Deceleration, Acceleration, and Impacts Are Strong Contributors to Muscle Damage in Professional Australian Football

Paul B. Gastin,[1] Shannon L. Hunkin,[2] Brendan Fahrner,[3] and Sam Robertson[4]

[1]*La Trobe Sport and Exercise Medicine Research Center, School of Allied Health, La Trobe University, Melbourne, Victoria, Australia;* [2]*Center for Sport Research, School of Exercise and Nutrition Sciences, Deakin University, Burwood, Victoria, Australia;* [3]*Department of Dietetics, Human Nutrition and Sport, Richmond Football Club, Melbourne, Victoria, Australia; and* [4]*Institute of Health and Sport, College of Sport and Exercise Science, Victoria University, Melbourne, Victoria, Australia*

Abstract

Gastin, PB, Hunkin, SL, Fahrner, B, and Robertson, S. Deceleration, acceleration, and impacts are strong contributors to muscle damage in professional Australian football. *J Strength Cond Res* XX(X): 000–000, 2019—The purpose of this study was to investigate the relationships between serum creatine kinase [CK], an indirect marker of muscle damage, and specific indices of match load in elite Australian football. Twenty-six professional players were assessed during a competitive Australian Football League (AFL) season. [CK] was collected 24–36 hours before match and 34–40 hours after match during 8 in-season rounds. An athlete-tracking technology was used to quantify match load. Generalized estimating equations and random forest models were constructed to determine the extent to which match-load indices and pre-match [CK] explained post-match [CK]. There was a 129 ± 152% increase in [CK] in response to AFL competition. Generalized estimating equations found that number of impacts $>3g$ ($p = 0.004$) and game time ($p = 0.016$) were most strongly associated with post-match [CK]. Random forest, with considerably lower errors (130 vs. 316 $U \cdot L^{-1}$), found deceleration, acceleration, impacts $>3g$, and sprint distance to be the strongest predictors. Pre-match [CK] accounted for 11% of post-match [CK], and considerable interindividual and intraindividual variability existed in the data. Creatine kinase, an indicator of muscle damage, was considerably elevated as a result of AFL competition. Parametric and machine-learning analysis techniques found several indices of physical load associated with muscle damage during competition, with impacts $>3g$ and high-intensity running variables as the strongest predictors. [CK] may be used as a global measure of muscle damage in field team sports such as AF, yet with some caution given cost, invasiveness, and inherent variability. Quantifying physical load and the responses to that load can guide athlete management decision-making and is best undertaken within a suite of practical, sport-specific measures, where data are interpreted individually and with an understanding of the limitations.

Key Words creatine kinase, physical load, body contact, eccentric load, athlete monitoring, machine learning

Introduction

Australian football (AF) is a contact team sport played over a duration of approximately 120 minutes and characterized by repeated high-intensity passages of play interspersed with active recovery periods (20). Repeated collisions through tackling, shepherding (bumping/blocking an opponent), and contested possessions are fundamental elements of the game (19,20). Success requires high levels of aerobic fitness, in combination with physical attributes such as agility, speed, power, and strength (14,20,54).

The Australian Football League (AFL) represents the highest level of competition in AF. As the game has evolved, greater physical demands are placed on players, with observed increases in the speed and intensity of elite AF (20,54). Players are known to cover more than 3 kilometers in high-speed running zones ($>4.17\ m \cdot s^{-1}$) and complete more than 80 maximal accelerations ($>2.78\ m \cdot s^{-2}$) per match (2,52). Sprinting generates large eccentric-based contractions, with the deceleration phase of the running gait exacerbating the strain (25,27). High degrees of eccentric loading such as these are recognized as a major contributor to muscle damage (4,9,25,56). The tactical evolution of the game has seen increases in the number of disposals, contested possessions, and tackles (55), and elite AF players are becoming larger and stronger (38). As such, player collisions are more likely to induce muscle damage due to the increased velocity and kinetic energy generated by each player upon impact (18,19,38). As a result of these combined

Address correspondence to Paul B. Gastin, p.gastin@latrobe.edu.au.

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Journal of Strength and Conditioning Research

Table 1. Creatine kinase and match-load indices across the season (n = 126, rounds = 8).*

	Mean ± *SD*	95% CI	Range
Creatine kinase			
Baseline [CK] ($U \cdot L^{-1}$)	73 ± 53	52–95	24 to 188
Pre-match [CK] ($U \cdot L^{-1}$)	354 ± 170	325–384	78 to 891
Post-match [CK] ($U \cdot L^{-1}$)	691 ± 345	631–752	189 to 2000
%ΔCK	129 ± 152	102–155	−55 to 838
Match load			
Game time (min)	101 ± 11	99–103	66 to 124
Distance (m)	11,954 ± 1,259	11,734–12,174	7,572 to 14,948
Sprint distance (>7 $m \cdot s^{-1}$) (m)	80 ± 55	71–90	0 to 253
Acceleration (3–15 $m \cdot s^{-2}$) (n)	29 ± 8	28–31	8 to 53
Deceleration (−3 to −15 $m \cdot s^{-2}$) (n)	38 ± 11	37–40	15 to 72
Player Load (au)	1,250 ± 131	1,227–1,273	657 to 1,581
Impacts >3*g* (*n*)	6.5 ± 4.4	5.7–7.3	0 to 31

*CI = confidence interval; [CK] = serum concentration of creatine kinase; %ΔCK = percent delta change in [CK] from pre- to post-match; au = arbitrary units; *g* = gravitational force.

physical loads in elite AF, there is potential for a significant muscle damage to occur.

