Relationships between model estimates and actual match-performance indices in professional Australian footballers during an in-season macrocycle

Graham, Stuart R., Cormack, Stuart, Parfitt, Gaynor and Eston, Roger

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Authors: Stuart R. Graham [1,2], Stuart Cormack[3], Gaynor Parfitt[2] and Roger Eston[2]

Affiliations: [1]Port Adelaide Football Club, Allan Scott Headquarters, Alberton Oval Brougham Place Alberton, SA 5014, Australia. [2] Alliance for Research in Exercise, Nutrition and Activity; Sansom Institute for Health Research, University of South Australia, Adelaide, SA 5000, Australia. [3]Australian Catholic University, Melbourne Campus, VIC 3065, Australia.

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Stuart R. Graham [1,2]• Stuart Cormack[3] • Gaynor Parfitt [2] • Roger Eston[2]

[1]Port Adelaide Football Club, Allan Scott Headquarters, Alberton Oval Brougham Place Alberton, SA 5014, Australia

[2] Alliance for Research in Exercise, Nutrition and Activity; Sansom Institute for Health Research, University of South Australia, Adelaide, SA 5000, Australia

[3]Australian Catholic University, Melbourne Campus, VIC 3065, Australia

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Corresponding author:
Stuart Graham
Head of Sports Science
Port Adelaide Football Club
Allan Scott Headquarters,
Alberton Oval Brougham Place
Alberton, SA 5014, Australia
Tel: +61 413608037
email: Sgraham@pafc.com.au

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Abstract

Purpose: To assess and compare the validity of internal and external Australian Football (AF) training load measures for predicting match exercise intensity (MEI.min^{-1}) and player rank score (PR^{Score}) using a variable dose-response model. **Methods:** 25 professional AF players (23 ± 3 y, 188.3 ± 7.2 cm and 87.7 ± 8.4 kg) completed a 24-week in-season macrocycle. In-season internal training and match load was quantified using session-RPE (sRPE) and external load from satellite and accelerometer data. Using a training impulse (TRIMPs) calculation; external load (au) was represented as distance (TRIMP^{Dist}), distance ≥ 4.16m.s^{-1} (TRIMPs$^{HS Dist}$) and player load (TRIMP^{PL}). In-season training load, MEI.min^{-1} and PR^{Score} were applied to a variable dose-response model, which provided estimates of MEI.min^{-1} and PR^{Score}. Predicted MEI.min^{-1} and PR^{Score} were correlated with actual measures from each match. The magnitude of the difference between MEI.min^{-1} and PR^{Score} estimates for each model input and the difference between the precision of internal and external load measures to predict MEI.min^{-1} and PR^{Score} were calculated using the effect-size ± 90% confidence interval [CI]. **Results:** Estimates of MEI.min^{-1} demonstrated very large associations with actual MEI.min^{-1} (r, 90% CI) (e.g. TRIMPs^{Dist} 0.76, 0.73-0.78 and sRPE^{Skills} 0.73, 0.70-0.76). Estimates of PR^{Score} demonstrated associations of large magnitude with actual PR^{Score} using the same inputs. Precision of actual MEI.min^{-1} was lowest using sRPE compared to (ES ± 90% CL) TRIMPS^{Dist} -0.67 ± 0.34 and, TRIMPs^{PL} -0.91 ± 0.39. There were trivial and unclear differences in the precision of PR^{Score} estimates between TRIMPS and sRPE inputs. **Conclusions:** Dose-response models from multiple training load inputs can predict within-individual variation of MEI.min^{-1} and PR^{Score}. Internal and external training input methods exhibited comparable predictive power.

Keywords: internal training load, external training load, variable dose-response model

Introduction

Mathematical fitness-fatigue models have been proposed to assist sport science and conditioning staff to prescribe the optimal distribution of training load with a higher degree of precision[1,2]. With a systems model approach, physical training represents the input dose and performance represents the responses or system output. A mathematical model approach to training was first proposed by Bannister et al., in 1975[2]. Studies have attempted to validate the predictive power of the first and more recently refined variable dose-response model versions, using empirical data from different training scenarios: recreational runners[3-5,] elite swimmers[6,] elite female gymnasts[7] and weightlifters[8.] These studies have reported associations between modelled and actual performance ranging in magnitude from moderate to very large [3-7].

Quantification of training load is paramount for variable-dose-response model construction[1,2.] Numerous studies have examined the effectiveness of methods for quantifying training load, each with varying degrees of ecological validity [4,9]. In professional Australian Football (AF), micro technology devices provide satellite and accelerometer data, enabling the quantification of external match and training load [10-12]. Due to its simplicity, strong validity and global representative nature, the quantification of internal match and training load occurs using the session-RPE method [13]. To build robust models and increase the predicative power, it has been recommended that individual athletes undertake between 15 and 200 performance assessments within a short time.

