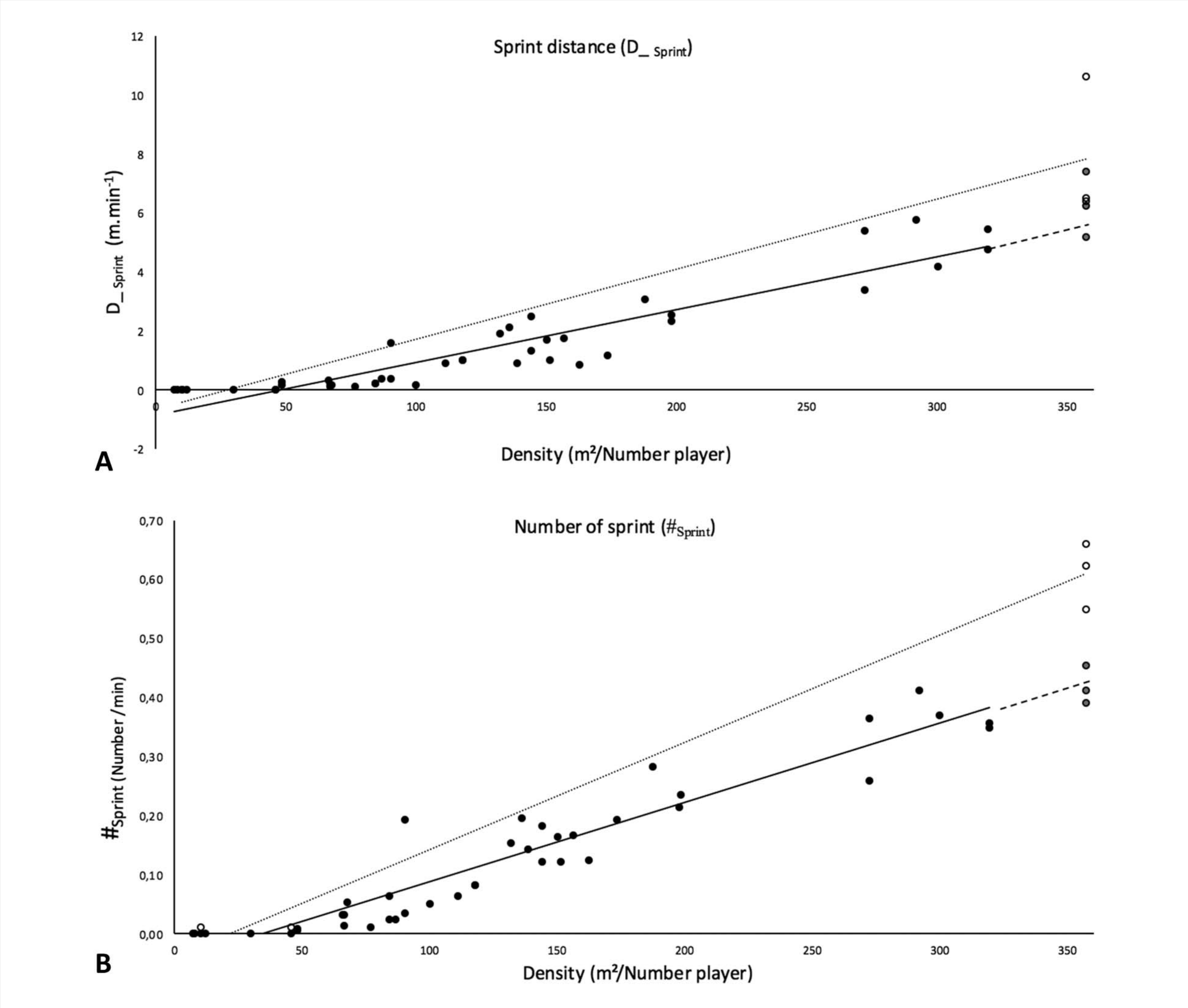

Figure 2. A) Sprint distance per minute ($m \cdot min^{-1}$); (B) number of sprints per minute ($n \cdot min^{-1}$) as a function of the player density per meter squared in SSGs (●), during the full 90-minute match (◎), and during the first 8 minutes of the match (○). ———Linear regression model based on the performance of SSG, ……………linear regression model based on the performances of the first 8 minutes of the match, and - - - - - -extrapolation of the regression models for the SSGs using match density. SSG = small-sided game.

Subjects

All the players belonged to the same team, which is in the professional French championship (league 1) and the European league. They were all professional players (mean ± *SD*, body mass: 80.7 ± 7.0 kg; height: 1.83 ± 0.05 m; age: 26.4 ± 4.9 years [age range: 19-32 years old]; and number of years' experience: 16.9 ± 3.4 years). Of the 25 recorder players, 11 were internationals. All subjects gave written consent to participate in the study, which was conducted in accordance with the University of Saint Etienne's ethical procedures and according to the Declaration of Helsinki.

