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In-situ PFv profiling in sub-elite gaelic football: Implementation, comparison with isolated sprints, minimum data load requirements, and exploring "real-time" monitoring potential

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Abstract

In-game performance monitoring is of growing interest to sports science practitioners. This study presents a proof-of-concept methodology capable of tracking, on average, a 6.4% reduction in ballistic power (P_B) during competitive matches. The study investigated the linearity of in-situ *PFv* profiles in 34 sub-elite Gaelic footballers (aged 26.08 ± 6.84 years), compared in-situ to isolated sprint-derived profiles, determined minimum data requirements for producing stable, high-linearity profiles, and explored the utility of in-game monitoring. Linearity was comparable to previous studies, with *Fv* profiles R^2 values of 0.929 ± 0.110 for match data and 0.949 ± 0.105 for training data. Consistent, systematic differences were observed between in-situ and isolated profiles using Cohen's *d*. Acceleration (A_0; $1.00 \le d \le 1.93$) was significantly higher in-situ, while maximum power (P_{max}; $-1.36 \le d \le -1.02$) and the *Fv* offset (d_{Fv}; $-1.09 \le d \le -0.90$) were significantly lower, highlighting the two profiles are not interchangeable. Maximum speeds (S_0) exhibited context-dependent variance, being larger in matches than in isolated sprints (8.56 ± 0.31 m s^{-1} versus 8.33 ± 0.34 m s^{-1}; $d = +0.74$), but lower in training (8.04 ± 0.25 m s^{-1}; $d = -1.29$, $p < 0.001$). Minimum data load was determined via two methods: the time for R^2 to reach 0.9 (12-minutes) and the geometric knee of the R^2 versus data load curve (7-minutes). Using these sliding windows, P_B showed average reductions of 4.9% and 6.4%, respectively, across a full game. These findings suggest *PFv* profiling may offer a practical, scalable method for in-situ performance monitoring in team sports.

Keywords

Acceleration, ballistic movement, fatigue, global positioning system, in-game performance monitoring, power-force-velocity profiles, speed

Reviewer: Jean-Benoit Morin (University of Nice, France)

Introduction

Strength and conditioning practitioners, medical staff, and coaches frequently use the outcomes of fitness testing and profiling procedures to inform training protocols, assist with team selection, and assess the effectiveness of training interventions.[1] These profiles are not only used to guide performance strategies but also to monitor individual changes over time, and to compare those changes across a wider squad or team.[2] Athletes themselves have reported finding profiling useful for several reasons; it increases self-

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awareness, highlights areas of improvement, boosts motivation, helps set performance targets, allows for performance monitoring, and gives ownership over their own development.[3]

One of the key aspects of physical performance in team sports is sprinting.[4] As such, the assessment and monitoring of sprint performance, through individual power-force-velocity (*PFv*) profiles, is important for tailoring training regimes, and for managing and mitigating injuries. A number of methods have been used to generate *PFv* profiles, including using motorized instrumented treadmills,[5] timing gates,[6] and radar technology.[7] Recently, Global Positioning System (GPS) units have been shown to produce *PFv* profiles that are comparable with those obtained through these more traditional approaches.[4]

Laser devices, radar, and timing gates are typically deployed in pre-planned testing environments, where the computations of Samozino et al.[8] can be more readily applied. However, these methods require specific equipment, processing software, and are generally more labor intensive than the use of GPS units, especially since GPS units are already widely used in sporting sectors spanning professional to amateur levels.[9–11]

A proof of concept study by Morin et al.[4] explored the potential for deriving acceleration-speed profiles from in-situ GPS data (i.e., data that is collected during regular team activities such as training or competitive matches, and does not require bespoke drills in order to be acquired), and identified five key areas requiring further research, notably:

1. Comparison between single isolated sprint *PFv* profiles and those created with in-situ data;
2. The longitudinal changes in a player's profile observed over time;
3. Determination of the minimum data load needed to produce stable and reliable *PFv* profiles in team-sport athletes;
4. The influence of coaching decisions on *PFv* profiles, including different game formats (e.g., small-, medium- and large-sided games), speed/acceleration focused training, and the effects of tactical periodization; and
5. Examining the effect of strength and conditioning blocks, such as heavy resistance training, on *PFv* outputs.

The present study aims to investigate points (1), (2) and (3) above, which have been highlighted as priority areas by Morin et al.[4] Specifically, our study will investigate the agreement between in-situ *PFv* profiles and those derived from isolated sprint tests, and examine the factors influencing this agreement. Addressing point (3) also presents an opportunistic hypothesis, such that if sufficiently linear *PFv* profiles can be generated from short data windows, then these profiles may be applied within match settings to track temporal changes in performance; something that was also recently proposed by McGleenan et al.[12]

Upon determining a minimum data load, we also investigate the in-game changes in *PFv* metrics, with particular interest in power-related metrics (i.e., the 'ballistic' and 'maximum' powers, P_B and P_{max}, respectively) which have been shown to be the most sensitive indicators of neuromuscular fatigue,[12] and may therefore serve as effective markers in-situ. This objective aims to explore the utility of *PFv* metrics as an efficient, real-time performance-monitoring tool. While a full exploration of applied use cases is beyond the present scope, the framework lends itself to integration with machine learning and mixed-effects modeling approaches in line with the work presented by Wbaid et al.[13] and Mănescu et al.[14]

Our research questions (**Q**), underlying hypotheses (**H**), and the sections which address them are indicated below.

- **Q1:** Are the methods outlined by Morin et al.,[4] Clavel et al.,[15] and McGleenan et al.[12] suitable for characterizing the *PFv* metrics present within our current data set?
  - **H1:** Sub-elite Gaelic football activities monitored with 10 Hz GPS trackers will provide comparable *PFv* profiles to those existing in literature. This expectation is based on the methodological overlap with previous work, including the same fitting procedure as Clavel et al.,[15] comparable STATSports hardware, and the same Butterworth filtering approach. Therefore, profile linearity (R^2) was expected to fall within the ranges reported in previous in-situ acceleration-speed profiling studies.
  - Detailed in Section "Implementation of the Morin et al. (2021) techniques".
- **Q2:** How do in-situ and isolated sprint-derived *PFv* profiles compare?
  - **H2:** There will be differences observed between in-situ and isolated sprint-derived *PFv* profiles owing to the similarities of movement patterns and intermittent intensities of competitive field sports, although the different data-collection contexts may introduce systematic bias. While Cormier et al.[16] reported alignment between in-situ and isolated AS profiles in elite female soccer, the differences in the construction of the profiles mean all parameters are not expected to be interchangeable. We anticipate measurable, metric-dependent bias rather than equivalence.
  - Detailed in Section "Comparison Between In-Situ and Isolated Sprint *PFv* profiles".
- **Q3:** What is the minimum data load required to produce stable and reliable *PFv* profiles in team-sport athletes?

- **H3:** The minimum data load required to create a sufficiently linear ($R^2 \geq 0.9$) *PFv* profile will be dependent on the activity tracked (e.g., match, training, etc.), and will be on the order of one continuous, extended block of play (approximately 30 minutes). This estimate is anchored in Morin et al.,[4] which suggested that profiles stabilize over the order of an extended session rather than over only a few minutes. In sub-elite Gaelic football, a 30-minute half represents the largest uninterrupted competitive-play block available in-situ, making it a plausible a-priori candidate for the minimum data load. We expected match data to converge faster than training data because competitive match play is likely to provide more frequent high-speed exposures per unit time.
- Detailed in Section "Assessing Minimum Data Load".