At present, all previous investigations using a variable dose-response model have used training and performance data from athletes competing in individual, predominately endurance based sports. The broader application of applying a variable dose-response model approach in high performance team sport settings to predict performance responses is unsubstantiated within the literature. Specifically, despite refinements in modelling techniques leading to enhanced predictive accuracy, their adequacy has not been investigated at an individual level in professional AF. This is largely attributable to the fact that variable dose-response model construction requires a single measure to represent performance, which may limit their application in AF, whereby technical and tactical performance represents true performance and is difficult to quantify and express as a single measure.

Common practice in professional AF is to routinely assess the relevant sport-specific physical capacities through a variety of maximal field tests. However, these capacity assessments are fatiguing which is problematic during an AF in-season and potentially limits there use as model performance inputs.[14] Studies in professional soccer and AF have identified relationships between adaptation to prescribed external and internal load and improvements in physical capacity[15-17]. Further, these studies have identified links between physical capacity and the increased ability to produce high match exercise intensity (MEI.min^{-1}), which has further been correlated with individual player success[17-19] as assessed via coaches' perceptions of performance. Collectively, these findings suggest that MEI.min^{-1} may be a casual indicator of overall match technical/tactical performance. However, recent work indicates that skill performance rather than increased MEI.min^{-1} and physical activity profiles, is more important to coaches' perceptions of performance[20]. The official commercial statistical provider (Champion Data) of the Australian Football League (AFL) provide a global measure of player skill performance termed PR^{Score}, which has been reported to be largely associated with coaches' subjective ratings[20]. In comparison to maximal field-test assessments, both MEI.min^{-1} and PR^{Score} are able to be assessed, (i.e from each competitive match) during the in-season, at a frequency that satisfies the recommended requirements for model construction. Despite the widespread quantification of MEI.min^{-1} and availaibility of skill performance data in AF, little empirical knowledge relating to the individual cumulative dose-response effects of training load on subsequent MEI.min^{-1} and PR^{Score} exits. The present study, using a variable dose-response model and a longitudinal post facto experimental design, will compare the within-individual predictive accuracy of model estimates of $MEI.min^{-1}$ and PR^{Score} with actual measures obtained from an entire in-season macrocycle. The study will also compare and assess the validity of internal and external methods for quantifying in-season AF training load.

Methods

Subjects

Forty-five professional AF athletes from the same team (188.3 ± 7.2 cm, 87.7 ±8.4 kg, and 22.3 ± 3.3 y), participated in the study. Ethical approval was granted by the university research committee and informed consent was obtained before the commencement of the research.

Experimental Design

A retrospective longitudinal observational research study design was used to compare model predicted estimates of $MEI.min^{-1}$ and PR^{Score} with actual measures collected across an entire 24-week competitive season.

Methodology

Match exercise intensity performance

Four thousand and fifty-seven individual training sessions were analyzed during the investigative in-season training and competition macrocycle. Individuals completed an average of 190.3 ± 7.5 individual training sessions during the season. From each competitive match of the 2015 AFL premierships season, $MEI.min^{-1}$ (CV, 8.11 ± 3.75%), was quantified for each player in accordance with previous protocols[17]. To reduce the likelihood of reporting artificially low match intensities, rest time and any stoppage time during the match were excluded from the analyses for each participant. An individual player's $MEI.min^{-1}$ was excluded from analysis if he was injured (but was selected to play) or injured in game (but continued to play). Further, match performance data were removed for analyses if the game was played indoors or influenced by environmental conditions (i.e. rain). To reduce the likelihood of reporting artificially high MEI.min^{-1} intensities, activity profiles were only accepted if the participant played >75% of the total game time and absolute variables were divided by the on-field active duration. MEI.min^{-1} from each eligible match was converted into a percentage of seasonal best performance.

Champion Data Player Rank Score

After each competitive match, individual player match skill performance assessed via PR^{Score} (CV, 21.87 ± 5.91%) was retrieved from software provided by the official commercial statistical provider of the AFL (Champion Data, VIC, Australia). PR^{Score} is calculated from a player's involvement in selected match activities (i.e., specific skills) that are assigned positive or negative numerical value based on the outcome of the skill execution. The summative score objectively provides an index of an individual players' impact on a match.

Training load quantification

A variety of methods (n=5) were used to quantify each in-season training session as either internal or external load (au) to act as input data for a variable dose-response model for each individual athlete.

