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Section: Original Investigation

Article Title: Relationships Between Model-Predicted and Actual Match-Play Exercise-Intensity Performance in Professional Australian Footballers During a Preseason Training Macrocycle

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“Relationships Between Model-Predicted and Actual Match-Play Exercise-Intensity Performance in Professional Australian Footballers During a Preseason Training Macrocycle” by Graham SR, Cormack S, Parfitt G, Eston R
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Relationships between model-predicted and actual match-play exercise-intensity performance in professional Australian Footballers during a preseason training macrocycle.

Submission type: Original investigation

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Abstract

Purpose: To assess and compare the validity of internal and external Australian football (AF) training-load measures for predicting preseason variation of match-play exercise intensity (MEI sim/min) using a variable dose-response model. **Methods:** Twenty-on professional male AF players completed an 18-wk preseason macrocycle. Preseason internal training load was quantified using session RPE (sRPE) and external load from satellite and accelerometer data. Using a training-impulse (TRIMPs) calculation, external load expressed in arbitrary units (a.u.) was represented as $TRIMPs_{Dist}$, $TRIMPs_{HSDist}$, and $TRIMPs_{PL.}$ Preseason training load and MEI sim/min data were applied to a variable dose-response model, which provided estimates of MEI sim/min. Model estimates of MEI sim/min were correlated with actual measures from each match-play drill performed during the preseason macrocycle. Magnitude-based inferences (effect size ± 90% confidence interval [CI]) were calculated to determine practical differences in the precision of MEI sim/min estimates using each of the internal- and external-load inputs. **Results:** Estimates of MEI sim/min demonstrated very large and large associations with actual MEI sim/min with models constructed from external and internal training inputs (r ± 90% CI; $TRIMPs_{Dist}$ .73 ± .72–.74, $TRIMPs_{PL}$ .72 ± .71–.73, and $sRPE_{Skills}$ .67 ± .56–.78). There were trivial differences in the precision of MEI sim/min estimates between models constructed from $TRIMPs_{Dist}$ and $TRIMPs_{PL}$ and between internal input methods. **Conclusions:** Variable dose-response models from multiple training-load inputs can predict within-individual variation of MEI sim/min across an entire preseason macrocycle. Models informed by external training inputs ($TRIMPs_{Dist}$ and $TRIMPs_{PL}$) exhibited predictive power comparable to those of $sRPE_{Skills}$ models.

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

Introduction

At present, little empirical knowledge specifically relating to the individual cumulative dose-response effects of pre-season training load on physical adaptation for professional Australian Footballers (AF) exists. The practice of periodizing pre-season physical training loads has been embraced in professional AF, yet recommendations, at an individual level, for the optimal mesocycle duration and the training overload-recovery distribution within, remains unsubstantiated. Mathematical models have been proposed to assist sports science and conditioning staff with prescribing the optimal distribution of training load within mesocycles of training[1-3]. The majority of investigations assessing the efficacy of using a mathematical model approach to optimally guide the periodicity of physical training and forecast future physical performance outcomes have used empiric training and performance data from athletes competing in individual, predominately endurance-based sports[1,3-9]. This is largely attributable to the fact that, although, field-test batteries assessing specific physical capacities are implemented in high performance team sports they are fatiguing, potentially interrupting the training process and compromising training quality. Consequently, physical capacity assessments aren't implemented in pre-season macrocycles with sufficient frequency to satisfy the recommended criteria to build robust models with strong predictive capability.

From a physical perspective, one prerequisite aim of pre-season training in professional AF, is to enhance, at an individual level, the anaerobic and aerobic capacity of each player. In support of this, Young et al.,[10] found that yo-yoIR2 performance was significantly higher in starters compared to non-starters at the commencement of an Australian Football League (AFL) premiership season. Studies in professional soccer [11-13]and more recently in professional AF[14], have demonstrated association between aerobic capacity, assessed via a yo-yo intermittent recovery (level 2) test (yo-yo IR2) and match exercise intensity (MEI/min)[14]. Specifically, in professional AF, a high MEI/min, quantified as distance covered ≥ 4.16m.s^{-}