- **Q4:** Do the *PFv* profiles of players display temporal changes during a match, hence highlighting the usefulness of real-time performance monitoring?
  - **H4:** Temporal changes in *PFv* metrics (analyzed with the minimum required data) during games will exhibit some decline, particularly in power-based metrics such as P_B and P_{max}. This prediction is grounded in our prior work, McGleenan et al.,[12] which identified power-based *PFv* metrics as being particularly responsive to changes consistent with neuromuscular fatigue during repeated sprint testing. We hypothesized this sensitivity would translate into the in-situ match context.
  - Detailed in Section "Producing In-Match Trends".

Hence, the main goals of this study are to: (1) test the suitability of current methodologies for extracting stable, high-linearity *PFv* performance metrics, (2) compare isolated sprints (e.g., those performed during bespoke training exercises) with those extracted from passively observed in-situ data, (3) determine the minimum data load required to produce meaningful *PFv* measurements, and (4) perform a proof-of-concept analysis examining whether in-situ *PFv* monitoring can detect temporal performance trends during match play.

Materials & methods

Participants & study design

A group of 34 adult male subjects aged between 19 and 43 (26.08 ± 6.84 years) voluntarily took part in this study. All participants are physically active competing at the sub-elite level of an invasion team sport (Gaelic football), typically training collectively between $2-3$ times per week. Sessions include technical, tactical, conditioning, and game replication work. Written, informed consent was obtained from the participants and the study was approved by the Engineering and Physical Sciences Faculty Research Ethics Committee of Queen's University Belfast (reference number: EPS 24_48). Participant anthropometric data were not available. Data were acquired during collective training and competitive matches over the course of one season (March 2024 – September 2024), including 70 training sessions and 18 competitive games. Training sessions lasted on average 86.6 ± 12.6 minutes, with 891 training player sessions in total. Each match half was cropped to 30 minutes, the regulation playing time for each half at sub-elite Gaelic football, to avoid anomalous half durations that vary randomly from match to match, providing 234 match player sessions in total. Although 34 participants were included in the overall dataset, subsequent analyses applied additional inclusion criteria, including a minimum of five complete sessions and completion of the repeated sprint ability (RSA) test. Therefore, the number of participants differs between specific analyses.

Instruments

The hardware and software used to gather data were both developed by the Northern Ireland company STATSports. STATSports Apex Pro series units were utilized (Apex Pro series unit, STATSports, Newry, Northern Ireland), while initial data import and validation was performed using the STATSports Sonra software (Sonra Version 5.0.6, STATSports, Newry, Northern Ireland). The data gathered were exported in its raw format into a series of comma-separated values (CSV) files, which allowed further analysis through various customized computational methods. Specifically, Python 3[17] was used as the primary programming language for the data analyses undertaken in the present study.

STATSports Apex Pro series units have been validated for data reliability and accuracy independently through the FIFA Quality Programme, against the industry gold standard Vicon motion capture system.[18] In measuring linear and simulated team sport running, GPS-based devices (such as the STATSports Apex Pro series units) with a sampling frequency of 10 Hz are among the most accurate and reliable currently available.[19] As a result, the technology embedded within the STATSports Apex Pro series units is sufficient to provide reliable measurements of horizontal *PFv* values (i.e., within the plane of the playing surface) across individual samples of maximal effort sprints.[16]

The number of satellites connected was 20.8 ± 1.3 for the collection events, with the Horizontal Dilution of Precision (HDOP) value measured to be 0.41 ± 0.07, allowing for accurate horizontal position calculations from the GPS devices.[20]

Implementation of the Morin et al. (2021) techniques

Method

The statistical analysis performed on each dataset follows the procedure outlined by Morin et al.[4] Raw speed was imported via the CSV files, with a sampling frequency of

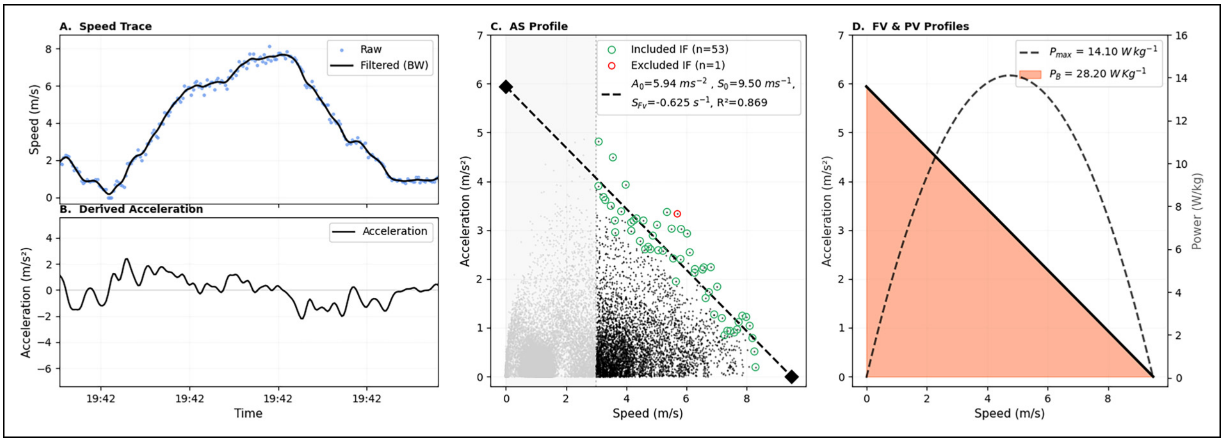

Figure 1. Speed (panel A) and derived acceleration (panel B) displayed as a function of time, where raw speed values are shown as blue points and the Butterworth-filtered speeds are displayed using a solid black line. Note, the speed- and acceleration-time plots are cropped to a small portion of the overall data collection period for better visualization. Panel C is a scatter plot of acceleration values as a function of athlete speed, with values below the minimum speed (3 $m\,s^{-1}$) shown in light-grey, while those used in the analyses (i.e., >3 $m\,s^{-1}$) shown in black. The top two acceleration values in each 0.2 $m\,s^{-1}$ speed window are extracted following the methods detailed by Morin et al.,[4] then fitted with a linear regression, ensuring outliers beyond a 95% confidence interval are excluded (circled in red). The remaining points (circled in green) were then re-fitted using linear regression to produce the final acceleration-speed profile (solid black line). Panel D displays the resulting mass-normalized force-velocity (solid black line) and power-velocity (dashed black line) profiles for the same athlete data depicted in panel C, where the ballistic power, P_B, is computed via integration across the *Fv* profile (orange shading) according to McGleenan et al.[12]

10 Hz. The raw speed data were then convolved with a second-order, low-pass Butterworth filter. This filter allows signals with frequencies lower than a selected cut-off frequency to pass through, while attenuating signals with higher frequencies. Following the work of Clavel et al.,[15] a conservative low-pass cut-off frequency of 1 Hz was chosen. The authors also noted that filtering should be specific to the make and model of the GPS units; indeed in the Morin et al.[4] study, the sampling frequency was higher than the present study (18 Hz versus 10 Hz), resulting in Morin et al.[4] applying a custom Gaussian filter.

Acceleration values were subsequently calculated from the filtered speed data by computing its numerical derivative, specifically by employing the `numpy.gradient`[21] function in the Python 3 computing environment which uses second order accurate central differences. Following Morin et al.[4] and Clavel et al.,[15] only data where speeds exceeded 3.0 $m\,s^{-1}$ were considered. This threshold is commonly used in in-situ acceleration-speed profiling to avoid low-speed accelerations that may not reflect the linear sprint acceleration-speed relationship targeted by the method. Further to this, existing literature has shown the 3.0 $m\,s^{-1}$ threshold is appropriate across a variety of sports and cohorts of different characteristics.[4,15] Within the defined speed range (i.e., from 3.0 $m\,s^{-1}$ to the individual's maximum speed contained within the data set), the two highest acceleration values were extracted from each 0.2 $m\,s^{-1}$ speed window (e.g., $3.0-3.2$ $m\,s^{-1}$, $3.2-3.4$ $m\,s^{-1}$, etc.). These extracted data points are highlighted using solid green/red circles in the middle panel of Figure 1.