Creatine kinase (CK) is a commonly used indirect marker of muscle damage (4,8,9). After muscle damage, such as that caused by strenuous physical exercise (25,50), excessive eccentric loading (17), and muscle strain injury (33), CK and other intracellular proteins leak out of the muscle cell into the blood (8). This is a result of a change in membrane permeability after tensile loading exceeds a certain limit and seems to be influenced by both intensity and training status (8,11). In contrast to muscle strains, compressive forces from direct impacts (33,42) result in traumatic contusions where muscle fibers rupture at or directly adjacent to the area of impact (30). Serum levels reflect total circulating CK, with post-exercise increases believed to be indicative of CK release from damaged muscle tissue (9), although some uncertainty exists around the mechanisms of release, and there have been suggestions that disturbances to muscle energy processes may also contribute to elevated CK levels after exercise (4). This has led to the measurement of serum CK concentration [CK] as an indicator of the status of skeletal muscle in sport (9,24,36,47).

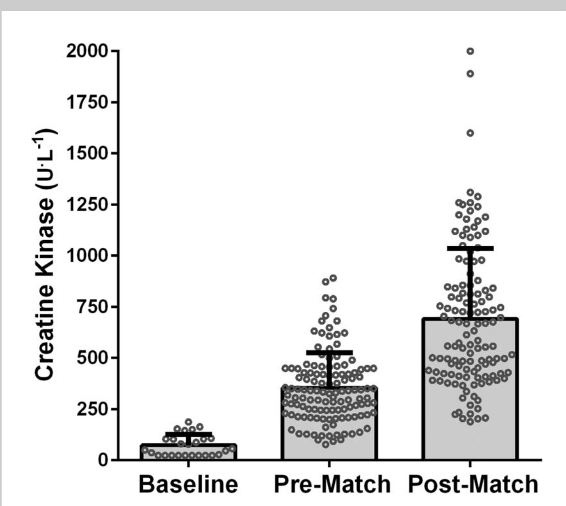

Figure 1. Creatine kinase concentrations for players' baseline (n = 26), and pre-match and post-match (n = 126) paired samples. Data are presented as individual data points and as mean and *SD*.

Player management strategies require the implementation of accurate and sensitive athlete-monitoring tools (6). Although subjective measures may demonstrate superior sensitivity in response to changes in training load (43), it is generally recommended that monitoring programs incorporate both objective and subjective measures. In a recent systematic review of the literature, CK was found to be one of the few objective measures to respond to acute increases and decreases in training load; although CK was unresponsive to chronic training (43), it was likely a result of reduced sensitivity and habituation to repeated bouts of exercise (34,35). The interpretation of CK monitoring as a basis to make practical amendments to athlete training and recovery practices over the course of a season has not been established in AF. Most of the literature has focused on the CK response in rugby (13,36,47) and soccer players (1,27). In elite rugby, strong associations have been observed between post-match [CK] and the number and magnitude of body contacts (13,36,47). Given that rugby tackles and impacts are of a greater intensity and higher number than in elite AF (18–20), it has been postulated that high-intensity running, accelerations, and decelerations are the primary source of muscle damage in AF (56). In elite junior AF, differences in activity profiles based on high-intensity running, acceleration, deceleration, and impact-related movement indices have been reported between players exhibiting high post-match [CK] and low post-match [CK] (56). However, these findings may not be generalizable to elite senior levels, given differences in match activity profiles and player characteristics (53) and study limitations such as a small sample size and single-sample measurements. Regardless, this research (56) indicates that CK may be influenced by variations in match-load indices in AF and holds potential for improving the individualization of athlete training and recovery practices to optimize performance in team sport athletes (56).

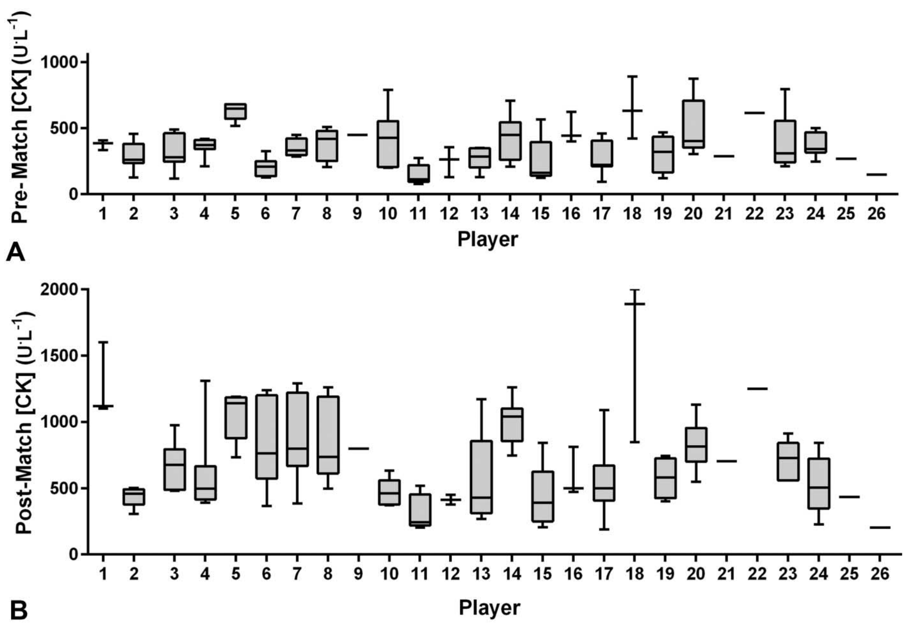

Figure 2. Individual player's (n = 26) pre-match (A) and post-match (B) creatine kinase concentrations. Data are presented as box and whisker plots with median, the 25th–75th percentile, and minimum-maximum. Single lines are for players with only one paired data for pre-post [CK].

The quantification of physical load in competitive sport has been enhanced through the introduction and widespread use of an athlete-tracking technology (3,6,12,54). This technology integrates global positioning system (GPS) devices with accelerometer microsensors, allowing players to be monitored in training and competition. Several indices are indicative of intensity, duration, eccentric loading, and body contact; all contributes to high levels of muscle damage (9,36). Weekly variations in training and match load are influenced by match turnaround time, the difficulty of previous matches, and travel (31). Elevated pre-match [CK] has been attributed to inadequate recovery within a week and/or residual muscle damage across consecutive weeks of an elite AF season (26). Although most of the literature has focused on post-match [CK], a more practical measure of the muscle damage incurred after competition should account for the effect of previous training and competition load. Measuring and accounting for pre-match [CK] is therefore important when interpreting post-match [CK] and the impact of competition on muscle status.