^{1}.min during match-play, has been shown to be indicator of an individual's overall anaerobic and aerobic capacity. During a pre-season macrocycle, professional AF teams frequently expose their players to competitive match-play, enabling MEI/min to be captured at a high frequency. The presence of the relationship between MEI/min and yo-yo IR2 performance, suggests, MEI/min could be used as a more frequent alternate to assess anaerobic and aerobic capacity than the exhaustive yo-yo IR2 protocol. Variable dose-response models, describing adaptations to training, mathematically relate the amount of training (system input) undertaken to change in performance (system output). A prerequisite to construct dose-response models is a single measure to represent physical performance. Importantly, to construct robust models with strong predictive power, the performance input variable needs to be captured at a high frequency. The documented association between MEI/min and yo-yo IR2 performance, in professional AF, coupled with the ease at which MEI/min can be quantified during match-play training drills via micro-technology, makes it a suitable performance input for model construction. The present study, using an established variable dose-response model will compare the within-individual predictive precision of model estimates of MEI sim/min with actual measures obtained across an entire pre-season macrocycle of training. This study will also ascertain whether differences in MEI sim/min precision accuracy exists between models constructed from internal or external load input methods.

Methods

Subjects

Forty-five professional male AF athletes were recruited from the same team for the study, however exclusion criteria limited the training and performance data from 21 participants (age: 22.3 ± 3.3 y, height: 188.3 ± 7.2 cm, and mass: 87.7 ±8.4 kg,) to be modeled in this study. Ethical approval (Application ID 0000031146) was granted by the university research committee and informed consent was obtained before the commencement of the research.

Experimental Design

A longitudinal post facto experimental design was used to compare actual MEI sim/min measures across an entire 18-week pre-season macrocycle, with predicted estimates derived from variable dose-response models constructed using internal and external quantitative input methods.

Methodology

Match-play exercise intensity performance

From each 25-minute match-play training drill performed during the 2015-2016 pre-season training macrocycle, MEI sim/min (CV, 7.28 ± 3.69%), was quantified for each player in accordance with previous protocols[14]. To reduce the likelihood of reporting artificially low match-play MEI sim/min, rest time and any stoppage time during the training drill were excluded from the analyses for each participant. An individual player's MEI sim/min was excluded from analysis if he was injured (but was participating in training) or injured in drill (but continued to play). Further, MEI sim/min data were removed for analyses if the participant played a 'foreign' position or the training session was influenced by environmental conditions (i.e. rain). To reduce the likelihood of reporting artificially high MEI sim/min, activity profiles were only accepted if the participant played ≥85% of the total drill time, conversely absolute variables were divided by the on-field active duration to prevent reporting low MEI sim/min. From each eligible match-play training drill MEI sim/min was converted into a percentage of pre-season peak performance so as the peak value forms the baseline for MEI sim/min performance across the pre-season macrocycle[15].

Training load quantification

All individual (n=4498) training sessions (i.e. all field based, skill, strength and conditioning, rehabilitative and active recovery sessions) were analyzed during the investigative pre-season macrocycle. Individuals completed an average of 186.3 ± 13.45 individual training sessions during the pre-season. A variety of valid external and internal methods (n=5) were used to quantify each individual pre-season training session, which acted as input data to construct variable dose-response models for each individual participant.

External Load

External load data for each pre-season skills and conditioning training session and match simulation training drill was captured using a portable global positioning system (GPS) micro technology device (Optimeye S5, Catapult Innovations, Melbourne, Australia). Satellite data sampled at 10Hz provided measures of total distance and high speed running distance (quantified as distance covered ≥ 4.16$m.s^{-1}$)[14]. Player Load (PL), 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 100Hz and has been reported to be reliable and valid[16]. At the conclusion of each training 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 zones corresponding to (Zone 1 - 0-1.5$m.s^{-1}$, Zone 2 - 1.5-3$m.s^{-1}$, Zone 3 - 3-4.16$m.s^{-1}$, Zone 4 - 4.16-5.5$m.s^{-1}$, Zone 5 - 5.5-7$m.s^{-1}$, Zone 6 - >7$m.s^{-1}$) and PL relative to specific intensity zones 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 $m.s^{-1}$)[17]. The validity and reliability of GPS devices and the metrics used in this study have been extensively reviewed elsewhere (for review[16,18,19]). In brief, it appears that the validity and reliability for measuring distance, PL and velocity is improved with a higher sampling frequency[19-21]. Pre-season external load was expressed in arbitrary units, using an adapted TRIMPs calculation, proposed by Edwards et al.,[20]. Distance and PL accumulated in each of the six velocity and PL 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).

