Decomposing the variability of match physical performance in professional soccer: Implications for monitoring individuals

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Abstract

The aims of this study were to establish sources of variability in match physical performance of professional soccer players and provide a method for monitoring individual between-match changes. Eleven players meeting the final inclusion criteria were monitored through an entire in-season competition phase (n = 240 individual match observations). Ten Hertz global positioning systems were used to measure match total distance (TD), total high-speed running distance (≥21 km·h⁻¹; HSRD), total accelerations (TAcc) and maximum running velocity (Vmax). Between-player, between-position, between-match and within-player variability were determined through linear mixed effects models. These data were then used to establish the practical significance of individual changes using a Minimum Effects Testing framework. All sources of variability were greater for HSRD (13–36%) when compared with all other metrics (<6%). Using combined between-match and within-player variability along with the smallest worthwhile change (0.2 × between-player SD), between-match individual changes of ±10–15% in TD, TAcc and Vmax were established as practically significant. For HSRD, these thresholds were considerably higher (≥60%). In conclusion, the ability for soccer practitioners to identify meaningful changes in match physical performance can aid decision making around player management following competition. Our study provides a method to flag changes beyond the normal match-to-match variability and by a substantial magnitude. This may have implications for recovery but should be combined with other sources of data (internal load and response) and used only as an adjunct to practitioner domain knowledge/experience.

Keywords: Team sport, match performance, competition, game analysis

Highlights

1. The ability for soccer practitioners to identify meaningful changes in match physical performance has the potential to aid decision making around player management following competition.
2. Through decomposing the variability of match physical performance and using a minimum effects testing framework, this study is the first to apply a probabilistic method for monitoring individuals in professional soccer.
3. The main finding was that after accounting for seasonal trends and inter-position heterogeneity, between-match individual changes of ±10–15% in representative GPS-derived measures of match physical performance (TD, TAcc and Vmax) can be considered practically significant. This was with the exception HSRD, where thresholds were considerably higher (≥60%).

Introduction

In recent years, load monitoring in sport has evolved through the increasing use of Global Positioning Systems (GPS) (Cummins, Orr, O’Connor, & West, 2013; Linke, Link, & Lames, 2018; Rojas-Valverde, Gómez-Carmona, Gutiérrez-Vargas, & Pino-Ortega, 2019). Current GPS allows the measurement of velocity and acceleration through doppler-derived methods, which allow the quantification of external training and competition loads such as distance covered, the count of efforts and identification of peak speed (Buchheit & Simpson, 2017; Oliva-Lozano, Fortes, & Muyor, 2020; Oliva-Lozano, 2019).
The aims of our study were therefore twofold. We first aimed to provide a comprehensive breakdown of the variability in match physical performance of professional soccer players, including seasonal trends, variability between positions, players, and matches, and within players. Secondly, we aimed to apply a minimum effects testing framework for interpreting practically meaningful individual changes in soccer match physical performance.

Materials and methods

Study design

A cohort study was conducted in a professional soccer team from LaLiga123 during 2018–2019 season. The team played a total of 42 official matches (21 home matches and 21 away matches). Every match was played on natural grass fields with a 4–4–2 playing formation. The length of between-match microcycles varied from 3 to 9 days. The club authorized the data collection and this study was approved by the Bioethics Committee of the university.

Subjects

An initial sample of 14 professional soccer players was monitored over a single in-season phase (n = 515 individual match observations). Goalkeepers were not included in the analysis, given their vastly different match activity-demands (Oliva-Lozano, Gómez-Carmona, et al., 2020), and players were categorized as central defenders, full-backs, midfielders, wide-midfielders, and forwards. In an attempt to provide a representative seasonal profile of match external load, we elected to only include players who: (a) completed the total duration of each match, (b) played at least 5 matches during the season, and (c) had at least one match observation in each trimester of the season (to avoid range effects). The final sample, therefore, included 240 individual match observations from 11 players (age: 28 ± 3 years; height: 180.9 ± 4.8 cm; body mass: 74.9 ± 4.1 kg; central defenders, n = 3 [67 individual match observations]; full-backs, n = 2 [42]; midfielders, n = 2 [48]; wide-midfielders, n = 2 [45]; forwards, n = 2 [38]). The median (range) number of match observations per player was 21 (15–31).