A preliminary linear regression was fitted to the peak acceleration data points as a function of player speed, using the `numpy.polyfit` function in the Python 3 coding environment. Residuals were calculated as being the difference between observed and predicted acceleration values, with data points falling outside a 95% confidence interval of this initial model being treated as outliers and excluded (red circles in the middle panel of Figure 1). Miguens et al.[22] proposed an automated alternative for outlier handling in GPS-derived AS profiling (source code available on the authors' GitHub page (https://github.com/NthnMgns/acceleration-speed-profiling). In a sensitivity check within the present cohort, applying the Miguens et al.[22] approach produced only trivial differences in the derived *PFv* and linearity metrics compared with the present pipeline. Therefore, the original processing approach was retained for consistency with Morin et al.[4] and Clavel et al.[15] A second linear regression was then applied (i.e., to the green circles in the middle panel of Figure 1), which excluded outliers from the previous fit, to establish the final acceleration–speed profile of the athlete, with the R^2 value of this fit stored as a measure of goodness of fit for each profile. Miguens et al.[22] also used quantile regression to estimate uncertainty around acceleration-speed profile metrics. Although formal per-metric uncertainty estimation was beyond the scope of the present proof-of-concept study, this represents an important methodological extension for future work, particularly for defining smallest worthwhile change thresholds and decision-support limits. Less than 5% of data points are found to be outliers. Following the

Table 1. Metrics investigated in this study, including their denotation, unit, definition, and mean values (± SD) calculated from: (i) pooled in-situ training sessions (n = 27 players, ≥ 5 sessions each), (ii) pooled in-situ competitive match data (n = 16 players, ≥ 5 matches each), and (iii) isolated sprints reproduced from McGleenan et al.[12] where the values are from the first repetition of an RSA test.

Metric	Unit	Definition	In-Situ (Training)	In-Situ (Match)	Isolated Sprint
S_0	m s^{-1}	Theoretical maximal speed estimated from the *x*-intercept of the fitted acceleration-speed profile.	8.85 ± 0.94	9.44 ± 1.03	8.25 ± 0.47
A_0	N kg^{-1}	Theoretical maximal mass-normalized force (i.e., N kg^{-1} or m s^{-2}) estimated from the *y*-intercept of the fitted acceleration-speed profile.	7.07 ± 0.56	7.18 ± 0.77	5.34 ± 0.51
P_{max}	W kg^{-1}	Maximum value of the fitted power-velocity relationship derived from the acceleration-speed profile.	15.56 ± 1.14	16.85 ± 1.85	14.04 ± 1.46
P_B	W kg^{-1}	Ballistic power provided by the area underneath the *Fv* curve for each player.	31.11 ± 2.28	33.70 ± 3.71	21.51 ± 3.22
S_{Fv}	s^{-1}	Slope of the linear line of best fit applied to the *Fv* curve for each player.	-0.811 ± 0.119	-0.771 ± 0.118	-0.75 ± 0.07
d_{Fv}	N/A	Shortest perpendicular distance from the origin to the linear line fitted to the *Fv* curve for each player.	5.47 ± 0.22	5.65 ± 0.38	8.58 ± 0.32

Abbreviations: Fv = Force Velocity. In-situ training and match profiles derived using the Morin et al.[4] A–S profiling method (second-order Butterworth filter, 1 Hz cut-off, STATSports Sonra 10 Hz).
It should be noted that there are some differences in the values shown in this table when compared to those in table 2, as only players who completed both the RSA test and met the in-situ inclusion criteria are included here.

robust fitting of the acceleration–speed data, a number of performance metrics were extracted, as defined in Table 1. Here, S_0, A_0, P_{max} and S_{Fv} are 'standard' metrics that have been employed in previous studies,[4] while P_B and d_{Fv} represent novel metrics that have only recently been proposed as more sensitive indicators of neuromuscular performance degradation than their traditional counterparts.[12] Figure 1 illustrates how acceleration metrics (lower-left panel) can be derived from the initial raw speed values (upper-left panel), which enables both acceleration and power profiles to be displayed as a function of athlete speed (middle and right panels).

It should be noted that when referring to *PFv* profiles (this may also be termed in literature as acceleration–speed (*AS*) profiles), the maximum mass-normalized force, F_{max}, is analogous to A_0, since Newton's second law of motion ($F = ma$) can be rearranged as $a = F/m$. This means that subsequent calculations employing the A_0 metric are also mass-normalized, e.g., power. We note that from the fitted *Fv* profile, the S_0 metric represents the maximum hypothetical speed of an athlete. However, often $S_0 \neq v_{max}$, where v_{max} is the actual observed maximum speed of the player. As a result, when terms like "$\geq$ 95% v_{max}" are described in the following sections, we are referring to percentage thresholds of a player's physically observed maximum speed (i.e., v_{max}) and not their hypothetical maximum (i.e., S_0).

In Morin et al.[4] it was suggested a minimum of five pooled training sessions (approximately 90 minutes in length) would be suitable to generate each player's *PFv* profile. Clavel et al.[15] created a week-to-week comparison of *PFv* profiles in elite youth soccer players who completed technical, small- and large-sided games, and sprint specific training. Miguens et al.[22] extended the approach to professional rugby union using an automated, refined pipeline. The present study has processed data from training (N=27) and matches (N=16), with only players who had participated in at least five of each session type included. Similarities and differences in study characteristics and profile variables between Morin et al.,[4] Clavel et al.,[15] and the present study are detailed in Table 2.

Results & discussion

Fit quality compared to literature. From Table 2 we can see good general agreement between the metrics from this study and the existing literature. Morin et al.[4] and Clavel et al.[15] reported *PFv* profiles that exhibited very strong linearity, showing coefficients of determination greater than 0.97 (i.e., $R^2 \geq 0.97$). The R^2 values from training and matches (0.949 ± 0.105, 0.929 ± 0.110) are lower than in the existing literature Figure 2. Factors which may influence these differences are noted in Section "Factors influencing agreement".

Individual metric comparison. As seen in Table 2, A_0 values from training and matches sit within the reported ranges from literature. S_0 is lower in training in the Gaelic football cohort than reported by Morin et al.[4] and Clavel et al.[15] S_0 from matches falls within the literature range. S_{Fv} values are consistent with Morin et al.[4] and Clavel et al.,[15] with a slightly flatter slope seen in matches, again reflecting a more velocity-orientated profile when compared with training data. The number of data points used in the linear regression (training: 52 ± 7, match: 51 ± 4) are comparable to Morin et al.[4] (52 ± 5) and notably higher than in Clavel et al.[15] (39 ± 3).

Table 2. Comparison of in-situ acceleration–speed profile variables across studies.