Internal load

The sRPE method was used to quantify internal load and represent the "global" (all field based, skill, strength and conditioning, rehabilitative and active recovery sessions) in-season training load [21]. Subsequently, perception of effort (RPE) for the skills and conditioning component was differentiated from the total in-season sRPE load. All participants were familiar with the RPE process for over 12 months leading up to the study period.

External Load

For each in-season match and training session a portable micro technology device (Optimeye S5, Catapult Innovations, Melbourne, Australia) activity profile data. Satellite data sampled at 10Hz provided measures of total distance and high speed running distance (Distance covered ≥ 4.16m.s^{-1}). Player Load (PL au), which is a vector of magnitude representing the square root of the sum of the instantaneous rate of change in acceleration in the *x*, *y* and *z* axes divided by 100 was obtained from the accelerometer sampling at 100Hzs and has been reported to be reliable and valid[22]. At the conclusion of each session, data was downloaded and analyzed using the manufacturer specific software (Catapult Openfield v 11.1.2 software, Catapult Innovations, Melbourne, Australia). Outcome variables to quantify external load were relative distance to specific velocity bands corresponding to (Zone 1 - 0-1.5m.s^{-1}, Zone 2 - 1.5-3m.s^{-1}, Zone 3 - 3-4.16m.s^{-1}, Zone 4 - 4.16-5.5m.s^{-1}, Zone 5 - 5.5-7m.s^{-1}, Zone 6 - >7m.s^{-1}) and Player Load relative to specific intensity bands corresponding to (Zone 1 - 0-1 m.s^{-1}, Zone 2 - 1-2 m.s^{-1}, Zone 3 - 2-3 m.s^{-1}, Zone 4 - 3-4 m.s^{-1}, Zone 5 - 4-5 m.s^{-1}, Zone 6 >5 m.s^{-1}). The validity and reliability of GPS devices and the metrics used in this study have been extensively reviewed elsewhere (for review[18,20,22]). In brief, it appears that the validity and reliability for measuring distance, player load and velocity is improved with a higher sampling frequency[18,20]. External load was expressed in arbitrary units, using an adapted TRIMP calculation, proposed by Edwards et al., (1993)[23]. Distance and player load accumulated in each of the six velocity and player load zones was multiplied by a corresponding exponentially weighted intensity coefficient, which placed greater weighting to higher intensities (Table 1). The multiplying coefficient factors used were provided in the manufacturer specific software (Catapult Sprint v 5.0.9 software, Catapult Innovations, Melbourne, Australia).

Fitting the Model

Individual in-season training load, MEI.min^{-1} and PR^{Score} data units for each player were applied to a variable dose-response model proposed by Busso et al., 2003[1]. Mathematically, the variable dose-response model used has been previously described[1]. The set of individual parameters were determined by fitting the model performances with actual performance via successive minimizations of a recursive least squares algorithm[24] using the GRC Nonlinear Solver function in Microsoft Excel (Microsoft, Redman, USA). Ten models were generated for each player, representing each of the training input methods and MEI.min^{-1} and PR^{Score}, respectively.

Statistical Analyses

Within-individual correlations between actual and predicted estimates of MEI.min^{-1} and PR^{Score} were analyzed using Pearson's correlation coefficient (r) and reported with 95% confidence intervals (CI). The magnitude of the correlation between predicted and actual MEI.min^{-1} and PR^{Score} was described as <0.1 trivial, 0.1-0.3 small, 0.3-0.5 moderate, 0.5-0.7 large, 0.7-0.9 very large and 0.9-1.0 almost perfect. Traditionally, a 1-way analysis of variance (ANOVA) has been used to compare the predictive power of variable dose-response models using different quantitative training input methods.[4] In this study, magnitude based inferences (effect-size statistic ± 90% CI) were calculated to determine the practical differences between MEI.min^{-1} and PR^{Score} estimates for each model input (i.e. difference in correlation between actual and predicted). In addition, the magnitude of the difference ± 90% CI between the precision of internal and external load measures to predict MEI.min^{-1} and PR^{Score} was also calculated. Differences were represented as ES ± 90% CI and classified as *trivial* (< 0.2), *small* (0.2 – 0.59) and *moderate* (0.6 – 1.19)[25]. Where the 90% CI simultaneously overlapped the smallest important ES (0.2) the magnitude of the difference was considered "*unclear*"[25]. The results are presented as mean ± SD and differences as effect size ± 90% CI with a qualitative descriptor to represent the likelihood of exceeding the 0.2 threshold.