Increased activity profiles coupled with the frequency and impact velocity of physical collisions in AF highlight the potential for substantial muscle damage. The influence of indices of match load on the CK response in elite AF has not been established. Quantifying the muscle damage associated with measures of match load has direct implications for the weekly modification of recovery and training loads according to the physical demands imposed by previous matches and training sessions. Investigating muscle damage over a competitive season will establish findings that have practical relevance for effective long-term athlete management. The purpose of this study was to document the changes in serum [CK] as a result of AFL competition and to investigate the extent to which indices of match load can explain post-match [CK] in elite AF.

Methods

Experimental Approach to the Problem

A prospective repeated-measures single cohort longitudinal study design was used to investigate the relationships between serum creatine kinase [CK], an indirect marker of muscle damage, and specific indices of match load in elite AF. Professional players from a single AFL club were monitored across a competitive AFL season. Matches were played on a weekly basis from March to August (in-season excluding finals), with players completing weekly physical activity comprising football-related training, running, weights, supplementary conditioning such as cycling and swimming, and recovery modalities. The athlete-tracking wearable technology was used to assess physical activity and load during matches in the national AFL competition, and serum [CK] was used to assess muscle damage at baseline, before and after match.

Subjects

Twenty-six elite male professional AF players (mean ± SD: age: 22.8 ± 3.3 years, range: 18-30 years; height: 187.1 ± 7.2 cm;

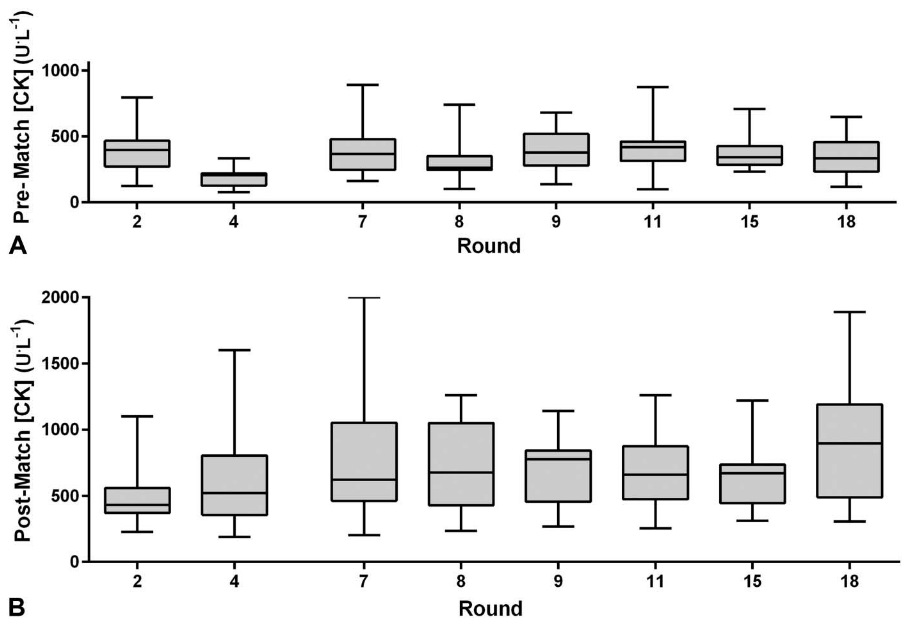

Figure 3. Pre-match (A) and post-match (B) creatine kinase concentrations for each competition round ($n = 8$). Data are presented as box and whisker plots with median, the 25th–75th percentile, and minimum-maximum.

and body mass: 85.8 ± 7.4 kg) representing a single club participated in the study. Approval of the study protocol was granted by Deakin University Human Research Ethics Committee, in accordance with the Helsinki Declaration. Participants were informed of the benefits and risks of the study, and written informed consent was obtained from all subjects before commencement of the study.

Procedures

Creatine kinase levels were measured using a fingertip blood sample with a disposable spring-loaded lancet. A sample of 30-μl capillary blood was collected into a heparinized capillary tube and pipetted onto a test strip (50). The blood sample was analyzed by Reflotron machinery (Roche Diagnostics, North Ryde, NSW, Australia) for the determination of serum [CK]. Capillary blood analyzed using this method displays an intra-assay reliability of <3% coefficient of variation (CV) (25).

Baseline serum [CK] was measured at the start of the preseason when players were in a rested state. In-season prematch and post-match, [CK] was collected during 8 rounds (round 2, 4, 7, 8, 9, 11, 15, and 18) of the AFL home and away season (22 rounds in total) to determine the extent of muscle damage incurred as a result of an elite AF match. All matches were played in the club's home state, did not require extensive travel, and except for one, were played at the Melbourne Cricket Ground (the league's premier ground and venue of the AFL Grand Final). The number of days turnaround from the preceding match varied based on the weekly competition schedule (2 × 6-day turnaround [e.g., Sunday to Saturday], 3 × 7-day turnaround, 2 × 8-day turnaround, and 1 × 9-day turnaround). As such, training and recovery varied during these weeks, which necessitated the need to control for this. Pre-match [CK] was collected 24–36 hours before match to control for the extent to which players had recovered from previous training and competition when entering the match. Post-match [CK] was collected 34–40 hours after match to coincide with the reported timeframes of peak [CK] after field team sport match-play (1,27). The change in [CK] from pre-match to post-match was expressed as a percent delta change (%ΔCK).