Procedures

The study was conducted over a 3-month period all along the 2015–2016 competitive season. During this period, 65 SSGs were recorded. Available studies have shown that rules of the game (12,13) and coach encouragement (39,41,43,45) are among the factors that can modify physical responses during the SSG training drills. The different SSG training efforts, either intermittent or continuous, could have an impact on the game intensity. Finally, to control the impact of length of time of play (44), only those sequences of 8 minutes were kept for the SSGs. To monitor the time played, only SSGs with duration of 8 minutes with no intervention of the coach and no planned intervals for recess were considered. Thus, of 65 SSGs, 41 were selected for this article. Among them, 32 different densities were studied: 7, 8, 10, 12, 30, 46, 48, 66, 67, 76, 84, 86, 90, 100, 111, 117, 132, 136, 138, 144, 150, 151, 156, 162, 173, 187, 197, 198, 272, 291, 300,

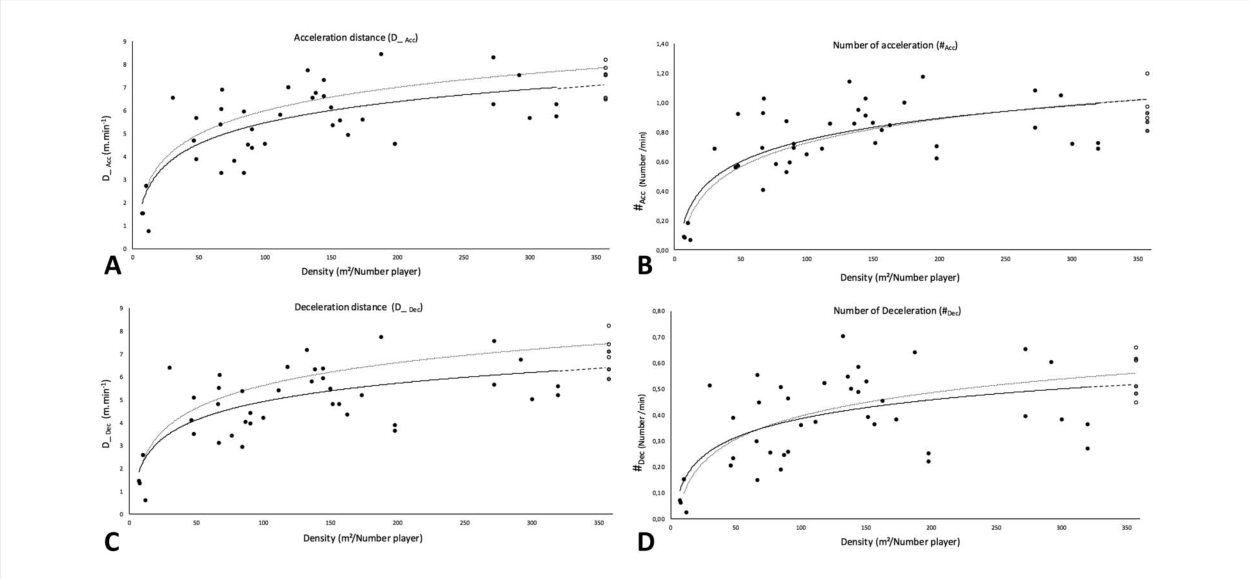

Figure 3. A) Acceleration distance per minute ($m \cdot min^{-1}$); (B) number of accelerations per minute ($n \cdot min^{-1}$); (C) deceleration distance per minute ($m \cdot min^{-1}$); and (D) deceleration distance per minute ($m \cdot min^{-1}$) as a function of the player density per meter squared in SSGs (●), during the full 90-minute match (◉), and during the first 8 minutes of the match (○). ———Logarithmic regression model based on the performance of SSG, ··········logarithmic regression model based on the performances of the first 8 minutes of the match, and - - - - - -extrapolation of the regression models for the SSGs using match density. SSG = small-sided game.

and 319 m^2. The player density was obtained as follows: (field length field width)/total number of playing players = density (m^2). All the games were scheduled at the same time of the day, at 10:00 AM

No time was deducted for free-kicks, corner kicks, or scored goals during the SSGs. Each time the ball went out of the field, it was thrown back in by an assistant coach and stoppage time related to major injury was not counted in the total duration of the training. Moreover, friendly games (density is 357 m^2) against European teams were analyzed in addition to the training sessions.

The data of 10 GPS variables used to quantify the external training load of professional soccer players were monitored and analyzed during 41 training and 3 games. Players' physical performances were assessed using GPS technology with an operational sampling frequency of 10 Hz (K-Gps; K-Sport, Montellabate, Italy). The GPS devices inserted into a purpose-built backpack positioned on the upper part of their backs. Castellano et al. (8) shown the validity and reproducibility of GPS device (Minimax v4.0, Catapult Innovations, Melbourne, Australia); these GPS had the same sampling frequency of 10 Hz as GPS used in our study. All data were converted to a 1-minute baseline as a reference for comparison. The recorded GPS data were downloaded from K-Sport to Playsharp data analytics platform (Innovation Performance Analytics, version 2.1.1, Clermont-Ferrand, France). The recorded data were included and classified into 4 categories of parameters: endurance, power, speed, and strength.