Results

Weekly mean values for training duration, distance, Player Load, and sRPE were 443 ± 27 min, of 25259 ± 2015 m, 2513.5 ± 231.5 au, and 3846 ± 232.4 au, respectively. The difference in the precision of estimates was greater for MEI.min^{-1}, compared to PR^{Score} using (Training input, effect size ± 90% CL, qualitative descriptor); TRIMPs^{Dist} 0.60 ± 33, 97% moderate, TRIMPs^{PL} 0.58 ± 0.34, small, TRIMPs^{HSDist} 0.58 ± 0.34, 89% small, and sRPE^{Skills} 0.47 ± 0.38, small. Trivial differences between MEI.min^{-1} and PR^{Score} were evident using sRPE as the training input method.

Modeled match exercise intensity

Fluctuations in MEI.min^{-1} were observed across the entire in-season macrocycle and presented as Mean ± SD (Fig 1. a). Modeled MEI.min^{-1} showed a strong fit with actual MEI.min^{-1} over season. The average within-individual correlations between predicted and actual MEI.min^{-1} for the various training input methods were (Training input, r Mean ± SD, qualitative descriptor), TRIMPs^{Dist}, 0.76 ± 0.13, very large, TRIMPs^{PL}, 0.77 ± 0.12, very large, TRIMPs^{HSDist}, 0.75 ± 0.14, very large, sRPE, 0.68 ± 0.12 large, and sRPE^{Skills}, 0.73 ± 0.14, very large for the, respectively. Fig 2 shows an example of model simulation for one participant using in-season TRIMPs^{Dist} and MEI.min^{-1} data. Table 2 shows the retrospective precision of actual MEI.min^{-1} using the different internal and external training input methods. The mean ± SD of the difference between predicted and actual performance is presented in (Fig. 3, a-e).

Modeled Player Rank Score performance

Fluctuations in PR^{Score} were observed across the entire in-season macrocycle and presented Mean ± SD (Fig 1. b). Modeled PR^{Score} showed a strong fit with actual performance over season. The average within-individual correlations were (Training input, r Mean ± SD, qualitative descriptor); $TRIMPs^{Dist}$, 0.62 ± 0.20 , large, $TRIMPs^{PL}$, 0.63 ± 0.19, large, $TRIMPs^{HSDist}$, 0.67 ± 0.16, large, sRPE, 0.63 ± 0.16, large, and $sRPE^{Skills}$, 0.65 ± 0.17, large, respectively. Table 3 shows the retrospective precision of actual PR^{Score} using the different internal and external training input methods. The mean ± SD of the difference between predicted and actual performance are presented in (Fig. 4, a-e).

Discussion

The main purpose of this study was to validate the within-individual retrospective predictive power of $MEI.min^{-1}$ and PR^{Score} performance using a variable dose-response model. The main finding was that model derived estimates of $MEI.min^{-1}$ and PR^{Score}, appropriately predicted actual in-season $MEI.min^{-1}$ and PR^{Score}. Since the initial systems proposed by Bannister et al., in 1975[2] the approach has been used to improve the understanding of the training process and has been applied to forecast training loads to maximize performance responses for individual athletes[3-8.] Several studies, using empirical training and performance data from highly trained endurance athletes, have demonstrated moderate to very large correlations between model predicted and actual performance[3-7,26]. Unfortunately, however, the broader application of a model approach to predict performance at an individual level within high performance team sport, such as professional AF, is unsubstantiated within the scientific literature. This is largely attributable to the fact that it is difficult to characterize or define performance in AF, as it involves complex interactions between physical capacity and skill proficiency which in combination is difficult to quantify and express as a single measure of performance, an essential prerequisite for the construction of a variable dose-response model. To counteract the limitations associated with maximal capacity testing and the conjecture surrounding the relationship between MEI.min^{-1} and coaches' perception of match performance, the researchers used both MEI.min^{-1} and PR^{Score} as performance representative input data to a variable dose-response model. The magnitudes of association between predicted and actual representatives of match performance were of comparable magnitude to those previously reported in model research using highly trained endurance athletes and assessments of physical capacity. Most notably a trivial relationship between actual MEI.min^{-1} and PR^{Score} was observed, accordingly these findings are in agreement with research suggesting MEI.min^{-1} is unrelated to skill performance.[20] The variable dose-response models constructed in this study were able to predict actual MEI.min^{-1} with greater precision than PR^{Score} using the equivalent training input method. Although the within-individual correlations for the internal and external load - PR^{Score} predictive models were large, on average, the model estimates only explain 41% of the variance in actual PR^{Score}. Hence, multiple factors, besides in-season training load variability, which can't be accounted for using a variable dose-response model, contribute to individual player on-field skill performance.