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) pre-season training load[21,22]. Subsequently, perception of effort (RPE) for the skills and conditioning component ($sRPE_{Skills)}$ was differentiated from the total pre-season sRPE load. All participants were familiar with the RPE process for over 12 months leading up to the study period.

Fitting the Model

Individual pre-season training load and MEI sim/min data for each player were applied to a 3-component variable dose-response model proposed by Busso et al.,[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[23] using the generalized reduced gradient (GRC) nonlinear solver function in Microsoft Excel (Microsoft, Redman, USA). Five models were generated for each player, representing each of the training input methods and MEI sim/min.

Statistical Analyses

Within-individual correlations between actual and predicted estimates of MEI sim/min were analyzed using Pearson's correlation coefficient (*r*) and reported with 90% confidence intervals (CI). The magnitude of the correlation between predicted and actual MEI sim/min 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[24]. Magnitude based inferences (effect-size statistic ± 90% CI) were calculated to determine the practical differences between the precision of internal and external load measures to predict MEI sim/min. Differences were represented as ES ± 90% CI and classified as *trivial* (< 0.2), *small* (0.2 – 0.59) and *moderate* (0.6 – 1.19)[24]. Where the 90% CI simultaneously overlapped the smallest important ES (0.2) the magnitude of the difference was considered "*unclear*"[24]. 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[24].

Results

Weekly mean values for training duration, distance, PL, and sRPE were 368 ± 83 min, of 34843 ± 5125 m, 3319 ± 3121 a.u., and 4346 ± 263.4 a.u., respectively.

Modeled match simulation exercise intensity

Fluctuations in MEI sim/min were observed across the entire pre-season macrocycle and presented as mean ± SD (Fig 1). The average within-individual correlations between predicted and actual MEI sim/min for the various training input methods were (Training input, r mean ± SD, qualitative descriptor), $TRIMPs_{Dist}$, 0.73 ± 0.12, very large, $TRIMPs_{PL}$, 0.72 ± 0.10, very large, $TRIMPs_{HSDist}$, 0.70 ± 0.14, very large, sRPE, 0.65 ± 0.11 large, and $sRPE_{Skills}$, 0.67 ± 0.12, large, respectively. Fig 2 shows an example of model simulation for one participant using in-season $TRIMPs_{Dist}$ and MEI sim/min data. Table 2 shows the precision of actual MEI sim/min using the different internal and external training input methods. Accuracy of MEI sim/min estimates was greater for external training load inputs compared to each of the internal inputs. Trivial differences between precision of estimates of MEI sim/min were evident using either sRPE or $sRPE_{Skills}$. The mean ± SD of the difference between predicted and actual performance is presented in (Fig. 3, a-e).

Discussion

The main purpose of this study was to assess the level of association between modelled estimates and actual MEI sim/min performance measures obtained across an entire pre-season macrocycle. Recently, the adequacy of using a systems model approach to predict the within-individual variation of match performance metrics across an in-season training macrocycle was investigated in professional AF[17]. The in-season models were able to predict actual fluctuations in MEI sim/min with a high level of precision. The adequacy of using a model approach at an individual level during a pre-season macrocycle is unsubstantiated within the literature. Due to the established association between yo-yo IR2 performance and MEI sim/min in professional AF and to also counteract the limitations associated with administering a high frequency (15-200 assessments) of maximal capacity tests during a pre-season macrocycle to build robust models[9], the researchers used MEI sim/min as a single representative of aerobic and anaerobic capacity, to act as a single performance input measure to a variable dose-response model. Very large and large magnitudes of associations were observed between model predicted and actual MEI sim/min using each of the training input methods. The strength of these associations is equivalent to those reported in previous in-season model work using the same professional AF cohort[17]. Furthermore, the level of observed association between model and actual performance is comparable to those documented in model studies using empirical training and physical capacity performance data from highly trained endurance athletes[1,4-6,25]. For example, Wallace et.al.,[5] demonstrated large correlations between each of the different internal and external methods used for quantifying training load and modelled running performance in trained triathletes.