Endurance or metabolic parameters aerobically dominated, corresponding to total distance (D_Tot) covered per minute by the player and to estimated energy expenditure (EEE). Estimated energy expenditure was calculated by multiplying metabolic power (MP) by time. Metabolic power is a measure of the overall amount of energy required, per unit of time, to reconstitute the ATP used for work performance. The product of the instantaneous velocity (v, $m \cdot s^{-1}$) and the corresponding energy cost per unit body mass and distance (Cr, $J \cdot kg^{-1} \cdot m^{-1}$), as obtained from the acceleration (and hence the equivalent slope), yields the instantaneous MP ($W \cdot kg^{-1}$) necessary to run at the required speed. Power or metabolic parameters anaerobically dominated, corresponding to distance MP (D_Mp): Total distance covered at high MP ($>20\ W \cdot kg^{-1}$) and the number of MP (#_Mp) defined as number of times the player passes the high MP threshold of $20\ W \cdot kg^{-1}$ and maintains this MP for at least 0.4 seconds. Speed parameters corresponding to sprint distance (D_Sprint) covered at high-intensity speed ($>21\ km \cdot h^{-1}$) and to number of sprints (#_Sprint) defined as the number of times the player passes $21\ km \cdot h^{-1}$ and maintains this speed for at least 0.5 seconds. Strength parameters corresponding to the acceleration distance (D_Acc) covered with acceleration above $+2\ m \cdot s^{-2}$; to the number of accelerations (#_Acc) defined as number of time the player passes $+3\ m \cdot s^{-2}$ and maintains this value for at least 0.4 seconds; to deceleration distance (D_Dec) covered with acceleration above $-2\ m \cdot s^{-2}$; and to number of decelerations (#_Dec) defined as number of time the player passes $-3\ m \cdot s^{-2}$ and maintains this value for at least 0.4 seconds. Acceleration and deceleration were defined according to Samozino et al. (42) to access the strength parameters.