This study also compared the validity and retrospective predictability of model estimates of MEI.min^{-1} and PR^{Score} using various internal and external quantitative input methods. The player load (PL) algorithm is suggested to incorporate all forms of movement including change of direction, skill- and contact-based activities relevant to professional AF and therefore provide a more global representation of external load than speed and distance metrics[11,12]. However, trivial differences in predictive power for both MEI.min^{-1} and PR^{Score} using TRIMPs^{Dist} and TRIMPs^{PL} were observed. These findings are in accordance with related research, that has observed very large and near perfect correlations between distance and PL[12,22]. The strength of the relationship between PL and distance depends on the type of training performed. The comparable retrospective predictability between $TRIMPs^{Dist}$ and $TRIMPs^{PL}$ observed in this study suggests that a relatively small proportion of the in-season training load, involved impacts, collisions and/or multi-planar movements, consequently, foot strikes (vertical plane accelerations) and locomotor activity (forward acceleration) heavily contributed to and influenced the in-season PL. Certainly, within professional AF the capture of both satellite and accelerometer data is common practice, however for teams regularly training or competing indoors, or situations where satellite variables are unavailable, these results support the use of a variable dose-response model using exclusively PL.

Due to its simplicity, in-expensive nature and strong validity, high performance team sports commonly utilize sRPE to quantify the internal training and match load. Unlike the external load measures obtained from microtechnology in this study, sRPE was the only indicator of the "global" in-season training load (i.e. rehabilitative, strength and all skills and conditioning sessions). However, despite this, differentiating the $sRPE^{Skills}$ from the total sRPE arbitrary units, so as to align with all the external load measures, resulted in a comparable or in some cases enhanced level of prediction accuracy. For example, the sRPE-MEI.min^{-1} model demonstrated the lowest retrospective predictive capability of MEI.min^{-1}. Differentiating $sRPE^{Skills}$ from sRPE internal load enhanced the predictive power of actual MEI.min^{-1}, equaling the predictive accuracy of all the external training load-MEI.min^{-1} models. Collectively, these results suggest that the in-season skills and conditioning load is relatively more important to MEI.min^{-1} performance than other training modalities during an in-season AFL program. The equivalent predictive power of both MEI.min^{-1} and PR^{Score} using internal $sRPE^{Skills}$ load or external load input methods in this study, further validates the use of sRPE, and is consistent with previous research in high performance team sport demonstrating that sRPE load has very large association with external load measures from microtechnology[27,28].

Anecdotally, training loads in professional AF are often planned and prescribed with biased consideration to external load parameters. Recent research has indicated that individual variability in characteristics such as, fitness, physiological, psychological status, training experience and position type are all mediators of the relationship between external training load and sRPE load[27]. Accordingly, relying entirely on sRPE to prescribe professional AF training load could compromise the likelihood of individual players achieving a predetermined external load, as individual players will modify their external output based on these mediating factors. Consequently, to optimize the in-season training process for professional AF, it appears that the desired approach, is to monitor the internal load response while prescribing and subsequently adjusting the in-season training dose using external load. However, from a perspective of predicting performance responses using a systems modelling approach, distinct from load management, results from this study indicate that both external and internal training inputs have comparable predictive power. From a practical standpoint, quantification of in-season training load using GPS micro technology is not an essential prerequisite to apply a systems modelling approach in professional AF to predict MEI.min^{-1} and PR^{Score}.

It has been reported that to gain stable fits and build robust models, 15 and 200 performance tests are required within a short period of time[29]. Despite an average of 17 ± 5 games being played by each participating athlete across the entire in-season macrocycle, exclusion criteria limited the amount of suitable match assessments to 11. Although high in comparison with previous modeling studies[3-7,26], the stability of each of the models may be inadequate to fully describe the dose-response relationships reliably. Accordingly, a systems modeling approach to training and performance data may be limited to laboratory studies or highly trained endurance athlete cohorts. Although it is unlikely that a single external or internal training load measure will describe all the variation in MEI.min^{-1} and PR^{Score}, alternate variables to those investigated in this study may be able to provide enhanced predictive power.