The majority of previous model research has failed to evaluate the influence that all of the training stimuli (i.e. internal vs external load, conditioning vs. strength load) has on performance responses[1-6,8-10,25]. Similarly, to the in-season work by Graham et al.,[17] sRPE was used in this study, as a quantitative training input representing the "global" pre-season training load (i.e. rehabilitative, strength and all skills and conditioning sessions). Despite sRPE representing the internal load of the entire pre-season training stimuli, differentiating the $\text{sRPE}_{\text{Skills}}$ component from the total sRPE, so as to align with all the external load measures, didn't lower the prediction accuracy of MEI sim/min. These results, in combination with previous work[17], suggest that, regardless of the training macrocycle being undertaken (i.e in-season or pre-season), the skills and conditioning load in professional AF is relatively more important and specific to MEI/min performance than other training modalities prescribed and represented by the global sRPE method[17]. The comparable, small magnitude of difference in predictive power of MEI sim/min using internal $\text{sRPE}_{\text{Skills}}$ load compared to each of the external load input methods in this study, aligns itself with previous findings[17]. Anecdotally, training loads in professional AF are often planned and prescribed with biased consideration to external load parameters. Importantly though, these results suggest that if applying a systems model approach to guide training periodicity with the intention of maximizing and potentially forecasting future MEI/min performance responses in professional AF, both external and internal training inputs methods have equivalent predictive power. From the perspective of selecting the most appropriate training input method this finding has obvious practical implication. Quantifying training load using sRPE is an easily administered, inexpensive method with capability of quantifying the entire training process in standardized arbitrary units irrespective of training modality and location.

In high performance team sport settings, quantifying the pre-season external load using satellite and accelerometer data captured from portable micro technology devices is an established practice. Velocity data provided by GPS devices, possess the advantage of being easily interpreted, adjustable in real-time and objectively conducive to coach, athlete performance feedback[26], however, requires satellite lock in outdoor locations without overhead obstructions or interference, which may result in erroneous or missing data. When comparing the investigated external quantitative training input methods, $TRIMPs_{PL}$ derived from the accelerometer integrated and embedded within the GPS device, predicted MEI sim/min with the equivalent precision as $TRIMPs_{Dist}$. The comparative ability to predict pre-season fluctuations in MEI sim/min using models informed by either $TRIMPs_{Dist}$ or $TRIMPs_{PL}$ is in accord with related research[17,27]. This finding suggests that a relatively small proportion of the pre-season training load, involved impacts, collisions and/or multi planar movements. Consequently, foot strikes (vertical lane accelerations) and locomotor activity (forward acceleration) heavily contributed to and influenced the pre-season PL[27]. Derivatives of PL which weren't examined in this study and potentially offer additional quantitative specificity for professional AF have been presented within the literature[27]. For example, research has extracted PL activity below 2m. s^{-1}, from total PL, which has been termed player load slow (PL_{Slow})[27]. Studies have demonstrated that PL_{Slow} has small associations with distance, indicating that it provides different information than PL[27]. Authors have suggested that this variable may better represent multi planar movements performed at relatively low speed (e.g. grappling). Another derivative variable of PL is two-dimensional PL (PL_{2D}). This variable, like PL_{Slow}, differentiates from PL, by just including the acceleration vectors from two planes (medio-lateral and anterior- 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[27]. Potentially, derivatives of PL may quantify professional AF activity with greater specificity and reliability than satellite-based variables[27]. Additionally, accelerometer data has the advantage of being captured independent of satellite, allowing external load from training sessions performed indoors or situations whereby satellite variables are unavailable to be recorded. In comparison to satellite data, the increased continuity in data collection that PL offers is an important practical consideration, as large longitudinal training datasets, without interruption, are required to inform and construct robust variable dose-response models.