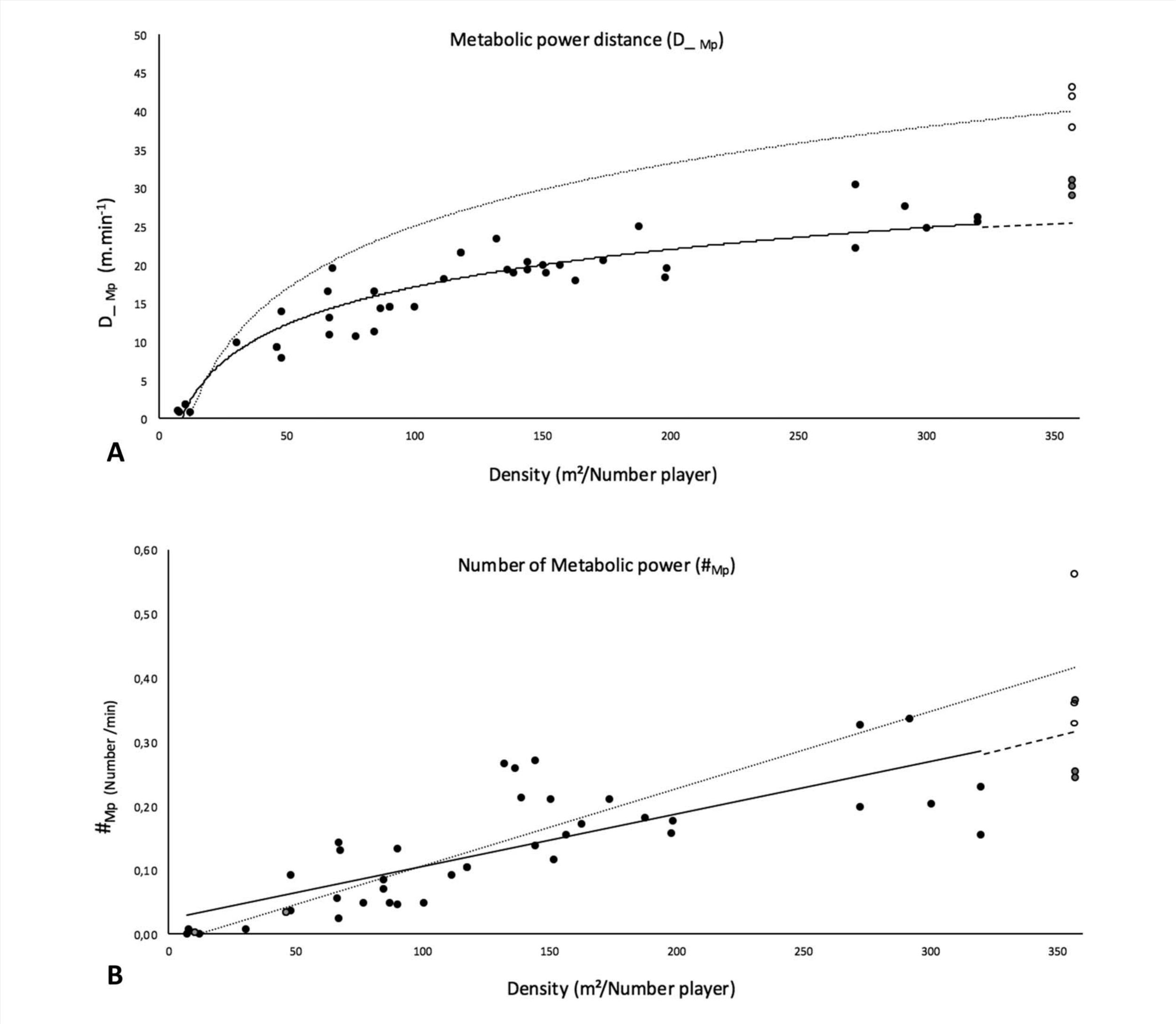

Figure 4. A) Distance of metabolic power per minute ($m \cdot min^{-1}$); as a function of the player density per meter squared in SSGs (●), during the full 90-minute match (◉), and during the first 8 minutes of the match (○). ———Logarithmic regression model based on the performance of SSG, ··········logarithmic regression model based on the performances of the first 8 minutes of the match, and - - - - - - -extrapolation of the regression models for the SSGs using match density. B) Number of MP per minute ($m \cdot min^{-1}$); as a function of the player density per meter squared in SSGs (●), during the full 90-minute match (◉), and during the first 8 minutes of the match (○). ———Linear regression model based on the performance of SSG, ··········Linear regression model based on the performances of the first 8 minutes of the match, and - - - - - - -extrapolation of the regression models for the SSGs using match density. SSG = small-sided game; MP = metabolic power.

Statistical Analyses

First, to analyze the correlation between the GPS values and the density, the statistical analysis has tested the following models: linear, polynomial of second degree, power, exponential, and logarithmic models. Three common statistical methods were used to compare and to choose between the regression models. Three statistical methods were used to compare and to assess models using: an approximation of R-squared (R^2), the root-mean-square error (RMSE), and the Akaike information criterion (AIC).

The selected regression model was the one with the strongest R^2 and the weakest RMSE and AIC. The statistical significance has been searched to validate the relationship between GPS values and density. The statistical significance was checked using the F test with the significance level set to $\alpha < 0.05$. This selected model was used to predict GPS values including confidence interval (CI) for games density. As a next step, the selected regression model helped to predict the outcome of each GPS parameter in game situation, i.e., a 357 m^2 density per player. For each GPS variable, the model predicted with a CI of 95% (CI). Finally, the model's performance was assessed by comparing actual GPS data recorded during games and results predicted from the model. All data for the statistical analyze were retrieved from

Table 3. Density (square meters per number of players) of the SSG required to allow a level of game intensity which will meet the expected development of physical qualities of force, endurance, speed, and power.*†

% of game intensity	Density for endurance development (m^2/N° players)	Ex. of field for 6 v 6	Density for power development (m^2/N° players)	Ex. of field for 6 v 6	Density for speed development (m^2/N° players)	-Ex. of field for 6 v 6	Density for force development (m^2/N° players)	Ex. of field for 6 v 6
85	155	38 × 49	225	45 × 59	347	56 × 74	115	33 × 42
75	90	29 × 38	160	38 × 50	250	48 × 63	70	25 × 33
65	50	21 × 28	125	34 × 44	220	45 × 59	45	20 × 27
50	25	15 × 20	85	28 × 36	160	38 × 50	20	14 × 18

*SSG = small-sided game.
†Example of SSG field for 6 vs 6 players.

the Playsharp data analytics platform. The statistical computing and graphics were performed using cran R software.

Results

The results of this study have shown that there was a positive correlation between the surface density per player during SSGs and the different parameters recorded by GPS (Table 1). The results have not revealed that all the physical parameters evolved after the same regression model (Table 1), nor were they all proportional to the increase in density of the game.

Logarithmic regression model could be used to represent the evolution of the total distance covered ($R^2 = 0.873$), the distance MP ($R^2 = 0.867$), and the energy expenditure ($R^2 = 0.849$) as a function of the density. These 3 R^2 values showed a high correlation between each of these parameters and the player density for SSGs. Concerning acceleration ($R^2 = 0.515$) and deceleration ($R^2 = 0.469$) distances, the number of accelerations ($R^2 = 0.562$) and decelerations ($R^2 = 0.347$), their R^2 values were all below 0.57, which meant that up to 57% of the variation from these parameters could be explained by these models. Table 2 shows that the data recorded during the games were within the CIs predicted by the models, except for the number of accelerations and the distance MP. The models predicted a number of accelerations per minute between 0.97 and 1.06, whereas the recorded average match performance was 0.87 accelerations per minute. Concerning the distance MP, the model forecasted performances between 25.4 and 26.9 meters per minute, whereas the recorded average was 30.1 meters per minute.

The sprint distance and the number of sprints could be represented by a linear regression model. These 2 parameters had a very strong correlation, with $R^2 = 0.898$ and 0.900, respectively. Finally, if the MP value was fitted to the same linear regression model, its $R^2 = 0.605$ is termed strong. The comparison between the predicted values, from recordings of the SSGs, with values recorded during the matches indicated that the different regression models provided valid means of predicting match performance, apart from the MP number, where the model predicted values between 0.19 and 0.26 when the average values recorded during a match was 0.29 (Table 2).