Research has extracted player load activity below 2m.s^{-1}, from total PL, which has been termed player load slow PL_{Slow}[12]. Studies have demonstrated that PL_{Slow} has small associations with distance, indicating that it provides different information than PL[12]. It has been suggested that this variable may better represent multi planar movements performed at relatively low speed (e.g. grappling)[12]. Another variable available from the microtechnology device which was not examined, was 2D PL[12]. This variable, like $PL_{slow,}$ differentiates from PL, by just including the acceleration vectors from two planes (medio-lateral and anterio posterior). The exclusion of the vertical vector, potentially reduces the influence of foot strikes and may provide insight into more non-locomotor load aspects applicable to professional AF[12]. Similarly, previous model research, using highly trained endurance athletes has demonstrated improved fits using individualized TRIMP calculations (iTRIMPs), in comparison to sRPE methods[4]. In the current study arbitrary zones and generic intensity coefficients were used to calculate TRIMPs for the respective external load input methods. iTRIMPs that better account for individual performance characteristics[4] may demonstrated stronger predictive capability. Finally, even though sRPE was used as an internal load quantitative input, discrepancies between modeled and actual estimates of MEI.min^{-1} and PR^{Score} may further be explained by the fact that the variable dose-response model does not take into consideration the effect of recovery strategies, inter-individual variability in recovery potential, exercise capacity, non-training stress factors, and stress tolerance which all contribute to individual fitness, fatigue and performance responses.

Practical Applications

Variable dose-response models applied to in-season quantitative internal and external training input methods may be an appropriate planning and forecasting tool to assist with the maximization of both MEI.min^{-1} and PR^{Score} at the individual level. As in-season external and internal $sRPE^{Skills}$ quantitative training load methods provide the same level of prediction, systems modelling can be used without the need for microtechnology.

Conclusions

The main findings of this study are that variable dose-response models constructed from multiple training load input methods, can retrospectively predict, the within-individual variation of $MEI.min^{-1}$ and PR^{Score}. Variable dose-response models were able to predict $MEI.min^{-1}$ with greater precision in comparison to PR^{Score} using the equivalent training input methods. Both external and internal quantitative input methods can predict in-season $MEI.min^{-1}$ and PR^{Score} with the same level of precision. Future research should aim to cross validate variable dose-response model application in other AF teams and high performance team sports. Further the prospective predictive capability, and the adequacy of applying a systems model approach during different training phases (i.e pre-season macrocycle) should be established. Finally, the ecological validity of individual model estimates of fitness and fatigue should be examined.

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"Relationships Between Model Predicted and Actual Match Performance in Professional Australian Footballers During an In-Season Training Macrocycle" by Graham SR, Cormack S, Parfitt G, Eston R
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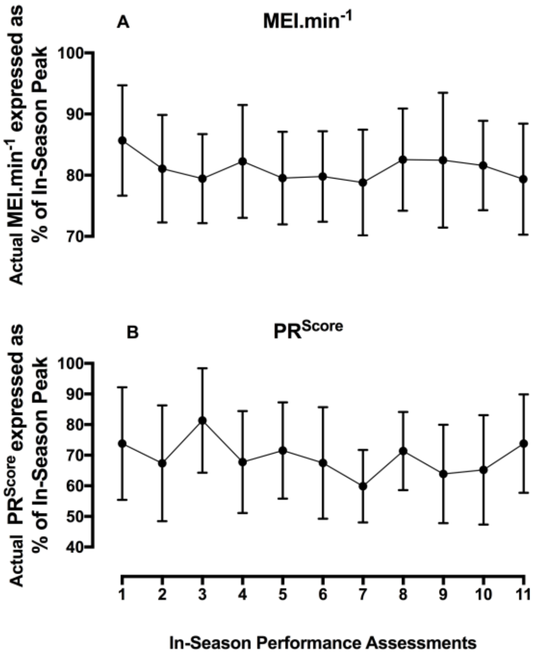

Figure 1: Mean ± SD of the fluctuations in **a** MEI.min^{-1} and **b** PR^{Score} across the 24-week in-season macrocycle.