The athlete-tracking technology incorporating a 10-Hz GPS unit integrated with a 100-Hz triaxial accelerometer (MinimaxX v4.0; Catapult Sports, Melbourne, VIC, Australia) was used to quantify indices of match load. Notwithstanding acknowledged limitations (22), wearable GPS and microtechnology sensors are now common place in team sports to measure physical activity and impact loads (12,45) and provide meaningful data for coaches and performance support staff. The units were positioned on the upper thoracic spine area within a stitched pocket located on the player's guernsey (7,15,36). The GPS unit provides distance, time, speed, and geospatial position data (15). The intradevice reliability of this unit for measuring sprint distances of 15 and 30 m has been reported at 1.3 and 0.7% CV, with validity assessment demonstrating a *SEM* of 10.9% and 5.1%, respectively, for these sprint distances (10). Measurement of acceleration and deceleration, in reference to

Table 2. Generalized estimating equation model for post-match creatine kinase concentration [CK].*†

Indices	β (mean ± *SE*)	χ^2	*p*
Intercept	−88.87 ± 246.36	0.13	0.718
Impacts >3*g* (n)	14.63 ± 5.13	8.14	0.004
Game time (min)	8.38 ± 3.49	5.77	0.016
Distance (m)	−0.08 ± 0.05	3.41	0.065
Pre-match [CK]	0.27 ± 0.16	2.76	0.097
Player Load (au)	0.56 ± 0.43	1.72	0.189
Deceleration (−3 to −15 $m \cdot s^{-2}$) (*n*)	3.48 ± 3.32	1.10	0.295
Sprint distance (>7 $m \cdot s^{-1}$) (m)	−0.44 ± 0.44	1.00	0.320
Acceleration (3–15 $m \cdot s^{-2}$) (n)	−1.76 ± 3.06	0.33	0.565
Scale value	107,493		

*β = beta coefficient; χ^2 = Wald chi-square.
†Match-load indices are ordered from highest to lowest based on their ability to explain post-match [CK] (*n* = 114).

a player's change in velocity from GPS data, has demonstrated good-moderate validity (acceleration: CV = 1.9–4.3% and deceleration: 6.0%) (51). The in-built accelerometer measures physical and impact load across 3 axes (forward, vertical, and sideways) (7,56). Acceleration of the unit, and therefore the frequency and magnitude of movement, is measured in *g*-force equivalents for each movement axis and reported in *g*-force equivalents of standard gravity (*g*), with 1*g* equal to known gravity of 9.8 $m \cdot s^{-2}$ (19,36). Player Load incorporates the load experienced during all movements such as running, skill execution, and the impact experienced during body contact (56), and has a reported within- and between-device reliability of 1.9% CV (7). After each match, GPS and accelerometer data were downloaded and analyzed using the Catapult Sprint 5 software package. Quarter- and half-time breaks were manually omitted from the analysis, whereas data for a player known to suffer an injury during a match were also omitted for that week. Players were assumed to be injury-free or selected on the basis that they could successfully compete for the full duration of the match (comprising 4 ~30-minute quarters).

Indices indicative of total physical load, eccentric muscle loading, body contact, and high impact events were used as descriptors of match load. Individual game time, accelerometer-derived Player Load and impact events, and GPS-derived distance and number of entries into acceleration/deceleration zones were reported. Acceleration/deceleration and running speed zones were recorded in the software based on the zones used by Young et al. (56). Based on the literature, preliminary analysis of the data, and discussions focusing on the likely predictors of muscle damage, the following indices of match load were used in the analysis: game time (minutes), total distance (m), sprint distance (>7 $m \cdot s^{-1}$) (m), high acceleration (3–15 $m \cdot s^{-2}$) (m) and high deceleration (−3 to −15 $m \cdot s^{-2}$) entries (count), Player Load (AU), and impacts >3*g* (count). Impacts >3*g* was used as an index most likely to represent body contact in AF (19), with high-speed movements accounted for in alternate indices (e.g., acceleration/deceleration and sprinting).

Statistical Analyses

Each of the 26 players was represented by 5 ± 2 (range = 1–8) rounds of data, for a total of 126 individual weekly data files. Preliminary analyses included assessments of normality, linearity, and homoscedasticity, along with calculation of descriptive statistics (mean ± *SD* and range) and 95% confidence intervals (CIs).

All analyses were undertaken in the R statistical computing software version 3.4.1 (48). To determine the extent to which the 7 above-mentioned match-load indices and pre-match [CK] levels explained post-match [CK], 2 separate models were constructed. First, a generalized estimating equation (GEE) model was built using the Geepack package (21). For this, an exchangeable correlation structure, Gaussian distribution of the response variable (post-match [CK]), and identity link function were assumed. Second, a random forest (RF) was built using the randomForest package (32). A variable importance plot was constructed to identify the most informative match-load indices. For both models, predicted [CK] for each instance was outputted and visualized for comparison with observed values, whereas overall model performance was determined as the root mean square error (RMSE) of the prediction.

Results

Individual player baseline [CK] was 73 ± 53 $U \cdot L^{-1}$ (95% CI: 52–95; range = 24–188). In-season pre-match [CK] was 345 ± 170 $U \cdot L^{-1}$ and post-match [CK] was 691 ± 345 $U \cdot L^{-1}$. The pre- to post-match change in [CK] (%ΔCK) was 129 ± 152% (Table 1 and Figure 1). Considerable variability in [CK] was observed within and between players (Figure 2), between rounds (Figure 3), and from pre- to post-match (range = −55 to 838 $U \cdot L^{-1}$).

Results from the GEE revealed multiple indices of match-load explanatory of post-match [CK] (Table 2). Specifically, higher numbers of impacts >3*g* ($\chi^2 = 8.14$, $p = <0.004$) and longer game time ($\chi^2 = 5.77$, $p = <0.016$) were most strongly associated with higher post-match [CK]. The RMSE of the model was 316 $U \cdot L^{-1}$. Generalized estimating equation χ^2