Metric	Morin et al. (2021) Training	Clavel et al. (2023) Training	Present Study Training	Present Study Match
Study characteristics				
Sport	Professional soccer	Elite U19 soccer	Senior sub-elite Gaelic football	
GPS device	Catapult S5	STATSports APEX	STATSports Apex	
Sampling rate (Hz)	18	10	10	
Filter	Custom Gaussian filter	BW 2nd order, 1 Hz cut-off	BW 2nd order, 1 Hz cut-off	
n (players)	16	18	27	16
Sessions per player	5–10	5–6	6–27	6–15
Session type	Training only	Training only	Training only	Match only
Profile variables				
R^2	> 0.984	0.97–0.99	0.949 ± 0.105	0.929 ± 0.110
A_0 (m s^{-2})	7.20–7.70	6.96–7.30	7.07 ± 0.56	7.18 ± 0.77
S_0 (m s^{-1})	9.21–9.47	9.39–9.61	8.85 ± 0.94	9.44 ± 1.03
S_{Fv} (s^{-1})	−0.764 to −0.839	−0.75 to −0.78	−0.811 ± 0.119	−0.771 ± 0.118
Data points fitted	52 ± 5	39 ± 3	52 ± 7	51 ± 4

Note. Morin et al.[4] values represent the range across two 2-week training periods (16 professional male soccer players, Catapult S5 18 Hz). Clavel et al.[15] values represent the range across three consecutive training weeks using the "All sessions" condition including a sprint-specific session (18 elite male U19 soccer players, STATSports APEX 10 Hz, 1 Hz Butterworth cut-off). Present study values represent pooled profiles across the full observation period (March – September 2024, senior amateur male Gaelic football players, STATSports Sonra 10 Hz, 1 Hz Butterworth cut-off). Match profiles were constructed using first- and second-half drill data only, excluding half-time periods. Training profiles used information from the entire session. Values are presented as mean ± SD unless otherwise stated. A_0 = theoretical maximal acceleration; S_0 = theoretical maximal speed; S_{Fv} = slope of the acceleration–speed linear relationship; R^2 = coefficient of determination of the final linear regression; IF points = number of individual filtered data points used in the regression; BW = butterworth filter.

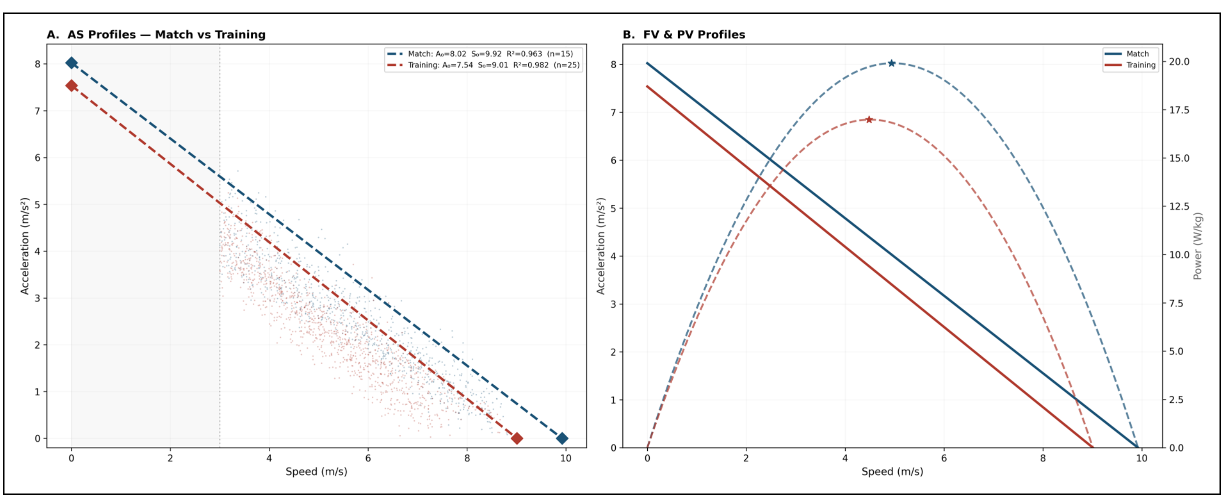

Figure 2. Panel A shows the acceleration against speed scatterplot for multiple training ($N = 25$) and match ($N = 15$) sessions for a single player. Training data is shown in red, with match data in blue. The vertical dotted line represents the minimum speed criteria of 3 m s^{-1}, while the red and blue diamonds highlight the hypothetical maxima of the acceleration (A_0) and speed (S_0) profiles for the training and match data, respectively. *Fv* and quality of fit measures are shown in the legend for each dataset, with both exhibiting very strong linearity. Panel B documents the complete *PFv* metrics for the same athlete. Again, training data is shown in red, with match data in blue, while the red and blue stars represent the maximum athlete power (P_{max}) values for the training and match data, respectively.

Factors influencing agreement. While our present work still exhibits high linearity, there are several factors that may be contributing to small differences when compared to previous studies. Firstly, when compared to Morin et al.,[4] the lower sampling frequency may provide less temporal granularity as a result of fewer data points. However, the Morin et al.[15] work used the same trackers with the same sampling frequency as our current study, indicating that other factors are more influential. The tested cohort, i.e., sub-elite Gaelic footballers versus elite senior and youth soccer players, may also contribute to differences in linearity. This cohort is notable in that, anecdotally, club-level

Gaelic football squads exhibit a large spread of physical ability, with some participants displaying elite characteristics, and others considerably less so. There appears to be a greater spread in each of the metrics for the Gaelic football cohort, indicating a larger inter-player variability in *PFv* profiles; some players may not be able to produce high-quality acceleration efforts in the data window to produce a clear linear fit. The difference between sports is also worth noting; McIntyre et al.[23] reported that Gaelic footballers tended to have superior strength and speed endurance when compared to soccer players, who presented greater aerobic capacity, strength endurance, and flexibility. Reduced linearity relative to soccer has also been observed in rugby union[22] again highlighting the significance of the variation of the sport from which the data is collected.

The agreement between A_0 values indicates sub-elite Gaelic footballers may have comparable acceleration characteristics to elite senior and youth soccer footballers. S_0 being lower in training than in matches suggests players may be exposed to more high-end speed opportunities in games rather than in training, and is reinforced by S_0 from matches being within the reported range from literature. Additionally, Clavel et al.[15] found that S_0 is dependent on maximal speed exposure ($\geq 95\%\, v_{\max}$).

The number of data points utilized in the *Fv* profile fitting suggests sufficient data are pooled, despite slightly lower R^2 values. The same filtering process is used in Clavel et al.,[15] which indicates comparison with this study may be more appropriate, while Morin et al.[4] used a custom Gaussian filter, so differences in measured values must take this data processing difference into consideration.

Assessment of suitability. Despite the marginally lower degree of linearity, the comparable values of key metrics observed (S_{Fv}, S_0, A_0), as well as the number of data points used to produce the fits and the high linearity observed ($R^2 \geq 0.9$), indicate that the Morin et al.[4] method of generating in-situ *PFv* profiles is suitable for this dataset.

Comparison between in-situ and isolated sprint *PFv* profiles

Method

To compare *PFv* profiles created through isolated sprints and those created with in-situ data, pooled in-situ profiles were compared with the first repetition of a 50 m RSA test.[12] The first repetition was selected as it represents un-fatigued maximal sprint performance.

Three in-situ conditions were analyzed: (i) match data only, (ii) training data only, and (iii) combined match and training data. The inclusion criteria for each player under each condition were a minimum of five sessions and a pooled profile with $R^2 \geq 0.9$. Players who completed both the RSA protocol and met the in-situ inclusion criteria have been retained for paired analysis, leaving n=10, 15, and 12 for conditions (i), (ii), and (iii), respectively.

Paired Wilcoxon signed-rank tests were used to assess differences between in-situ and isolated sprint profiles, with significance set at $p < 0.05$. Effect sizes were calculated using Cohen's d from the paired differences (i.e., $d = \bar{d}/s_d$, where $\bar{d}$ is the mean difference and s_d its standard deviation), and interpreted as small ($|d| < 0.2$), medium ($|d| = 0.2 - 0.8$), or large ($|d| > 0.8$). The mean bias and 95% limits of agreement were also computed for each metric.

Results & discussion

Acceleration and speed intercepts (A_0, S_0). Table 3 shows the comparison between in-situ and isolated sprint *PFv* metrics across all three conditions. Testing context appears to systematically shift the *PFv* profile, with large effect sizes ($|d| > 0.8$) observed for the majority of metrics.