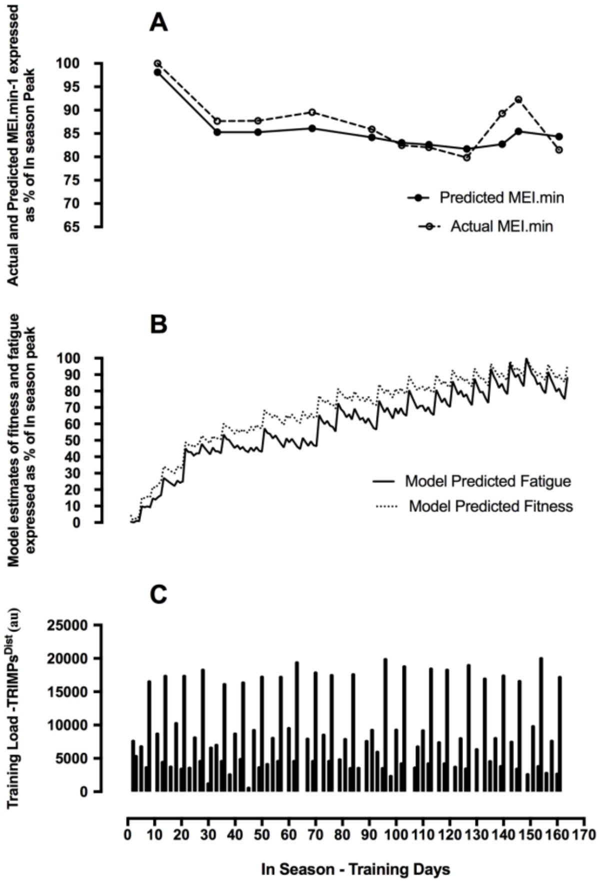

Figure 2: Variable dose-response model simulation from one athlete constructed from in-season TRIMPs^{Dist} and MEI.min^{-1} data **a** predicted and actual MEI.min^{-1} performance **b** Individual model estimates of fitness and fatigue **c** daily in-season TRIMPs^{Dist} training load.

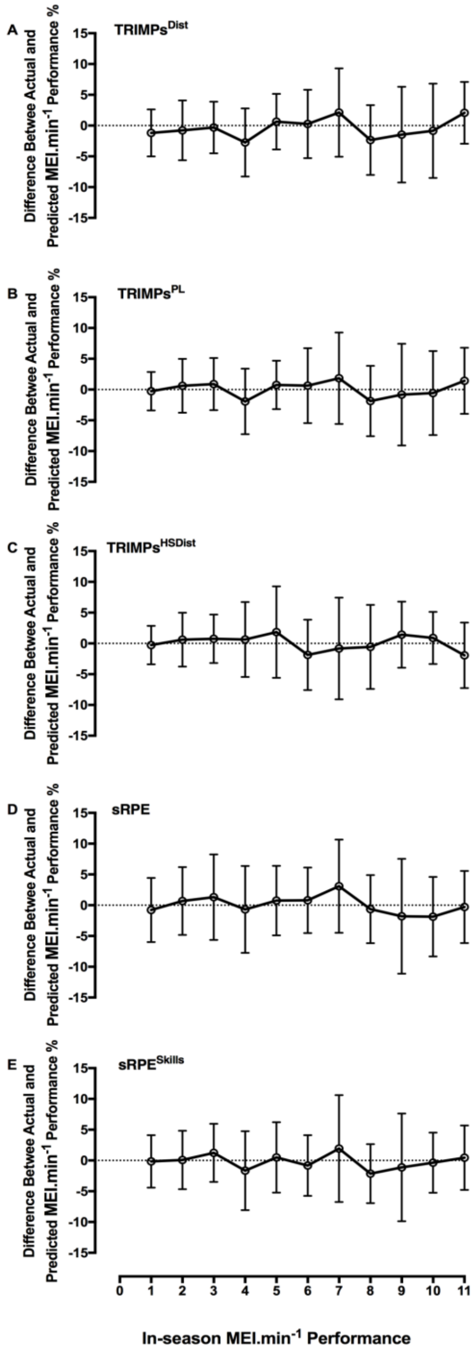

Figure 3: Mean ± SD of the difference between modelled and actual MEI.min^{-1} performance using **a** TRIMPs^{Dist} , **b** TRIMPs^{PL} **c** TRIMPs^{HSDist} **d** sRPE **e** sRPE^{Skills} training input methods respectively, during the 24-week in-season macrocycle.