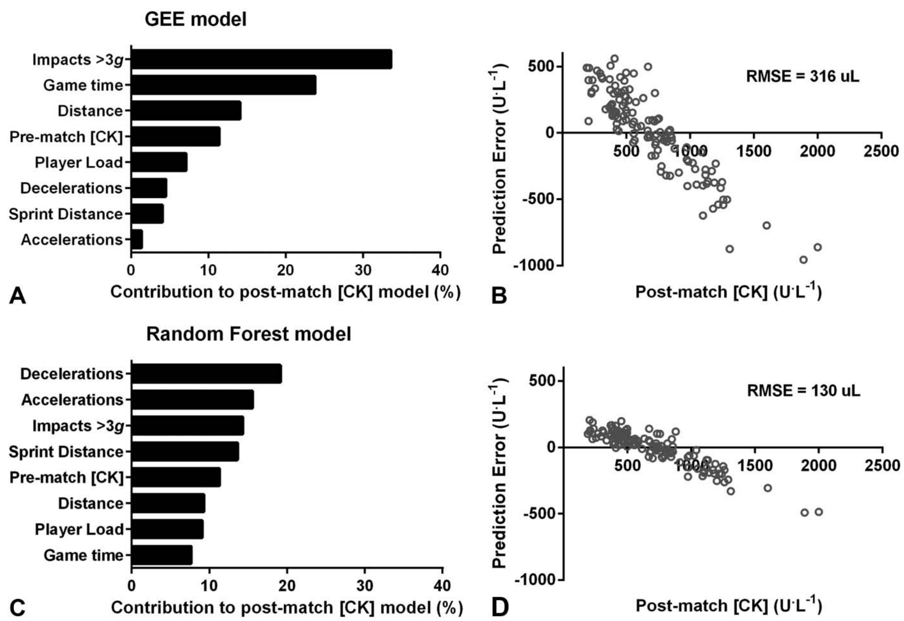

Figure 4. Relative importance of the match-load variables (A and C) and model error (B and D) to predict post-match creatine kinase concentration from the generalized estimating equation model (A and B) and the random forest model (C and D). GEE = generalized estimating equation; RMSE = root mean square error.

values for each match-load index were converted to a relative format (Figure 4A) in an attempt to apportion percent contribution and for purposes of comparison with the RF model. Impacts >3*g* accounted for 34%, along with game time (24%) and total distance (14%). Prediction error plotted against each observed [CK] value in the GEE model is shown in Figure 4B.

The variable importance plot from the RF model is displayed in Figure 4C, with the number of decelerations, accelerations, impacts >3*g*, and sprint distance to be the most influential in explaining post-match [CK]. Sprint actions (i.e., sprint distance, number of acceleration and deceleration events) accounted for 48% of post-match [CK], with impacts >3*g* contributing a further 14%. The corresponding prediction error for each observed [CK] value is shown in Figure 4D, and the RMSE was 130 $U \cdot L^{-1}$. In both the RF and GEE models, pre-match [CK] explained about 11% of post-match [CK].

Discussion

Creatine kinase, an indirect marker of muscle damage, was substantially elevated after elite AF competition, with an average 129% increase in [CK] from pre- to post-match. Both parametric and machine-learning analyses noted several indices of physical load that likely elicit this muscle damage during competition, with impacts >3*g* and high-intensity running variables (i.e., deceleration, acceleration, and sprint distance) to be the strongest predictors of post-match [CK]. These acute changes are in addition to already elevated pre-match [CK] levels (>4-fold above baseline), which seem indicative of residual muscle damage throughout a season (26,36). These findings highlight the physically demanding nature of elite AF, and the challenges in-season of individual player load management and match-to-match recovery.

Post-match [CK] values (691 ± 345 $U \cdot L^{-1}$) are representative of those reported in the literature for AF and other football codes. Examples include elite junior AF (413 ± 67 $U \cdot L^{-1}$) (56), elite rugby union (750 ± 99 $U \cdot L^{-1}$) (13), and elite soccer (520 ± 224 $U \cdot L^{-1}$) (44), (727 ± 235 $U \cdot L^{-1}$) (37). The variability (i.e., *SD*) in the current data is greater than that in other studies, which is likely a result of a larger sample size and/or matches played over multiple competition rounds. The average %ΔCK of 129% indicates that considerable muscle damage occurred during elite AF competition. Although the expression of [CK] values as a function of the percentage change from pre- to post-match is limited in the literature, this value is similar to those determined 24 hours after match in subelite rugby league (126%) (28), whereas in soccer, values as low as 84% (49) and as high as 710% (27) have been reported. Comparisons with previous research are made with caution due to methodological differences in the timeframes and method of CK collection, sample sizes, in-season competition or experimental friendlies, and the known differences between the level of competition (11) and the football codes (52).

Regardless, the results of the current study support the notion that the physical demands of elite AF competition elicit considerable muscle damage, and that events such as eccentric-based movements (4,9) and body contacts (36,47) are major contributors.

Running at a high speed places large eccentric strain on the body, with eccentric strain documented as a leading cause of muscle damage (4,25). Acceleration and deceleration are purported to exacerbate this damage response (25,27,56). In these instances, sarcomeres within individual muscle fibers may be overstretched or damaged from excessive load, resulting in sarcomeric degeneration from Z-disk fragmentation, changes to membrane permeability, and CK leak into interstitial fluid and ultimately the blood (8). In elite junior AF, Young et al. (56) segregated players into high and low post-match [CK] groups, with greater activity profiles (moderate to large effect sizes) reported for the high [CK] group. Correlations between [CK] and movement demands ranged from small to very large in the high [CK] group ($n = 7$), with high acceleration ($r = 0.75$), high deceleration ($r = 0.48$), running (0.60), and sprinting ($r = 0.42$) showing the strongest relationships. Thorpe and Sunderland (49) reported strong associations between %ΔCK and sprint number ($r = 0.86$), sprint distance ($r = 0.89$), and high-intensity running distance ($r = 0.92$) during a competitive soccer match, albeit within a small sample ($n = 7$). By contrast, and in a more comprehensive data set from an English Premier League club across an entire season, Scott et al. (44) found no relationship ($r = 0.002$–0.15) between any indicator of physical match performance and [CK] measured 48 hours after match. Unfortunately, pre-match [CK] was not measured, and although considerable individual player variability was noted, it was not accounted for in the analysis. All these studies draw their conclusions from correlation analysis or group comparison, whereas the current study used stronger analysis techniques that accounted for individual responses and/or the complexity of relationships that might exist. In addition, the analysis models used in our study included pre-match [CK], which was found to explain approximately 11% of the variance in post-match [CK]. This is important and was included to control for individual player pre-match [CK] values, which displayed considerable interindividual and intraindividual variability (Figure 2). Such pre-match variability is likely a result of variation in recovery from the previous week's match, for example, differences in previous post-match [CK], the turnaround time and number of days between matches, and the training program and adherence to recovery practices during each week.