Procedures

Selection of match external load metrics. Given the amount of plausible external load metrics that can be used to represent the physical performance profile of professional soccer players (Haddad et al.,...
2018; Miñano-Espin, Casáis, Lago-Peñas, & Gómez-Ruano, 2017; Trewin, Meylan, Varley, & Cronin, 2018), we opted for a parsimonious selection that would explain the most information through the least number of variables. Previous investigations employing dimension reduction techniques have suggested that 70% of the variance in soccer match external loads can be expressed by four principle components, each containing 2–4 variables (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, Fortes, & Pino-Ortega, 2020b). Variables within a given component are thought to be similar (i.e. highly correlated and interchangeable), while components themselves provide different information (i.e. uncorrelated and unique). We, therefore, used a combination of both the previously reported component loadings (where a greater loading indicates a higher importance to the component) and our professional judgment to select four match external load indicators. These were total distance (TD), total high-speed running distance (≥ 21 km·h⁻¹; HSRD), total accelerations (TAcc) and maximum running velocity ($V_{\text{max}}$).

**Instruments.** Every player was given a WIMU Pro device (RealTrack Systems, Almeria, Spain) in order to collect physical performance variables. The device was placed on a vertical position in the back pocket of a specific chest vest (Rasán, Valencia, Spain). This device is considered as an electronic performance tracking system which mainly consists of 3D accelerometers, gyroscopes, and magnetometers as well as positioning sensors through 10 Hz Global Positioning System (GPS). These GPS are have demonstrated good criterion validity (bias in mean velocity: 1.18–1.32 km·h⁻¹; bias in distance: 2.32–4.32 m) and reliability (intraclass correlation coefficients: above 0.93) for the collection of physical performance variables in soccer (Bastida-Castillo et al., 2018).

All the devices were calibrated following manufacturer’s instructions (Oliva-Lozano, Fortes, Krustrup, & Muyor, 2020; Oliva-Lozano, Rojas-Valverde, et al., 2020b). In consequence, all the devices were first fully charged and placed on a Smart Station (RealTrack Systems, Almeria, Spain). The station was placed on a flat surface without magnetic devices surrounding and then, the devices were turned on. Sixty seconds later, the start recording button was pressed and the calibration procedure was completed. Once this procedure finished, the devices were given to the players before the start of the match. Finally, the session was analyzed at the end of the match using SPro software (RealTrack Systems, Almeria, Spain).

**Statistical analysis**

Our design located units of analysis (individual match observations) nested within clusters of units (Players), which were nested within larger clusters of clusters (Positions). To properly account for this hierarchical (correlated) nesting and to accurately quantify the variability in match physical performance, data were analysed using separate three-level linear mixed effect models. We used the MIXED procedure in SAS® Software (University Edition, SAS Institute Inc., Cary, NC, USA) to analyse both the original and log-transformed data, to quantify effect estimates in raw and percentage units. Model appropriateness was verified by examining plots of the studentized residual and predicted values, which were well behaved for both the raw and log-transformed data.

To determine the linearized seasonal trend in each external load measure, season week was re-scaled to range from −0.5 to 0.5 before being specified as a fixed effect (continuous covariate). Subsequently, separate random effects were added for Player ID, Position and Match Number. These effects were specified with a variance components covariance structure and estimated via Restricted Maximum Likelihood. Estimates – expressed as standard deviations (SD) and coefficients of variation (CV) – therefore included between-player, between-position, between-match and the remaining (residual) within-player variability, which is analogous to the typical error from a re-test reliability design. Uncertainty in all effects and ranges of values compatible with our data and statistical models were expressed as 90% confidence limits (CL). Boundary constraints were removed from covariance estimates to allow for negative variance. While negative variance (variability below zero) is illogical, it allows for an appropriate approximation of the uncertainty in the estimate when the true variability is close to zero.