It is unlikely that a single external or internal load measure will describe all the variation in MEI sim/min across an entire pre-season macrocycle. However, future model investigations in professional AF should ascertain whether larger magnitudes of association between actual and model estimates of MEI sim/min could be established using PL_{Slow} , PL_{2D} or other accelerometer derived metrics as external training inputs. If future research demonstrates larger magnitudes of association (i.e enhanced prediction of MEI sim/min) using derivatives of PL, then accelerometer data should be used in preference to satellite data to inform variable dose-response models in professional AF. Aside from assessing the adequacy of different training inputs, models utilizing different performance inputs, captured at a higher frequency than MEI sim/min, may demonstrate a smaller amount of unexplained variance, providing a better framework to understand and guide the training dose-response process. Authors have reported to achieve stable fits and build robust models, between 15 and 200 assessments of the single measure representing the performance input for the model are required within a short period of time[9]. Although an average of 21 ± 4 match-play drills were completed by the participants across the investigated pre-season macrocycle, exclusion criteria limited the amount of suitable MEI sim/min performance inputs to 12 for each player. This is high in comparison with previous modeling studies[1,3,4,6], however, future model investigations in professional AF, due to the difficulty obtaining sufficient MEI sim/min measurements should focus on using alternate quantitative physical performance approaches to act as model inputs. For example, authors have suggested that parameters of the autonomic nervous system (ANS) collected from submaximal test protocols show potential to act as a suitable performance input candidates, while at the same time satisfying the criteria to build robust models[25]. Recent model work using competitive swimmers, demonstrated the ability of both Bannisters original 2-component model and Busso's 3-component variable dose-response model to predict performance and parasympathetic activity (represented by the high frequency power (HF) component of heart rate variability) in response to training with the highest level of precision reported to date[25]. In this study, the authors were able to obtain 30 consecutive HF power measures over a 15-week macrocycle of training[25]. Numerous studies have reported on the strong correlations between parameters of the ANS and variations in performance in both cross-sectional and longitudinal studies[28,29]. Heart rate response, perceptual and external load indices (i.e. integrated internal/external load approach) to controlled submaximal running protocols has documented support[29], providing information of the physiological adaptive status of team sport athletes, and may have implication from a modelling perspective.

The model predicative accuracy of MEI sim/min observed in this study is high, although, using alternate training and performance quantitative input approaches, captured at higher frequency to potentially reduce the amount of unexplained variance between actual and model estimates seems a worthwhile focus for future research. However, the adaptive and performance responses to professional AF pre-season training is likely non-linear and influenced by a myriad of factors, including inter-individual variability in recovery potential, exercise capacity, non-training stress factors, and stress tolerance all of which are not accounted for by a variable dose -response model. This limitation further explains the discrepancies between modeled and actual estimates of MEI sim/min using each of the investigated internal and external load inputs in this study. Considering this, other complex predictive model methods such as, non-linear, multi-layer perception neural networks have been proposed and may be more appropriate in comparison to using variable dose-response models[26].

Practical Applications

Variable dose-response models applied to pre-season quantitative internal and external training input methods may be an appropriate planning and forecasting tool to assist with periodicity of training and maximization of the adaptation response during a professional AF pre-season macrocycle. As pre-season external and internal ($sRPE_{Skills}$) quantitative training load methods provide a comparable level of prediction, it appears systems modelling can be used without dependence on GPS micro technology devices.

Conclusions

Variable dose-response models constructed from multiple training load input methods, demonstrated a high level of 'after the fact' predictive power of the within-individual variation of MEI sim/min across an entire pre-season macrocycle. Variable dose-response models using external training load inputs were able to predict MEI sim/min with a comparable precision to internal training input methods. Future research should aim to assess the adequacy of using alternate physical performance quantitative approaches, and cross validate variable dose-response model application in other AF teams and high-performance team sports. Finally, the prospective performance predictive capability (i.e. predictive power on 'unseen' MEI sim/min performance data) and the ecological validity of individual model estimates of fitness and fatigue should be examined.

“Relationships Between Model-Predicted and Actual Match-Play Exercise-Intensity Performance in Professional Australian Footballers During a Preseason Training Macrocycle” by Graham SR, Cormack S, Parfitt G, Eston R
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References

1. Busso T. Variable dose-response relationship between exercise training and performance. *Med Sci Sports Exerc*. 2003;35:1188-1195.