The nature of AF competition exposes players to repeated collisions throughout the course of a competitive match (19,20). The speed and intensity of elite AF (20,54), coupled with increases in player size and strength (38), leads to a propensity for large impact forces during these physical collisions (18,19,38). The current study identified the number of impacts $>3g$ as a major contributor to elevated [CK] after elite AF competition. Research within rugby has reported that body contact is equally, if not, more damaging than eccentric-based movements, with strong correlations reported between the magnitude and frequency of contact events with [CK] (13,29,47). McLellan et al. (36) reported strong associations between the number of hit-ups (player being tackled) and [CK] 24–72 hours after elite rugby league competition. Despite the greater frequency and magnitude of physical collisions in rugby compared with AF (18,20,36), the current study demonstrates that body contact is also a significant cause of muscle damage in AF.

Our analysis methods attempted to apportion the contribution of contact and noncontact events to the level of muscle damage in AF competition. In the RF model, which showed considerably lower prediction errors, sprint actions (i.e., sprint distance, and number of acceleration and deceleration events) accounted for 48% of post-match [CK], with impacts $>3g$ contributing a further 14%. In the GEE model, impacts $>3g$ accounted for 34%, along with game time (24%) and total distance (14%). In practical terms, it is very difficult to apportion contribution, as many events will contribute, and in combination, as our results demonstrate. Furthermore, this will vary between players and rounds depending on the unique circumstances of each match. Experimental studies designed to address this question have been equally challenged because contact events have been added to running activities (29,46). The literature does suggest that running (acceleration, deceleration, and change of direction) will result in increased [CK] and that physical contact will result in further increases if the level of contact is good enough. For example, in small-sided games with and without contact, [CK] was elevated immediately after both conditions yet was larger and continued to rise 24 hours after the contact condition (29).

Comparisons between the performance of the GEE and RF models clearly indicated that the latter showed reduced error in predicting post-match [CK], particularly at low and high [CK] levels. Differences in the relative importance of the match-load indices were also noted between the 2 analysis approaches. These 2 considerations highlight the limitations of parametric, linear analyses when modeling dynamic, complex phenomena. The ability of the RF technique to account for nonlinearity in its output and to assign value to various interactions between the match-load indices is responsible for these differences in performance. Findings supporting machine learning as a preferred option in similar circumstances is noted in other recent research in the sports sciences. Examples include predicting athlete-perceived exertion during training (5) and match outcome (40) in AF.

Given the knowledge that individual player circumstances influence player management (41) and the individual variability evident in serum [CK] (4,23,39), the interpretation of [CK] and %ΔCK must be implemented on an individual basis. Supporting this, considerable variability was observed in %ΔCK (range = −55 to 838) in the current study. The observed variability may indicate that %ΔCK was influenced by variations in match demands, as well as interindividual and intraindividual variability in both pre-match and post-match [CK] (Figures 2 and 3). The literature suggests that individuals can be classified as "high responders" who exhibit high [CK] values with high variability and "low responders" who exhibit low [CK] with low variability, with level of training, muscle size, fiber type, and release of CK after exercise to be potential factors (9). This inherent variability may limit its usefulness as a monitoring tool in elite team sports beyond understanding the overall demands of match-play (44). Alternately, and provided individual baselines and player characteristics are taken into account (23), it may provide useful insights into instances when certain players, or the team as a whole, have experienced muscle damage greater than usual or are displaying residual levels of fatigue. As with any monitoring tool to facilitate coach decision-making, data need to be analyzed using appropriate techniques, interpreted individually and cautiously, and is best undertaken within a suite of practical, sport-specific measures (6,41,43).

Several limitations in the conduct of this study should be acknowledged and considered when interpreting the findings. Creatine kinase was the only marker of muscle damage used, and although it has been recommended as a preferred indicator to monitor fatigue in team sport athletes (24), many other blood-borne markers exist (e.g., aldolase, aspartate aminotransferase, lactate dehydrogenase, myoglobin, and troponin) (8). Furthermore, using more than one marker, and from both blood and urine, will provide a better estimation of muscle stress (8). The findings also need to be considered in light of known limitations of the application of GPS and accelerometer microtechnology in team sports (22), yet from a practical perspective and for the summation of data over an entire match, the units used in this study seem to have acceptable validity and reliability (16,45). The selection of match-load indices was intended to capture the main physical movements or actions within elite AF, although it is acknowledged that some overlap and correlation between indices will be evident. For example, total distance will encapsulate all running events, including acceleration, deceleration, and sprinting. Player load will encapsulate all impacts, including those from foot strikes in running and impacts from body contact. The results identified that impacts $>3g$ was a major contributor to post-match [CK], and although most of these impact events are likely to have come from body contact, some will be from noncontact events, including rapid change in direction and acceleration/deceleration (19). In addition, the inability to collect data in the instances of interstate travel and indoor matches resulted in the exclusion of a substantial number of potential data points. These omissions may have limited the ability to identify accurate trends in [CK] values. Despite these limitations, the current study investigated CK responses during multiple matches in a competitive season, reported both individual player and round data, and matched these to routinely collected match-load indices in elite team sport, thereby enhancing the practical interpretation and ecological validity of the findings.

Practical Applications

Creatine kinase, as an indicator of muscle damage, was considerably elevated as a result of elite AF competition. Specifically, impacts $>3g$ and high-intensity running variables (i.e., deceleration, acceleration, and sprint distance) were the strongest predictors of the post-match [CK]. This supports the application of CK as a global measure of muscle damage in elite AF, although with some caution given its cost, invasiveness, and inherent interindividual and intraindividual variability. Notwithstanding this, changes from post- to pre-match can provide an indication of recovery between matches, whereas changes from pre- to post-match can provide an indication of muscle damage elicited during competition. Furthermore, it appears that many match-load variables contribute to elevated post-match [CK], usually in combination, although extremely large values may be overly influenced by a single event (e.g., excessive impact from a collision). In a contact sport such as AF, impacts within a match are unavoidable. From a training perspective, however, repeated and regular exposure to manageable amounts of high-speed running and eccentric loading should help minimize muscle damage and develop habitual adaptations to accustomed, sport-specific activities.