Building on previous approaches (McLaren et al., 2016; Weston et al., 2015), we used our variability estimates to provide a framework for practitioners to interpret individual changes in match physical performance indicators. This approach is founded on identifying changes that that appear unusual and potentially meaningful. Here, an unusual change can be viewed as one beyond the normal match-to-match variability seen in any given player, after accounting for any seasonal trend and positional differences. We determined the observed match-to-match variability as the pooled (added) between-match SD and within-player typical error. These values were then multiplied by the square root of 2 and the appropriate value from the $t$ distribution with the model degrees of freedom to establish 80%
and 90% confidence limits, giving likely ranges for a normal or ‘usual’ individual change. A meaningful change can be viewed as one which exceeds a pre-established threshold of practical importance. Through lack of a known conceptual or empirical anchor between our match physical performance indicators and key match outcomes (e.g. result), we used a distribution-based approach to establish these boundaries (Cook et al., 2018). Upon electing for a threshold equivalent to a small standardized change, reference values were given as 0.2 multiplied by the between-player SD or CV. Finally, we applied minimum effects tests (MET) (Murphy & Myors, 1999) to establish probabilistic reference values for interpreting individual changes in match external loads, which combine both match-to-match variability and thresholds of practical importance. The \( t \)-statistic for a change relative to practical importance (change – threshold/ [match-to-match variability × \( \sqrt{2} \)]) was converted to a probability via the one-tailed \( t \)-distribution. These probabilities were represented as continuous estimates across a plausible range of changes, as well as the changes associated with more conventional alpha levels (0.10 and 0.05).

Results

The overall (mean) match external loads for TD, HSRD, TAcc and \( V_{\text{max}} \) were 10257, 699 m, 2976 (\( n \)) and 31.6 km\( \cdot \)h\(^{-1} \). Observed external loads and the associated seasonal trends (individual and mean) are presented in Figure 1. There was a seasonal reduction in TD (mean slope: \( -220 \) m [90% confidence interval: \(-638–197\)]), \(-2.1\%\) [\(-6.1\%\) to \(-1.9\%\)], and a seasonal increase in both HSRD (126 m [3 m to 249 m], 25% [3% to 52%]) and TAcc (112 [\(-16–241\)], 3.8% [\(-0.8\%\) to 8.5%]). The magnitude and direction of the seasonal trend in \( V_{\text{max}} \) was inconclusive (0.23 km\( \cdot \)h\(^{-1} \) [\(-0.49 \) km\( \cdot \)h\(^{-1} \) to 0.95 km\( \cdot \)h\(^{-1} \)], 0.8% [\(-1.5\%\) to 3.2%]).

Estimates of between-player, between-position, between-match and within-player variability in each external load metric, expressed in raw (SD) and percentage (CV) units, are presented in Table I, respectively. All sources of variability were greater for HSRD (13–36%) when compared with all other external load metrics (<6%). The observed match-to-match variability (combined between-match and within-player) for TD, HSRD, TAcc and \( V_{\text{max}} \) was 568 m (5.7%), 159 m (31%), 157 (5.6%) and 1.58 km\( \cdot \)h\(^{-1} \) (5.2%).

Reference values and methods for interpreting individual changes in match external loads are presented in Table II and Figure 2. Based on our thresholds for practical importance (0.2 × between-player SD or CV), between-match individual changes of ±10–12% (for a 80% CI/ \( \alpha = 0.10 \)) and ±13–15% (for a 90% CI/ \( \alpha = 0.05 \)) in TD, TAcc and \( V_{\text{max}} \) would be required to suggest practical significance or substantially unusual. For HSRD, these thresholds were considerably higher (±58% and ±74%, respectively).