2. Bannister EW, Calvert TW, Savage MV, and Bach T. A systems model of training for athletic performance. *J Sports Sci Med Exerc*. 1975;7.

3. Fitz-Clarke JR, Morton RH, and Banister EW. Optimizing athletic performance by influence curves. *J Appl Physiol*. 1991;71:1151-1158.

4. Sanjez AMJ, Galbes O, Fabre-Guery F, Thomas L, Douillard A, Py G, Busso T, and Candau R. Modelling training responses in elite female gymnasts and optimal strategies of overload training and taper. *J Sports Sci*. 2013;31:1510-1519.

5. Wallace LK, Slattery KM, and Coutts AJ. A comparison of methods for quantifying training: Relationships between modelled and actual training responses. *Eur J Appl Physiol*. 2014;114:11-20.

6. Mujika I, Busso T, Lacoste L, Barale F, Geyssant A, and Chatard JC. Modeled responses to training and taper in competitive swimmers. *Med Sci Sports Exerc*. 1996;28:251-258.

7. Busso T, Hakkinen K, Parakinen A, Kavhanen H, Komi PV, and Lacour JR. Hormonal adaptations and modelled responses in elite weightlifters during 6 weeks of training. . *Eur J Appl Physiol*. 1992;64:381-386.

8. Wood R, Hayter S, Rowbottom D, and Stewart I. Applying a mathematical model to training adaptation in a distance runner. *Eur J Appl Physiol*. 2005;94:310-316.

9. Taha T. Systems modeling of the relationship between training and performance. *Sports Med*. 2003;33:1061-1073.

10. Young W, Burge P, Russell A, and Carlon T. Comparison of playing positions in elite Australian football: A case study of one club. *J Aust Strength Cond*. 2010;18:11-13.

11. Castagna C, Impellizzeri F, and Cecchini E. Effect of intermittent-endurance fitness on match performance in young male soccer players. *J Strength Cond Research*. 2009;23:1954-1959.

12. Mohr M, Krustrup P, and Bangsbo J. Match performance of high-standard soccer players with special reference to development of fatigue. *J Sports Sci*. 2003;21:519 - 528.

13. Helgerud J, Engen L, and Wisloff U. Aerobic endurance training iproves soccer performance *Med Sci Sports Exerc*. 2001;33:519-528.

14. Mooney MM, Cormack SJ, Coutts AJ, Berry J, and Young WB. The relationship between physical capacity and match performance in elite Australian Football: A mediation approach. *J Sci Med Sport*. 2011;14:447-452.

15. Busso T, Candau R, and Lacour J. Fatigue and fitness modelled from the effects of training on performance. *Eur J Appl Physiol*. 1994;69:50-54.

16. Boyd LJ, Ball K, and Aughey RJ. The reliability of minimaxX accelerometers for measuring physical activity in Australian Football. *Int J Sports Physiol Perform*. 2011;6:311-321.

17. Graham S, S C, Parfitt G, and Eston R. Relationships between model predicted and actual match performance in professional Australian Footballers during an in-season macrocycle. *Int J Sports Physiol Perform*. 2017:In Press.

18. Augey RJ. Increased high-intensity activity in elite australian football finals matches. *Int J Sports Physiol Perform*. 2011;6:367-379.

19. Sullivan C, Bilsborough JC, Cianciosi M, Hocking J, Cordy JT, and Coutts A. Factors affecting match performance in professional Austalian Football. *Int J Sports Physiol Perform*. 2014;9:561-566.

20. Edwards S. High performance training and racing. In: *The heart rate monitor book*. S. Edwards (Ed.) Sacramento: Feet Fleet Press, 1993, pp. 113-123.

21. Foster C. Monitoring training in athletes with reference to overtraining syndrome. *Med Sci Sports Exerc*. 1998;30:1164-1168.

22. Coutts A, Reaburn P, Murphy A, Pine ML, and Impellizzeri FM. Validity of the session RPE method for determining training load in team sport athletes. *J Sports Sci Med Exerc*. 2003;6:525.

23. Busso T, Denis C, Bonnefoy R, Geyssant A, and Lacour JR. Modeling of adaptations to physical training by using a recursive least squares algorithm. *J Appl Physiol*. 1997;82:1685-1693.