Acknowledgments

The authors thank the players and staff of the AFL club for their participation and support of this project. No external financial support was provided for this study.

References

1. Ascensão, A, Rebelo, A, Oliveira, E, Marques, F, Pereira, L, and Magalhães, J. Biochemical impact of a soccer match - analysis of oxidative stress and muscle damage markers throughout recovery. *Clin Biochem* 41: 841–851, 2008.
2. Aughey, RJ. Australian Football player work rate: Evidence of fatigue and pacing? *Int J Sport Physiol Perform* 5: 394–405, 2010.
3. Aughey, RJ. Applications of GPS technologies to field sports. *Int J Sport Physiol Perform* 6: 295–310, 2011.
4. Baird, MF, Graham, SM, Baker, JS, and Bickerstaff, GF. Creatine-kinase- and exercise-related muscle damage implications for muscle performance and recovery. *J Nutr Metab* 2012: 1–13, 2012.
5. Bartlett, JD, O'Connor, F, Pitchford, N, Torres-Ronda, L, and Robertson, SJ. Relationships between internal and external training load in team-sport athletes: Evidence for an individualized approach. *Int J Sport Physiol Perform* 12: 230–234, 2017.
6. Bourdon, PC, Cardinale, M, Murray, A, Gastin, P, Kellmann, M, Varley, MC, et al. Monitoring athlete training loads: Consensus statement. *Int J Sport Physiol Perform* 12: S2161–S2170, 2017.
7. Boyd, LJ, Ball, K, and Aughey, RJ. The reliability of MinimaxX accelerometers for measuring physical activity in Australian Football. *Int J Sport Physiol Perform* 6: 311–321, 2011.