Discussion

The ability for soccer practitioners to identify meaningful changes in match physical performance has the potential to aid decision making around player management following competition. Through decomposing the variability of match physical performance and using a minimum effects testing framework, our study is the first to apply a probabilistic method for monitoring individuals in professional soccer. Our main finding was that after accounting for seasonal trends and inter-position heterogeneity, between-match individual changes of ±10–15% in representative GPS-derived measures of match physical performance (TD, TAcc and \( V_{\text{max}} \)) can be considered practically significant. This was with the exception HSRD, where thresholds were considerably higher (≥ 60%).

Our match physical performance values appear similar to those reported in other investigations and may therefore be considered representative of professional soccer competition (Haddad et al., 2018; Palucci-Vieira et al., 2019). Previous investigations have also observed that professional soccer players usually cover ~10 km per match (Haddad et al., 2018; Palucci-Vieira et al., 2019), but only 4–6% of the TD is covered at high intensity (Haddad et al., 2018). In addition, soccer players are exposed to bouts of activity requiring running speeds in excess of 30 km\( \cdot \)h\(^{-1} \) (Aquino, Munhoz-Martins, Palucci-Vieira, & Menezes, 2017; Haddad et al., 2018), as well as multiple changes of direction and duels, which significantly contribute to TAcc (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, Fortes, & Pino-Ortega, 2020a). We found HSRD and TAcc to increase throughout the season, whereas TD reduced and the trend in \( V_{\text{max}} \) was not clear. Previous studies have also found HSRD to increase from the start to the end of the season (Mohr, Krstrup, & Bangsbo, 2003; Rampinini, Coutts, Castagna, Sassi, & Impellizzeri, 2007), but our observed decline in TD is not consistent with these studies, (Mohr et al., 2003; Rampinini et al., 2007), which reported a lower TD at the start of the season when compared to the middle and end. In this regard, there are several
factors (e.g. ball possession, tactics, improved fitness, or adaptations to competitive league) that may explain these different trends (Rampinini et al., 2007). For example, the team analyzed in our study adopted a direct style of play with fast transitions and high defensive lines during the season, which may be another factor to explain the increase in HSRD and TAcc (Fernandez-Navarro, Fradua, Zubillaga, & McRobert, 2018). Also, a previous investigation observed that the teams with low-percentage ball possession covered more TD than teams with high-percentage ball possession (da Mota, Thiengo, Gimenes, & Bradley, 2016). Therefore, the seasonal trends need to be analyzed from a context-specific perspective in order to understand the potential practical applications of this type of analysis.

Regarding the estimates of between-player, between-position, between-match and within-player variability in each physical performance metric, a key finding was that all sources of variability were greater for HSRD (13–36%) in comparison with all other external load metrics (<6%). These results are consistent with previous investigations which reported that the variability tended to increase with running intensity (Carling et al., 2016; Gregson et al., 2010; Haddad et al., 2018; Mohr et al., 2003; Rampinini et al., 2007). For instance, the match-to-match variability in TD from professional soccer players has been shown to be around 3.1% (Mohr et al., 2003), 2.4 (Rampinini et al., 2007) and 5.3 (Haddad et al., 2018) while the variability for HSRD was around 9.2% (Mohr et al., 2003), 14.4 (Rampinini et al., 2007), 17.7% (Gregson et al., 2010), 19.8% (Carling et al., 2016), 53% (Haddad et al., 2018). Compared to previous investigations, however, a novel finding of our study was the ability to further partition the usual sources of variability into their specific components. We show, for example, that HSRD is far more variable between positions (36%) than it is between players within a given position (13%). Furthermore, we separate the observed match-to-match variability into true between-match variability (i.e. factors occurring at the level of a

![Figure 1. Seasonal trends in match physical performance. Data are presented as individual match observations (points), individual linear trends (faint lines) and the overall mean trend (bold line) with 90% confidence intervals (dotted line).](image-url)
match) and within-player variability (i.e. factors occurring at the level of an individual). To our knowledge, this is the first attempt to do so in soccer. Our results indicate that the between-match and within-player variability of HSRD are similar, whereas the within-player variability of $V_{\text{max}}$ was over 3 times that of the between-match variability. However, $V_{\text{max}}$ did appear relatively stable, for all sources of variability (<5%), which is supported by previous research (Haddad et al., 2018). Our lower estimates (between match: 1.5%, within-player: 4.9%) compared to Haddad and colleagues (observed match-to-match: 6–8%) are likely due to variance partitioning, but may also be influenced by different positional roles or playing styles (Haddad et al., 2018).