24. Hopkins W, Marshall S, and Batterham A. Progressive statistics for studies in sports medicine and exercise science *Med Sci Sports Exerc*. 2009;41:3-12.

25. Chalencon S, Pichot V, Roche F, Lacour JR, Garet M, Connes P, Barthelemy JC, and Busso T. Modeling of performance and ANS activity for predicting future response to training *Eur J Appl Physiol* 2015;115:589-596.

26. Bourdon P, Cardinale M, Murray A, Gastin P, Kellmann M, Varley M, Gabbett T, Coutts A, Burgess D, Gregson W, and Cable N. Monitoring Athlete Training Loads: Consensus Satement *Int J Sports Physiol Perform*. 2017;12:S2-161 - S162 - 170.

27. Boyd L, Ball K, and Aughey R. Quantifying external load in Australian Football matches and training using accelerometers. *Int J Sports Physiol Perform*. 2013;8:44-51.

28. Pichot V. Relation between heart rate variability and training load in middle distance runners. *Med Sci Sports Exerc*. 2000;32:1729-1736.

29. Bucheit M. Monitoring training status with HR measures: do all roads lead to rome? *Front Phsyiology*. 2014;27:73.

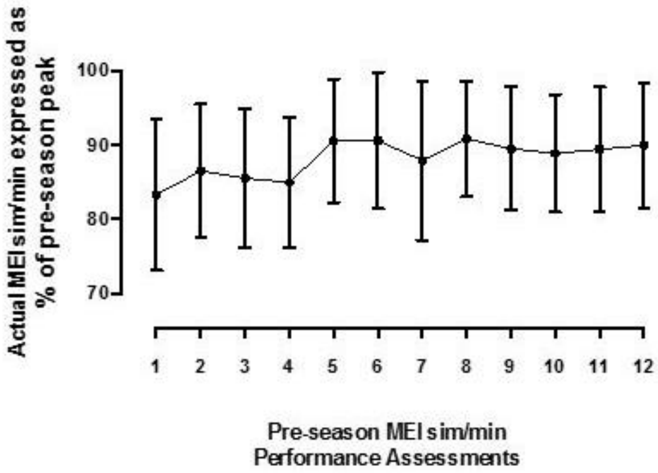

Figure 1: Mean ± SD of the fluctuations in MEI sim/min across the 18-week pre-season macrocycle.

*match-play exercise intensity (MEI sim/min).

“Relationships Between Model-Predicted and Actual Match-Play Exercise-Intensity Performance in Professional Australian Footballers During a Preseason Training Macrocycle” by Graham SR, Cormack S, Parfitt G, Eston R
International Journal of Sports Physiology and Performance

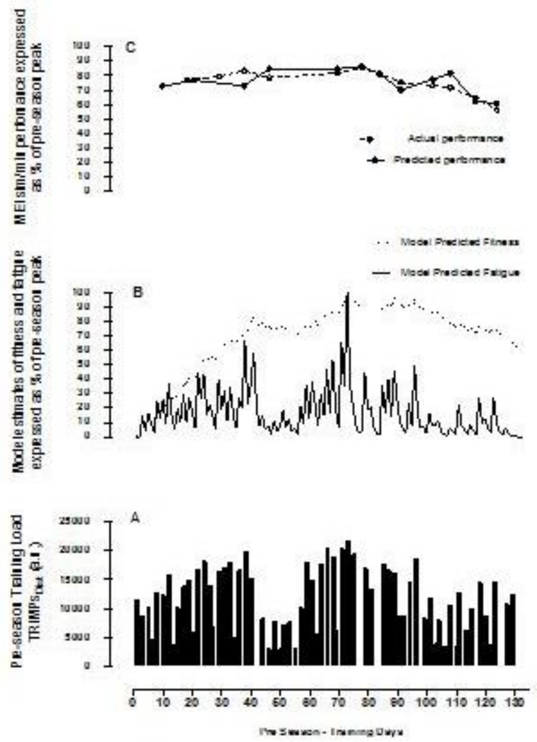

Figure 2: Variable dose-response model simulation from one athlete constructed from pre-season TRIM$_{sDist}$ and MEI sim/min data **a** predicted and actual MEI sim/min performance **b** Individual model estimates of fitness and fatigue **c** daily pre-season TRIM$_{sDist}$ (a.u.) training load.