Figure 1 represents the logarithmic evolution of the total covered distance, in meters per minute ($m \cdot min^{-1}$), as a function of the player density in the SSGs, the entire game (gray-filled circles) and the 8 first minutes of the 3 recorded games (open circles). We could see that the total covered distances during the 8 first minutes were 20% higher than the ones from the entire games. It showed that the SSGs did not reproduce the start of a game. The dotted line represents the required rhythm that needs to be achieved during the different densities of SSG in order for the logarithmic model to be correlated with the maximum intensity recorded during a game.

Figure 2 shows the sprint distance per minute (Figure 2A) and the number of sprints per minute (Figure 2B) as a function of the player density per m^2 during the SSGs and games. The distance and the number of sprints had a positive linear correlation with the player density per m^2. This regression line showed that SSGs with a player density of less than 50 m^2 did not produce a sprint distance. On the other hand, the frequency of sprints for the first 8 minutes of the matches was 30% higher than the average for the entire match. The dotted line represents the required rhythm that needs to be achieved during the different densities of SSG in order for the linear model to be correlated with the maximum intensity recorded during a game.

Figure 3 shows a logarithmic evolution of the accelerations (Figure 3A, B) and decelerations (Figures 3C, D) of players as a function of the player density in the SSGs and during the games. It should be noted that there was no significant difference between the number of accelerations and decelerations for the overall match average and those for the first 8 minutes of the match.

Figure 4 shows that the distance of MP (Figure 4A) followed a logarithmic regression curve, whereas the number of MP actions (Figure 4B) followed a linear regression. Although the match average lied along the model regression line, the frequency of actions and the distance sustained at the metabolic level under predominantly anaerobic or power conditions was much higher in the average of the first 8 minutes of the match compared with the SSGs (+30% vs. match). The dotted line represents the required rhythm that needs to be achieved during the different densities of SSG in order for the logarithmic and linear models to be correlated with the maximum intensity recorded during a game.

Table 3 presents the number of players per m^2 needed to achieve a certain percentage of the intensity of the match. Thus, for example, to attain 85% of the intensity of the match, a density of 225 m^2 per player was needed to target development of speed, and only 155 m^2 to target development of aerobic qualities.

DISCUSSION

The purpose of the current study was to identify that training load evolved as a function of the surface area of play for the SSGs and the number of players involved. Therefore, to focus on the increasingly exacting constraints of match conditions, the SSGs integrated into the physical training of players had to address either match situations or the training of players in terms of developing a specific physical component (power, strength, speed, and endurance). This study served as a means of directing the trainer toward the most appropriate combinations for achieving their objectives and helps them draw up a training schedule. In practical terms, the study demonstrates that to achieve an objective on the 4 targeted physical components, the player density in the SSGs is different. For example, to reach 85% of game intensity, players should play SSGs of 115 m^2 to develop strength, whereas they should play SSGs of 150, 225, and 280 m^2 to develop endurance, power, and sprint, respectively.

In addition to determining the player densities in the SSGs to target specific training objectives, this study also made it possible to predict the workload ahead of training. This evaluation of the training load was indispensable both in terms of optimizing the players' performances by avoiding undertraining through conditions which were too far removed from those of matches, as well as preventing overtraining and injuries. Using GPS to construct models was innovative because these data took into consideration the external training load imposed on players by the action on the pitch as opposed to many SSGs that have been analyzed using biological markers or RPE (4,10,31,38). This type of analysis was used to evaluate HR$_{max}$, [La], and RPEs, which have been shown to be limited in terms of their application to professional soccer. Little and Williams (31) showed that using the HR as a marker resulted in an underestimation of the training load imposed on players during anaerobic drills. In addition, Borg (4) highlighted that, since 1982, RPE may be used as a reliable indicator of physical activity. Nevertheless, although different studies (10,28) considered RPE as a good general indicator of intensity, it was difficult to measure the sincerity of players' responses (1), as competition between them and economic interests could prevail over it. Given these limits, these indicators seemed to be insufficient or difficult to use to quantify the training load during specific soccer activities. Therefore, this study focused on parameters of external load recorded by GPS. The results have shown that it was possible to establish regression models that were representative of the evolution of movement parameters with respect to the player density of SSGs. However, not all the physical components evolved in the same way or with the same ratios relative to an increase in player density.

The indicators of the volume of training load such as total distance run and estimated energy expended could reach, for the same player density as in matches, 108 $m \cdot min^{-1}$ and 0.609 $KJ \cdot kg^{-1} \cdot min^{-1}$, respectively. These results were in agreement with those found in the literature for total distance run per minute, with Pereira et al. (37) finding similar results for the Brazilian U20 team, and Casamichana et al. (6) for Spanish semi-professionals. When the surface area of the pitch was reduced, this study showed that the total distance run and the EEE decreased. This evolution was in agreement with the findings of Casamichana and Castellano (5) who found a decrease in distance run to 125, 113, and 87 m per minute, respectively, for player densities of 273, 175, and 74 m^2 per player. These results were between 10 and 20% higher than the performances of our chosen population, despite the latter being of a higher level. This could be explained by the difference in age between the 2 populations. Pereira Da Silva et al. (37) have shown that the under 15-second run was significantly more than the under 20 seconds (118 vs. 109 $m \cdot min^{-1}$). This difference could be partly explained by better technical mastery and tactical organization.