It should be highlighted that A_0 is not a single observed peak acceleration. Rather, it is an extrapolated y-intercept derived from the linear acceleration-speed relationship and therefore reflects the fitted acceleration-speed profile as a whole. As such, both in-situ and isolated A_0 values are theoretical maxima derived from the linear regression process. A_0 was higher for all in-situ conditions compared to isolated sprints ($d = +1.00$ to $+1.93$, all $p < 0.05$), with the largest effect observed in training. This was considered an unexpected result, as one would not expect many opportunities for unimpeded linear sprinting in match or training scenarios. However, the in-situ method selects the highest acceleration values across several sessions, whereas the isolated sprint profile is derived from a single sprint effort from a standing start. The in-situ profile may therefore represent a best-case acceleration-speed envelope accumulated across multiple training or match exposures, rather than a single maximal sprint effort. The methodological difference must also be acknowledged since this may contribute, at least partially, to the magnitude of the bias between test conditions. This effect may also be partly an artifact of how the in-situ envelope is constructed. For example, while it is thought that in-situ data that pools maxima across sessions creates a "best-case composite", it is possible these metrics more clearly describe a session state, as opposed to an individual's maximal possible output. Because A_0 is extrapolated rather than directly observed, it is subject to fitting uncertainty. Approaches that report metric-specific uncertainty, such as Miguens et al.,[22] may therefore provide useful additional context when comparing testing environments.

The match condition provided higher S_0 values than isolated sprint values (8.56 ± 0.31 m s^{-1} versus 8.33 ± 0.34 m s^{-1}; $d = +0.74$); this may indicate there are more opportunities for maximal speed exposure in competitive match play. Training data returned S_0 metrics lower than isolated

Table 3. Comparison of *PFv* metrics derived from pooled in-situ data (match, training, and combined) and isolated 50 m sprints (first repetition of the RSA protocol).

Metric	Condition	In-Situ (mean ± SD)	Isolated (mean ± SD)	Bias	d	p
A_0 ($m\,s^{-2}$)	Match ($n = 10$)	6.10 ± 0.49	5.51 ± 0.58	+0.59	+1.00	**.027**
	Training ($n = 15$)	6.30 ± 0.25	5.51 ± 0.58	+0.79	+1.93	**<.001**
	Combined ($n = 12$)	6.29 ± 0.26	5.51 ± 0.58	+0.78	+1.62	**<.001**
S_0 ($m\,s^{-1}$)	Match ($n = 10$)	8.56 ± 0.31	8.33 ± 0.34	+0.23	+0.74	**.049**
	Training ($n = 15$)	8.04 ± 0.25	8.33 ± 0.34	−0.29	−1.29	**<.001**
	Combined ($n = 12$)	8.11 ± 0.27	8.33 ± 0.34	−0.22	−0.84	**.027**
S_{Fv} (s^{-1})	Match ($n = 10$)	−0.71 ± 0.05	−0.76 ± 0.06	+0.05	+0.89	**.027**
	Training ($n = 15$)	−0.78 ± 0.04	−0.76 ± 0.06	−0.02	−0.46	.151
	Combined ($n = 12$)	−0.78 ± 0.04	−0.76 ± 0.06	−0.02	−0.25	.569
P_{max} ($W\,kg^{-1}$)	Match ($n = 10$)	13.07 ± 1.30	14.28 ± 1.61	−1.21	−1.02	**.014**
	Training ($n = 15$)	12.65 ± 0.70	14.28 ± 1.61	−1.63	−1.36	**<.001**
	Combined ($n = 12$)	12.75 ± 0.76	14.28 ± 1.61	−1.53	−1.23	**.002**
P_B ($W\,kg^{-1}$)	Match ($n = 10$)	26.13 ± 2.60	22.61 ± 3.39	+3.52	+1.02	**.020**
	Training ($n = 15$)	25.30 ± 1.40	22.61 ± 3.39	+2.69	+1.36	**<.001**
	Combined ($n = 12$)	25.51 ± 1.51	22.61 ± 3.39	+2.90	+1.43	**.001**
d_{Fv}	Match ($n = 10$)	4.96 ± 0.30	5.24 ± 0.34	−0.28	−1.09	**.010**
	Training ($n = 15$)	4.95 ± 0.15	5.24 ± 0.34	−0.29	−0.98	**.003**
	Combined ($n = 12$)	4.96 ± 0.16	5.24 ± 0.34	−0.28	−0.90	**.012**

Values are mean ± SD. Bias = in-situ − isolated. Cohen's *d* calculated from paired differences. Statistical comparison via paired Wilcoxon signed-rank test. Significant results ($p < 0.05$) in bold.

sprint values (8.04 ± 0.25 m s^{-1} versus 8.33 ± 0.34 m s^{-1}; $d = -1.29$, $p < .001$). This may reflect limited opportunities for players to reach top speeds during training regimes. This result aligns with the work of Clavel et al.,[15] who stated that S_0 is dependent on speed exposures ($\geq 95\,\%$ of v_{max}). The RSA protocol returns S_0 values that are between match and training in-situ derived values, suggesting the 50 m RSA sprint distance permits higher speeds than training, but does not replicate the full speed exposures of competitive match play.

Slope (S_{Fv}, d_{Fv}). S_{Fv} did not differ significantly from isolated sprint values in either training ($p = 0.151$) or combined ($p = 0.569$) conditions. A significant difference was observed between match and isolated sprint conditions ($d = +0.89$, $p = 0.027$), with a flatter slope likely arising from typically higher S_0 metrics under match conditions. The stability in S_{Fv} may indicate that this is an individual neuromuscular characteristic that appears robust irrespective of the testing environment.

d_{Fv} was consistently lower in-situ ($d \approx -1.0$, all $p < 0.05$), indicating that the in-situ force–velocity line sits closer to the origin than the isolated sprint profile. This geometric shift reflects the altered balance between A_0 and S_0 across differing conditions.

Power metrics (P_{max}, P_B). P_{max} was significantly lower during in-situ conditions compared to isolated sprints ($d = -1.02$ to -1.36). This highlights that in-situ profiles do not represent a maximum performance in all metrics; the isolated sprint protocol, by eliciting near-simultaneous high force and high velocity, produces a higher peak power output.

On the other hand, P_B was observed to have higher values in all in-situ conditions ($d = +1.02$ to $+1.43$), where the elevated A_0 in-situ has a greater proportional influence on P_B than on P_{max}.[12] The divergence between P_B and P_{max} across conditions underscores that these metrics represent different aspects of the force–velocity profile and may respond differently to changes in testing context.

Taken together, these results demonstrate that in-situ and isolated sprint *PFv* profiles are not interchangeable: systematic differences exist across most metrics, and no single methodology captures the maximum of every parameter. Practitioners should therefore establish and track baseline values within a consistent testing framework. Isolated sprint tests may provide clearer measures of sprint capacity, whereas in-situ monitoring may provide noisier but more ecologically valid expressions of that capacity during sport-specific activity.

Assessing minimum data load

Method

In order to assess the minimum data load required to create a sufficiently linear *PFv* profile, we applied the method outlined by Morin et al.[4] to data of increasing time durations across both training and match scenarios. For training data, the entire session is processed, including the warm-up, technical drills, conditioning, and game-replication drills (e.g., small- to large-sided games). For match data, only game play is included, i.e., the warm-up, half time interval, and post-match cool-down periods are excluded. For both training and match data, only players who completed the full session are included for consistency. For each analyzed session, each player's data was processed starting with the first five minutes, with the resulting *PFv* and linearity values stored. The observation window was then extended by five minutes and the resulting *PFv* metrics recomputed. This process repeated until the full session was processed. For the purpose of this section, match data are considered continuous (i.e., the half-time interval is neglected), with each half normalized to be 30 minutes long as described in Section "Participants & study design".