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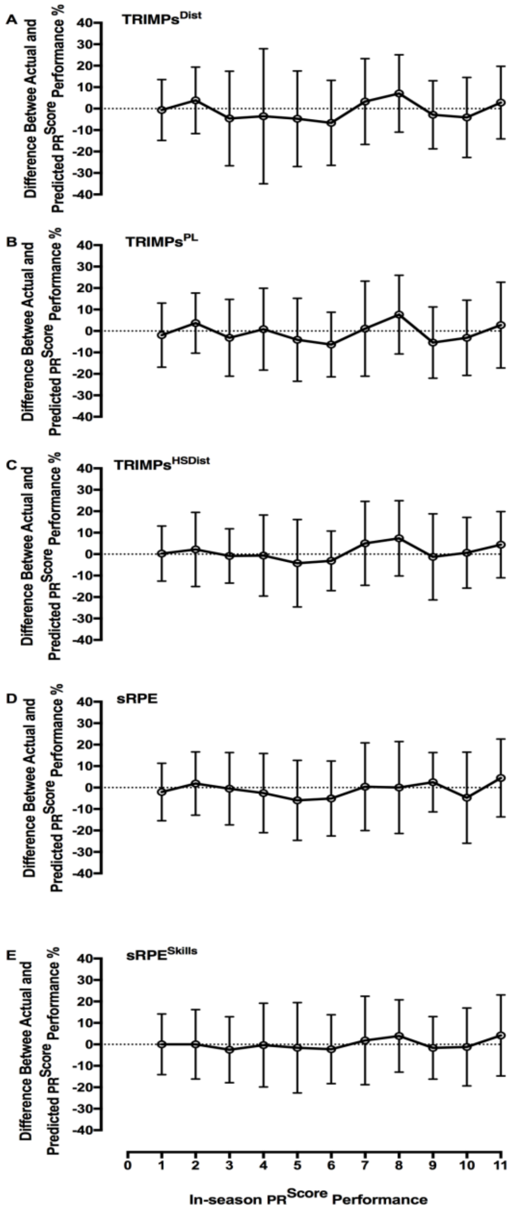

Figure 4: Mean ± SD of the difference between predicted and actual PR^{Score} performance using **a** TRIMPs^{Dist}, **b** TRIMPs^{PL} **c** TRIMPs^{HSDist} **d** sRPE **e** sRPE^{Skills} training input methods respectively, during the 24 week in-season macrocycle.

Table 1: TRIMP calculations used to covert the in-season external load into arbitrary units.

TRIMPs^{Dist} = (Zone 1 Distance x 1) + (Zone 2 Distance x 1.2) + (Zone 3 Distance x 1.5) + (Zone 4 Distance x 2.2) + (Zone 5 Distance x 4.5) + (Zone 6 Distance x 9)

TRIMPs^{HSDist} = (Zone 4 Distance x 2.2) + (Zone 5 Distance x 4.5) + (Zone 6 Distance x 9)

TRIMPs^{PL} = (Zone 1 PL au x 1) + (Zone 2 PL au x 1.2) + (Zone 3 PL au 1.5) + (Zone 4 PL au x 2.2) + (Zone 5 PL au x 4.5) + (Zone 2 PL au x 9)

Table 2: Matrix of the difference between the retrospective precision of actual MEI.min^{-1} using different internal and external training input methods

Training Input Method	**TRIMPs^{Dist}**	**TRIMPs^{PL}**	**TRIMPs^{HSDist}**	**sRPE**
TRIMPs^{PL}	-0.11 ± 0.15 trivial			
TRIMPs^{HSDist}	0.06 ± 0.28 unclear	0.19 ± 0.31 trivial		
sRPE	0.67 ± 0.15 **moderate ↑**	0.91 ± 0.39 **large ↑**	0.58 ± 0.32 **small ↑**	
sRPE^{Skills}	0.16±0.32 trivial	0.31 ± 0.34 **small↑**	0.10 ± 0.21 trivial	-0.50 ± 0.27 **small ↓**

Differences in the retrospective precision of actual MEI.min^{-1} using internal and external training input methods, represented as ES ±90% CI and classified as *trivial* (< 0.2), *small* (0.2 – 0.59) and *moderate* (0.6 – 1.19). Where the 90% CI simultaneously overlapped the smallest important ES (0.2) the magnitude of the difference was considered "*unclear*".

↑ denotes greater predictive accuracy of quantitative training input on y axis compared to x axis.

↓ denotes lower predictive accuracy of quantitative training input on y axis compared to x axis.

Table 3: Matrix of the difference between the retrospective precision of actual PR^{Score} using different internal and external training input methods

Training Input Method	TRIMPs^{Dist}	TRIMPs^{PL}	TRIMPs^{HSDist}	sRPE
TRIMPs^{PL}	-0.06 ± 0.10 trivial			
TRIMPs^{HSDist}	-0.18 ± 0.31 trivial	-0.19 ± 0.33 trivial		
sRPE	-0.08 ± 0.29 unclear	-0.02 ± 0.28 unclear	0.17 ± 0.45 unclear	
sRPE^{Skills}	-0.16±0.20 trivial	-0.10 ± 0.23 trivial	0.18 ± 0.41 unclear	-0.09 ± 0.32 unclear

Differences in the retrospective precision of actual PR^{Score} using internal and external training input methods, represented as ES ±90% CI and classified as *trivial* (< 0.2), *small* (0.2 – 0.59) and *moderate* (0.6 – 1.19). Where the 90% CI simultaneously overlapped the smallest important ES (0.2) the magnitude of the difference was considered "*unclear*".