The primary aim of our study was to break down the sources of variability in soccer match physical performance and use these data to shed light on monitoring individual between-match changes. We approached this twofold. First, between-match and within-player variability were combined to construct confidence intervals for an individual change in physical performance. This is similar to principles of the minimum detectable change (smallest detectable difference) and can be used to determine those which are beyond the observed match-to-match variability. For example, a change in whole match TD of +10.4% could be interpreted as higher than usual, using an alpha of 0.1 (80% CI). This can be a useful way to incorporate performance variability into decision making, but it does not consider the practical importance of a change. Building on the TD example, a whole match change of +10.5% is

Table I. Variability of match physical performance expressed in raw units and coefficients of variations (%)

| Metric          | Between-player | Between-position | Between-match | Within-player |
|-----------------|----------------|------------------|---------------|---------------|
| TD (m)          | 546 (147–759)  | 376 (–416–675)   | 428 (322–513) | 373 (344–408) |
| HSRD (m)        | 72 (–24–104)   | 222 (–107–331)   | 101 (72–123)  | 124 (114–136) |
| TAcc (#)        | 74 (12–104)    | 27 (–60–72)      | 137 (106–162) | 76 (70–83)    |
| $V_{\text{max}}$ (km·h$^{-1}$) | 0.90 (–0.30–1.31) | 0.93 (–0.86–1.57) | 0.44 (–0.23–0.66) | 1.52 (1.40–1.66) |

Table II. Reference values for interpreting individual changes in match physical performance

| Metric | Unit      | ± Confidence limits for a true change$^{ab}$ | Change (±) required to be practically significant$^{ab}$ |
|--------|-----------|-------------------------------------------|---------------------------------------------------|
| TD     | m         | 1036 1333 1145 1442                       | $\alpha = 0.10$ 1145 1442                        |
| HSRD   | %         | 10.4 13.4 11.5 14.5                       | $\alpha = 0.05$ 11.5 14.5                        |
| TAcc   | #         | 291 374 305 383                          | $\alpha = 0.10$ 305 383                          |
| $V_{\text{max}}$ | %         | 286 368 301 383                          | $\alpha = 0.05$ 301 383                          |

$^{a}$Based on the combined between-match and within-player variability (Table I): TD = 568 m (5.7%), HSRD = 159 m (31%), TAcc = 157 (5.6%), $V_{\text{max}}$ = 1.58 km·h$^{-1}$ (5.2%). See methods section for more details.

$^{b}$The threshold for a practically important change is given as a small effect size: 0.2 multiplied by the pure between-player SD (Table I). Changes are then estimate based on a minimum effects test against these thresholds at the given alpha level.
greater than the smallest detectable difference for an 80%, but only by 0.1% which is unlikely to have any real-world relevance. Therefore, we additionally used effect size principles to estimate values of the smallest worthwhile change, given as 0.2 of the pure between-player variability (Table I). Using a minimum effects testing framework, we then calculated the probability ($p_{\text{MET}}$) that a match change could be considered truly meaningful; that is, ‘unusual’ (beyond the normal match-to-match variability) by a substantial magnitude. A smaller $p_{\text{MET}}$ indicates a greater practical significance and intuitively, $p_{\text{MET}}$ of 0.10 and 0.05 correspond to individual changes where the respective 80% and 90% CI fall completely beyond the threshold of practical importance. For TD, this value was 11.5% for an 80% CI.