In addition to the single-session analysis, a multi-session analysis was conducted in which each player's data were ordered chronologically by date, and then concatenated to form a continuous series. An expanding window analysis was carried out for each player, beginning with the first 10-minutes of data and increasing by 10-minute increments. Here, 10-minute increments were chosen, rather than the 5-minute increments used for individual match/training sessions, to reduce computational burden and avoid overinterpreting small fluctuations in season-long data. At each increment, quality and *PFv* metrics were computed using all the data available up to that point. This process continued until the entirety of each player's available data had been analyzed.

As in Section "Comparison between in-situ and isolated sprint *PFv* profiles", this analysis was performed across three data categories: (i) match only, (ii) training only, and (iii) combined match and training data. For the match- and training-only conditions, data were sorted chronologically by date for each session type prior to applying the expanding window procedure. For the combined data, match and training data were pooled and ordered chronologically before analysis.

To determine the minimum data load based on the above analysis, two selection methods were employed. First, the time for each data set to reach $R^2 \geq 0.9$ was identified; this threshold was chosen as a traditional indicator of goodness of fit. Second, the time corresponding to the geometric 'knee' of the R^2 values, when plotted as a function of window duration, was located. Here, the definition of the 'knee' point is that at the geometric knee, the relative cost of increasing the time window to increase the corresponding R^2 precision is no longer worth the corresponding performance benefit.[24] Calculating the time of the geometric knee required use of a Python library called `Kneed` (https://pypi.org/project/kneefinder/), which employed the `KneeFinder` function. The results for this method are outlined in Table 4, with the method shown graphically in Figure 3.

Results & discussion

Profile quality was assessed using the coefficient of determination (R^2) of the linear fit. From Table 2, *Fv* profiles that include data from multiple matches and/or training sessions typically exhibit very strong linearity with $R^2 \geq 0.97$ in literature and $R^2 \geq 0.929$ within the present study. The minimum window required to achieve $R^2 \geq 0.9$ was 12 minutes for matches, 42 minutes for training, and 36 minutes for combined data (see Figure 3 and Table 4). The geometric knee occurs at approximately half these times (i.e., 7 minutes, 17 minutes, and 12 minutes, respectively), suggesting it represents a practical point of data convergence, while the $R^2 \geq 0.9$ threshold serves as a more conservative benchmark.

Table 4. Observation times required to reach the $R^2 \geq 0.9$ and geometric knee thresholds across different data sets, where the value given is the group mean with associated 95% confidence intervals.

Data Set	Time for $R^2 \geq 0.9$ (mins)	Time for Geometric Knee (mins)
Match	12 ± 7	7 ± 1
Training	42 ± 5	17 ± 1
Combined	36 ± 5	12 ± 1

Match play is clearly the more efficient data source, likely because it produces more high-end speed exposures per unit time than training due to the competitive nature of the session. Notably, the combined data set was slower to converge than match data alone, indicating that pooling training data may dilute the high-intensity efforts that form the resulting *Fv* profiles. These window sizes, particularly the 7- and 12-minute match-derived values, form the basis for the in-game temporal analysis presented in Section "Producing In-Match Trends".

It should be stated explicitly there are key distinctions between the terms 'fit validity', 'metric reliability', and 'decision utility'. Here, we describe the fit validity as being assessed through the R^2 value of the linear fits applied to the *PFv* profiles, the metric reliability as the stability of the derived *PFv* values across repeated windows, and the decision utility as whether the metric is stable enough to trigger a subsequent action. Accordingly, the 7- and 12-minute thresholds should be interpreted as minimum windows for producing acceptable linear fits, rather than as definitive evidence that all derived *PFv* metrics are reliable enough for individual-level decisions.

Producing in-match trends

Method

To determine in-match trends in *PFv* metrics, data from competitive matches were analyzed using a sliding window approach. For each participant in each game played, analysis windows of 7 minutes and 12 minutes (as determined in Section "Assessing Minimum Data Load") were applied

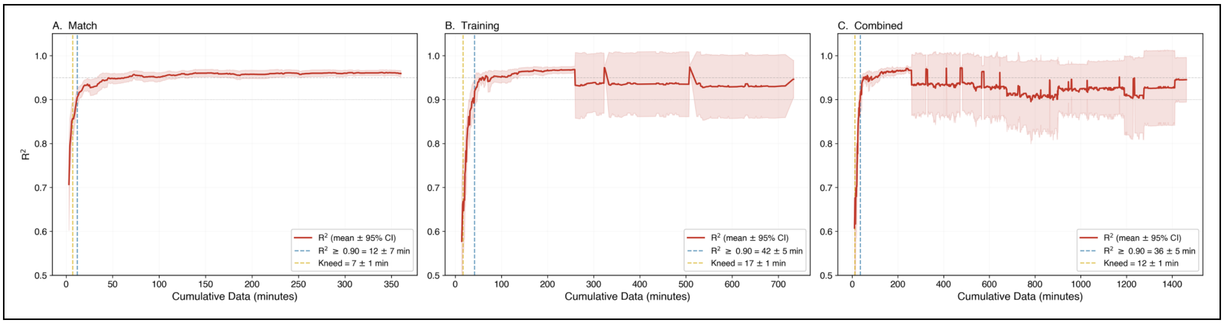

Figure 3. Average R^2 values against cumulative window size in minutes for the examined cohort across three data sets: match (panel A), training (panel B), and combined (match and training data; panel C). The red line indicates the mean R^2 value, while the red shaded area indicates the 95% confidence interval. Vertical blue and yellow dashed lines in each panel reflect the window size times corresponding to $R^2 \geq 0.9$ and the position of the geometric knee, respectively.

to each half, with the first and second halves treated as discrete events due to the halftime interval. Within each half the following procedure was followed:

1. Initial window was defined (i.e., both 7- and 12-minute window durations), beginning at the start of the respective half.
2. *PFv* metrics were computed following the method outlined in Section "Implementation of the Morin et al. (2021) techniques", with the corresponding R^2 value stored.
3. The analysis window was then moved forward by 10 seconds (preserving the same overall window duration), with the resulting *PFv* and R^2 metrics computed.
4. Step (3) was repeated until the entire half was processed.
5. Any analysis windows that contained no data points exceeding 3 $\mathrm{m\,s^{-1}}$ were excluded, with no value returned.

This procedure is analogous to a traditional rolling window analysis used in time-series modeling,[25] where each data point represents the aggregate of data contained solely within the current window. With the nature of match play, data samples with high enough speeds to return a sufficiently linear *PFv* profile may only occur intermittently,[26] hence a rolling aggregation as described above, provides a continuous *PFv* estimation, while still providing sufficient granularity of the temporal changes.

The time series of *PFv* metrics is then normalized by the value obtained from analysis of the entire game (i.e., the *PFv* metrics returned from analyzing the full 60 minutes of each game), which allows for comparison between participants. Such normalization also allows for interpretation of match-wide trends, with overlapping windows smoothing short term fluctuations, while still representing *PFv* performance trends over time. This allowed us to assess, retrospectively, whether the selected sliding-window sizes could detect temporal performance trends from in-situ GPS-based measurements.

Table 5. Mean change (Δ) in full-game-normalised *PFv* metrics across match periods ($n = 193$ player-matches).