8. Brancaccio, P, Lippi, G, and Maffulli, N. Biochemical markers of muscular damage. *Clin Chem Lab Med* 48: 757–767, 2010.
9. Brancaccio, P, Maffulli, N, and Limongelli, FM. Creatine kinase monitoring in sport medicine. *Br Med Bull* 81–82: 209–230, 2007.
10. Castellano, J, Casamichana, D, Calleja-González, J, San Román, J, and Ostojic, SM. Reliability and accuracy of 10 Hz GPS devices for short-distance exercise. *J Sports Sci Med* 10: 233–234, 2011.
11. Clarke, AC, Anson, JM, and Pyne, DB. Neuromuscular fatigue and muscle damage after a women's rugby sevens tournament. *Int J Sport Physiol Perform* 10: 808–814, 2015.
12. Cummins, C, Orr, R, O'Connor, H, and West, C. Global positioning systems (GPS) and microtechnology sensors in team sports: A systematic review. *Sports Med* 43: 1025–1042, 2013.
13. Cunniffe, B, Hore, AJ, Whitcombe, DM, Jones, KP, Baker, JS, and Davies, B. Time course of changes in immunoendocrine markers following an international rugby game. *Eur J Appl Physiol* 108: 113–122, 2010.
14. Dawson, B, Hopkinson, R, Appleby, B, Stewart, G, and Roberts, C. Player movement patterns and game activities in the Australian Football League. *J Sci Med Sport* 7: 278–291, 2004.
15. Edgecomb, SJ and Norton, KI. Comparison of global positioning and computer-based tracking systems for measuring player movement distance during Australian Football. *J Sci Med Sport* 9: 25–32, 2006.
16. Gabbett, TJ. Quantifying the physical demands of collision sports: Does microsensor technology measure what it claims to measure? *J Strength Cond Res* 27: 2319–2322, 2013.
17. Gao Smith, TT and Gallagher, S. Impact of loading and work rest intervals on muscle micro-trauma. *Int J Ind Ergon* 66: 161–168, 2018.
18. Gastin, PB, McLean, O, Spittle, M, and Breed, RV. Quantification of tackling demands in professional Australian football using integrated wearable athlete tracking technology. *J Sci Med Sport* 16: 589–593, 2013.
19. Gastin, PB, Mclean, OC, Breed, RV, and Spittle, M. Tackle and impact detection in elite Australian football using wearable microsensor technology. *J Sports Sci* 32: 947–953, 2014.
20. Gray, AJ and Jenkins, DG. Match analysis and the physiological demands of Australian Football. *Sports Med* 40: 347–360, 2010.
21. Halekoh, U, Højsgaard, S, and Yan, J. The R package geepack for generalized estimating equations. *J Stat Soft* 15: 1–11, 2006.
22. Haugen, T and Buchheit, M. Sprint running performance monitoring: Methodological and practical considerations. *Sports Med* 46: 641–656, 2016.
23. Hecksteden, A, Pitsch, W, Julian, R, Pfeiffer, M, Kellmann, M, Ferrauti, A, et al. A new method to individualize monitoring of muscle recovery in athletes. *Int J Sport Physiol Perform* 12: 1137–1142, 2017.
24. Hecksteden, A, Skorski, S, Schwindling, S, Hammes, D, Pfeiffer, M, Kellmann, M, et al. Blood-borne markers of fatigue in competitive athletes–Results from simulated training camps. *PLoS One* 11: e0148810, 2016.
25. Howatson, G and Milak, A. Exercise-induced muscle damage following a bout of sport specific repeated sprints. *J Strength Cond Res* 23: 2419–2424, 2009.
26. Hunkin, SL, Fahrner, B, and Gastin, PB. Creatine kinase and its relationship with match performance in elite Australian Rules football. *J Sci Med Sport* 17: 332–336, 2014.
27. Ispirlidis, I, Fatouros, IG, Jamurtas, AZ, Nikolaidis, MG, Michailidis, I, Douroudos, I, et al. Time-course of changes in inflammatory and performance responses following a soccer game. *Clin J Sport Med* 18: 423–431, 2008.
28. Johnston, RD, Gabbett, TJ, Jenkins, DG, and Hulin, BT. Influence of physical qualities on post-match fatigue in rugby league players. *J Sci Med Sport* 18: 209–213, 2015.
29. Johnston, RD, Gabbett, TJ, Seibold, AJ, and Jenkins, DG. Influence of physical contact on neuromuscular fatigue and markers of muscle damage following small-sided games. *J Sci Med Sport* 17: 535–540, 2014.
30. Kary, JM. Diagnosis and management of quadriceps strains and contusions. *Curr Rev Musculoskelet Med* 3: 26–31, 2010.
31. Kelly, VG and Coutts, AJ. Planning and monitoring training loads during the competition phase in team sports. *Strength Cond J* 29: 32–37, 2007.
32. Liaw, A and Wiener, M. Classification and regression by RandomForest. *R News* 2: 18–22, 2002.
33. Maffulli, N and Del Buono, A. Muscle strains: Pathophysiology and new classification models. In: *Nuclear Medicine and Radiologic Imaging in Sports Injuries.* AWJM Glaudemans, RAJO Dierckx, JLMA Gielen, and J Zwerver, eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2015. pp. 939–948.
34. Margaritelis, NV, Theodorou, AA, Baltzopoulos, V, Maganaris, CN, Paschalis, V, Kyparos, A, et al. Muscle damage and inflammation after eccentric exercise: Can the repeated bout effect be removed? *Physiol Rep* 3: e12648, 2015.
35. McHugh, MP. Recent advances in the understanding of the repeated bout effect: The protective effect against muscle damage from a single bout of eccentric exercise. *Scand J Med Sci Sports* 13: 88–97, 2003.
36. McLellan, CP, Lovell, DI, and Gass, GC. Biochemical and endocrine response to impact and collision during elite rugby league match play. *J Strength Cond Res* 25: 1553–1562, 2011.
37. Nedelec, M, McCall, A, Carling, C, Legall, F, Berthoin, S, and Dupont, G. The influence of soccer playing actions on the recovery kinetics after a soccer match. *J Strength Cond Res* 28: 1517–1523, 2014.
38. Norton, KI, Craig, NP, and Olds, TS. The evolution of Australian football. *J Sci Med Sport* 2: 389–404, 1999.
39. Prelle, A, Tancredi, L, Sciacco, M, Chiveri, L, Comi, GP, Battistel, A, et al. Retrospective study of a large population of patients with asymptomatic or minimally symptomatic raised serum creatine kinase levels. *J Neurol* 249: 305–311, 2002.
40. Robertson, S, Back, N, and Bartlett, JD. Explaining match outcome in elite Australian Rules football using team performance indicators. *J Sports Sci* 34: 637–644, 2016.
41. Robertson, S, Bartlett, JD, and Gastin, PB. Red, amber, or green? Athlete monitoring in team sport: The need for decision-support systems. *Int J Sport Physiol Perform* 12: 73–79, 2017.
42. Saengsirisuwan, V, Phadungkij, S, and Pholpramool, C. Renal and liver functions and muscle injuries during training and after competition in Thai boxers. *Br J Sports Med* 32: 304–308, 1998.
43. Saw, A, Main, LC, and Gastin, PB. Monitoring the athlete training response: Subjective self-reported measures trump commonly used objective measures: A systematic review. *Br J Sports Med* 50: 281–291, 2016.
44. Scott, A, Malone, JJ, Morgans, R, Burgess, D, Gregson, W, Morton, JP, et al. The relationship between physical match performance and 48-h post-game creatine kinase concentrations in English Premier League soccer players. *Int J Sports Sci Coach* 11: 846–852, 2016.
45. Scott, MTU, Scott, TJ, and Kelly, VG. The validity and reliability of global positioning systems in team sport: A brief review. *J Strength Cond Res* 30: 1470–1490, 2016.
46. Singh, TKR, Guelfi, KJ, Landers, G, Dawson, B, and Bishop, D. A comparison of muscle damage, soreness and performance following a simulated contact and non-contact team sport activity circuit. *J Sci Med Sport* 14: 441–446, 2011.
47. Takarada, Y. Evaluation of muscle damage after a rugby match with special reference to tackle plays. *Br J Sports Med* 37: 416–419, 2003.
48. Team, RC. *R: A Language and Environment for Statistical Computing.* Vienna, Austria: R Foundation for Statistical Computing, 2013.

49. Thorpe, R and Sunderland, C. Muscle damage, endocrine, and immune marker response to a soccer match. *J Strength Cond Res* 26: 2783–2790, 2012.

50. Twist, C and Eston, R. The effects of exercise-induced muscle damage on maximal intensity intermittent exercise performance. *Eur J Appl Physiol* 94: 652–658, 2005.

51. Varley, MC, Fairweather, IH, and Aughey, RJ. Validity and reliability of GPS for measuring instantaneous velocity during acceleration, deceleration, and constant motion. *J Sports Sci* 30: 121–127, 2012.

52. Varley, MC, Gabbett, T, and Aughey, RJ. Activity profiles of professional soccer, rugby league and Australian football match play. *J Sports Sci* 32: 1858–1866, 2014.

53. Veale, JP and Pearce, AJ. Profile of position movement demands in elite junior Australian rules footballers. *J Sports Sci Med* 8: 320–326, 2009.

54. Wisbey, B, Montgomery, PG, Pyne, DB, and Rattray, B. Quantifying movement demands of AFL football using GPS tracking. *J Sci Med Sport* 13: 531–536, 2010.

55. Woods, CT, Robertson, S, and Collier, NF. Evolution of game-play in the Australian Football League from 2001 to 2015. *J Sports Sci* 35: 1879–1887, 2017.

56. Young, WB, Hepner, J, and Robbins, DW. Movement demands in Australian Rules football as indicators of muscle damage. *J Strength Cond Res* 26: 492–496, 2012.