However, looking in detail at only 3 player densities, Casamichana and Castellano (5) could not predict the total distance run for all the other player densities. The results of our study showed that the reduction in total distance run per minute and the EEE followed a logarithmic regression curve. This information allowed the training load to be calibrated with respect to a match, and in addition, this can be performed for any player density in SSGs. For example, to obtain 85% of the match intensity (92 m per minute), the density of the SSGs game should be around 155 m^2 per player, which was only 40% of the match density. Although the physical parameters cited above were indicators of the volume of SSGs and matches, other features, such as sprint distance, accelerations, decelerations, and MP were indicators of the intensity of training.

In terms of sprints, increasing the number of meters squared per player provided more space, which in turn favored longer, high-intensity sprints. This increase followed a linear regression both for the number and distance of the sprint. Thus, in contrast to the parameters for the training load, a player density of 280 m^2 was needed to attain 85% of the match intensity. During the 3-month period of this study, the trainers only chose 3 SSGs which exceeded this player density. As a result, during this time, the anaerobic lactate process was not at all, or very little solicited by this type of workout, at least compared with the requirements of match conditions. These results backed the findings of Gabbett and Mulvey (18) highlighted that, in women's soccer, SSGs stimulated all the movement patterns found in international competitions, with the exception of those linked to the demands of high-intensity movements and repeated sprints. Casamichina et al. (6) confirmed the existence of significant differences between friendly matches and SSGs for almost all the repeated-sprint variables. These authors concluded that SSGs should have been mainly used to develop aerobic qualities and tactical skills. However, it was not impossible to stimulate the demands of high intensity and repeated sprints to a sufficient degree, although our study revealed that during the study period, the necessary player density to achieve a high percentage of the match intensity was rarely chosen by the trainers. These results should have been used to raise trainers' awareness about the choice of player density for SSGs to achieve specific physiological performance objectives (43).

Finally, the results of this study showed that the acceleration, deceleration, and MP parameters followed logarithmic regression curves, with the exception of the number of MP events, which followed a linear regression. Castellano et al. (7) found a frequency of around 0.6 accelerations per minute for a player density of 210 m^2. These results are lower than in our study, which found a frequency of 0.9 accelerations per minute for the same player density. The explanation for this discrepancy was probably due to the difference in level of play between semi-professionals and professionals. Apart from the study by Castellano et al. (7), few studies have looked at these parameters for high-intensity activity. This might have seemed surprising given that Osgnach et al. (34) have shown that energy used by this type of action accounts for more than 20 $W \cdot kg^{-1}$, equivalent to 42% of the total energy budget for the match. The low utilization and interpretation of this parameter was probably partly due to the modest correlation of this parameter with the player density of SSGs (0.562 and 0.347 for the number of accelerations and decelerations, respectively). Hypothetically, one could postulate that accelerations and decelerations happened mainly in the area of the pitch containing the ball when players moved toward the person controlling the ball, or when moving away from an opponent. In addition, with the exception of the distance of MP and the number of accelerations, the average match intensities for all the physical parameters correlated with the mathematical models based on the SSGs. The results of this study were not intended to predict match performance in competitions, which is affected by other factors (e.g., score and choice of tactics). However, these results indicated that the average intensity of the match followed the mathematical model based on the training session recordings. On the other hand, comparison of the data per minute for the first 8 minutes of the match with the SSGs, apart from the number of accelerations and decelerations, showed that they cannot be used to predict the data for the start of a match. This new information comparing intensity data from the start of the match with the average data for the match should be taken into consideration by coaches and physical trainers in deciding the amount and load of training. Thus, the data for the SSGs for each physical parameter could be expressed with respect to the intensity at the start of a match (in other words be considered as a reference for the maximum intensity attainable during a game) and with respect to the average intensity for the entire match.

PRACTICAL APPLICATIONS

The results of this study show that there is a relationship between the physical performance and the density of the pitch surface area per player in SSGs. It is thus possible to construct regression models for all the physical parameters as a function of player density in SSGs. In the first place, this research offers practitioners fresh insight that should enable the resultant training load of SSGs to be anticipated. For example, using the regression models, it is possible to see that a 10-minute 7 v 7 game on a pitch 40 m × 52 m (providing a player density of 150 m^2) is equivalent to around 760 m total distance run, 40 m sprint, 40 m acceleration, 34 m deceleration, and 160 m MP. This objective prediction is of major importance in quantifying the training load and consequently in avoiding overtraining. Second, by inverting this reasoning, these new data should make it possible to choose the most appropriate player density for the development of a target physical quality during integrated physical training. Thus, thanks to this innovative information, coaches and physical trainers can achieve the target training load by altering objective parameters such as the size of the pitch, the number of players, and the length of play. For example, to develop speed capacity, the player density should be around 280 m^2, which is equivalent to a pitch size of 55 m by 72 m for a total of 14 players. Finally, by knowing the intensity of the match as well as the maximum intensity at the start of the match for each of the physical parameters, the trainers are able to calibrate the training load with respect to the intensity of the match and the day of training. Working at 85% of the match intensity in terms of the parameter linked to anaerobic metabolism (power) requires a player density of 225 m^2, which is equivalent to 49 m by 64 m for a 7 v 7 game. This calibration provides the best conditions for the players to prepare for the rigors of a match.