Metric	Window	1st Half	2nd Half	Full Game
A_0	7-min	$-3.0^{0.0}_{-6.0}$	$-6.1^{-3.1}_{-9.1}$	$-7.4^{-4.2}_{-10.7}$
	12-min	$-0.5^{+1.8}_{-2.7}$	$-4.0^{-1.6}_{-6.3}$	$-3.8^{-1.4}_{-6.3}$
S_0	7-min	$-0.1^{+3.1}_{-3.0}$	$+3.6^{+8.2}_{-1.0}$	$+2.4^{+7.3}_{-2.5}$
	12-min	$-0.8^{+1.0}_{-2.6}$	$+1.1^{+3.1}_{-1.0}$	$-0.8^{+1.4}_{-3.0}$
S_{Fv}	7-min	$-1.3^{+4.2}_{-6.9}$	$-6.4^{-1.7}_{-11.1}$	$-7.6^{-2.1}_{-13.0}$
	12-min	$+1.2^{+4.9}_{-2.5}$	$-4.2^{-0.5}_{-8.0}$	$-1.9^{+2.1}_{-5.9}$
P_B	7-min	$-3.8^{-2.0}_{-5.6}$	$-4.5^{-2.2}_{-6.8}$	$-6.4^{-4.1}_{-8.7}$
	12-min	$-1.7^{-0.2}_{-3.1}$	$-3.2^{-1.4}_{-5.0}$	$-4.9^{-3.2}_{-6.7}$
d_{Fv}	7-min	$-3.2^{-1.3}_{-5.2}$	$-5.4^{-3.2}_{-7.6}$	$-6.4^{-4.2}_{-8.6}$
	12-min	$-1.3^{+0.1}_{-2.6}$	$-3.1^{-1.5}_{-4.7}$	$-3.8^{-2.2}_{-5.5}$

Values are expressed as percentage points of the full-game profile (last − first window), with 95% confidence intervals.

Results & discussion

In Table 5 we can see how typical *PFv* metrics vary across each half, and across a full game by each window size. Plots of squad- and match-averaged ballistic power (P_B) against time are shown in Figure 4 for both the 7-minute and 12-minute sliding window sizes. Both window sizes present similar trends, with a gradual reduction in P_B with time. These results agree with the findings of McGleenan et al.,[12] who stated power-based metrics may be the most sensitive to neuromuscular fatigue.

Across a full competitive match, ballistic power for each player declined by an average of 6.4% and 4.9% for the 7-minute and 12-minute windows, respectively. The sustained nature of this reduction is further illustrated when the squad is considered as an entire cohort, with the group-averaged P_B remaining below its opening value for more than 95% of the tracked match time across both window sizes (7-minute: 95.3%; 12-minute: 96.6%), with 100% of the second half spent below the first-half opening value.

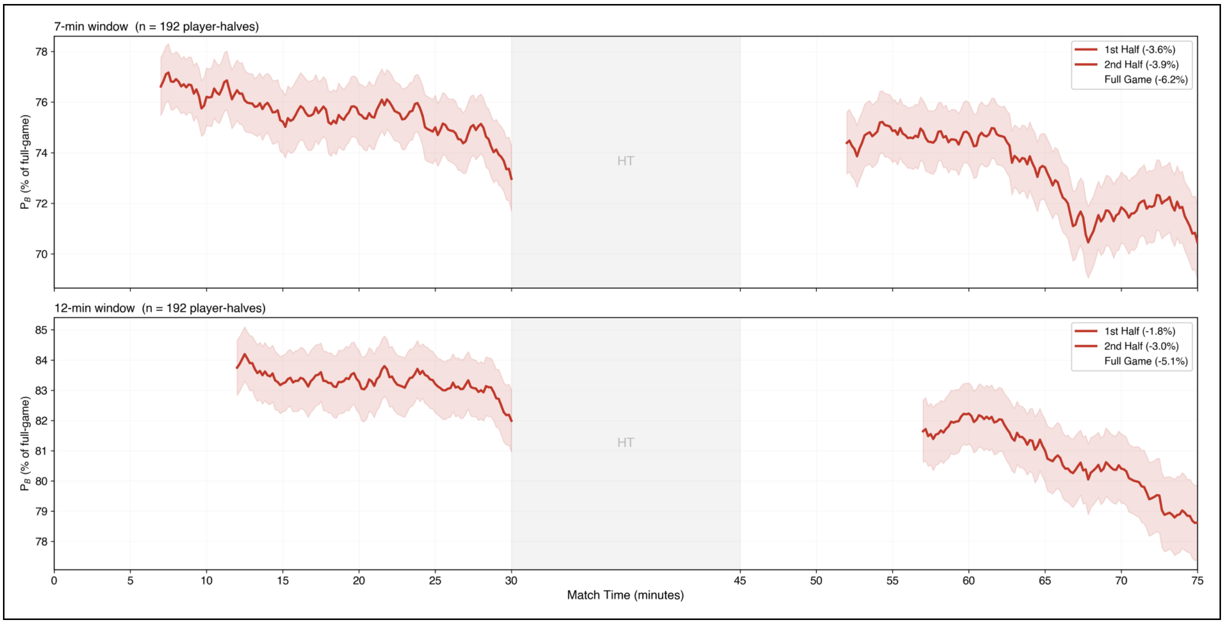

Figure 4. Squad- and match-averaged ballistic power (P_B; solid red line) trajectories calculated from in-situ match data, using 7-minute (top) and 12-minute (bottom) sliding windows that are advanced in 10-second intervals. Each half is treated discretely, with all metrics normalized to the corresponding full-game values. Shaded regions represent 95% confidence intervals. The shaded gray region represents the half time interval. The percentage decline observed over each half for each window size is indicated in the legend.

This highlights the usefulness of the ballistic power metric when characterizing progressive performance degradation.

In both the upper and lower panels of Figure 4, it can be seen that many P_B values at the start of the second half are larger than those found at the end of the first half. This is consistent with partial neuromuscular recovery during the half-time period, irrespective of whether a 7-minute or 12-minute sliding window is employed. Again, this agrees with the work of McGleenan et al.,[12] who identified increases in ballistic power following a short recovery period present within an RSA test. However, it should be acknowledged that other factors, such as tactical and/or positional changes, introduction of substitutes, and other early-second-half game-state effects are also plausible justifications of this change alongside neuromuscular recovery.

In reference to other *PFv* metrics, the hypothetical maximum athlete speed, S_0, remains essentially unchanged across both halves and the entire collective match. This agrees with Snyder et al.,[27] who suggest that maximal speed events may not occur frequently enough to be of use as an athlete monitoring aid. Reductions in metric values were also observed for both A_0 and d_{Fv} across the full game for both sliding window sizes, with these reductions consistently observed within both halves and the full game.

S_0 did not exhibit a clear reduction trend, either within a single half or across the full game. With S_0 remaining relatively stable, the *Fv* profile appears to be anchored near the velocity intercept. A reduction in A_0 would therefore reduce the absolute magnitude of the negative slope, producing a flatter profile and a lower d_{Fv}. This pattern suggests that the observed match-related changes are driven more by reductions in force-production capacity than by reductions in maximum-speed exposure.

It should be noted that at this time, while these trends are consistent with neuromuscular fatigue, they cannot yet be treated as specific markers of fatigue in isolation. Alternative explanations include individual role changes, tactical changes, pacing, and opposition effects.

Practical applications

The methods presented in this study have potential use-cases requiring further investigation across three distinct domains. At present, the methods outlined here are best positioned as an adjunct monitoring signal that complements existing performance monitoring workflows. Given further validation, they may support retrospective, longitudinal analysis and exploratory live monitoring of performance trends. Finally, if robustly validated and integrated into decision-support workflows, these metrics may contribute to substitution prompts, return-to-play monitoring, and/or training adjustments. However, these applications will require individual baselines, smallest worthwhile change thresholds, and integration of contextual and ecological factors. Potential use-cases presented here are (1) in-game decision-making, (2) return-to-play protocols, and (3) training program evaluation. Real-time *PFv* monitoring during matches and training may allow practitioners to identify performance trends and make adjustments accordingly. For example, looking at the trend in *PFv* of a certain player during a game, staff could assess whether a player's *PFv* trajectory deviates significantly from that of the other players, or from their own typical value for a given point during a match, with values significantly below baseline potentially signaling evidence of a performance reduction consistent with neuromuscular fatigue, lack of recovery before the match, or an excessively high workload.[28] If this trend cannot be accounted for by tactical adjustments, it may indicate a potential injury concern for coaching staff to consider. A significantly low *PFv* trajectory may act as a trigger for enhanced contextual review alongside observed movement quality, tactical role, medical status, and existing load history. Existing live metrics, such as total distance, high-speed running, and rolling external-load summaries, may be used alongside P_B. This combined approach would retain familiar threshold-based metrics while adding a summary of the force-velocity relationship captured by P_B.