We have presented $p_{\text{MET}}$ as both the value associated with fixed and conventional alpha levels (Table II) and also as continuous estimates (Figure 2). The former is typical to making inference from sample-based research studies but in the practice of monitoring individuals, this approach may be too conservative. The reality is that soccer practitioners are likely to interpret match physical performance data in a heuristic sense, so knowing if individual changes are trending towards practical significance might be of better use. The charts presented in Figure 2 could therefore be used to determine the actual practical significance, by drawing a vertical line up from the observed change (X-axis) and drawing a perpendicular horizontal line at the intercept of the Y-axis to determine the corresponding $p_{\text{MET}}$. These values can then be interpreted in the context of the decisions being made and the contextual constraints (e.g. associated time, resources and impact on players). For example, a lower $p_{\text{MET}}$ for a positive change in HSRD and/or TAcc might be indicative.
of substantially more high-intensity match activity than normal. This might warrant the considerations for additional recovery, medical or nutritional intervention in the days following the match to ensure appropriate regeneration prior to the next competitive fixture.

We understand that it would be naïve to directly make an inference on fatigue or recovery from match physical performance alone, and this should be taken into consideration when making decisions using the aforementioned methods. External load is the means by which an internal load is induced; which is then the stimulus for consequential responses to the body’s systems and functional performance (e.g. fatigue and recovery). Therefore, we do not advocate that changes in match physical performance are used to make direct and definitive inference on fatigue or recovery. Rather, these changes could imply a differential fatigue or recovery time-course response when compared to usual. This may seem a semantic interpretation, but it has a clear practical implication: if practitioners detect changes in match physical performance that are substantially higher than usual (e.g. +10–15% for TD, TAcc or \( V_{\text{max}} \)) then an assessment of the subsequent ‘response’ might be warranted to inform athlete management decisions. This could include post-day subjective measures of fatigue or objective measures such as heart rate variability or stiffness (e.g. leg/whole body). Or, it may simply be used as an avenue to start a conversation with the player, where clinical and practical judgment can precede generic advice (e.g. sleep, nutrition) or further intervention.

There are some general limitations, which need to be acknowledged and may also guide future investigations. First, only one professional soccer team was included in the analysis, so the sample size was limited to the most regular players of the league (\( n = 13 \)). A multi-club study would therefore help extend our current findings. Additionally, recently implemented local positioning systems may provide more accurate data than GPS (Bastida-Castillo et al., 2018; Linke et al., 2018), particularly for match physical performance measures such as HSRD and \( V_{\text{max}} \) (Buchheit & Simpson, 2017), and should therefore be considered both for interpreting our findings to data collected with these systems and future research into the variability of soccer match physical performance. Finally, we have stressed the importance of including concepts such as the smallest worthwhile change to interpret differences in match physical performance, but this distribution-based approach is in itself limited. The extent to which group-based effect sizes principles can be used at the individual level can be questioned and this is likely a less-robust approach than using anchor-based methods, which are yet to be established for match physical performance in soccer.

Competitive fixtures present as the most demanding sessions within a professional soccer microcycle. Practitioners are responsible for quantifying weekly match demands to inform subsequent player management and the training schedule. Understanding the variability of match physical performance can aid this decision-making process by determining the practical significance of between-match changes. In our study applying this approach alongside a minimum effects testing framework, we found that individual changes in representative GPS-derived measures of match physical performance (TD, TAcc and \( V_{\text{max}} \)) of ±10–15% can be considered practically significant. That is, beyond the normal match-to-match variability and by a magnitude greater than the smallest worthwhile change. This was with the exception HSRD, where thresholds were considerably higher (≥ 60%). Soccer practitioners might therefore consider this approach to facilitate decision making. However, we maintain that other sources of data (internal load and the associated response) are needed to properly evaluate match demands and any athlete management decisions should be primarily based on domain knowledge (training principles and physiological or biomechanical theory) and experience.

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