REFERENCES

1. Alexiou, H and Coutts, AJ. A comparison of methods used for quantifying internal training load in women soccer players. *Int J Sports Physiol Perform* 3: 320–330, 2008.
2. Atli, H, Köklü, Y, Alemdaroğlu, U, and Koçak, FU. A comparison of heart rate response and frequencies of technical actions between half-court and full-court 3-a-side games in female high school basketball players. *J Strength Cond Res* 27: 352–356, 2013.
3. Barbero-Alvarez, JC, Coutts, AJ, Granda, J, Barbero-Alvarez, V, and Castagna, C. The validity and reliability of a Global Positioning Satellite system device to assess speed and repeated sprint ability (RSA) in athletes. *J Sci Med Sport* 13: 232–235, 2010.
4. Borg, G. Psychophysical basis of perceived exertion. *Med Sci Sports Exerc* 14: 377–381, 1982.
5. Casamichana, D and Castellano, N. Time–motion, heart rate, perceptual and motor behavior demands in small-sides soccer games: Effects of pitch size. *J Sports Sci* 28: 1615–1623, 2010.
6. Casamichana, D, Castellano, J, and Castagna, C. Comparing the physical demands of friendly matches and small-sided games in semiprofessional soccer players. *J Strength Cond Res* 26: 837–843, 2012.
7. Castellano, J, Casamichana, D, and Dellal, A. Influence of game format and number of players on heart responses and physical demands in small-sided soccer games. *J Strength Cond Res* 27: 1295–1303, 2013.
8. Castellano, J, Casamichana, D, Calleja-Gonzalez, J, Roman, JS, and Ostojic, SM. Reliability and Accuracy of 10 Hz GPS devices for short-distance exercise. *J Sports Sci Med* 10: 233–234, 2011.
9. Coutts, AJ and Duffield, R. Validity and reliability of GPS devices for measuring movement demands of team sports. *J Sci Med Sport* 13: 133–135, 2010.
10. Coutts, AJ, Rampinini, E, Marcora, SM, Castagna, C, and Impellizeri, FM. Heart rate and blood lactate correlates of perceived exertion during small sided soccer games. *J Sci Med Sport* 12: 79–84, 2009.
11. Dellal, A, Chamari, K, Pintus, A, Girard, O, Cotte, T, and Keller, D. Heart rate responses during small-sided games and short intermittent running training in elite soccer players: A comparative study. *J Strength Cond Res* 22: 1449–1459, 2008.
12. Dellal, A, Hill-Haas, S, Lago-Penas, C, and Chamari, K. Small sided games in soccer: Amateur vs. professional players' physiological responses, physical and technical activities. *J Strength Cond Res* 25: 2371–2381, 2011.
13. Dellal, A, Jannault, R, Lopez-Segovia, M, and Pialoux, V. Influence of the numbers of players in the heart rate responses of youth soccer players within 2 vs. 2, 3 vs. 3 and 4 vs. 4 small-sided games. *J Hum Kinet* 28: 107–114, 2011.
14. Drust, B, Reilly, T, and Cable, N. Physiological responses to laboratory-based soccer-specific intermittent and continuous exercise. *J Sports Sci* 18: 885–892, 2000.
15. Edgecomb, S and Norton, K. Comparison of global positioning and computer-based tracking systems for measuring player movement distance during Australian soccer. *J Sci Med Sport* 9: 25–32, 2006.
16. Esposito, F, Impellizzeri, FM, Margonato, V, Vanni, R, Pizzini, G, and Veicsteinas, A. Validity of heart rate as an indicator of aerobic demand during soccer activities in amateur soccer players. *Eur J Appl Physiol* 93: 167–172, 2004.
17. Fanchini, M, Azzalin, A, Castagna, C, Schena, F, Mcall, A, and Impellizzeri, FM. Effect of bout duration on exercise intensity and technical performance of small-sided games in soccer. *J Strength Cond Res* 25: 453–458, 2011.
18. Gabbett, T and Mulvey, M. Time-motion analysis of small-sided training games and competition in elite women soccer players. *J Strength Cond Res* 22: 543–552, 2008.
19. Gabbett, T, Jenkins, D, and Abernethy, B. Game-based training for improving skill and physical fitness in team sport athletes. *Int J Sports Sci Coach* 4: 273–283, 2009.
20. Gabbett, T. Skill-based conditioning games as an alternative to traditional conditioning for rugby league players. *J Strength Cond Res* 20: 309–315, 2006.
21. Gamble, P. A skill-based conditioning games approach to metabolic conditioning for elite rugby soccer players. *J Strength Cond Res* 18: 491–947, 2004.
22. Gregson, W and Drust, B. The physiology of soccer drills. *Insight* 3: 1–2, 2000.
23. Hill-Haas, S, Coutts, A, Rowsell, G, and Dawson, B. Generic versus small-sided game training in soccer. *Int J Sports Med* 30: 636–642, 2009.
24. Hill-Haas, SV, Dawson, B, Impellizzeri, FM, and Coutts, AJ. Physiology of small-sided games training in soccer: A systematic review. *Sports Med* 41: 199–220, 2011.
25. Hill-Haas, SV, Dowson, BT, Coutts, AJ, and Rowsell, GJ. Time motion characteristics and physiological responses of small-sided games in elite youth players: The influence of player number and rule changes. *J Strength Cond Res* 24: 2149–2156, 2010.
26. Hill-Haas, SV, Rowsell, G, Dawson, BT, and Coutts, AJ. Acute physiological responses and time-motion characteristics of two small-sided training regimes in youth soccer players. *J Strength Cond Res* 23: 111–115, 2009.
27. Impellizzeri, FM, Marcora, S, Castagna, C, Reilly, T, Sassi, A, Laia, FM, and Rampini, E. Physiological and performance effects of generic versus specific aerobic training in soccer players. *Int J Sports Med* 27: 483–492, 2006.
28. Impellizzeri, FM, Rampinini, E, Coutts, AJ, Sassi, A, and Marcora, SM. Use of RPE based training load in soccer. *Med Sci Sports Exerc* 36: 1042–1047, 2004.
29. Kennett, DC, Kempton, T, and Coutts, JA. Factors affecting exercise intensity in rugby-specific small-sided games. *J Strength Cond Res* 26: 2037–2042, 2012.
30. Krustrup, P, Mohr, M, Steensberg, A, Bencke, J, Kjaer, M, and Bangsbo, J. Muscle and blood metabolites during a soccer game: Implications for sprint performance. *Med Sci Sports Exerc* 38: 1165–1174, 2006.
31. Little, T and Williams, G. Measures of exercise intensity during soccer training drills with professional soccer players. *J Strength Cond Res* 21: 367–371, 2007.
32. Little, T. Optimizing the use of soccer drills for physiological development. *Strength Cond J* 31: 1–8, 2009.
33. Macleod, H, Morris, J, Nevill, A, and Sunderland, C. The validity of a nondifferential global positioning system for assessing player movement patterns in field hockey. *J Sports Sci* 27: 121–128, 2009.
34. Osgnach, C, Poser, S, Bernardini, R, Rinaldo, R, and Di Prompero, PE. Energy cost and metabolic power in elite soccer: A new match analysis approach. *Med Sci Sports Exerc* 42: 170–178, 2010.
35. Owen, A, Twist, C, and Ford, P. Small-sided games: The physiological and technical effect of altering pitch size and player numbers. *Insight* 7: 50–53, 2004.
36. Owen, A, Wong, DP, McKenna, M, and Dellal, A. Heart rate responses and technical comparison between small vs. large sided games in elite professional soccer. *J Strength Cond Res* 25: 2104–2110, 2011.
37. Pereira Da Silva, N, Kirkendall, DT, and Barros, TL. Movement patterns in elite Brazilian youth soccer. *J Sports Med Phys Fitness* 47: 270–275, 2007.
38. Petersen, C, Pyne, D, Portus, M, and Dawson, B. Validity and reliability of GPS units to monitor cricket-specific movement patterns. *Int J Sports Physiol Perform* 4: 381–393, 2009.