PFv metrics, such as the ballistic power (P_B; which we have shown to be the most sensitive of *PFv* metrics to neuromuscular fatigue) may be incorporated into existing real-time data streams that pass data from wearable sensors through machine learning (ML) and artificial intelligence (AI) pipelines to inform decision making,[29] facilitating the mitigation of injury risk while also maintaining team performance. Through ML/AI approaches, it will be possible to streamline the identification and characterization of *PFv* trends during both real-time game evaluations and longitudinal summaries across multiple seasons. This direction is a logical development of our current work, but requires further investigation through multi-season and multi-squad analysis.

Our results indicate that a 7-minute sliding evaluation window is able to produce acceptable fit quality of each athlete's *PFv* profile. Utilizing this window, we are able to identify statistically significant reductions in both power- and force-related metrics during the course of a competitive game with, on average, reductions in P_B and A_0 equal to -6.4% and -7.4%, respectively. A 7-minute monitoring window is also able to identify evidence of performance changes consistent with neuromuscular recovery during the halftime period, hence indicating its suitability for the real-time evaluation of player/team fatigue levels, with the potential to offer coaching staff greater tactical insight in the latter stages of matches.

The procedures demonstrated in our present study may also inform return-to-play protocols following injuries. Full-sided, full-pitch training games of sufficient duration may provide an indication of a player's current physical status. Once a player's *PFv* metrics exceed a club-defined threshold, or return to within an agreed percentage of their pre-injury baseline, the player may be considered physically prepared for progression toward competitive play. Establishing a robust process to determine baseline values may follow on from the present work. This is in line with Kovoor et al.,[28] who framed data from wearable sensors as a means to assess when an injured player has recovered sufficiently, reporting an observed 20% reduction in soft-tissue injuries when following model feedback. This illustrates that working within a data-informed threshold-based structure may guide return-to-play practices. An important future direction for work will be establishing thresholds for decision making using live *PFv* feedback or determining the smallest worthwhile change (SWC). Baseline or pre-injury assessments may also be useful for identifying players at high-risk for injury.[29] It should be acknowledged that the present study has not established any potential threshold for return to play (RTP) protocols, or whether match- and rehab-derived values are comparable. This area is highlighted as a potential use-case requiring substantial further development before incorporation into decision-support.

Previous methods of monitoring *PFv* profiles have been used as a means to evaluate the response of players to bespoke training programs. The effectiveness of these regimes may also be seen from in-situ data, with changes in the *PFv* profiles reflecting changes in speed, force, and power output capabilities. This mirrors applications of laboratory-derived *PFv* using, e.g., force plates, which have been presented as a means to evaluate the response of players to bespoke training programs.[30] Future work may wish to investigate how training interventions affect both in-situ and isolated sprint-derived *PFv* metrics, whereby comparing changes between the methods may shed further light on the utility of each of the metrics. The sliding-window framework and minimum data-load thresholds established in the present study provide the methodological foundation upon which these applications may be built, and we place significant importance on determining a SWC via linking *PFv* metrics with internal load measures. These prerequisites must be met before these processes can become functional.

In summary, our findings suggest that in-situ *PFv* monitoring, particularly through P_B, may be a useful addition to practitioners' existing performance-monitoring toolkits. This is indicated by the group-level performance trends that are detected within a single game as shown in Figure 4. The current proof-of-concept may become a regular part of operational procedures following the determination of individual baselines, SWC thresholds, contextual factors, and links with internal load measures. Addressing these conditions in future work will determine if the methods here can transition from proof-of-concept into a validated tool for in-game, return-to-play, and training evaluation decisions.

Limitations

The study presented here employed 34 physically active male participants from one amateur invasion sports team. Hence, the results reported may not fully extend to the entire athletic community, including female athletes, elite professionals, adolescents, and players from other sports. Follow-up studies may wish to explore how the results from the methods described here compare across more diverse samples. The relevancy of these procedures will also need to be tested with endurance and/or strength-based sports to assess their potential across these disciplines. Gaelic football has specific characteristics (e.g., fluid positions, high degree of contact, intermittent running demands, etc.) that may limit the transferability to more structured sports such as rugby, American football, or soccer. It should also be noted the assigned positions are approximate, with players and managers shifting roles within (and between) matches. Furthermore, team-level tactical and coaching decisions, in addition to the composition of the competition calendar, may affect the observed trends, limiting generalizations.

The methods presented here were developed using GPS units, which are most commonly used in outdoor, invasion field sports that are characterized by intermittent activity. Because these methods rely on athlete-worn sensor data, their reliability can be influenced by environmental conditions, such as temperature, humidity, pitch surface, and altitude, which were not controlled or reported on during data acquisition. Quantitative indicators, such as HDOP and satellite count, should be monitored to ensure data quality related to GPS-derived metrics. Furthermore, a 10 Hz GPS sampling frequency combined with a 1 Hz Butterworth filter may smooth genuine high-acceleration events, causing underestimation of peak values when compared with higher-frequency systems.

The present study relies on a conceptual link to GPS derived metrics to act as indicators of external load. To more comprehensively associate the effects observed within this work, further metrics should be collected and analyzed, particularly those which may more readily provide indications of internal load, e.g., heart rate, blood lactate concentration.

The in-situ nature of the data collection, in which participants were directly competing, subjected athletes to a wide range of stressors that may also contribute to the observed performance and fatigue levels. The data employed in our present study only includes locomotion-related information via GPS sensors, and therefore does not account for factors such as mental stress, physical contacts, game-specific intensity, etc. The extent of the effects of these factors is beyond the scope of this study, but may form a basis for future work incorporating elements of time-dependent, mixed-effects models to better understand the contributions and interplay between a diverse assortment of athlete metrics.[31]

Suggested future directions for this work include creating mixed-effects models with the player as a random effect, which would account for the repeated measures and improve interpretability. Larger multi-squad and multi-season analysis would allow for further investigations into the sub-group frameworks. Establishing smallest worthwhile change (SWC) thresholds while monitoring injury and performance outcomes would help move the method from proof-of-concept toward applied decision-support. The work of Miguens et al.,[22] which provides per-metric uncertainty estimates, offers a useful starting point for this process. Comparison with internal load measures, such as heart rate and lactate concentration, may give a more complete physiological basis to the observed *PFv* metrics.

Despite any potential limitations, our novel method of in-situ *PFv* monitoring (particularly the ballistic power, P_B) shows promise as a tool for real-time fatigue and performance monitoring. Its practical value warrants further investigation.

AI diligence statement

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Ethical considerations

This study was approved by the Engineering and Physical Sciences Faculty Research Ethics Committee of Queen's University Belfast (reference number: EPS 24_48).

Consent to participate

Written informed consent was obtained from all participants.

Consent for publication

Informed consent for publication was obtained from all participants.

Notes on contributors (CRediT roles)

EMcG: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft; **SDTG:** Data Curation, Methodology, Resources, Supervision, Writing – original draft; **LMMcF:** Formal analysis, Methodology, Supervision, Writing – original draft; **JCJB:** Formal analysis, Methodology, Software, Validation, Writing – original draft; **RH:** Conceptualization, Investigation, Methodology, Writing – original draft; **TdMM:** Data curation, Funding acquisition, Methodology, Writing – original draft; **RM:** Methodology, Software, Writing – original draft; **RMcC:** Methodology, Writing – original draft; **DBJ:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing – original draft;

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Data availability statement

The data that support the findings of this study are available on reasonable request from one of the co-authors, SDTG.

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