*match-play exercise intensity (MEI sim/min).

“Relationships Between Model-Predicted and Actual Match-Play Exercise-Intensity Performance in Professional Australian Footballers During a Preseason Training Macrocycle” by Graham SR, Cormack S, Parfitt G, Eston R
International Journal of Sports Physiology and Performance

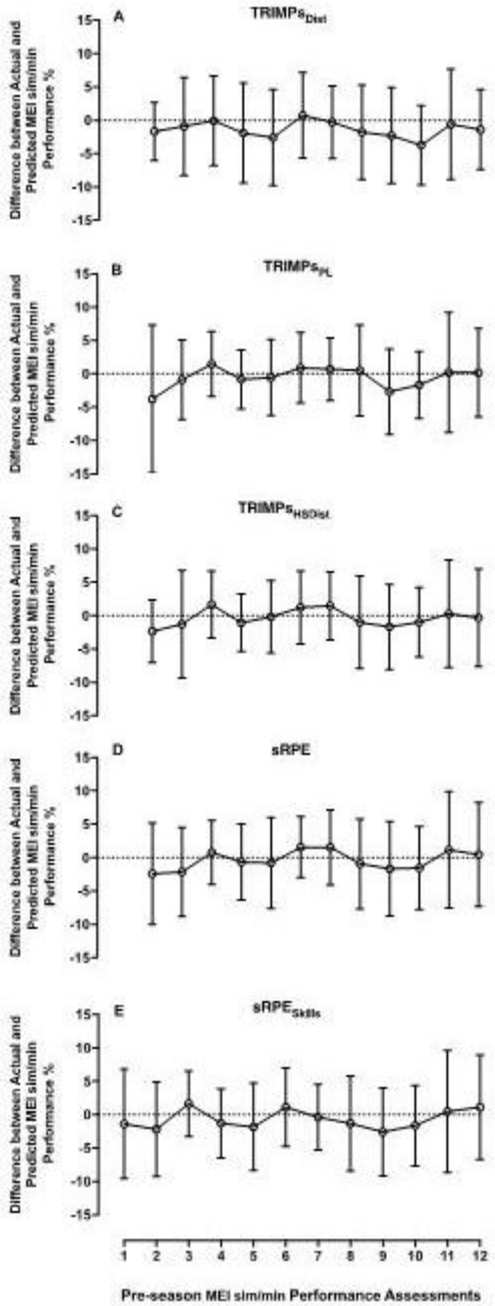

Figure 3: Mean ± SD of the difference between modelled and actual $MEI^{sim}.min^{-1}$ performance using **a** $TRIMPs_{Dist}$, **b** $TRIMPs_{PL}$ **c** $TRIMPs_{HSDist}$ **d** sRPE **e** $sRPE_{Skills}$ training input methods respectively, during the 18-week pre-season macrocycle.

*match-play exercise intensity (MEI sim/min)

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

TRIMPs$_{\mathbf{Dist}}$	=	(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$_{\mathbf{HSDist}}$	=	(Zone 4 Distance x 2.2) + (Zone 5 Distance x 4.5) + (Zone 6 Distance x 9)
TRIMPs$_{\mathbf{PL}}$	=	(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 sim/min using different internal and external training input methods

Training Input Method	**TRIMPs^{Dist}**	**TRIMPs^{PL}**	**TRIMPs^{HSDist}**	**sRPE**
TRIMPs^{PL}	-0.13 ± 0.34 unclear			
TRIMPs^{HSDist}	-0.30 ± 0.33 **small ↓**	-0.11 ± 0.32 unclear		
sRPE	-0.62 ± 0.32 **moderate ↓**	-0.47 ± 0.34 **small ↓**	-0.41 ± 0.33 **small ↓**	
sRPE^{Skills}	-0.50±0.34 **small ↓**	-0.38 ± 0.33 **small ↓**	-0.29 ± 0.30 **small ↓**	-0.12 ± 0.22 trivial

Differences in the retrospective precision of actual MEI sim/min 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.