39. Rampinini, E, Impellizzeri, FM, Castagna, C, Abt, G, Chamari, K, Sassi, A, and Marcora, SM. Factors influencing physiological responses to small-sided soccer games. *J Sports Sci* 25: 659–666, 2007.
40. Rampinini, E, Sassi, A, Morelli, A, Mazzoni, S, Fanchini, M, and Coutts, AJ. Repeated-sprint ability in professional and amateur soccer players. *Appl Physiol Nutr Metab* 34: 1048–1054, 2009.
41. Reilly, T and White, C. Small-sided games as an alternative to interval training for soccer players. *J Sports Sci* 22: 559, 2004.
42. Samozino, P, Rabita, G, Dorel, S, Slawinski, J, Peyrot, N, Saez de Villarreal, E, and Morin, JB. A simple method for measuring power, force, velocity properties, and mechanical effectiveness in sprint running. *Scand J Med Sci Sports* 26: 648–658, 2016.
43. Sampaio, J, Garcia, G, Macas, V, Ibanez, SJ, Abrantes, C, and Caixinha, P. Heart rate and perceptual responses to 2 x 2 and 3 x 3 small-sided youth soccer games. *J Sports Sci Med* 6(Suppl 10): 121–122, 2007.
44. Sassi, R, Reilly, T, and Impellizzeri, FM. A comparison of small sided games and interval training in elite professional soccer players [abstract]. *J Sports Sci* 22: 562, 2004.
45. Townshend, A, Worringham, C, and Stewart, I. Assessment of speed and position during human locomotion using nondifferential GPS. *Med Sci Sports Exerc* 40: 124–132, 2008.